

Essays on Direct-to-Consumer Sales Models in the Automotive Industry

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Zusammenfassung

Die Umgestaltung von Vertriebs- und Preismodellen in der Automobilindustrie hat in den letzten Jahren erheblich an Bedeutung gewonnen. Motiviert durch den zunehmenden Wettbewerbsdruck, Fortschritte im Bereich digitaler Technologien und sich ändernde Kundenbedürfnisse haben mehrere Automobilhersteller begonnen, eine Umstellung vom vorherrschenden indirekten, händlerbasierten Vertriebsmodell mit kundenindividuell verhandelten Preisen hin zu einem Direktvertriebsmodell mit nicht verhandelbaren Einheitspreisen in Erwägung zu ziehen. Obwohl dieser Wandel möglicherweise zu den tiefgreifendsten Veränderungen im Automobilhandel seit Jahrzehnten zählt, sind die Auswirkungen auf die maßgeblichen Akteure – Kund/innen, Händler/innen und Hersteller – bislang noch kaum untersucht. Die vorliegende Dissertation adressiert diese Lücke und untersucht die Auswirkungen solcher Transformationen hin zu einem Direktvertriebsmodell aus einer Multi-Stakeholder-Perspektive. Der erste Aufsatz (Kapitel 2) untersucht, wie Kund/innen den Wegfall von Preisverhandlungen wahrnehmen, und quantifiziert die psychologischen Kosten, die sie mit Preisverhandlungen verbinden. Basierend auf einer Online-Befragung von 510 Neuwagenkund/innen in Deutschland wird ein neues empirisches Vorgehen zur Schätzung individueller *Verhandlungskosten* entwickelt. Die Ergebnisse zeigen, dass die meisten Kund/innen Preisverhandlungen nicht mögen, sie aber als notwendiges Übel erachten, um den Preis zu senken. Der zweite Aufsatz (Kapitel 3) analysiert, wie sich der Übergang zu einem Direktvertriebsmodell auf die Wettbewerbsintensität und das Differenzierungsverhalten zwischen Autohändler/innen auswirkt. Auf Grundlage eines natürlichen Experiments und zweier Telefonbefragungen deutscher Neuwagenhändler/innen deuten die Ergebnisse darauf hin, dass Händler/innen in einem Direktvertriebsmodell den Preiswettbewerb mit Händler/innen, welche die gleiche Marke vertreiben, als signifikant weniger intensiv wahrnehmen als Händler/innen, die unter traditionellen Vertriebs- und Preismodellen agieren. Außerdem scheinen diese Händler/innen weniger stark auf preisbezogene Differenzierungstaktiken zurückzugreifen, kompensieren dies jedoch nicht durch stärkere nicht-preisbezogene Differenzierung. Der dritte Aufsatz (Kapitel 4) untersucht die Auswirkungen von Direktvertriebstransformationen auf das Absatzvolumen der Automobilhersteller. Unter Verwendung zweier Fallstudien, monatlicher Absatzdaten und der synthetischen Kontrollmethode deuten die Ergebnisse darauf hin, dass beide Umstellungen auf Direktvertriebsmodelle mit einem Rückgang des monatlichen Absatzes von Neuwagen einhergehen. Zusammengefasst bieten die drei Aufsätze eine umfassende empirische Bewertung einiger tiefgreifender Auswirkungen von Direktvertriebsmodelltransformationen im Automobilhandel und liefern relevante Erkenntnisse sowohl für die akademische Forschung als auch für die Entscheidungsfindung von Führungskräften.

Summary

The transformation of sales and pricing models in the automotive industry has gained considerable importance in recent years. Motivated by increasing competitive pressure, advancements in digital technologies, and changing customer needs, several car manufacturers have started to consider transitioning from the prevailing indirect, dealer-based sales model with customer-individually negotiated prices to a direct-to-consumer sales model with uniform, non-negotiable prices. While this change is potentially among the most profound shifts in automotive retailing in decades, its implications for the key stakeholders – customers, retailers, and manufacturers – are still scarcely studied. This dissertation addresses this gap and examines the effects of such direct sales model transformations from a multi-stakeholder perspective. The first paper (Chapter 2) investigates how customers perceive the elimination of price negotiations and quantifies the psychological costs they associate with negotiating the price. Based on an online survey of 510 recent new car customers, this paper develops a novel empirical approach to estimate customer-individual *bargaining costs*. The results suggest that most buyers dislike price negotiations but perceive them as a necessary evil to lower the price. The second paper (Chapter 3) examines how the transition to direct sales affects competitive intensity and differentiation behavior among car dealers. Drawing on a natural experiment and two telephone surveys of German new car dealers, the results suggest that under a direct sales model, dealers perceive price competition with other dealers selling the same brand as significantly less intense than dealers operating under traditional sales and pricing models. Furthermore, these dealers appear to use price-related differentiation tactics less strongly but do not compensate for this through stronger non-price differentiation. The third paper (Chapter 4) investigates the sales volume effects of transitioning to direct sales for car manufacturers. Using two real-world event studies, monthly sales volume data, and the synthetic control method, the results indicate that both transitions to direct-to-consumer sales models are followed by a decline in monthly new car sales volumes. Together, the three papers offer a comprehensive empirical assessment of several profound effects of direct sales model transformations in automotive retailing and give useful insights for both academic research and managerial decision-making

Contents

1 Introduction	1
2 Who Enjoys Going to the Bargaining Table? An Empirical Analysis of Bargaining Costs in Automotive Transactions	11
2.1 Introduction.....	13
2.2 Related Literature and Contribution	15
2.2.1 Choice of pricing schemes	16
2.2.2 Bargaining costs	17
2.2.3 Determinants of bargaining initiation propensity	19
2.2.4 Choice under uncertainty	20
2.3 Theory and Framework.....	21
2.3.1 Individual bargaining costs	21
2.3.2 Drivers of bargaining costs	22
2.4 Data and Methodology.....	24
2.4.1 Measurement of bargaining costs.....	24
2.4.2 Data description	27
2.4.3 Drivers of bargaining costs	28
2.5 Results.....	29
2.5.1 Description of bargaining perceptions and bargaining costs	29
2.5.2 Investigation of drivers of bargaining costs	34
2.5.3 Robustness check	39
2.6 Discussion, Conclusion, and Implications	45
3 Competing within the Brand – Intra-Brand Competition and Differentiation in the Automotive Direct-to-Consumer Sales Era	49
3.1 Introduction.....	51
3.2 Related Literature, Contribution, and Theoretical Framework.....	54
3.2.1 Vertical restraints and competition	54
3.2.2 Vertical restraints and price versus non-price competition.....	56
3.2.3 Intra-brand competition and dealer service offering	57
3.2.4 Gap in existing literature and contribution.....	58
3.2.5 Theoretical framework	59
3.3 Data and Methodology.....	60
3.3.1 Data collection and research approach.....	60
3.3.2 Variable description	61
3.3.3 Data cleaning and missing value data imputation.....	63
3.3.4 Data description	64
3.3.5 Methodology	66
3.4 Analysis and Results	68

3.4.1 Evaluation of perceived intra-brand competition intensity	68
3.4.2 Analysis of differentiation tactics and efforts	76
3.4.3 Robustness check	79
3.5 Discussion, Conclusion, and Implications	88
4 Shifting Gears – Evaluating the Sales Volume Impact of Direct-to-Consumer Sales Model Transformations	93
4.1 Introduction.....	95
4.2 Literature Review, Research Contribution, and Theoretical Framework	97
4.2.1 Studies on sales models and their transformations	97
4.2.2 Studies on pricing models and their transformations.....	100
4.2.3 Gap in existing literature, research contribution, and theoretical framework...	103
4.3 Data and Methodology.....	106
4.3.1 Overview and justification of methodology.....	106
4.3.2 Empirical model	108
4.3.3 Variable selection, data collection, and data description	109
4.4 Analysis and Results	111
4.4.1 Initial monthly sales volume analyses.....	111
4.4.2 Construction and composition of synthetic control groups.....	113
4.4.3 Detailed monthly sales volume analyses.....	116
4.5 Robustness check and model validation	121
4.5.1 Alternative model specifications.....	121
4.5.2 Leave-one-out analyses	125
4.5.3 Placebo-in-space tests	125
4.6 Discussion, Conclusion, and Managerial Implications.....	129
5 Conclusion.....	135
References	143
A Appendix Chapters 1 and 2	157
A.1 List of direct sales model introductions	158
A.2 Distribution of respondents’ transaction prices and leasing rates	159
A.3 Customer survey questions.....	160
A.4 Confirmatory factor analysis (CFA) methodology and results	171
A.5 Correlation matrices latent factors	174
A.6 Control variables regression analyses	175
A.7 Overview absolute values bargaining costs (including components)	175
A.8 Additional figures adaptive and non-adaptive bargaining cost estimations.....	176
A.9 Additional regression outputs.....	178
A.10 Classification of respondents as offline and online customers	188
B Appendix Chapter 3	189
B.1 List of direct sales model implementation plans by sampled OEMs	190

B.2 List and description of focal variables.....	191
B.3 Additional sample summary statistics	193
B.4 Additional descriptive figures for focal variables	204
B.5 Additional regression outputs.....	207
C Appendix Chapter 4	223
C.1 Summary statistics and composition of synthetic control groups	224
C.2 Additional confounder analyses	228
C.3 Additional robustness checks	230

List of Figures

Figure 1.1: Comparison wholesale versus direct sales model.....	4
Figure 1.2: Conceptual framework and chapter overview for this dissertation	7
Figure 2.1: Measurement of bargaining costs	26
Figure 2.2: Distribution and mean of the expected relative discount (adaptive version).....	31
Figure 2.3: Distribution of the mean indifference fixed price discount	33
Figure 2.4: Distribution of mean bargaining costs	34
Figure 3.1: Perceived intra-brand competition intensity - frequency distribution by treatment and control groups.....	68
Figure 3.2: Perceived main competitor - frequency distribution by treatment and control groups	68
Figure 3.3: Perceived competition intensity for different competitive dimensions - frequency distribution by treatment and control group.....	72
Figure 3.4: Comparison of perceived intra-brand general competition intensity between control and treatment groups.....	75
Figure 3.5: Comparison of perceived inter-brand general competition intensity between control and treatment groups.....	76
Figure 3.6: Brand-level coefficients from multiple linear regression analyses of perceived competition intensity variables.....	85
Figure 4.1: Normalized monthly sales volume of BMW South Africa versus control group units	111
Figure 4.2: Normalized monthly sales volume of Mercedes Austria versus control group units	112
Figure 4.3: Monthly absolute sales volume comparison between BMW South Africa and its synthetic control group	117
Figure 4.4: Monthly absolute sales volume comparison between Mercedes Austria and its synthetic control group.....	117
Figure 4.5: Monthly relative sales volume gap between BMW South Africa and its synthetic control group.....	117
Figure 4.6: Monthly relative sales volume gap between Mercedes Austria and its synthetic control group	117
Figure 4.7: Monthly relative sales volume gap between BMW South Africa and its synthetic control for different model specifications.....	123
Figure 4.8: Monthly relative sales volume gap between Mercedes Austria and its synthetic control for different model specifications	124
Figure 4.9: Placebo in-space analyses of pseudo-treatment effects for donor pool units of BMW South Africa	128
Figure 4.10: Post-/ pre-treatment MSPE ratios for placebo analyses for donor pool units of BMW South Africa	128
Figure 4.11: Placebo in-space analyses of pseudo-treatment effects for donor pool units of Mercedes Austria	128
Figure 4.12: Post-/ pre-treatment MSPE ratios for placebo analyses for donor pool units of Mercedes Austria	128

LIST OF FIGURES.

Figure A.1: Distribution of transaction prices of respondents in previous transaction.....	159
Figure A.2: Distribution of monthly leasing rates of respondents in previous transaction....	159
Figure A.3: Distribution of the adaptive indifference fixed price discount	176
Figure A.4: Distribution of adaptive bargaining costs	176
Figure A.5: Distribution of the non-adaptive indifference fixed price discount.....	176
Figure A.6: Distribution of non-adaptive bargaining costs.....	177
Figure A.7: Illustration of average discount ranges, expected discounts, and indifference fixed price discounts for the adaptive, non-adaptive, and mean version	177
Figure A.8: Distribution of the mean expected discount	178
Figure B.1.a: Regional dealership distribution by first digit of ZIP-code.....	196
Figure B.1.b: Regional Mercedes dealership distribution by first digit of ZIP-code.....	197
Figure B.2: Agency model evaluation - frequency distribution by treatment and control groups	204
Figure B.3: Uniform price evaluation - frequency distribution by treatment and control groups	204
Figure B.4: Usage intensity of customer-individually negotiated discounts to differentiate - frequency distribution by treatment and control groups	204
Figure B.5: Usage intensity of general, customer-independent discounts to differentiate - frequency distribution by treatment and control groups	205
Figure B.6: Usage intensity of product-related extras to differentiate - frequency distribution by treatment and control groups	205
Figure B.7: Usage intensity of service-related extras to differentiate - frequency distribution by treatment and control groups	205
Figure B.8: Usage intensity of measures to improve customer targeting to differentiate - frequency distribution by treatment and control groups	206
Figure B.9: Usage intensity of measures to improve the product offering to differentiate - frequency distribution by treatment and control groups	206
Figure B.10: Usage intensity of measures to improve the service offering to differentiate - frequency distribution by treatment and control groups	206
Figure B.11: Usage intensity of measures to improve customer loyalty to differentiate - frequency distribution by treatment and control groups	207
Figure B.12: Brand-level coefficients from multiple linear regression analyses of price-related differentiation tactics variables	217
Figure B.13: Brand-level coefficients from multiple linear regression analyses of non-price-related differentiation tactics variables.....	218
Figure B.14: Brand-level means for all focal variables with visualization of interquartile ranges and median values for brand-level means.....	219
Figure C.1: Covid-19 stringency index for BMW South Africa and its donor pool units.....	228
Figure C.2: Covid-19 stringency index for BMW South Africa and the top-weighted control units in its synthetic control group.....	228
Figure C.3: Covid-19 stringency index for Mercedes Austria and its donor pool units	229
Figure C.4: Covid-19 stringency index for Mercedes Austria and the top-weighted control units in its synthetic control group.....	229

Figure C.5: Covid-19 stringency index for Mercedes Austria and the top-weighted control units in its synthetic control group for alternative model specification with Covid-19 stringency index-restricted donor pool.....	230
Figure C.6: Leave-one-out distribution of monthly relative sales volume gaps between BMW South Africa and its synthetic control group.....	231
Figure C.7: Leave-one-out distribution of monthly relative sales volume gaps between Mercedes Austria and its synthetic control group.....	231

List of Tables

Table 1.1: Literature overview on negotiation research.....	20
Table 2.1: Sample summary statistics	28
Table 2.2: Descriptive statistics discount expectations, indifference fixed price discounts, and relative bargaining costs	30
Table 2.3: Multiple linear regression results for different model specifications (dependent variable: mean relative bargaining costs)	36
Table 2.4: Multiple linear regression results for different model specifications (dependent variable: adaptive relative bargaining costs)	40
Table 2.5: Multiple linear regression results for different model specifications (dependent variable: non-adaptive relative bargaining costs).....	42
Table 3.1: Summary statistics for the 2024 and 2022 samples	65
Table 3.2: Multiple linear regression results for different model specifications (REP_IntraIntensity)	70
Table 3.3: Logistic regression results for different model specifications (REP_MainComp). 71	
Table 3.4: Multiple linear regression results for perceived competition intensity variables ..	74
Table 3.5: Multiple linear regression results for price-related differentiation tactics variables	78
Table 3.6: Multiple linear regression results for non-price-related differentiation tactics variables	78
Table 3.7: Overview of robustness checks	80
Table 3.8: Multiple linear regression results for perceived competition intensity variables with raw (uncleaned, non-imputed) data.....	81
Table 3.9: Multiple linear regression results for perceived competition intensity variables for different subsamples	83
Table 4.1: Balancing properties of main models' predictor sets for BMW South Africa and Mercedes (MB) Austria.....	115
Table 4.2: Multiple linear regression results of logarithmic monthly sales volumes with respect to Covid-19 stringency index for Mercedes Austria and its donor pool units.....	119
Table 4.3: Subsample multiple linear regression results of logarithmic monthly sales volumes with respect to Covid-19 stringency index for Mercedes Austria and its donor pool units.....	120
Table 4.4: Overview of alternative model specifications for BMW South Africa and Mercedes Austria for the respective main models	122
Table 5.1: Summary of research design, main findings, and implications across chapters ...	139
Table A.1: List of direct sales model introductions by OEMs.....	158
Table A.2.a: Confirmatory factors analysis (CFA) results – search behavior-specific factors	172
Table A.2.b: Confirmatory factors analysis (CFA) results – general personality traits.....	173
Table A.3.a: Correlation matrix for latent factors with factor loading-weighted items.....	174
Table A.3.b: Correlation matrix for latent factors with equal-weighted items	174
Table A.4: Control variables multiple linear regression analyses.....	175

LIST OF TABLE.

Table A.5: Absolute values for transaction prices/ leasing rates, expected discounts, indifference fixed price discounts, and bargaining cost.....	175
Table A.6: Multiple linear regression results for different model specifications (dependent variable: difference between adaptive and non-adaptive relative bargaining costs).....	178
Table A.7: Multiple linear regression results for different model specifications (dependent variable: (explicit) bargaining willingness).....	179
Table A.8: Logistic regression results for different model specifications (dependent variable: bargaining indicator)	180
Table A.9: Subsample regression results for female, male, younger, and older respondents	181
Table A.10: Subsample regression results for purchase, leasing, financing, lower vehicle price, and higher vehicle price respondents in their most recent new car transaction	182
Table A.11: Subsample regression results for online and offline respondents, as well as respondents that did and did not bargain in their most recent new car transaction.....	183
Table A.12: Multiple linear regression results including different interaction effects with quality consciousness	184
Table A.13: Multiple linear regression results including different interaction effects with sale proneness.....	185
Table A.14: Multiple linear regression results including different interaction effects with car enthusiasm	186
Table A.15: Multiple linear regression results including different interaction effects with risk propensity	187
Table B.1: List of direct sales model implementation plans for the German market by OEMs	190
Table B.2.a: List and description of focal variables (repeated survey questions and perceived competitive intensity)	191
Table B.2.b: List and description of focal variables (differentiation tactics usage).....	192
Table B.3.a: Brand split 2024 sample by sales partnerships and main brands (based on revenue) compared to actual market shares	193
Table B.3.b: Brand split 2022 sample by sales partnerships and mono-brand dealerships compared to actual market shares	194
Table B.4: Additional summary statistics 2024 sample	195
Table B.5: Distribution of annual car sales and new car sales 2022 and 2023	197
Table B.6: Distribution of annual car sales and new car sales 2021	198
Table B.7: Distribution of new car sales shares 2022 and 2023, online sales channel shares 2022, and electric vehicle sales shares 2022	198
Table B.8: Distribution of new car sales shares 2021 and average online sales channel shares	199
Table B.9: Descriptive statistics for annual car sales, new car sales, and new car sales shares 2022 and 2023, stock vehicles, employees, online channel sales shares, and EV sales share 2022	199
Table B.10: Descriptive statistics for annual car sales, new car sales, and new car sales shares 2021, and average online channel sales shares	199
Table B.11. Descriptive statistics for OEM-level numbers of sales partners, service partners, and branches (“Niederlassungen”) 2024	200

Table B.12: Descriptive statistics for OEM-level numbers of sales partners, service partners, and branches (“Niederlassungen”) 2022	200
Table B.13: Summary statistics for Mercedes dealers of the 2024 and 2022 samples	200
Table B.14: Additional summary statistics for Mercedes dealers of the 2024 sample	201
Table B.15: Distribution of annual car sales and new car sales 2022 and 2023 (Mercedes dealers of the 2024 sample).....	201
Table B.16: Distribution of annual car sales and new car sales 2021 (Mercedes dealers of the 2022 sample)	202
Table B.17: Distribution of new car sales shares 2022 and 2023, online sales channel shares 2022, and electric vehicle sales shares 2022 (Mercedes dealers of the 2024 sample).....	202
Table B.18: Distribution of new car sales shares 2021 and average online sales channel shares (Mercedes dealers of the 2022 sample).....	203
Table B.19: Descriptive statistics for annual car sales, new car sales, and new car sales shares 2022 and 2023, stock vehicles, employees, online channel sales shares, and EV sales share 2022 (Mercedes dealers of the 2024 sample)	203
Table B.20: Descriptive statistics for annual car sales, new car sales, and new car sales shares 2021, and average online channel sales shares (Mercedes dealers of the 2022 sample)	203
Table B.21: Multiple linear regression results for different model specifications (REP_AgencyEval, REP_UniPriceEval)	207
Table B.22.a: Multiple linear regression results for different model specifications (IntraPriceIntensity) – part 1/2	208
Table B.22.b: Multiple linear regression results for different model specifications (IntraPriceIntensity) – part 2/2	209
Table B.23: Multiple linear regression results for different model specifications (InterPriceIntensity)	210
Table B.24: Multiple linear regression results for different model specifications (IntraGenIntensity)	210
Table B.25: Multiple linear regression results for different model specifications (InterGenIntensity)	211
Table B.26: Multiple linear regression results for repeated cross-sectional variables with raw (uncleaned, non-imputed) data	211
Table B.27: Logistic regression results for different model specifications with raw (uncleaned, non-imputed) data (REP_MainComp).....	212
Table B.28: Multiple linear regression results for price-related differentiation tactics variables with raw (uncleaned, non-imputed) data	212
Table B.29: Multiple linear regression results for non-price-related differentiation tactics variables with raw (uncleaned, non-imputed) data	213
Table B.30: Multiple linear regression results for focal variables with different data cleaning and imputation specifications (2024 data).....	214
Table B.31: Multiple linear regression results for price-related differentiation tactics variables for different subsamples.....	215
Table B.32: Multiple linear regression results for non-price-related differentiation tactics variables for different subsamples.....	216

LIST OF TABLE.

Table B.33: Multiple linear regression results of within-respondent deltas in perceived competition intensities (IntraVsInterPrice, IntraVsInterGen)..... 220

Table B.34: Multiple linear regression results of within-respondent deltas in perceived competition intensities (IntraPriceIntensity, InterGenVsPrice) 220

Table B.35: Proportional odds logistic regression results for perceived competition intensity variables..... 221

Table C.1: Summary statistics BMW South Africa and donor pool units 224

Table C.2: Summary statistics Mercedes Austria and donor pool units 225

Table C.3: Control markets and their weights for the main model for BMW South Africa.. 226

Table C.4: Control markets and their weights for the main model for Mercedes Austria 227

Table C.5: Overview of root mean square prediction errors and donor pool sizes for alternative model specifications for BMW South Africa and Mercedes Austria..... 230

1 Introduction

What if the most powerful driver reshaping today's automotive industry is not electrification or autonomous driving, but the question of who controls the point of sale? For about a century, the basic architecture of automotive retailing has remained largely unchanged. While the automotive value chain has strongly changed in areas such as production, product development, and electrification, global car manufacturers have been outsourcing large parts of their private (B2C) new car sales and distribution activities to car dealers (Buzzavo et al., 2023; Buzzavo, 2023). This remains the prevailing sales and pricing model for most incumbent manufacturers in most markets (Buzzavo, 2023). In this traditional model, the responsibilities of original equipment manufacturers (OEM) mainly include research and development, manufacturing, final assembly, and the distribution of the cars to retailers, i.e., car dealers (Staeblein & Aoki, 2015). In addition, OEMs are responsible for branding and marketing activities, designing dealer incentives, and setting the vehicles' list prices (Jacobides et al., 2016). Car dealers typically are independent franchises that partner with OEMs to promote the brand, sell new cars, and offer repair as well as maintenance services to customers (Genzlinger et al., 2020). They are responsible for nurturing customer relationships, providing information, and offering test drives (Genzlinger et al., 2020). In short, manufacturers build the cars, but it is the dealers who build the customer relationships. As dealers in this *indirect wholesale model* operate as independent contractors who buy cars from OEMs and retail them to customers, they usually determine the final transaction price, and the sales contract is signed between dealer and customer (Schellong et al., 2023). The buying process typically involves price negotiations, and potential buyers often visit one or more dealers and enter negotiations with the aim of reducing the final purchase price below the list price or the initial offer price (Scott Morton et al., 2011).

While this traditional wholesale model offers benefits like the outsourcing of activities and the ability to price discriminate across customers (Byrne et al., 2022), it entails two important drawbacks for manufacturers. First, as dealers determine the final prices, OEMs often struggle to directly and dynamically implement price adjustments. Instead, dealers independently set prices. Particularly when dealers operate at different cost levels and potential customers shop around for the best price, this can lead to different dealers attempting to undercut one another with lower prices for the same car (Heuser et al., 2023). Indeed, recent media reports have highlighted intense "discount battles" in the automotive industry (Merkur.de, 2024), where identical vehicles are often sold at price differences of 15–20% or more, depending on the customer and dealer (Gissler et al., 2021). Second, since OEMs do not sell their cars directly to their customers, they are unable to control customer interactions and to collect comprehensive customer data. Instead, this data is scattered across dealers, which makes it difficult for OEMs to manage customer relationships effectively. For instance, the online car marketplace *carwow*

processes over 10 million data points daily, while OEMs need to hire market research and mystery shopping agencies to obtain (price) data for their own cars (Schmidt et al., 2020).

Recently, this established system has come under increasing pressure. Advancements in digital technologies, changing customer needs, and stronger competitive pressure challenge the long-standing division of roles between manufacturers and dealers (Buzzavo, 2023). At the same time, the arrival of greenfield entrants such as Tesla has begun to challenge the traditional wholesale model in automotive retailing (Schmidt et al., 2020). Tesla could thus not only have changed the car's drivetrain, but it might have also rewritten the rules of automotive retail. With its *direct-to-consumer* or *direct sales models*, in which the OEM directly sells its cars to customers, Tesla bypasses the traditional, indirect dealership system and has proven that large-scale vehicle sales can be achieved without a single independent dealer (Schmidt et al., 2020). The intensity of industry discourse in reports such as Gissler et al. (2021), Heuser et al. (2023), and Schmidt et al. (2020) underscores that the strategic implications of direct sales models are no longer hypothetical but rather highly relevant for practitioners. Consulting reports, including Tschödrich et al. (2020), even boldly claim that the direct sales model is no longer an option but rather a necessity for car manufacturers. In their study, they show that 96% of dealers view the current sales models as outdated from a customer perspective, which underlines a potential need for change. However, so far, there is still a lack of academic research on how such sales and pricing model transformations affect key stakeholders in automotive retailing.

Under a direct-to-consumer sales model, the contract is finalized between the OEM and the customer (often online), and crucially, potential buyers cannot negotiate prices but can only accept a given fixed, non-negotiable price that is set directly by the OEM (Heuser et al., 2023). Otherwise, the transaction would not take place. These fixed prices are consistent across all private customers and sales channels. Under a direct sales model, OEMs transform dealers into *agents* who pursue leads, provide customers with information, and handle transactions and after-sales services for the OEM (Buzzavo, 2023; Schellong et al., 2023). In exchange, they earn a commission fee for every new car sold and additional services provided to customers or OEMs, depending on the contractual agreements (Heuser et al., 2023). I provide a simplified, illustrative comparison of the traditional wholesale model and the direct sales model in *Figure 1.1*. In this dissertation, I use the expressions *direct sales model*, *direct-to-consumer sales model*, and *agency model* interchangeably. For the sake of simplicity and readability, I also refer to *dealers* and *agents* synonymously to some extent, although their roles differ substantially in practice.

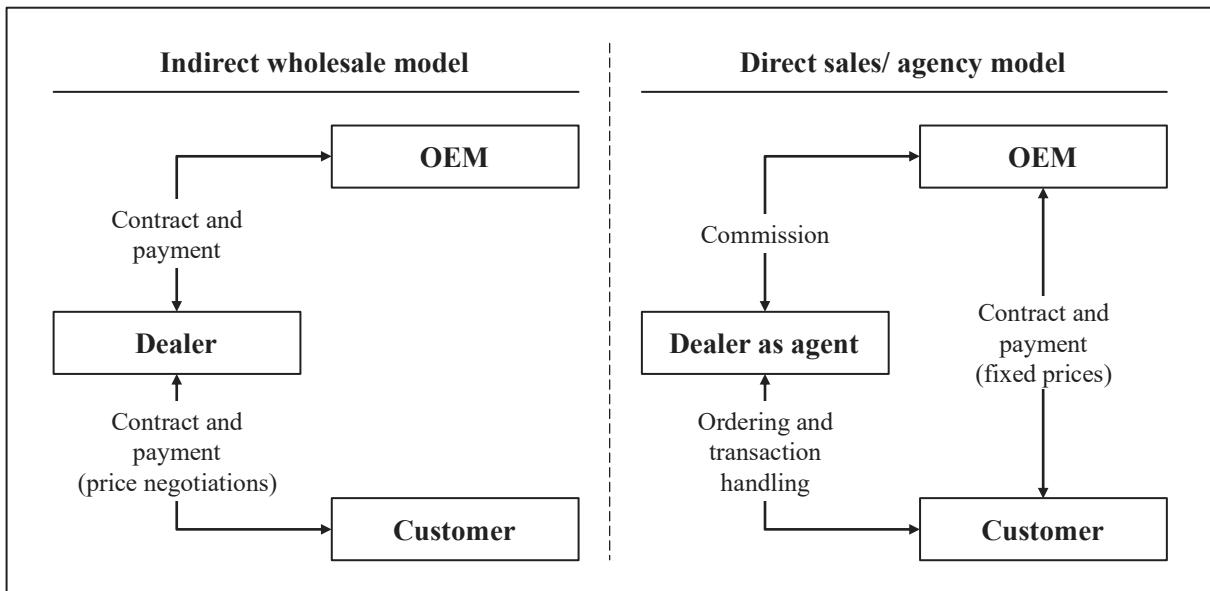


Figure 1.1: Comparison wholesale versus direct sales model (based on Schellong et al., 2023)

Over the past years, established manufacturers such as Mercedes and BMW have adopted direct sales models in some of their markets and/or for specific product lines but have also started to consider switching to direct sales on a global scale (Schmidt et al., 2020).¹ These initial launches and further considerations by manufacturers mark the “most radical attempt” in a long time to change the decades-old automotive retailing architecture (Buzzavo, 2023, p. 178). Yet, there currently seems to be no industry-wide consensus among automotive manufacturers on whether, how, and to what extent direct-to-consumer sales models should be implemented. While some OEMs have moved forward in selective markets, others have encountered severe operational and implementation difficulties such as IT failures or complaints by agents (e.g., Plate, 2023; Seyerlein, 2023, 2025), and in some cases, sales volume declines (e.g., Rehberg, 2024; Seyerlein, 2025). In light of this, several OEMs have reassessed, postponed, or entirely abandoned their implementation plans (Seyerlein, 2024; Autohaus, 2024a; Bäuchle, 2024).

Transitioning from a traditional dealer-based wholesale model to a direct sales model with fixed OEM-imposed pricing changes the way new cars are priced and marketed and entails substantial implications for manufacturers, dealers (agents), and customers. First, it leads to a fundamental shift in pricing authority, which transfers power from dealers to manufacturers (Schmidt et al., 2020). In addition, the transition eliminates individual price negotiations, and all customers pay the same fixed price through each sales channel at any given time. Since customers are used to price negotiations when buying a new car, this is likely to substantially change their purchase process and customer experience (Gissler et al., 2021). Apart from this

¹ I provide a (non-exhaustive) list of direct sales model introductions by OEMs in *Table A.1* in the *Appendix*.

change in how prices are set, the transition marks a strategic shift from a business-to-business (B2B) model, in which OEMs sell new cars to dealers without direct customer interaction, to a business-to-consumer (B2C) model, in which manufacturers directly engage with customers (Schellong et al., 2023). Thus, this entails a shift from wholesale to retail for OEMs, requiring them to build previously unfamiliar retail operations capabilities (Köstring et al., 2020; Buzzavo, 2023). Furthermore, this transition to direct sales changes the role of car dealers considerably, as they are transformed into *agents* who receive a commission fee for handling fixed price transactions on behalf of the OEM (Buzzavo, 2023). Over time, dealers may therefore evolve from haggling, independent salespeople to product specialists who are expected to provide a “pressure-free car-buying experience” rather than to negotiate prices (Köstring et al., 2020, p. 29). As a result, overall customer perceptions and experiences are likely to change as well (Buzzavo, 2023). In theory, as dealers operate directly at the point of sale, they should have a distinct advantage in determining and capturing each customer’s maximum willingness to pay (Demirag et al., 2010). However, in practice, incentive structures often result in dealers setting prices to achieve sales targets rather than setting them to maximize the OEM’s profitability (Joas et al., 2017).

If implemented effectively, the transition to a direct sales model potentially promises three important benefits to manufacturers. First, this new sales model enables manufacturers to set final transaction prices and maintain full pricing authority without risking adverse price cannibalization between dealers selling the same brand (Heuser et al., 2023). Incumbent OEMs have recently witnessed how Tesla is able to effectively and dynamically enforce sales steering levers and particularly price adjustments through its direct sales model (Reuters, 2023a). Second, manufacturers can potentially save costs by replacing dealer margins with standardized agent commissions, which are usually lower and more predictable, as well as through reduced total marketing and sales expenses (Tschödrich et al., 2020). In addition, the new price consistency across sales channels can increase the attractiveness of the more cost-effective online sales channel for customers and thus strengthen online sales (Schmidt et al., 2020). Accordingly, greenfield OEM Tesla exhibits substantially lower sales costs per vehicle sold, mainly due to faster and more digitized B2C sales journeys (Schmidt et al., 2022). Finally, OEMs could be able to offer more seamless and personalized customer experiences as they are able to collect large amounts of valuable customer data, which may allow them to better understand customer preferences (Buzzavo, 2023; Heuser et al., 2023).

Drawn by the potential benefits and the apparent success of these greenfield manufacturer approaches and pressured by profound industry trends such as advancements in digital technologies and changing customer needs, incumbent OEMs are also considering switching to

a direct sales model with fixed, non-negotiable prices (Tschödrich et al., 2020). However, the far-reaching implications for the key stakeholders, customers, retailers (i.e., former dealers, now agents), and manufacturers raise important yet unresolved questions: How do customers perceive the removal of price negotiations, and what are the psychological costs they may associate with the traditional negotiation process? How does moving to a direct sales model with fixed prices affect competition and differentiation tactics among retailers? And ultimately, how does this fundamental sales and pricing model transformation affect manufacturers' sales volumes? This thesis addresses these questions by examining the profound effects of direct sales model adoptions across the three stakeholder levels in the context of new car retailing.

Thereby, this dissertation contributes to the existing literature across a broader set of research domains, including economics, psychology, marketing, and industrial organization. I structure these contributions along the three stakeholder levels: customers, retailers, and manufacturers. First, regarding the customer perspective, it extends prior negotiation research in the fields of economics, psychology, and consumer behavior. Previous research has examined individual propensities to initiate negotiations or engage in risky choices, focusing, for instance, on gender differences (e.g., Kugler et al., 2018; Small et al., 2007). Yet, no prior study has empirically estimated the individual psychological costs of participating in price negotiations and explored how these might vary based on personality traits. This thesis aims to bridge this gap in literature. Second, concerning the retailer perspective, this dissertation contributes to previous literature on vertical relationships and restraints between manufacturers and retailers (e.g., Mathewson & Winter, 1984), competition among retailers (e.g., Beard et al., 2021), and the trade-off between price and non-price competition (e.g., Stigler, 1968). Several theoretical studies investigate contractual restrictions placed on retailers by manufacturers, such as retail price regulation, and their effect on competition and retailer behavior (e.g., Wang, 2005). Others focus particularly on the consequences of regulating price competition for quality competition (e.g., Telser, 1960). Furthermore, some studies examine how competition among same-brand retailers affects their service offerings and advertising efforts (Murry, 2018). However, no study has yet empirically examined how a transition to direct sales with fixed prices affects both competition (*between* and *within* brands) and differentiation tactics among agents. Lastly, with respect to the manufacturer perspective, this thesis contributes to research in marketing, economics, and industrial organization. As the transition to direct sales with fixed prices entails a transformation of both the sales and pricing model, this thesis extends prior research on sales and pricing models, as well as on their respective transformations. Prior literature on sales models has focused on vertical manufacturer-retailer relationships (e.g., Donna et al., 2024) and on hybrid sales channel structures, where firms employ coexisting direct and indirect retailer-based sales

channels (e.g., Yan & Pei, 2009). Pricing model research has studied the implications of retail price regulations (e.g., Telser, 1960), discounting practices (e.g., Kopalle et al., 1999), and the comparative effectiveness of fixed versus negotiable pricing schemes (e.g., Zeng et al., 2016). However, previous studies have typically considered sales and pricing model transformations in isolation. In this dissertation, I seek to fill this void by analyzing the combined effects of manufacturers' transitions from traditional, retailer-based sales models with negotiable prices set by retailers to direct sales models with fixed, non-negotiable prices.

This dissertation is structured along the three stakeholder levels. Following this overall introduction (Chapter 1), the remainder of this thesis presents one essay for each of the three stakeholder perspectives in Chapters 2 to 4. The order here does not follow that of a supply chain but rather a *micro* (customer)-*meso* (retailer)-*macro* (manufacturer) logic (Dopfer et al., 2004). Each essay builds on the identified research gaps, and collectively, they shed light on the profound implications of automotive OEMs' transformations to direct sales models with centralized pricing across the three central stakeholder levels: customers, retailers (i.e., dealers or agents), and manufacturers. *Figure 1.2* summarizes the conceptual framework of this dissertation in a simplified way. The direct sales transformation affects each of these stakeholders differently. Accordingly, each essay focuses on the mechanism that is most profound, critical, and/or decision-relevant for the respective stakeholder group. Chapter 5 concludes this dissertation by synthesizing the main findings across the three essays, discussing overarching implications, and outlining avenues for future research.

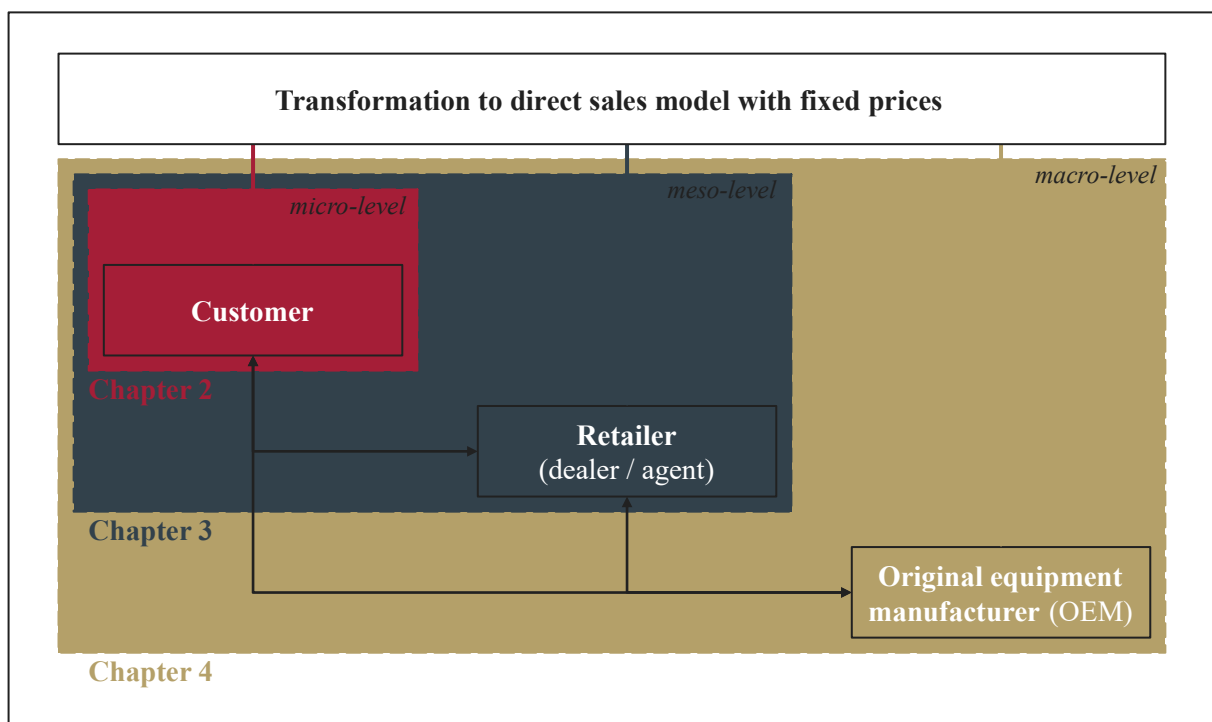


Figure 1.2: Conceptual framework and chapter overview for this dissertation

Chapter 2, titled “*Who Enjoys Going to the Bargaining Table? An Empirical Analysis of Bargaining Costs in Automotive Transactions*”, is joint work with Dominik Papies (University of Tübingen) and Mario Farsky (The Boston Consulting Group). This essay focuses on the customer view by examining their attitudes towards price negotiations in new car transactions. Specifically, this paper aims to understand whether new car customers prefer price negotiations (as in the traditional sales model) or fixed, non-negotiable prices (as in the direct sales model). We therefore estimate the costs that customers assign to participating in price negotiations and further investigate personality traits that might explain heterogeneity across customers. For this study, we develop a novel metric to estimate these buyer-individual *bargaining costs* and conduct an online survey of recent new car customers from Germany. Our results suggest that buyers do not enjoy price negotiations but perceive them as unavoidable to lower the price. On average, buyers associate price negotiations with a *bargaining cost* of 1.05% (or €435) relative to the initial offer price. We find strong heterogeneity in these costs and show that this aversion toward price negotiations is largely driven by customers’ time and effort considerations as well as post-purchase concerns regarding the final price they were able to negotiate.

Chapter 3 is also a joint project with Dominik Papies (University of Tübingen) and Mario Farsky (The Boston Consulting Group) and titled “*Competing within the Brand – Intra-Brand Competition and Differentiation in the Automotive Direct-to-Consumer Sales Era*”. This study takes the retailer perspective and examines how the shift to direct sales with fixed pricing affects competition and differentiation behavior among dealers (agents). It uses telephone surveys of German car dealers and a quasi-experimental design. In particular, we assess differences in perceived competitive intensities and differentiation tactics between traditional wholesale dealers and those acting as agents under recently introduced direct sales models. Our results indicate that direct sales agents perceive both general and, particularly, price competition with other agents of the same brand (i.e., intra-brand competition) as significantly less intense. We further show that introducing a direct sales model might lead to rebalancing effects in the competitive dynamics within new car retailing. That is, for direct sales brands, the competitive focus may shift from intra-brand to inter-brand competition (i.e., with other brands), and within the intra-brand domain, from non-price to price rivalry. Conversely, we show that although direct sales agents in fact appear to scale back their price-related differentiation tactics, they do not seem to compensate for this with stronger non-price or quality differentiation initiatives.

The single-authored Chapter 4, titled “*Shifting Gears – Evaluating the Sales Volume Impact of Direct-to-Consumer Sales Model Transformations*” adopts the manufacturer perspective. It examines how transitioning from a traditional wholesale model to a direct sales model with non-negotiable prices affects OEMs’ new car sales volumes. The study uses two real-world

case studies in which BMW and Mercedes introduced direct sales models in their South African and Austrian regional markets, respectively. Using a synthetic control group method (following e.g., Abadie & Gardeazabal, 2003; Abadie, 2021) and other regional markets of the respective OEM as potential counterfactuals, I estimate the treatment effects with respect to monthly new car sales volumes. My empirical results indicate that both manufacturers' transformations are associated with a decrease in monthly new car sales volumes relative to the synthetic control groups. For Mercedes, monthly sales volumes decline by 9.5% on average over the first two years after the transition, while BMW's sales volumes are, on average, 25.3% lower than those of the control group over the same period. These results offer empirical insights into the consequences of OEMs transitioning to a direct sales model with fixed prices and suggest that this entails realistic and substantial volume risks for OEMs.

Overall, with this thesis, I aim to shed light on the profound and potentially disruptive implications of automotive manufacturers transitioning from traditional retailer-based sales with negotiable prices to direct sales models with fixed prices. By addressing how customers, retailers, and manufacturers are affected by this shift, this dissertation provides a comprehensive, multi-level perspective. Moreover, it offers empirical insights across the three stakeholder levels that may also prove valuable to decision-makers in the automotive industry.

2 Who Enjoys Going to the Bargaining Table? An Empirical Analysis of Bargaining Costs in Automotive Transactions

Julian Feldhäuser, Mario Farsky, and Dominik Papies

Statement of contribution: Julian Feldhäuser developed the research idea and study design jointly with Mario Farsky (*The Boston Consulting Group*) and Dominik Papies (*University of Tübingen*). Julian Feldhäuser and Mario Farsky coordinated the data collection, which was executed by the market research firm *NativeResearch* and funded by *The Boston Consulting Group*. Julian Feldhäuser conducted all statistical analyses and wrote the full manuscript, including the literature review. He was also responsible for the finalization of the paper. Dominik Papies provided continuous supervision and feedback on the manuscript.¹

Acknowledgements: The authors gratefully acknowledge the support and funding of the data collection by *The Boston Consulting Group*. Moreover, the authors acknowledge all participants of the study's presentation at the *European Marketing Academy Conference 2023* in Odense (Denmark) for their helpful comments and constructive feedback.

¹ Chapter 2 is based on the published article “Farsky, M., Feldhäuser, J., Harries, F., Levin, A., & Papies, D. (2024). Car Selling Without Price Negotiations: Wishful Thinking or the New Normal?. *Marketing Review St. Gallen*, 41(1), 60-65.” as well as the conference proceeding “Feldhaeuser, J., Papies, D., Farsky, M. (2023). Who enjoys going to the bargaining table? - An empirical analysis of bargaining costs in automotive transactions. *Proceedings of the European Marketing Academy*, 52nd, (114296)”

Abstract

Price negotiations remain deeply embedded in new car sales and often drive substantial price competition between different car dealers selling the same brand. While this practice can serve as a price discriminatory tool to attract price-sensitive customers, such intra-brand price wars can result in substantial margin pressure for car manufacturers. In response, a growing number of manufacturers are currently considering shifting their sales and price structures to direct sales models with fixed, non-negotiable prices. However, it remains unclear how customers perceive this profound change. This paper studies whether customers prefer price negotiations or fixed prices and examines the psychological costs they associate with negotiating the price. To do so, we develop a novel empirical approach based on an online survey of 510 recent new car customers from Germany. Specifically, we estimate customer-level *bargaining costs* using respondents' negotiation expectations and repeated hypothetical trade-offs between fixed and negotiable price options. Our findings suggest that customers dislike price negotiations but perceive them as a necessary evil to lower the price. While the majority of customers state they would try to negotiate, most are willing to pay a price premium to avoid doing so. On average, customers assign *bargaining costs* of 1.05% relative to the initial offer price to negotiating. These costs appear to be primarily driven by time and effort considerations as well as post-purchase concerns about the final price they were able to negotiate.

2.1 Introduction

For customers, price negotiations are said to be more painful than “a visit to the dentist” (Wehner, 2024). And yet, while negotiations may feel painful, they remain deeply embedded in today’s new car sales practice (Gissler et al., 2021). According to industry estimates, only five percent of new cars are sold at list price (Schmidt et al., 2020), and steep discounts of 15–20% or more are common (Gissler et al., 2021). Especially recently, media reports have highlighted intense “discount battles” in the automotive industry (e.g., Autohaus, 2025; Merkur.de, 2024). This reflects a highly competitive market environment and underlines the topicality and relevance of price negotiations and discounts in new car retailing. These discount battles are often fought between different car dealers selling the same brand, lead to downward price spirals, and severely cut manufacturers’ margins (Beard et al., 2021). On the one hand, such price discounts can serve as a tool for attracting more price-sensitive customers (Desai & Purohit, 2004). On the other hand, considering that the new car industry generates annual sales revenues of around 2.5 trillion US dollars worldwide (IBISWorld, 2023), even a reduction in the discount levels by one percentage point could, *ceteris paribus*, translate into tens of billions of dollars in additional revenue for manufacturers and dealers.

With the adoption of direct sales models, manufacturers seek, among other goals, to end this decades-old tradition of price negotiations in new car retailing and replace them with centrally steered, non-negotiable fixed prices that are the same for all buyers and across all sales channels (Schmidt et al., 2020). This is intended to put an end to the price wars within brands (Gissler et al., 2021). It aims to stop buyers from shopping around and negotiating prices with multiple dealers in order to reduce the purchase price below the list price or the initial offer price (Scott Morton et al., 2011). The new price consistency across sales channels should further make the more cost-efficient online sales channel more attractive for customers (Schmidt et al., 2020).

This deviation from the established retail model may be perceived as a fundamental change by customers. It is, however, unclear how favorably they would view this move and whether they would appreciate giving up the opportunity to negotiate the price. Buyers may find price negotiations unpleasant, tedious, and time-consuming (Zhang et al., 2021), but they may also value the opportunity to save money on their new car transactions and may perceive the time and effort spent negotiating as worthwhile. Since discounts of 15–20% have been broad market knowledge since the early 2000s (Gissler et al., 2021; Ilg, 2018), it is not clear whether customers prefer a direct sales model without price negotiations or the traditional, negotiation-based retail model. The fact that the shift toward direct sales is fundamentally changing the retail model and the role of dealers makes a solid empirical foundation particularly important.

With this study, we contribute to four specific strands of literature in the field of negotiation research in economics, psychology, and consumer behavior. Interestingly, while these disciplines have intensively studied personality traits determining the propensity to negotiate or individual risky choices, not much is known about the magnitude and determinants of the costs that buyers assign to negotiating prices, and we address this literature gap with this study. Specifically, we add to prior research on (1) firms' choices of optimal pricing schemes, (2) buyer-individual *bargaining costs*, (3) negotiation initiation propensity, and (4) customer choice under uncertainty. To the best of our knowledge, this is the first study to empirically estimate buyer-individual *bargaining costs* and to examine specific (personality) determinants.

In this study, we aim to answer three overarching research questions. First, we aim to investigate whether customers in the automobile sector prefer price negotiations (traditional sales model) or fixed non-negotiable prices that are uniform for all customers (direct sales model). For this research question, we seek to determine what share of customers explicitly state that they would negotiate the price when acquiring a new car, but more importantly, also what proportion of customers implicitly reveal that they are willing to pay a price markup to avoid having to negotiate. Second, we want to study the magnitude of the (bargaining) costs that customers assign to negotiating the price. For this purpose, our approach draws on two components, namely the expectations that customers have with respect to price reductions through price negotiations and the fixed price required for customers to be indifferent between a non-negotiable fixed price and the current negotiable offer price. Third, we seek to investigate specific (personality) factors that can explain potential heterogeneity in these *bargaining costs*.

To address these research questions and the timely management issue, as well as to fill the gap in academic literature, we conduct an online survey of 510 recent new car customers in Germany and develop a new measure to empirically estimate buyer-individual *bargaining costs*. We define *bargaining costs* as the psychological cost customers assign to “coming to the bargaining table” and initiating negotiations as well as the expected costs of time and effort of negotiating (Zhang et al., 2021). Conceptually, a retail setting with buyers negotiating prices can be viewed as a risky choice setting in which the negotiation outcome is uncertain. The worst outcome for customers (i.e., the upper price bound) is the offer price, and the outcome depends on personality traits as well as the effort potential buyers invest in negotiations. In contrast, in the direct sales model without price negotiations, the outcome is certain. We derive our *bargaining cost* metric based on respondents' repeated choices between price negotiations (i.e., the risky option) and fixed non-negotiable prices (i.e., the safe option) and their expectations regarding discounts through price negotiations.

We find that 67% of customers explicitly state that they would try to negotiate the dealer's initial offer price for a new car. On the other hand, 63% of respondents implicitly reveal a willingness to pay a price markup over their expected negotiated price to avoid having to negotiate. This suggests that new car customers do not enjoy negotiating the price but perceive negotiations as a necessary evil. On average, customers assign *bargaining costs* of 1.05% relative to the initial offer price to negotiating the price of a new car. We find strong variation in these costs and show that *bargaining costs* are primarily driven by a lower willingness to search, higher opportunity cost of time, and stronger post-purchase price confirmation.

Our findings indicate that the majority of new car customers dislike the prevailing, decades-old pricing model with negotiations. Customers appear to be used to substantial negotiation discounts but are willing to pay higher fixed prices to avoid negotiating the price. Customer aversion to price negotiations seems to be mainly driven by time and effort considerations as well as post-purchase concerns regarding the final price paid. Our results further suggest that moving to direct sales is unlikely to be successful if manufacturers seek to enforce current offer prices as non-negotiable fixed prices. A transition to a direct sales model with non-negotiable prices only appears feasible if manufacturers reduce prices slightly to below current offer prices.

In the next section, we outline our contribution to related literature. In *Section 2.3*, we provide the theoretical framework before describing data and methodology in *Section 2.4* and our results in *Section 2.5*. We provide a discussion, conclusion, and implications in *Section 2.6*.

2.2 Related Literature and Contribution

This study contributes to the literature on negotiation research in economics, psychology, and consumer behavior. Although these disciplines have intensively studied negotiations, not much is known about the magnitude and determinants of *bargaining costs*, a literature gap that we address with this study. Specifically, this paper contributes to four distinct strands of literature. First, this article adds to research focused on firms' choices of optimal pricing schemes by providing empirical evidence of buyers' preferences between a direct sales model without price negotiations and a negotiation-based retail model. Second, this study contributes to research on buyer-individual *bargaining costs* by introducing and empirically applying a novel approach to quantifying buyer-individual costs associated with negotiating. Third, our paper is related to psychological literature investigating the impact of personality characteristics on negotiation initiation preferences. Last, since the respondents of our survey choose between uncertain (i.e., price negotiation) and safe options (i.e., fixed price), this paper also adds to the literature on customer choice under uncertainty. We provide an overview of the studies that are most relevant and closely related to our own research in *Table 1.1*.

2.2.1 Choice of pricing schemes

For more than four decades, there has been (mostly theoretical) research focused on firms' choices of optimal pricing schemes, and particularly on the decision between fixed pricing schemes and individual price negotiations.

One literature strand focuses on the optimal choice of pricing policy in response to the competitive situation (e.g., Adachi, 1999; Bester, 1994; Huang, 2020). In one of the few empirical studies, Zeng et al. (2016) study the impact of an automotive manufacturer switching to a fixed pricing policy in a market where its main competitors continued to negotiate prices. Specifically, the authors investigate the implications of Toyota Canada's introduction of a fixed one-price policy in the early 2000s and show that the pricing scheme transformation led to increased prices for both Toyota and its main competitor, Honda, who retained a bargaining policy, while sales remained constant. They thereby provide evidence that moving to a pricing strategy designed to distinguish oneself from competitors can have beneficial price effects for firms in markets with sufficiently heterogeneous customers without adversely affecting sales.

Other studies investigate the choice of pricing schemes depending on bargaining power and abilities. Wang (1995), for instance, examines the relative advantages of fixed versus negotiable pricing schemes in a monopoly setting by using a theoretical approach. The author shows that the favorability of price negotiations for monopoly sellers increases with their bargaining power as long as the negotiation pricing scheme is not substantially more expensive than a fixed pricing policy. Arnold & Lippman (1998) also consider a monopoly market situation and demonstrate that, for sufficiently high (average) buyer bargaining abilities, the monopolist is better off choosing a fixed pricing policy. Furthermore, buyers with stronger bargaining abilities create positive externalities for all buyers, as it is less beneficial for the seller to reject such buyers in the hope that a more attractive buyer in terms of lower bargaining abilities arrives when average bargaining abilities appear to be increasing.

Further research addresses the role of buyers' willingness to pay (e.g., Chen & Rosenthal, 1996) or the role of information and search cost (e.g., Wernerfelt, 1994; Bester, 1994) in a firm's choice between price negotiations and fixed pricing schemes.

Lastly, there are also a few theoretical studies that incorporate buyers' propensity and costs of bargaining into the optimal firm decision on the pricing scheme. Zeng et al. (2014) study a firm's strategy of offering two different pricing formats, a fixed and a negotiable price, through two different sales channels with different buyer types that vary in their *bargaining costs*. By using a theoretical model, they show that such a dual-pricing strategy is optimal for a firm when the share of customers with high *bargaining costs* is sufficient but not too large and when buyers

do not differ too strongly in their *bargaining costs*. Desai & Purohit (2004) investigate a firm's choice between a bargaining and a fixed pricing scheme in a duopoly setting depending on buyers' *bargaining costs*. According to their theoretical model, negotiation pricing schemes are more profitable if the share of buyers with high *bargaining costs* is sufficiently large, as firms can achieve higher margins with this type of customer due to the lower amount of negotiations. Customers with high *bargaining costs* thus exert positive externalities on those with low *bargaining costs*, since the higher-margin, non-negotiating customers enable firms to offer discounts to negotiating ones. However, neither of the two studies empirically examines actual customer bargaining preferences or the distribution of *bargaining costs* and propensities among buyers. Overall, to our knowledge, there is no study that empirically explores determinants of buyers' *bargaining costs* as well as their impact on firms' choice of the optimal pricing scheme.

2.2.2 Bargaining costs

So far, there has been little empirical research on buyers' disutility and costs associated with bargaining as well as the corresponding impact on negotiation processes and outcomes.

Jindal and Newberry (2018) empirically investigate *bargaining costs* and bargaining power on a ZIP-code-level under a hybrid pricing policy with posted prices and the option for customers to initiate price negotiations. The authors use customer-level refrigerator transaction data of a U.S. home appliance retailer from 2009 and 2010. They are the first to empirically quantify the effect of buyers' *bargaining costs* on transaction prices and firm profits. The authors argue that *bargaining costs* should induce a gap in the distribution of transaction prices between the posted price and the expected price after negotiations. They derive ZIP-code-level *bargaining costs* as the minimum difference between the posted refrigerator price and the expected price after negotiations in a ZIP-code region. The expected negotiated price per transaction is calculated based on data on posted prices and wholesale costs, each weighted by the average bargaining power of the two parties in the respective ZIP-code. Bargaining power in turn is derived from the distribution of the transaction prices in relation to posted prices and wholesale costs. They find that customers encounter an average nonpecuniary cost of USD 28 to enter negotiations (approximately 2% of the average posted price) and that bargaining is still the dominant option for most buyers, as average discounts are substantially higher. However, in their analysis of transaction prices, the authors are only able to estimate buyer *bargaining costs* on a ZIP-code region rather than on an individual customer level. The final transaction price data prevents them from estimating buyers' expectations regarding the negotiated price. Furthermore, they cannot examine customer-individual determinants of *bargaining costs*. Moreover, the hybrid pricing scheme with posted prices and the option to negotiate does not

allow for explicit inferences about the fixed price levels required to render customers indifferent between accepting a lower fixed price or entering negotiations at a higher posted price.

Zhang et al. (2021) empirically quantify and examine the benefits and costs of negotiations for buyers, sellers, and platforms on a Chinese province level. They use phone transaction data from 2012 and 2013 from the Chinese online platform *Alibaba* and supplement it with primary data from a customer survey, which is matched at the provincial level. The authors develop a structural model of sellers' pricing choices and buyer demand while allowing for price discrimination and bargaining initiation costs. They define *bargaining initiation costs* as "the cost of time and effort as well as the psychological cost associated with the decision to bargain" (p. 1082). *Bargaining initiation costs* are estimated based on the customer survey. The authors first ask the respondents whether they would negotiate with the retailer when buying a cell phone with a certain offer price and then which discount they would expect after negotiations. For each province, bargaining initiation costs are derived from the variation in expected negotiation gains and buyers' negotiation intentions.¹ They find average bargaining initiation costs of USD 1.50 (0.6% of the phone's offer price) and provide evidence of strong variations in *bargaining initiation costs* across provinces driven mainly by economic development. Based on their results, the authors further show through simulations that eliminating negotiations would be beneficial for the platform and customers. Similar to Jindal and Newberry (2018), Zhang et al. (2021) only estimate individual *bargaining costs* on a regional level and are not able to examine customer-individual determinants of *bargaining costs* (except for gender). While the authors explicitly retrieve customers' negotiation expectations, due to the hybrid pricing policy, it is again not possible to explicitly determine which fixed price levels would render customers indifferent between paying a lower fixed price or negotiating the offer price.

Zettelmeyer et al. (2006) empirically study the role of the Internet and customer characteristics such as bargaining disutility on negotiated prices in new car transactions. They use matched customer survey and new car transaction data and derive individual bargaining disutility through a measure with two Likert-type scaled items, which they then use as an independent variable in their analyses of transaction prices. The authors show that buyers with a higher disutility of bargaining pay higher prices on average but benefit more from collecting information. However, they do not examine determinants of individual bargaining disutility and do not quantify *bargaining costs*, as their focus lies on investigating the impact of the Internet.

¹ For example, if a respondent expects a discount of one dollar but states that she would not negotiate, her *bargaining initiation costs* are expected to be greater than one dollar. If a respondent has the same expectations but indicates that she would negotiate, her *bargaining initiation costs* are assumed to be lower than one dollar.

2.2.3 Determinants of bargaining initiation propensity

While individual differences play a crucial role in determining bargaining propensity and results (Bear & Segel-Karpas, 2015), there is a scarcity of empirical evidence (Reyes et al., 2021). This study expands on the (primarily psychological) research examining the effects of personality traits on individual preferences for entering and engaging in (price) negotiations.

A larger body of research in this field is concerned with gender differences in individual propensity to enter negotiations. Small et al. (2007) use a combined experimental and survey approach to investigate gender differences in the propensity to negotiate about compensation for participating in a lab experiment. They provide evidence of the existence of such gender differences and show that it is explained by the framing conditions of a particular situation. Women appear to be intimidated by settings that are framed as opportunities for negotiation and are less likely to bargain in such environments. When settings are framed as opportunities to ask, the gender differences disappear. Kugler et al. (2018) use a meta-study from 1977 to 2016 to examine gender differences in negotiation initiation. While they conclude previous results to be heterogeneous, their study affirms that men are more likely to start negotiating and that gender differences are smaller when the appropriateness of bargaining was relatively clear.

Another crucial research stream, to which this paper makes a valuable contribution, delves into the influence of personality traits on negotiation initiation propensity. Marks and Harold (2011) examine the impact of individual differences on initiation propensity and results of starting salary negotiations. Through a survey of newly hired employees, the authors show that risk averse and less integrative-minded individuals (i.e., those who tend to aim for “win-win” solutions instead of maximizing personal gains) are less likely to initiate salary negotiations. Shalvi et al. (2013) analyze the propensity to enter as well as to leave price negotiations through a lab experiment and show that prevention-oriented buyers (i.e., those who try to prevent losing rather than securing a win) have a significant tendency to avoid such bargaining situations.

Further studies examine the effects of emotional and cognitive intelligence (e.g., Barry et al., 2004), social motives and incentives (e.g., Bowles et al., 2007), culture (e.g., Volkema & Fleck, 2012), negotiation ability (e.g., Kapoutsis et al., 2013), or power and the legitimacy of power (e.g., Magee et al., 2007) on individual preferences in entering negotiations.

Overall, while previous psychological research on price negotiations does not try to estimate the magnitude of buyer-level *bargaining costs* through customer choice behavior, it motivates the fact that negotiation initiation preferences and behavior are very likely to be influenced by specific personality characteristics, which we further examine in this paper.

Author(s) & year	Empirical study	Data origin	Industry focus	Price negotiations	Customer level	Bargaining costs	Personality traits
Zeng et al. (2016)	Yes	Price and sales data	Automotive	Yes	-	-	-
Wang (1995)	-	-	-	Yes	-	Yes ²⁾	-
Arnold & Lippmann (1998)	-	-	-	Yes	(Yes) ¹⁾	-	-
Zeng et al. (2014)	-	-	-	Yes	(Yes) ¹⁾	Yes	-
Desai & Purohit (2004)	-	-	-	Yes	(Yes) ¹⁾	Yes	-
Jindal & Newberry (2018)	Yes	Transaction data	Refrigerators	Yes	-	(Yes) ³⁾	-
Zhang et al. (2021)	Yes	Transaction & survey data	Cell phones	Yes	-	(Yes) ³⁾	-
Zettelmeyer et al. (2006)	Yes	Transaction & survey data	Automotive	Yes	Yes	(Yes) ⁴⁾	-
Small et al. (2007)	Yes	Experimental & survey data	-	-	Yes	-	Yes
Kugler et al. (2018)	Yes	Meta analysis	-	-	Yes	-	Yes
Shalvi et al. (2013)	Yes	Experimental data	-	Yes	Yes	-	Yes
<i>This study</i>	Yes	Survey data	Automotive	Yes	Yes	Yes	Yes

Note: ¹⁾ = consideration of customer types, ²⁾ = seller bargaining costs, ³⁾ = ZIP-code region level, ⁴⁾ = bargaining disutility used as independent variable

Table 1.1: Literature overview on negotiation research

2.2.4 Choice under uncertainty

In addition to the more specific negotiation research, we also contribute to the more general literature on decision theory and particularly to the research on choice under uncertainty.

For decades, *expected utility theory* largely dominated in the study of choice under uncertainty (Kahneman & Tversky, 2013). The theory assumes that most people, when faced with different choice alternatives that are (at least partly) uncertain, assess all possible outcomes as well as their respective probabilities and choose the action that generates the highest expected utility depending on their individual risk preference (Von Neumann & Morgenstern, 2007).

However, in 1979, through their *prospect theory*, Kahneman and Tversky (2013) propose a renewal of the theory on individual economic behavior under uncertainty by providing evidence that individual choices are systematically impacted by the framing of the situation. Particularly, they show that people tend to be risk-seeking in negatively framed situations and risk averse in positively framed situations. Reflecting this, utility functions are generally convex for losses, concave for gains, and less steep for gains compared to losses. Their theory and the existence of this framing effect have received strong support from other studies (e.g., Bazerman, 1984;

Fagley & Miller, 1990) and have been extended to individuals' tendency to interpret or mentally frame certain situations in their own way (i.e., to "self-frame"; e.g., McElroy et al., 2007).

We study consumer choice in the context of new car purchases by presenting customer survey participants with a choice between a risky option, in which the price is negotiable and the outcome is thus uncertain, and a safe, fixed price alternative, in which the outcome is certain. As the two options are not framed specifically as relative gains or losses, the framing in our setting can be considered rather neutral. However, since frames are usually not specified externally and individuals in general create their own frames for a given situation as a first step in decision-making (Peng et al., 2014), it is reasonable to assume that there is heterogeneity in the way that respondents in our survey perceive and frame the situation.

2.3 Theory and Framework

2.3.1 Individual bargaining costs

To address the described gaps in prior literature, in this study we estimate buyer-individual *bargaining costs* associated with entering distributive buyer-seller price negotiations (in which each party seeks to claim the greatest share of a "fixed-pie" resource with no option to maximize joint profit; Thompson et al., 1996) and explore individual factors explaining variation in *bargaining costs*. Following Zhang et al. (2021), we define *bargaining costs* as the psychological cost of "coming to the bargaining table" and initiating negotiations as well as the expected cost in terms of time and effort throughout the negotiation rounds. Our measurement of *bargaining costs* is inspired by previous research that studies individuals' choices between risky and safe outcomes (e.g., Schubert et al., 1999) and Zhang et al.'s (2021) approach of retrieving respondents' pre-negotiation expectations regarding the final price after negotiation. In our empirical application, we let respondents choose between different scenarios in which they must decide between entering risky price negotiations (i.e., the prevailing pricing model in the automotive industry) or paying a fixed price (i.e., the direct sales pricing scheme).

We assume that a respondent who is willing to pay a fixed price that is higher (lower) than the price she would expect to pay after price negotiations has positive (negative) *bargaining costs* associated with entering risky price negotiations. This individual is therefore willing to pay a markup (would require compensation) for not entering a negotiation. The magnitude of *bargaining costs* is determined by the difference between the chosen fixed price and the expected price after negotiations. We further expect this difference to be influenced by customer-specific factors. The notion of willingness to pay a markup to avoid having to negotiate follows the intuition of Jindal and Newberry (2018). However, in contrast to their

study, through our customer survey, we are able to explicitly capture customer-individual *ex ante* expectations of the final price after negotiations before entering price negotiations.

2.3.2 Drivers of bargaining costs

Based on a foundation of previous research, we identify two distinct categories of factors that are likely to influence individual negotiation preferences: search and purchase behavior-specific factors (e.g., Stigler, 1961; Zhang et al., 2021) and general personality traits (e.g., Marks & Harold, 2011). Within these two categories, drawing on existing literature, we carefully select and prioritize the most relevant factors to integrate into our survey approach. The search behavior-specific variables comprise willingness to search, opportunity cost of time, quality consciousness, sale proneness, post-purchase price confirmation, and car enthusiasm. In addition, the more general personality traits examined are risk propensity, (internal) locus of control, regulatory focus (i.e., prevention versus promotion focus), and patience.

Following Zettelmeyer et al. (2006) and Zhang et al. (2021), we expect that respondents with lower willingness to search and individuals with higher opportunity cost of time will exhibit higher *bargaining costs*, since participating in time-consuming price negotiations would be more costly to those individuals. This leads to the following two hypotheses, *H.1* and *H.2*:

H.1: Individuals with a higher willingness to search are related to lower bargaining costs.

H.2: Individuals with higher opportunity costs of time are related to higher bargaining costs.

With respect to quality consciousness, by definition, quality conscious individuals incur little or no disutility from paying a higher price (Ding et al., 2010) and use the price of a product to make inferences about product quality (Lichtenstein et al., 1993). While the most important aspect for quality conscious buyers is product quality, for price conscious customers, price savings and rebates are particularly relevant (Ailawadi et al., 2001). Based on those definitions, we expect quality conscious respondents to place lower importance on entering negotiations and seeking a better price, which leads us to the following hypothesis:

H.3: Quality conscious individuals are related to higher bargaining costs.

We further expect respondents with high sale proneness to be related to lower *bargaining costs* (*H.4*), as deal prone customers tend to be more susceptible to rebates and good deals (Hackleman & Duker, 1980), and sale proneness is defined as a particularly price-focused deal proneness dimension (Lichtenstein et al., 1993).

H.4: Sale prone individuals are related to lower bargaining costs.

Pizzutti et al. (2022) show that customer search does not end with the purchase itself, but rather that many customers continue to compare prices post-purchase. Building on that, we also incorporate post-purchase behavior. People with stronger post-purchase price confirmation tendencies seek to avoid post-purchase regret and tend to aim to confirm that they made the right choice (Pizzutti et al., 2022). Since the price uncertainty related to negotiations gives rise to potential regret about whether someone obtained the best price (Simonson, 1992), we expect that those who strongly tend to compare prices after the purchase show greater reluctance towards negotiating and therefore exhibit higher *bargaining costs* (H.5). This is also backed by industry reports showing that buyers increasingly opt for fixed prices, ensuring they do not miss out on a better deal, and that they value post-purchase “peace of mind” (Schmidt et al., 2020).

H.5: Individuals who more strongly engage in post-purchase price confirmation are related to higher bargaining costs.

Based on Zettelmeyer et al. (2006), we also study the relationship between enthusiasm for cars and negotiation initiation preferences and expect car enthusiastic respondents to exhibit lower *bargaining costs*. This hypothesis (H.6) is based on prior findings that enthusiasm is generally associated with positive affect (e.g., Moè, 2016) and on the fact that, by the design of the construct, car enthusiasts tend to be better informed. Barry & Oliver (1996), e.g., predict that positive affect increases a buyer’s propensity to enter negotiations. Other studies confirm that better informed individuals are associated with greater confidence (Peterson & Pitz, 1988) and tend to pay lower prices (Scott Morton et al., 2011).

H.6: Car enthusiastic individuals are related to lower bargaining costs.

With respect to our first of the general personality traits, risk propensity, we expect more risk seeking individuals to have lower *bargaining costs*. In a study of salary negotiations, Marks and Harold (2011) show that risk averse employees are significantly less likely to initiate salary negotiations compared to risk-seeking individuals. Furthermore, our study approach is based on respondents’ choices between risky (i.e., price negotiations) and safe options (i.e., fixed prices), and, by definition, risk-seeking individuals are more inclined to choose risky options (Schubert et al., 1999). This leads us to the following hypothesis:

H.7: Individuals that are more risk seeking are related to lower bargaining costs.

Based on previous psychological research, we expect that respondents with a strong internal locus of control (i.e., the extent to which someone believes that the occurrence of an event is dependent on her own behavior; Rotter, 1966) will be associated with lower *bargaining costs*. Bigoness (1976), e.g., shows that individuals with a stronger internal locus of control ask for

more in their initial bids, and Volkema and Fleck (2012) provide evidence of a positive relation between an internal locus of control and negotiation initiation, leading us to *hypothesis H.8*:

H.8: Individuals with a stronger internal locus of control are related to lower bargaining costs.

Building on findings by Shalvi et al. (2013), who show that, compared to promotion-oriented buyers, prevention-oriented buyers have a stronger tendency to avoid entering negotiations and to exit negotiations sooner when such an option arises, we derive the following hypothesis:

H.9: Compared to individuals with a stronger promotion focus, individuals with a stronger prevention focus are related to higher bargaining costs.

Ultimately, we expect more patient respondents to have lower *bargaining costs*, which is motivated by the finding of Scott Morton et al. (2011) that more patient new car customers are able to negotiate lower prices. This leads us to our last hypothesis (*H.10*):

H.10: More patient individuals are related to lower bargaining costs.

2.4 Data and Methodology

2.4.1 Measurement of bargaining costs

The focal dependent variable in this study is the buyer-individual cost of entering price negotiations. As the psychological aspects of these costs cannot easily be accounted for through transactional data, we rely on primary data collection, which is a common method in negotiation research (Zhang et al., 2021). We develop a novel approach to calculating these *bargaining costs* based on respondents' individual expectations regarding the final transaction price after negotiations and their repeated choices between bargaining and fixed price options.

After asking respondents ($i = 1, \dots, N$) how much they paid for their last new car, we present them with a hypothetical situation in which they want to acquire a new car and have found a dealer (*Dealer A*) in their area that offers the desired model (with an indicated manufacturer's suggested retail price, MSRP; e.g., €55,000) at a dealer-specific offer price (P_{max}^A ; e.g., €50,000). All reference prices are indicated either as purchase prices (for prior cash or finance customers) or as monthly leasing rates (for prior lease customers). The scale is based on the last price or leasing rate paid by a respondent. First, we assess the respondents' *explicit negotiation willingness* by openly asking whether they would try to further negotiate down the dealer's initial offer price. We then capture the respondents' expectations regarding the final price by first asking about the best possible price they could imagine for themselves after negotiating ($P_{i,min}^A$; e.g., €40,000) and about the likelihood they assign to receiving this price ($p_i(P_{i,min}^A)$; e.g., 50%). By incorporating their individual negotiation expectations, we implicitly capture the

respondents' level of negotiation confidence, as more positive expectations and optimism are empirically associated with greater confidence (e.g., Senft Everson et al., 2022).

Next, we introduce respondents to a second, identical, and equally distant dealer (*Dealer B*) that offers the same model at a price that is lower than *Dealer A*'s but that is non-negotiable and thus fixed (FP_t^B ; e.g., €49,250). We then repeatedly ask respondents which dealer they would like to acquire the car from, with the constraint that they can only visit one of them. With each iteration of the question ($t = 1, \dots, T$), we gradually lower the fixed price from *Dealer B* until the respondent ultimately decides in favor of the fixed price and thus against price negotiations. We then derive individual *bargaining costs* B_i based on the price difference between the chosen fixed price from *Dealer B* ($FP_{i,t}^B$) and the expected price after negotiations with *Dealer A* ($\mathbb{E}[P_i^A]$). Particularly, we calculate individual *bargaining costs* as follows:

$$B_{i,d} = \frac{1}{2}(FP_{i,t}^B - \mathbb{E}[P_{i,d}^A]) + \frac{1}{2}(FP_{i,t-1}^B - \mathbb{E}[P_{i,d}^A]) \quad (2.1)$$

To smooth the effect that might be attributable to the size of the fixed price steps between the iterations, we take the mean value of a respondent's chosen price difference (first part of *Equation 2.1*) and the last difference that she rejected (second part of *Equation 2.1*). The chosen price difference is implied by the selected fixed price from *Dealer B* and the expected price after negotiating with *Dealer A*. The last difference that was rejected by the respondent is calculated using the values of the prior iteration of the question. Furthermore, we base the size of the fixed price steps on the discount expectations specified by the respondents. Respondents that state higher (lower) relative discount expectations face larger (smaller) fixed price steps, so that the number of price steps until the fixed price alternative of *Dealer B* reaches the expected price after negotiating with *Dealer A* is similar for each respondent.

We illustrate a slightly simplified version (where we omit the smoothing) of the *bargaining costs* calculation in *Figure 2.1*. Here, we depict a case distinction between two fictitious respondents. In both cases, MSRP and offer price ($P_{a,max}^A$) are identical, and both have equal negotiation price expectations ($\mathbb{E}[P_i^A]$). However, respondent 1 chooses a fixed price ($B_1: FP_{1,t}^B$) that is higher than her negotiation price expectations, which is why she exhibits positive *bargaining costs* (1%), while the other one chooses a fixed price ($B_2: FP_{2,t}^B$) that is lower than his negotiation price expectations, which is why he exhibits negative *bargaining costs* (-1%).

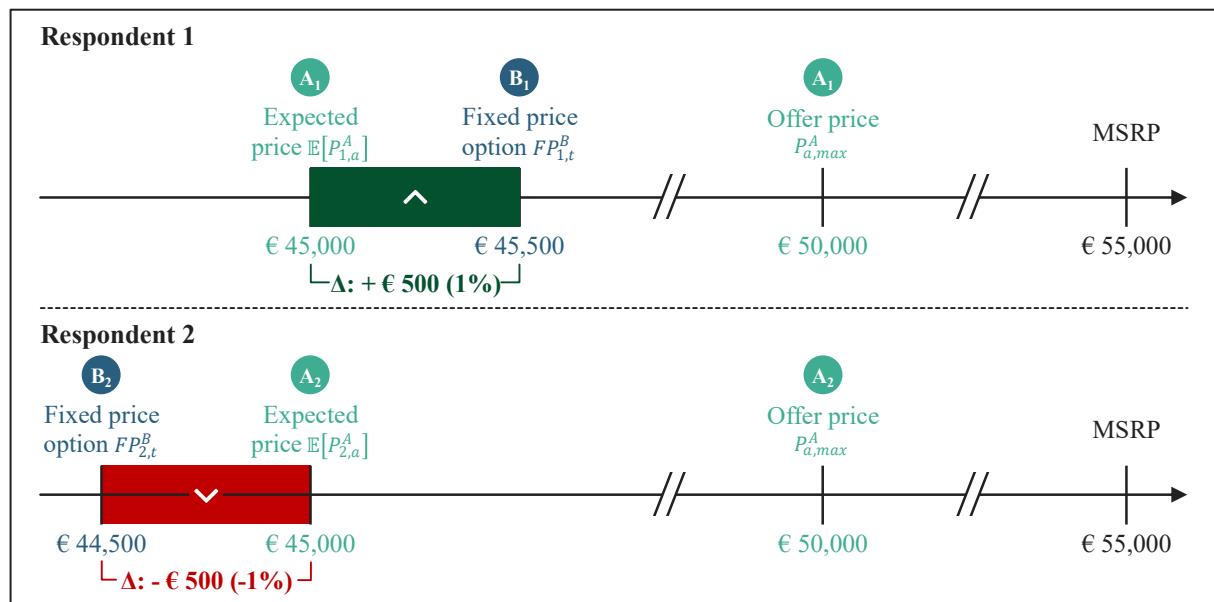


Figure 2.1: Measurement of *bargaining costs* (illustrative and simplified; positive *bargaining costs* for respondent 1, negative *bargaining costs* for respondent 2)

We use *Equation 2.2* to calculate the expected price after negotiations with *Dealer A*:

$$\mathbb{E}[P_{i,a}^A] = P_{i,a,\min}^A \cdot p_i(P_{i,a,\min}^A) + \frac{1}{2}(P_{a,\max}^A + P_{i,a,\min}^A) \cdot (1 - p_i(P_{i,a,\min}^A)) \quad (2.2)$$

Since we only have information on the best possible price, the corresponding likelihood (both self-indicated), and the maximum price (i.e., the offer price), but not on the expected distribution of intermediate outcomes (i.e., prices), we assume that these are equally distributed between the two extreme values. Only weighting the two extreme values by the stated likelihood and the counter-probability would not seem realistic to us for car price negotiations.²

For robustness, we measure individual *bargaining costs* through two different versions (d). In the adaptive version ($d = a$), we use the respondents' stated price expectations (as described above) to calculate *bargaining costs*. In the *non-adaptive version* ($d = n$), we exogenously provide the respondents with the expected price after negotiations by reporting (fictitious) information on the negotiation outcomes of previous customers of *Dealer A* (i.e., $\mathbb{E}[P_i^A]$ in *Figure 2.1* is exogenous). For this case, we specify that out of 100 customers in the past, 50 managed to negotiate a discount of, e.g., €3,250 ($P_{n,\min}^A$) and that the other 50 who also tried to negotiate only managed to negotiate a moderate discount of at best €520 ($P_{n,\mod}^A$).³ In the *non-*

² For the prior numeric example, this would imply an expected price after negotiations with *Dealer A* of €47,500: $\text{€}40,000 \cdot 50\% + \frac{1}{2}(\text{€}50,000 + \text{€}40,000) \cdot (1 - 50\%) = \text{€}47,500$.

³ The maximum discount corresponds to a discount of 6.50% relative to the initial offer price for all respondents. We here use the example values for a car model with an offer price of €50,000. We also provided respondents with the final transaction prices previous customers paid (in this case, 50% of previous customers paid €46,750).

adaptive version, we calculate the expected negotiation price slightly differently (see *Equation 2.3*). As we explicitly mention that 50% of previous customers paid the minimum price ($P_{n,min}^A$) and that the other 50% obtained at best a moderately discounted price ($P_{n,mod}^A$), only the price range between the moderately discounted price and the maximum price ($P_{n,max}^A$) is assumed to be equally distributed. The reference prices are again individual to each respondent, as they refer to the respective price of their last new car transaction.

$$\mathbb{E}[P_n^A] = P_{n,min}^A \cdot p(P_{n,min}^A) + \frac{1}{2}(P_{n,max}^A + P_{n,mod}^A) \cdot (1 - p(P_{n,min}^A)) \quad (2.3)$$

We then compute the equally weighted mean value (\bar{B}_i) of the *adaptive* and the *non-adaptive* versions of *bargaining costs*. We furthermore use *mean relative bargaining cost* (\bar{b}_i ; i.e., *mean absolute bargaining cost* relative to the initial offer price of *Dealer A*) to ensure comparability despite differences in scale (particularly between leasing and purchase or financing customers).

2.4.2 Data description

We collect the data for this study via an online customer survey in Germany between October and November 2022. Respondents were asked to fill out a 10- to 15-minute questionnaire, based on which we derive our measures. The sample consists of respondents who purchased, financed, or leased a new car for private purposes within 24 months prior to the survey. In addition, we *ex ante* restrict our sample to customers who were the sole or primary decision makers in their last transaction to capture customer preferences and purchase decisions most accurately.

After removing a total of 194 observations following predetermined rules, our final sample includes 510 respondents. The predetermined logic comprises (among others) sorting out respondents who failed a hidden attention check (“please select answer 3”; 74 observations), who can be classified as “speeders” (under five minutes’ completion time and thus 40% of the median time; 16 observations), or who evidently confused the best possible final price with the best possible absolute discount when indicating their price expectations (37 observations).

Overall, the sample can be considered as close to the actual distribution of new car customers in terms of several key dimensions, which can be expected to strengthen the validity of our findings. We provide summary statistics for the sample in *Table 2.1*. The sample contains 63% male and 37% female respondents, which is close to the actual female share among German new car customers at 32% (Niethammer, 2019). Except for younger participants (18–24 years), the respondents’ age is distributed equally across the different age groups, with a median age of 49 (compared to an average German new car customer age of 53; Kraftfahrt-Bundesamt, 2022). Regarding the split by contract type, purchase respondents are overrepresented at 53%

(versus 16% in 2021), while financing customers are underrepresented at 21% (vs. 62%), while the share of leasing customers among respondents, at 26%, is close to the actual figure of 22% (Deutsche Automobil Treuhand, 2021). This might be explained by most respondents indicating that they were financing customers only if they financed their car in full and not just in part. The median transaction price in the sample is €37,153 for purchase and financing respondents (compared to the average German new car transaction price of €37,790 in 2021; Deutsche Automobil Treuhand, 2023). The median monthly leasing rate is €284, which is slightly higher than the 2021 national average of €243 in Germany (LeasingMarkt.de, 2022). We provide the distributions of the transaction prices and leasing rates in *Figures A.1* and *A.2* in the *Appendix*. Overall, 63% of the respondents were sole decision-makers in their last transaction, while 37% were main decision-makers who received some support. The transactions are evenly distributed over the 24-month period prior to the survey.

Segmentation	N	Share	Segmentation	N	Share
Gender			Contract type		
Female	187	37%	Purchase	268	53%
Male	321	63%	Leasing	133	26%
Diverse and other	2	0%	Financing	109	21%
Age group			Transaction role		
18-24	35	7%	Single decision maker	319	63%
25-34	76	15%	Main decision maker	191	37%
35-44	104	20%	Transaction time		
45-54	93	18%	Within last 6 months	138	27%
55-65	101	20%	Within last 7-12 months	119	23%
65+	101	20%	Within last 13-24 months	253	50%

Table 2.1: Sample summary statistics

2.4.3 Drivers of bargaining costs

To test our hypotheses, we regress our focal variable, *mean relative bargaining costs* (\bar{b}_i), on several respondent-specific variables consisting of *search behavior-specific factors* (S_i), and general *personality traits* (P_i) of the respondents. We measure the different factors through Likert-type scaled factors with three to five items and rely on established scales from previous studies as far as possible. To retain the respondents' attention, we shorten parts of the scales, as some of the scales comprised more than ten items. We measure the following *search behavior-specific factors*: willingness to search, opportunity cost of time, quality consciousness, sale proneness, post-purchase price confirmation, and car enthusiasm. The general *personality traits*

comprise risk propensity, (internal) locus of control, regulatory focus, and patience. All survey questions, items, and literature references can be found in *Section A.3* in the *Appendix*.

To ensure data suitability and validity of our scales for subsequent analyses, we conduct initial item analyses and purification (where we exclude unsuitable items), maximum likelihood exploratory factor analysis (*EFA*), and maximum likelihood confirmatory factor analysis (*CFA*). We provide a stepwise description of our scale construction *Section A.4* in the *Appendix*. To construct the factors for our analyses, we use two different weighting approaches: one with items weighted by the factor loadings from the *CFA* and one with equal-weighted items. For the scales with factor loading-weighted items, there are three factor pairs with statistically significant correlation coefficients with absolute values greater than 0.4 (willingness to search and opportunity cost of time; car enthusiasm and quality consciousness; risk propensity and car enthusiasm). For the scales with equal-weighted items, no factor pairs exhibit correlation coefficients with absolute values greater than 0.4. We provide the correlation matrices for the latent factors for both weighting approaches in *Tables A.3.a* and *A.3.b* in the *Appendix*.

Control variables in our analyses include different *demographic controls* (DC_i), such as gender, age, education, household income, and marital status; *previous new car transaction controls* (TC_i), such as contract type, new car transaction time, transaction role, price segment, new car experience, an indicator of whether the respondent negotiated, car type, and powertrain; as well as additional *search and purchase behavior controls* (SC_i) related to the last transaction, such as the number of models for which information was researched, the length of the research period, and an indicator determining whether the respondent is classified as an online customer. We provide an overview with descriptions of the control variables in *Table A.4* in the *Appendix*.

2.5 Results

2.5.1 Description of bargaining perceptions and bargaining costs

When openly asking about the willingness to negotiate, 68% of all respondents explicitly indicate that they would try to further negotiate down the offer price of *Dealer A*. 18% of the respondents are not sure whether they would negotiate, and the remaining 14% would not do so. This is a strong indication of customers' awareness of the potential cost savings that can be achieved through price negotiations. However, this does not necessarily imply that customers *prefer* or even enjoy price negotiations. In fact, 63% of respondents implicitly reveal that they are willing to pay a price markup to avoid having to negotiate through their choice behavior in the iterative trade-off between the negotiating *Dealer A* and the fixed price *Dealer B*. These respondents are willing to accept a fixed, non-negotiable price from *Dealer B* that is higher than

the price they expect after negotiating with *Dealer A*, which means that they have positive *mean bargaining costs*. This suggests that most customers may dislike the prevailing, decades-old negotiation-based model compared to a fixed pricing model. For the *adaptive version* (in which respondents form their own negotiation price expectations), this share is even higher, with 76% of respondents willing to pay a markup to avoid negotiations, whereas for the *non-adaptive version* (in which price expectations are exogenously provided), the share equals 50%.

In the *adaptive version*, where we ask respondents to form their own discount expectations, respondents on average expect that they can achieve a price reduction of 6.60% (median: 5.75%) on the initial offer price through negotiations with *Dealer A*, implying a 15.69% discount relative to the MSRP. On average, they state that they consider a discount of up to 8.02% to be feasible at best and assign an average likelihood of 65.01% to this best possible discount. We derive each respondent’s expected discount through *Equation 2.2*. Detailed descriptive statistics can be found in *Table 2.2*. We provide the distribution of the expected relative discount in *Figure 2.2* and observe a widespread distribution of the discount expectations, with a standard deviation of 4.35. There are some extreme upward outliers with a maximum expected discount of 33.00% and some modest expectations with an expected discount slightly less than 1.00%. However, half of the respondents have discount expectations of between 3.64% and 8.20%. These findings indicate that customers have become used to price negotiations being a common practice in the new car market, which is in line with current industry reports and results in significant cost savings (Center Automotive Research, 2022). Thus, customers have formed price expectations that should make them less inclined to accept any quoted fixed price as the final price.

<i>in %</i>	Mean	Min.	Q _{0.25}	Median	Q _{0.75}	Max.	SD
Adaptive max. feasible relative discount	8.02	0.10	5.00	6.67	10.00	33.33	5.17
Adaptive likelihood of max. feasible discount	65.01	2.00	50.00	70.00	80.75	100.00	22.13
Adaptive expected relative discount	6.60	0.08	3.64	5.75	8.20	33.00	4.35
Non-adaptive expected relative discount	3.51	3.50	3.50	3.51	3.52	3.53	0.01
Mean expected relative discount	5.06	1.80	3.58	4.64	5.85	18.26	2.18
Adaptive indifference fixed price discount	4.31	0.02	1.20	3.25	6.25	31.85	4.29
Non-adaptive indifference fixed price discount	3.71	0.75	1.75	3.47	5.98	6.88	2.08
Mean indifference fixed price discount	4.01	0.40	1.75	3.47	5.80	19.26	2.92
Adaptive relative bargaining cost	2.30	-12.41	0.05	1.73	3.69	25.84	3.91
Non-adaptive relative bargaining cost	-0.20	-3.35	-2.47	0.05	1.75	2.75	2.08
Mean relative bargaining cost	1.05	-7.70	-0.78	0.87	2.52	13.48	2.55

Table 2.2: Descriptive statistics discount expectations, *indifference fixed price discounts*, and *relative bargaining costs* (variation in *non-adaptive* expected relative discount due to rounding)

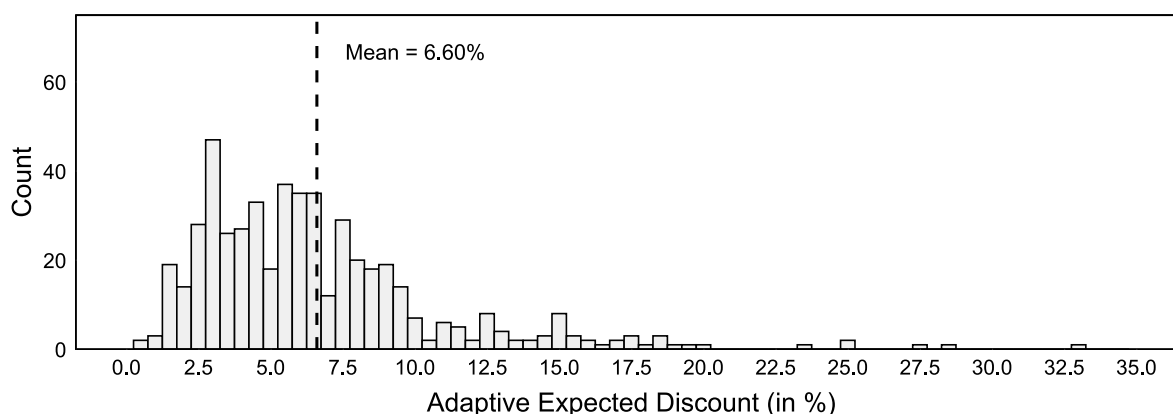


Figure 2.2: Distribution and mean of the expected relative discount (*adaptive version*)

Next, we introduce *Dealer B* with the fixed, non-negotiable price that we gradually reduce with each iteration of the trade-off decision we confront respondents with. We thereby find that the fixed price, which is required to make customers indifferent between a fixed, non-negotiable price and a negotiable offer price, is on average 4.31% (median: 3.25%) lower than the original offer price. We derive this *indifference fixed price* as the mean of the fixed price a respondent chooses and the last fixed price that she still rejected. We again do so to smooth the effect that might be attributable to the fixed price step sizes between the question iterations. Importantly, this fixed price discount of 4.31% (in the *adaptive version*) that makes customers indifferent is lower than the discount of 6.60% that customers expect after price negotiations. This implies that, on average, customers are willing to accept a 2.30% markup over their initial price expectations (relative to the offer price) to avoid price negotiations. This 2.30% price markup constitutes the focal variable in our study, which we define as the customer-individual *relative bargaining costs* (in this case in the *adaptive version*). In absolute terms, *adaptive bargaining costs* equal €911.37 for purchase and finance respondents and €8.77 per month (€105.20 p.a.) for lease customers (see *Table A.5* in the *Appendix*). We provide the distributions of the *adaptive indifference fixed price discount* and of *adaptive bargaining costs* in *Figures A.3* and *A.4* in the *Appendix*. The distribution of *adaptive bargaining costs* ranges from -12.41% to 25.84%, with half of the respondents exhibiting *adaptive bargaining costs* between 0.05% and 3.69%. The distribution is skewed to the right, indicating that a small share of respondents has much higher *adaptive bargaining costs* than the majority of respondents. Furthermore, there is a relatively large number of extreme outliers at both ends of the distribution.

In the *non-adaptive version*, we provide respondents with the expected discount by sharing information regarding the negotiation outcomes of previous customers. Specifically, we mention that 50% of previous customers achieved a discount of 6.50% on the offer price, and the other 50% obtained a moderate rebate of up to 1.05%. This leads to an expected discount

of 3.51% relative to the initial offer price (see *Equation 2.3*) and of 12.60% relative to the MSRP, which is in line with the new car discount levels in Germany during the survey period (Center Automotive Research, 2022). Based on the respondents' choice behavior between the two dealers, we again derive the fixed price discount that is required to make them indifferent between paying a fixed price or negotiating. This *indifference fixed price discount* averages 3.71% in the *non-adaptive version* and is thus relatively close to the *adaptive version* (4.31%). However, it is important to note that in the *non-adaptive version*, the (exogenously provided) expected negotiation discount is substantially lower than the average discount that respondents themselves expect in the *adaptive version* (3.51% versus 6.60%). As a result, by comparing required *indifference fixed price discounts* and expected negotiation discounts, respondents in the *non-adaptive version* on average demand a small financial compensation of 0.20% (relative to the offer price) for the absence of the option to negotiate. This required financial compensation corresponds to *non-adaptive bargaining costs*, which are negative on average (-0.20%). In absolute terms, *non-adaptive bargaining costs* equal -€40.70 for purchase and finance respondents and -€1.36 per month (-€16.33 p.a.) for lease customers (see *Table A.5* in the *Appendix*). We provide the distributions of the *non-adaptive indifference fixed price discounts* and of *non-adaptive bargaining costs* in *Figures A.5* and *A.6* in the *Appendix*. *Non-adaptive bargaining costs* range from -3.35% to 2.75%, with half of the respondents exhibiting *non-adaptive bargaining costs* between -2.47% and 1.75% and several observations at the two extreme bounds. The distribution is thus more centered and with fewer outliers than for the *adaptive version*, which can be explained by the exogenously provided discount expectations.

To explain the difference between *adaptive* and *non-adaptive bargaining costs*, two explanations appear likely. Both explanations concern the respondents' reference price.

First, respondents could be overconfident in the sense that they are strongly oriented towards previous customers who achieved the best possible discount (i.e., 6.50%) through negotiations with *Dealer A* instead of towards the expected discount of 3.51%. This would then lead them to select higher fixed prices at *Dealer B*, resulting in lower *non-adaptive bargaining costs*. *Non-adaptive bargaining costs* relative to the maximum discount would on average equal 2.80%. For comparison, *adaptive bargaining costs* relative to the maximum discount would average 3.70%. However, the range between the minimum (0.00%) and the (sample mean) maximum discount (8.02%) is wider in the *adaptive version* than in the *non-adaptive version* (from 0.00% to 6.50%). The required *indifference fixed price discount* equals 57% of the maximum discount in the *non-adaptive version* and 54% in the *adaptive version*, which is relatively similar (we provide an illustration of this relation in *Figure A.7* in the *Appendix*). Thus, the respondents' choice behavior across the two versions might be more consistent than it first appears.

Second, respondents might still use their initial price expectations from the *adaptive version* as their reference point in the *non-adaptive version* instead of considering the exogenous expected price at *Dealer A*. This would have similar implications for the *indifference fixed price discounts* as the first explanation. In this case, *bargaining costs* relative to those initial expectations would on average equal 2.90% (compared to *adaptive bargaining costs* of 2.30%).

Overall, both versions have conceptual advantages. Beyond the respondents' selected fixed price options, the *adaptive version* explicitly incorporates customers' price expectations and thus also a second crucial component of *bargaining costs*. These expectations are formed based on information gathered and past experiences, making it more reflective of real-life situations, since beliefs regarding results play a crucial part in negotiation behavior (Dickinson, 2009). However, some respondents may not have sufficient information or negotiation experience to derive informed discount expectations. In contrast, the *non-adaptive version* focuses solely on the central component of *bargaining costs*, namely the selected fixed price alternative, while holding expected prices constant. To increase the generalizability and robustness of results by using a more balanced measure of *bargaining costs*, we analyze the equal-weighted mean of the *adaptive* and the *non-adaptive version*, i.e., *mean bargaining costs*.

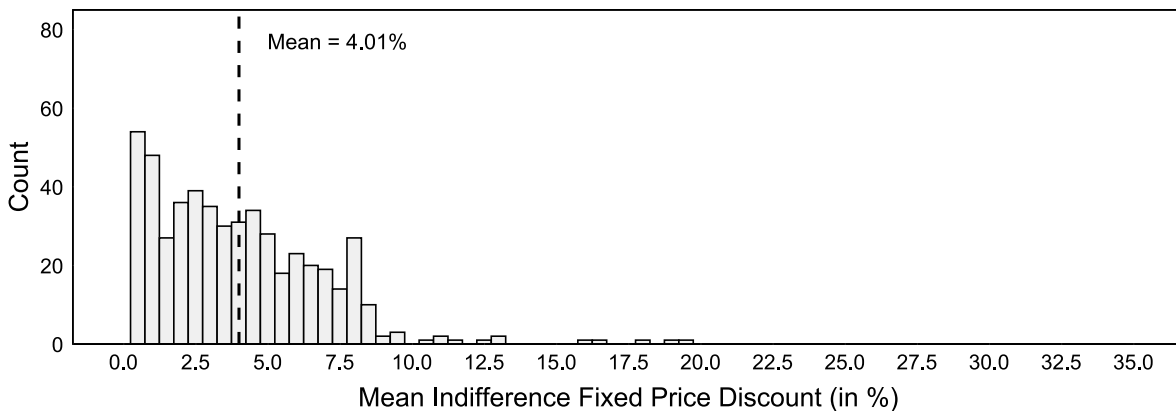


Figure 2.3: Distribution of the *mean indifference fixed price discount*

When considering the equal-weighted mean of the *adaptive* and the *non-adaptive* versions, respondents expect an average relative discount of 5.06% (distribution provided in *Figure A.8* in the *Appendix*) and require an *indifference fixed price discount* of 4.01%. *Figure 2.3* shows the distribution of the *mean indifference fixed price discount*, which is right-skewed, indicating that most respondents require relatively small discounts, while a minority need much higher rebates to be indifferent between a negotiable and a fixed price. Relative to the mean expected discount, customers are thus willing to pay an average markup of 1.05% (relative to the offer price) over their expected negotiated price to avoid having to bargain. We show the distribution of this markup (i.e., *mean bargaining costs*) in *Figure 2.4*. The distribution is also right-skewed,

with heavier tails compared to a normal distribution. 50% of all respondents fall within the range between -0.78% and 2.52% and are again rather equally distributed within this interval. Overall, 63% of all respondents show positive *mean bargaining costs*.

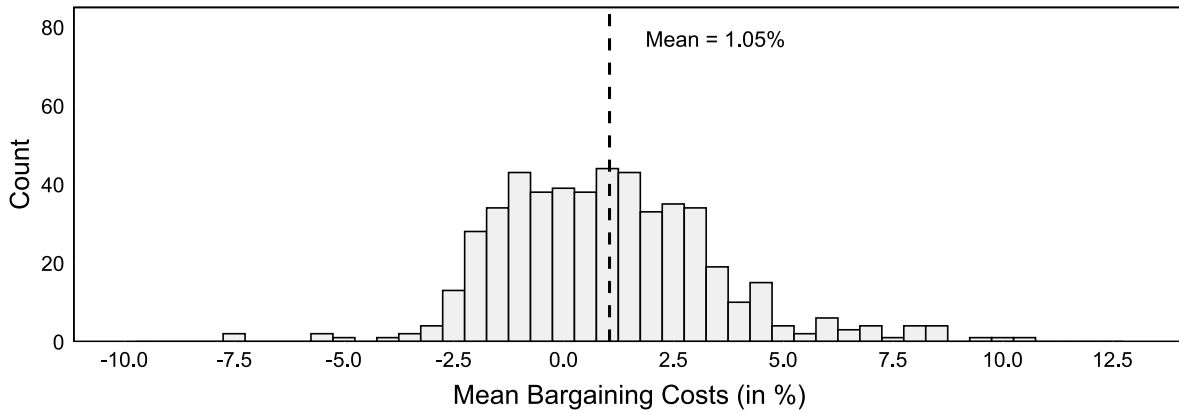


Figure 2.4: Distribution of *mean bargaining costs*

In absolute terms, *mean bargaining costs* amount to €435.34 for purchase and finance and €3.70 per month (€44.43 p.a.) for lease customers (see *Table A.5* in the *Appendix*). These *mean bargaining costs*, which are positive on average, have crucial implications for car OEMs as they could significantly increase their realized prices, with a substantial profit impact.

In conclusion, our findings indicate that customers are aware of the potential cost savings to be achieved through price negotiations and that most would actively attempt to negotiate down the initial offer price. Customers form substantial price expectations, which suggests that they are unlikely to accept any given price posted on a car as the final price. To retain customers, car brands might need to reduce their offer prices by approximately 4%, which is less than the discount customers expect in price negotiations. As a result, customers are on average willing to pay a markup of roughly 1% over their *ex ante* expected post-negotiation price to avoid negotiating. This corresponds to their individual (*mean*) *bargaining costs*. Our results suggest that there is again heterogeneity among respondents, which we will focus on in the next section.

2.5.2 Investigation of drivers of bargaining costs

In this section, we address our last research question and analyze the heterogeneity in *bargaining costs* to assess whether there are specific determining factors. To test our hypotheses from *Section 2.3*, we regress our focal variable, *mean relative bargaining costs* (\bar{b}_i), on our latent variables consisting of *search behavior-specific factors* (S_i) and more general *personality traits* (P_i), as well as on several control variables using the following regression model:

$$\bar{b}_i = \alpha + \beta \cdot S_i + \gamma \cdot P_i + \delta \cdot DC_i + \vartheta \cdot TC_i + \mu \cdot SC_i + \varepsilon_i \quad (2.4)$$

Matrix *S* is composed of *search behavior-specific variables*: willingness to search (*SEA*), opportunity cost of time (*OPP*), quality consciousness (*QUA*), sale proneness (*SAL*), post-purchase price confirmation (*PRI*), and car enthusiasm (*CAR*). Matrix *P* contains more general *personality traits* of the respondents: risk propensity (*RIS*), (internal) locus of control (*LOC*), prevention focus (*PRE*), promotion focus (*PRO*), and patience (*PAT*). Control variables consist of *demographic controls* (DC_i),⁴ *previous new car transaction controls* (TC_i),⁵ and *search and purchase behavior controls* (SC_i).⁶ We provide an overview with descriptions of the control variables in *Table A.4* in the *Appendix*.

We present the regression results in *Table 2.3*, where we estimate different model specifications to ensure robustness of results regarding potential multicollinearity and item-weighting approaches for our scales. We report the specifications in columns 1–5 of *Table 2.3*. For the latent factors with equal-weighted items (column 5), none are correlated with absolute correlation coefficients of 0.40 or higher, which is why we include all factors here.

Overall, three of the factors seem to be statistically significantly related to *mean bargaining costs*. This is consistent across all five specifications. First, respondents with higher willingness to search (*SEA*) are related to lower *bargaining costs*, supporting *hypothesis H.1*. This suggests that respondents willing to invest more time in research, information gathering, and the comparison process might be less likely to be willing to pay a premium to avoid negotiating. The finding is in line with prior research. Zettermeyer et al. (2006) show that individuals with a higher willingness to search generally do better in price negotiations and pay lower prices on average. Moreover, customers with greater willingness to search are, by the design of the construct, better informed and more knowledgeable. This is empirically found to be related to greater confidence (Peterson & Pitz, 1988). Further studies indicate that individuals with better negotiation skills and histories and more confident individuals are more likely to initiate negotiations (e.g., O'Connor et al., 2005; Reif & Brodbeck, 2017). Overall, our finding that a greater willingness to search is negatively associated with *bargaining costs* therefore points towards prior studies showing that individuals willing to invest more time and effort into information research are more likely to initiate price negotiations, as they tend to be more successful, knowledgeable, and confident in bargaining situations. Altogether, it appears that

⁴ Gender, age, education, household income, and marital status.

⁵ Contract type (purchase, financing, leasing), new car transaction time, transaction role, price segment, new car experience, indicator specifying whether the respondent negotiated in the last transaction, car type, and powertrain.

⁶ Number of models for which information was researched, length of the research period, and an indicator determining whether the respondent is classified as an online customer.

concerns about time and research efforts associated with price negotiations might be a crucial driver of *bargaining costs* and the willingness or aversion to participate in negotiations.

	Dependent variable: mean relative bargaining costs				
	(1)	(2)	(3)	(4)	(5)
Willingness to search (SEA)	-0.527*** (0.132)		-0.494*** (0.135)		-0.428** (0.171)
Opportunity cost of time (OPP)		0.671*** (0.140)		0.637*** (0.142)	0.391*** (0.114)
Quality consciousness (QUA)			0.065 (0.165)	-0.041 (0.159)	0.021 (0.161)
Sale proneness (SAL)	-0.098 (0.140)	0.044 (0.145)	-0.095 (0.142)	0.028 (0.147)	0.002 (0.149)
Post-purchase price confirmation (PRI)	0.547*** (0.156)	0.356** (0.158)	0.566*** (0.148)	0.380** (0.150)	0.434*** (0.132)
Car enthusiasm (CAR)	0.164 (0.147)	0.080 (0.144)			0.067 (0.111)
Risk propensity (RIS)			0.207 (0.147)	0.186 (0.146)	0.210 (0.132)
(Internal) locus of control (LOC)	-0.009 (0.120)	-0.081 (0.118)	-0.030 (0.123)	-0.079 (0.122)	-0.083 (0.139)
Prevention focus (PRE)	0.083 (0.123)	0.055 (0.121)	0.097 (0.126)	0.081 (0.125)	0.100 (0.152)
Promotion focus (PRO)	0.011 (0.115)	-0.026 (0.113)	-0.023 (0.118)	-0.039 (0.117)	-0.029 (0.115)
Patience (PAT)	-0.099 (0.113)	-0.102 (0.112)	-0.105 (0.113)	-0.102 (0.112)	-0.106 (0.116)
Demographic controls (DC)	yes	yes	yes	yes	yes
Transaction controls (TC)	yes	yes	yes	yes	yes
Search & purchase behavior controls (SC)	yes	yes	yes	yes	yes
Factor loading-weighted items (CFA)	yes	yes	yes	yes	no
Equal-weighted items	no	no	no	no	yes
N	510	510	510	510	510
R ²	0.214	0.225	0.217	0.227	0.236
Note	* p < 0.10; ** p < 0.05; *** p < 0.01; robust standard errors in ()				

Table 2.3: Multiple linear regression results for different model specifications (dependent variable: *mean relative bargaining costs*)

Second, our results support *hypothesis H.2*, which suggests that respondents with higher opportunity costs of time are associated with higher *bargaining costs*. This is mainly driven by the respondents' selected fixed price. Respondents with the highest opportunity cost of time (top quartile) have similar negotiation discount expectations to those with the lowest (bottom quartile) but are already indifferent between negotiating and paying a fixed price for substantially higher fixed price alternatives. Individuals with higher opportunity costs of time thus appear to be willing to pay higher markups to avoid price negotiations. This is in line with Zhang et al. (2021), who show that individuals with higher opportunity costs of time are less likely to participate in price negotiations, as they are time-consuming and would be more costly

to those individuals. Therefore, for some individuals, the cost of participating in negotiations seems to be not only limited to the time and effort required to negotiate but also includes the opportunity cost of time they could spend on other valuable activities. Together, the findings regarding *hypotheses H.1* and *H.2* are in line with previous studies and suggest that customer reluctance to negotiate is driven by time constraints, which could be particularly relevant for customers with high-paying jobs, busy schedules, or other responsibilities.

Third, the results indicate that respondents with a stronger tendency for post-purchase price confirmation are associated with higher *bargaining costs*, which supports *hypothesis H.5*. Individuals who continue to compare prices after their purchase, thus, appear to be willing to pay higher markups to avoid negotiating. This result is in line with the study by Pizzutti et al. (2022). The authors show that many buyers continue to compare prices after their purchase and seek to avoid post-purchase regret and to confirm that they made the right purchase decision. Since price negotiations are related to price uncertainty, which might lead to potential regret about whether someone got the best possible price (Simonson, 1992), it is expected that individuals with a stronger tendency to confirm prices post-purchase try to avoid this potential regret more strongly. This is supported by our results, which suggest that respondents that tend to confirm prices more strongly after a purchase exhibit higher *bargaining costs* and are thus less prone to initiating a price negotiation. Furthermore, we support industry reports indicating that customers value post-purchase “peace of mind” by ensuring that they do not miss out on a better offer (Schmidt et al., 2020).

Although statistically insignificant, our results imply two relations that are nonetheless noteworthy as they do not support our hypotheses. Contrary to *hypothesis H.6*, car enthusiastic respondents seem to be (insignificantly) associated with higher *bargaining costs*, which suggests that car enthusiasts are on average willing to accept greater price markups to avoid having to negotiate the price of a new car. This contradicts the logic underlying our hypothesis. Our rationale stems from combining previous research showing that enthusiasm is associated with positive affect (Moè, 2016) and that positive affect increases a buyer’s propensity to enter negotiations (Barry & Oliver, 1996). Instead, the finding might point towards Baron’s (1990) results that positive affect leads to higher individual concession-making in face-to-face negotiations, which aligns with car enthusiasts being willing to accept greater price markups to avoid negotiations. In addition, car enthusiastic respondents in our survey are (by construct design) more interested in the product itself, and Ramirez and Goldsmith (2009) find a negative relationship between product involvement and price sensitivity. Related to our study, this could imply that car enthusiastic respondents are less price sensitive and prefer focusing on the product and its quality during the purchase process rather than on potential price savings

through price negotiations. This is also indicated by the correlation of 0.54 between car enthusiasm and quality consciousness (for the factors with factor loading-weighted items).

Moreover, our results suggest an insignificantly positive relationship between individual risk propensity and *mean bargaining costs*. This does not support our *hypothesis H.7*. Interestingly, risk seeking respondents (top quartile) have both higher negotiation discount expectations and require lower *indifference fixed price discounts* than risk averse respondents (bottom quartile), resulting in risk-seeking respondents being willing to pay higher markups to avoid having to negotiate. *Hypothesis H.7* stems from the fact that our approach is based on respondents' choices between risky (i.e., price negotiations) and safe options (i.e., fixed prices), and risk-seeking individuals are by definition more inclined to choose risky options (e.g., Schubert et al., 1999). However, despite not being statistically significant, our findings point in the other direction, namely that risk-seeking individuals are more willing to choose the safe option (i.e., the fixed price), which is reflected in higher *bargaining costs* for risk-seeking individuals.

This relation might be explained by a phenomenon known as the *self-framing effect*, which is originally based on Tversky and Kahneman's (1981) framing effect and states that individual risk-taking behavior depends on how a person frames a specific situation. Our explanation based on the *self-framing effect* follows three steps: First, risk-seeking individuals tend to be more optimistic (Weinstock & Sonsino, 2014), which is also suggested by our data, in that more risk-seeking respondents have higher discount expectations. Second, optimists exhibit a stronger tendency toward positive self-framing. Optimistic individuals thus tend to perceive situations more positively – for instance, as opportunities to win rather than as risks of losing (Zhang et al., 2020). Third, people tend to behave more risk aversely under positive (self) frames (e.g., when maximizing gains) than under negative (self) frames (e.g., when minimizing losses) (Wang, 2004). Thus, in situations with ambiguous framing, the *self-framing effect* may ultimately lead respondents who are in fact risk seeking to behave more risk aversely than individuals who are intrinsically risk averse. In our setting, where the tradeoff between the two dealers is framed neutrally, i.e., neither as an opportunity to maximize profits nor to minimize losses, this may cause risk seeking individuals to perceive the tradeoff as an opportunity to maximize profits (i.e., as a positive frame) and thus to act more risk aversely by choosing a lower *indifference fixed price discount*.⁷ The *self-framing effect* and specifically the influence

⁷ A positive self-frame could imply that the original offer price of *Dealer A* serves as a reference point, and every euro saved through a lower fixed price from *Dealer B* is considered a profit that the customer tries to maximize. A negative self-frame could mean that an individual uses the expected negotiated price at *Dealer A* as a reference point, and every euro lost through a higher fixed price from *Dealer B* is considered a loss that she tries to minimize.

of risk propensity on self-framing have been researched very little in the context of negotiations. Future research could thus explicitly analyze these relationships and effects in more detail.

For the remaining hypotheses, we observe that the regression results for the (internal) locus of control, prevention focus, promotion focus, and patience factors do not support *hypotheses H.8 to H.10*. Stronger prevention focused respondents are statistically insignificantly associated with higher *bargaining costs*, while respondents with a stronger (internal) locus of control, a stronger promotion focus, and more patience tend to incur lower *bargaining costs*. Testing the equality of the regression coefficients with respect to prevention and promotion focus (*hypothesis H.9*) indicates a positive, but statistically insignificant, difference. According to the regression results, quality consciousness and sale proneness both do not appear to influence *mean bargaining costs*, which is why we cannot support *hypotheses H.3 and H.4*.

With respect to the control variables, there are four additional variables that appear to have a statistically significant impact on *mean bargaining costs*. Particularly, older respondents and respondents who acquired a diesel or a plug-in hybrid vehicle in their most recent new car transaction are associated with lower *mean bargaining costs*, whereas respondents who did not negotiate in their last transaction exhibit elevated *mean bargaining costs*. We do not observe any significant gender effects with respect to *bargaining costs* in our results.⁸

2.5.3 Robustness check

In this section, we provide a comprehensive set of robustness checks to validate the findings from our focal analyses. Particularly, we conduct separate regression analyses for *adaptive* and *non-adaptive bargaining costs*, examine the *explicit bargaining willingness* and our *bargaining indicator* through regression analyses, and extend our analyses with several subsample and interaction effect analyses. Through these varied analyses, we find relatively robust support for the main conclusions drawn from our focal analyses, underlining the robustness of our findings.

Regarding our two versions to derive customer-individual *bargaining costs*, the main benefit of the *adaptive version* is that we can explicitly incorporate respondents' negotiation discount expectations. This closely resembles real new car transactions. The *non-adaptive version*, on the other hand, avoids potential biases that might arise due to the inability of some respondents

⁸ Furthermore, none of the correlation coefficients between gender and the constructs have an absolute value greater than 0.20 (for both weighting approaches), which is why we can likely rule out indirect gender mediation effects. Due to extensive prior research on gender effects on negotiation initiation propensity and the fact that we do not observe any significant gender effects, we do not elaborate on gender differences in more detail.

to form reasonable expectations. In addition, the focus in this version lies more on the fixed price discount required to make customers indifferent between the two pricing schemes.

We report the regression results with *adaptive bargaining costs* as the dependent variable in *Table 2.4*. It is important to mention that model fit is substantially lower compared to our focal analyses, which is likely attributable to the greater dispersion in *adaptive bargaining costs*. In the regression analyses of *adaptive bargaining costs*, we find further support for our findings regarding the relationship between *bargaining costs* and willingness to search (*hypothesis H.1*), opportunity cost of time (*H.2*), and post-purchase price confirmation (*H.5*), all of which are again statistically significant. Again, the results do not support our hypotheses regarding the relationship between *bargaining costs* and car enthusiasm (*H.6*) and risk propensity (*H.7*). The remaining coefficients of the independent variables are all also statistically insignificant.

	Dependent variable: adaptive relative bargaining costs				
	(1)	(2)	(3)	(4)	(5)
Willingness to search (SEA)	-0.611 *** (0.208)		-0.605 *** (0.212)		-0.556 ** (0.271)
Opportunity cost of time (OPP)		0.750 *** (0.221)		0.707 *** (0.225)	0.397 ** (0.180)
Quality consciousness (QUA)			0.317 (0.259)	0.183 (0.252)	0.226 (0.254)
Sale proneness (SAL)	-0.028 (0.220)	0.129 (0.229)	0.026 (0.224)	0.154 (0.232)	0.091 (0.235)
Post-purchase price confirmation (PRI)	0.563 ** (0.245)	0.348 (0.249)	0.553 ** (0.233)	0.341 (0.237)	0.495 ** (0.209)
Car enthusiasm (CAR)	0.234 (0.231)	0.137 (0.228)			0.051 (0.176)
Risk propensity (RIS)			0.245 (0.231)	0.232 (0.231)	0.278 (0.208)
(Internal) locus of control (LOC)	-0.132 (0.188)	-0.214 (0.187)	-0.200 (0.193)	-0.258 (0.193)	-0.256 (0.220)
Prevention focus (PRE)	0.058 (0.194)	0.023 (0.192)	0.046 (0.198)	0.023 (0.197)	0.058 (0.241)
Promotion focus (PRO)	-0.039 (0.180)	-0.082 (0.179)	-0.122 (0.186)	-0.143 (0.185)	-0.111 (0.182)
Patience (PAT)	-0.093 (0.178)	-0.099 (0.177)	-0.119 (0.178)	-0.121 (0.177)	-0.114 (0.183)
Demographic controls (DC)	yes	yes	yes	yes	yes
Transaction controls (TC)	yes	yes	yes	yes	yes
Search & purchase behavior controls (SC)	yes	yes	yes	yes	yes
Factor loading-weighted items (CFA)	yes	yes	yes	yes	no
Equal-weighted items	no	no	no	no	yes
N	510	510	510	510	510
R ²	0.168	0.172	0.173	0.176	0.183
Note	* p < 0.10; ** p < 0.05; *** p < 0.01; robust standard errors in ()				

Table 2.4: Multiple linear regression results for different model specifications (dependent variable: *adaptive relative bargaining costs*)

We provide the regression results with *non-adaptive bargaining costs* as the dependent variable in *Table 2.5*. Here, we also find significant support for our hypotheses on the relationship between *bargaining costs* and willingness to search (*H.1*), opportunity cost of time (*H.2*), and post-purchase price confirmation (*H.5*). Again, the insignificant positive association between *bargaining costs* and car enthusiasm as well as risk propensity persists, which does not support *hypotheses H.6* and *H.7*. In the *non-adaptive version*, we observe a statistically significant negative relationship between sale proneness and *bargaining costs*, which supports our *hypothesis H.4*. This indicates that sale prone individuals might be associated with lower *bargaining costs*, which means that they have relatively strong preferences for negotiating the price instead of paying a fixed price. For the *non-adaptive version* (i.e., the one with exogenous discount expectations), this implies that sale prone respondents require lower fixed price options for being indifferent between paying a fixed price or negotiating. This is in line with Hackleman and Duker (1980), who show that sale prone customers are particularly susceptible to rebates. In our setting, this could lead sale prone customers to be more willing to invest time and effort in price negotiations to obtain a better deal, as they feel a sense of satisfaction when they negotiate a better price for their new car. The regression results further show a statistically significant negative relationship between *non-adaptive bargaining costs* and quality consciousness. This does not support *hypothesis H.3* and implies that quality conscious respondents might be associated with lower (*non-adaptive*) *bargaining costs*, which means that they also require relatively lower fixed price alternatives for being indifferent between paying a (lower) fixed price or negotiating. This is not in line with the rationale of our initial hypothesis that quality conscious buyers are more concerned with product quality than with price discounts, incur little or no disutility from paying higher prices, and are thus less inclined to enter price negotiations and seek a better deal (Ailawadi et al., 2001; Ding et al., 2010). A potential explanation for our results is based on Lichtenstein et al. (1993), suggesting that quality conscious individuals may try to optimize the “value for the money” ratio (i.e., the ratio of product quality to price). In our setting, quality conscious respondents might recognize that the quality of the new cars is the same between the two dealers and that they can thus optimize the “value for the money” ratio only through the final price paid. Hence, they might prefer to obtain the best possible price by negotiating, which can result in lower *bargaining costs* (i.e., a stronger preference for negotiating).

	Dependent variable: non-adaptive relative bargaining costs				
	(1)	(2)	(3)	(4)	(5)
Willingness to search (SEA)	-0.444 *** (0.108)		-0.383 *** (0.110)		-0.299 ** (0.140)
Opportunity cost of time (OPP)		0.591 *** (0.114)		0.567 *** (0.116)	0.386 *** (0.093)
Quality consciousness (QUA)			-0.187 (0.135)	-0.265 ** (0.130)	-0.183 (0.131)
Sale proneness (SAL)	-0.169 (0.114)	-0.040 (0.118)	-0.215 * (0.116)	-0.097 (0.119)	-0.086 (0.122)
Post-purchase price confirmation (PRI)	0.530 *** (0.127)	0.363 *** (0.129)	0.579 *** (0.121)	0.419 *** (0.122)	0.373 *** (0.108)
Car enthusiasm (CAR)	0.093 (0.120)	0.023 (0.118)			0.084 (0.091)
Risk propensity (RIS)			0.170 (0.120)	0.140 (0.119)	0.142 (0.108)
(Internal) locus of control (LOC)	0.115 (0.098)	0.053 (0.097)	0.141 (0.100)	0.099 (0.099)	0.090 (0.114)
Prevention focus (PRE)	0.108 (0.101)	0.087 (0.099)	0.148 (0.103)	0.140 (0.102)	0.142 (0.124)
Promotion focus (PRO)	0.060 (0.094)	0.029 (0.092)	0.076 (0.097)	0.065 (0.095)	0.053 (0.094)
Patience (PAT)	-0.104 (0.092)	-0.105 (0.091)	-0.090 (0.093)	-0.083 (0.091)	-0.099 (0.095)
Demographic controls (DC)	yes	yes	yes	yes	yes
Transaction controls (TC)	yes	yes	yes	yes	yes
Search & purchase behavior controls (SC)	yes	yes	yes	yes	yes
Factor loading-weighted items (CFA)	yes	yes	yes	yes	no
Equal-weighted items	no	no	no	no	yes
N	510	510	510	510	510
R ²	0.208	0.223	0.211	0.231	0.232
Note	* p < 0.10; ** p < 0.05; *** p < 0.01; robust standard errors in ()				

Table 2.5: Multiple linear regression results for different model specifications (dependent variable: *non-adaptive relative bargaining costs*)

Regarding the comparison of the *adaptive* and the *non-adaptive version*, we find that quality conscious respondents may react less to exogenously provided negotiation discount information than less quality conscious respondents. While in the *adaptive version*, the relationship between quality consciousness and *bargaining costs* is (statistically insignificantly) positive, in the *non-adaptive version* it is significantly negative. We confirm this observation by using the difference between *adaptive* and *non-adaptive bargaining costs* as the dependent variable in our regression analyses (see Table A.6 in the Appendix), which shows a statistically significant positive relationship for quality consciousness. In the *adaptive version*, quality conscious (top quartile) and less quality conscious (bottom quartile) respondents have similar discount expectations (6.4%) as well as *indifference fixed price discounts* (4.1% and 4.2%, respectively). When we introduce the *non-adaptive version* (i.e., exogenous discount expectations), the *indifference fixed price discount* declines by 9% (to 3.8%) for quality conscious respondents,

but by 18% (to 3.5%) for less quality conscious ones. This stronger reaction to exogenous price information might be attributable to less quality conscious individuals having less confidence in their own judgment (e.g., Peterson & Pitz, 1988). In contrast, quality conscious individuals may be focused more strongly on product quality and less impacted by external information.

For the regression of *non-adaptive bargaining costs* as the dependent variable, the remaining regression coefficients of the independent variables are again all statistically insignificant.

To further assess the robustness of our results, we regress the *explicit bargaining willingness* (i.e., the answer to our open survey question of whether a respondent would try to negotiate) as well as the *bargaining indicator* (i.e., the indicator specifying whether a respondent negotiated in the previous transaction) on our independent and control variables.

We show the results of the regression analyses of the *explicit bargaining willingness* in Table A.7 in the Appendix and observe two statistically significant relations. First, respondents with a stronger willingness to search are positively associated with *explicit bargaining willingness*, which again backs our findings that these individuals exhibit lower *bargaining costs*. Second, respondents with higher opportunity costs of time are negatively related to *explicit bargaining willingness*. This also supports our results that they are related to higher *bargaining costs*.

For the logistic regression analyses of the *bargaining indicator*, which we provide in Table A.8 in the Appendix, we observe three statistically significant relations. Again, respondents with higher opportunity costs of time are negatively related to the dependent variable. This implies that these individuals in fact negotiated significantly less than those with lower opportunity costs of time. This supports our previous results and shows that the statistically significant positive relationship between opportunity costs of time and *bargaining cost* observed in our study is also reflected in the actual negotiation behavior of the respondents. Furthermore, car enthusiasts and risk-seeking respondents are statistically significantly more likely to have negotiated during their most recent new car transaction. This is in line with our hypotheses but not with our previous findings that both car enthusiasts and risk seekers are (insignificantly) associated with higher *bargaining costs*. This might imply that car enthusiasts and risk-seekers in fact negotiate more frequently in actual transactions, but on the other hand, would prefer not having to negotiate and instead paying a fixed, non-negotiable price if given the choice. It is, however, important to note that, in reality, new car customers usually do not have the choice between fixed and non-negotiable prices for the same brand, and especially for the same model.

Overall, our findings regarding the relationship between *bargaining costs* and willingness to search (H.1), opportunity cost of time (H.2), and post-purchase price confirmation (H.5) appear highly robust to the applied checks and support our hypotheses. Concerning car enthusiasm and

risk propensity, the regression analyses of the different *bargaining cost* versions do not support our hypotheses (*H.6* and *H.7*). On the other hand, the regression analyses of the *bargaining indicator* show a significant positive relationship with both car enthusiasm and risk propensity, which (implicitly) indicates a negative relationship with *bargaining costs* and thus points towards supporting our hypotheses. For quality consciousness and sale proneness, we find statistically significant effects only for the regression of *non-adaptive bargaining costs*. We observe a negative relationship of quality consciousness, which does not support *hypothesis H.3*. For sale proneness, we also find a negative association, which supports *hypothesis H.4*. For the remaining hypotheses, we do not observe significant support in the robustness checks.

Since our overall findings regarding car enthusiasm, risk propensity, quality consciousness, and sale proneness are relatively ambiguous, we conduct several subsample and interaction effect analyses to further assess robustness and understand potential drivers of the observed effects.⁹ We apply subsample splits and interaction effects based on gender (following Small et al., 2007), variables capturing experience and knowledge (i.e., new car transaction experience, prior negotiation experience, and age, motivated by Peterson and Pitz, 1988), and customer segmentation by offline and online customers (based on Zettelmeyer et al., 2006), as well as referenced price levels (i.e., price segment and contract type, following Carlson et al., 2008).¹⁰ We report the subsample regression results in *Tables A.9* to *A.11* and the results of the regression analyses with interaction effects in *Tables A.12* to *A.15* (both in the *Appendix*).

With respect to car enthusiasm, we find a significantly negative interaction effect with new car transaction experience (*Table A.14*). This indicates that more experienced, car enthusiastic respondents exhibit lower *mean bargaining costs*, which supports *hypothesis H.6* but not the insignificant positive relation between car enthusiasm and all three *bargaining cost* versions.

Concerning risk propensity, we observe statistically significant positive relations with *mean bargaining costs* for the subsamples of women, older respondents (both *Table A.9*), lease customers, customers in the lower price segments (both *Table A.10*), and offline customers (*Table A.11*). These findings further increase the robustness of our previous results, which do not support *hypothesis H.7*, and thereby provide greater plausibility for the *self-framing effect* explanation for the positive relation between *mean bargaining costs* and risk propensity.

⁹ *Note:* In the subsample and interaction effect analyses, we regress *mean relative bargaining costs* on our independent and control variables and use latent factors with equal-weighted items, as they provide the highest R^2 values in the focal regression analyses, indicating a stronger explanatory power of these variables.

¹⁰ We provide the logic for classifying respondents into offline and online shoppers in the *Appendix (Section A.10)*.

Regarding quality consciousness, in the female subsample (*Table A.9*), the results indicate that quality conscious women are related to statistically significantly higher *bargaining costs*, which supports *hypothesis H.3*. Furthermore, the interaction between quality consciousness and being female has a significantly positive effect on *bargaining costs*, indicating that quality conscious women might be more averse to negotiating the price (*Table A.12*). Overall, gender might play a moderating role in the relationship between quality consciousness and *bargaining costs*. The results further suggest a statistically significant negative association between the interaction of quality consciousness and new car transaction experience and *mean bargaining costs*. This suggests that experienced, quality conscious new car customers may exhibit a weaker aversion towards price negotiations (*Table A.12*). Thus, the significant negative relation between quality consciousness and *bargaining costs* seems to be driven by more experienced and male respondents. This could, however, be further assessed in future research.

Ultimately, regarding the association between *bargaining costs* and sale proneness, we do not observe any additional significant associations in the subsample as well as the interaction effect analyses. Thus, we are unable to find further support for the significant negative relationship between sale proneness and *non-adaptive bargaining costs*.

2.6 Discussion, Conclusion, and Implications

In this study, we empirically estimate and investigate buyer-individual *bargaining costs* in buyer-seller price negotiations in the context of new car transactions. We analyze a carefully selected sample of recent new car customers in Germany, which we collected through an online customer survey. We find that 67% of respondents explicitly state that they would try to negotiate down the dealer's initial offer price for a new car, which suggests that most customers are aware that price negotiations are a common practice in the new car market. Conversely, 63% of respondents indicate that they are willing to pay a price markup over their expected negotiated price to avoid having to negotiate. This suggests that new car customers may dislike price negotiations but might consider them a necessary evil. On average, customers assign *bargaining costs* of 1.05% relative to the initial offer price to negotiating the price of a new car. We find strong variation in these costs, driven primarily by customers' willingness to search, opportunity cost of time, and post-purchase price confirmation. Additionally, we observe some indication of a negative relationship between *bargaining costs* and risk propensity that might be explained by the *self-framing effect*.

Based on our findings, it becomes evident that most new car customers may prefer the fixed pricing scheme and dislike the prevailing, decades-old pricing model with price negotiations. While customers have become accustomed to substantial negotiation discounts, they are willing

to pay higher fixed prices to avoid price negotiations. The aversion towards negotiating prices stems primarily from time and effort constraints as well as post-purchase price-related concerns. Our results further indicate that a transition to a direct sales model may face challenges if manufacturers intend to enforce current offer prices as non-negotiable fixed prices, since customers on average require a fixed price discount of 4.3% (relative to the current negotiable offer prices) to be indifferent between the two pricing schemes. Switching to a direct sales model with non-negotiable prices only appears feasible if OEMs slightly reduce their prices below current offer prices. In general, higher buyer *bargaining costs* (particularly driven by low indifference fixed price discount levels) are likely to be advantageous for OEMs that are considering a switch to direct sales, as this likely implies a higher customer willingness to pay under the fixed pricing scheme. It may therefore be useful to target customers with traits associated with higher *bargaining costs* to increase price realization. This highlights the importance of effectively understanding the customer base when designing pricing strategies, as firms that know their customers could be able to tailor their pricing strategies more effectively and increase profits. However, the customer (personality) characteristics considered in our study are not easily observable, which is why firms would need to find ways to make inferences about the key customer characteristics that appear to drive *bargaining costs*.

In setting the potential new fixed prices, it would further be crucial for manufacturers to conduct in-depth revenue and cost simulations that incorporate price elasticities and additional customer choice alternatives (e.g., other model configurations, models, or brands) to holistically evaluate the business case and make relevant strategic decisions for a direct sales transformation (Schmidt et al., 2020). Moreover, there are several additional success factors for OEMs for direct sales transformations besides understanding customer preferences with respect to the pricing model. In addition to substantial investments (Gissler et al., 2021), these include improving their own pricing capabilities, determining optimal offer prices and remuneration contracts with sales agents, or offering a frictionless omnichannel experience with full price consistency across all offline and online sales channels (Schmidt et al., 2020).

With respect to our theoretical contribution, we develop a novel approach to empirically estimate buyer-individual *bargaining costs*. We further identify several relevant *bargaining cost* determinants. Overall, it appears that search behavior-specific factors (e.g., willingness to search) have greater explanatory power than the more general personality traits. In addition, we find some indications of the relevance of the *self-framing effect* in the specific risky choice context of price negotiations, which might explain the indicated positive relationship between *bargaining costs* and risk propensity. We encourage further research into this matter.

We acknowledge the following limitations of this study: First, the generalizability of our results could be limited to the German new car market. Caution should be exercised when applying them to other countries or sectors with different market and cultural contexts. Additionally, our sample consists only of recent new car customers. Future research could, for example, benefit from including individuals who intend to acquire a new car but have not yet made a purchase. Moreover, our estimation of *bargaining costs* relies on hypothetical scenarios and respondents' expectations, which might not fully capture real-world dynamics. To address this, future research could employ experimental approaches or analyze real transaction data to measure *bargaining costs*. Furthermore, it is important to mention that in real-life situations, customers do not generally have the option to choose between negotiating and paying a lower fixed price for the same brand or even model. On the other hand, in real life, there are several alternatives for customers to choose from (e.g., other model configurations, models or brands, acquisition of a used car, no car purchase at all) and competitive dynamics at play (e.g., pricing schemes of competitors, but also the possibility to leverage price information or alternative offers in the negotiation process with a dealer), which we could not incorporate in our survey approach. For our analyses, we use self-reported personality traits based on Likert-type scaled items, which have certain shortcomings (e.g., dishonest responses) and do not necessarily reflect the respondents' true personalities (Galić et al., 2016). While we exercised procedural caution in designing our survey, the causal relationship between *bargaining costs* and the search and purchase behavior-specific constructs, as well as the general personality traits, remains uncertain. Our current approach does not provide insight into the thought processes underlying these relationships. To delve deeper into the direction of causality, future research could employ think-aloud protocols (e.g., Wang, 2004). We could also not control for or include all relevant latent variables (e.g., other individual personality traits). Accordingly, causality with respect to the relationship between the observed personality traits and *bargaining costs* cannot be clarified exhaustively. Future research could investigate *bargaining costs* by including additional independent variables (e.g., the belief in one's own bargaining skills, which we only implicitly incorporate in the estimation of our dependent variable by the negotiation discount expectations). Future research on this topic should aim to address and overcome these limitations. Additionally, it would be interesting to investigate the effects of the elimination of price negotiations on customer satisfaction and experience or brand perception.

3 Competing within the Brand – Intra-Brand Competition and Differentiation in the Automotive Direct-to-Consumer Sales Era

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Statement of contribution: Julian Feldhäuser developed the research idea and led the study design, with conceptual input from Mario Farsky (*The Boston Consulting Group*) and Dominik Papies (*University of Tübingen*). Julian Feldhäuser and Mario Farsky coordinated the data collection, which was conducted by the market research institute *MiiOS*. The study was funded by *The Boston Consulting Group*. Julian Feldhäuser performed all statistical analyses and wrote the full manuscript, including the literature review. He was also responsible for finalizing the paper. Dominik Papies provided ongoing supervision and feedback on the manuscript.

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Abstract

New car retailing is traditionally characterized by intense competition among same-brand dealers. In practice, the fiercest competitor of a new car dealership is often not another brand, but the geographically closest dealership selling the same brand. Due to product homogeneity and dealer-level pricing autonomy with customer-individual price negotiations, this rivalry is usually price-based and leads to substantial discounting and price pressure within brands. In light of these dynamics, several automotive manufacturers are currently considering launching direct-to-consumer sales models with uniform, non-negotiable prices to eliminate intra-brand competition and obtain full pricing authority. This paper examines the effects of such transitions to a direct sales model on competitive dynamics and differentiation efforts among car dealers. We leverage a natural experiment, the direct sales model introduction of Mercedes in Germany, and analyze cross-sectional data from two telephone surveys of German new car dealers conducted in 2022 and 2024. Our results indicate that direct sales agents perceive intra-brand price competition as significantly less intense than traditional wholesale dealers. They further suggest a shift in competitive focus for direct sales agents from intra- to inter-brand (i.e., with other brands) rivalry and within the intra-brand dimension from price to non-price or quality competition. However, while price-related differentiation efforts of direct sales agents appear to decrease, we do not observe an increase in their non-price-related differentiation activities.

3.1 Introduction

Currently, the automotive sector in Germany comprises more than 14,000 brand-affiliated, authorized dealerships with more than 300,000 employees (ZDK, 2024c). Around 80,000 of these employees work in sales functions, generate €67 billion in annual revenue with the sale of 1.6 million new cars in 2023, and represent a crucial interface between car manufacturers and customers (ZDK, 2024b). On average, customers visit a dealership four times to test drive cars and obtain information before finalizing their purchase (Autohaus, 2021). Many buyers only make their final purchase decision during or after a visit to a dealership, and 36% of new car customers state that the test drive at the dealership was the decisive factor in their vehicle purchase (MHP, 2023). However, this long-established, highly relevant sales and distribution structure is characterized by extraordinary competitive dynamics and is currently facing radical changes. This applies not only to Germany but is part of a broader international trend with similar developments in markets such as the United Kingdom and Austria (Seyerlein, 2023).

With respect to the competitive dynamics, one might assume that the fiercest rivalry for dealers stems from competing brands in the same price segment. Yet, in practice, the biggest rival of a Mercedes dealer, for instance, is often the closest Mercedes dealer and not a BMW or Audi dealer (Beard et al., 2021). For example, only in Hamburg, there are 11 different Mercedes dealers, and these are all more or less competing with each other (Mercedes-Benz AG, 2024).

In this particular new car retailing market environment, it might be worth distinguishing between inter-brand competition, the rivalry between sellers of different brands, and intra-brand competition, the (frequently spatial) rivalry among sellers of the same brand (Breton & Sbragia, 2021). Due to high within-brand product homogeneity and dealers' retail pricing authority, intra-brand competition is typically based on price, with customers shopping around and negotiating prices with multiple sellers of the same brand (Beard et al., 2021). On the one hand, this limits dealer market power and prevents price inflation (Sewell & Bodkin, 2009). On the other hand, this intra-brand rivalry with excessive price cutting by dealers often leads to severe within-brand price wars. This can reduce transaction prices substantially (Beard et al., 2021). In fact, discounts of up to 15–20% are common in most new car markets globally (Gissler et al., 2021). Relative to the annual new car sales revenue through authorized dealers, this could translate into potential revenue losses of up to €10–15 billion for car manufacturers in Germany alone, depending on final transaction prices and discount levels. While stronger competition with other brands obviously also lowers prices, the effect of intra-brand rivalry on lowering prices is found to be even stronger, to the extent that spatial intra-brand competition lowers final car prices by about 4–5% for every 25 miles in same-brand dealer proximity (Beard et al.,

2021). The internet further reinforces these effects by raising price transparency and facilitating price comparisons. Increased price searches by customers due to within-brand price discrepancies also increase the risk of buyers finding and purchasing competing products (Sewell & Bodkin, 2009). This price pressure often forces retailers to focus on price cutting instead of enhancing service quality (Sewell & Bodkin, 2009).

In order to limit intra-brand competition, mitigate price wars within the brand, and drive customer focus toward product and service quality as well as customer experience, automotive OEMs increasingly consider adopting direct-to-consumer sales models (Gissler et al., 2021; Schmidt et al., 2020). This is also in line with theoretical research suggesting that manufacturers of near-homogenous products should restrict intra-brand competition (Mycielski et al., 2000).

Implementing these considerations entails OEMs moving away from their long-established, indirect *wholesale models* and altering the dealers' role radically. Under the traditional sales model, *dealers* operate as independent entrepreneurs. They purchase new cars from the OEM at wholesale prices, own and manage inventories, and independently set retail prices to resell the vehicles (Buzzavo, 2023). On the other hand, under an *agency* or *direct sales model*, OEMs transform their *dealers* into *agents*, centrally set uniform retail prices, and directly invoice their customers. *Agents* no longer own the vehicles nor have control over prices. Instead, they earn a fixed commission for providing services and handling transactions (Buzzavo, 2023). These services, for example, comprise information provision, pre-sale product demonstrations, or test drives (Sewell & Bodkin, 2009). Despite these important differences in their respective roles, we use the terms *dealer* and *agent* interchangeably to some extent in this study.

So far, Mercedes is the only incumbent OEM that has already introduced a full agency model in Germany (in June 2023; Seyerlein, 2023), while others such as Volkswagen or Audi have launched an agency model for their electric vehicle sales only and BMW for its sub-brand Mini (Seyerlein, 2024, 2025). However, the effect of this new sales model on competitive dynamics, the role of dealers or agents, and their differentiation strategies is yet largely unknown in academic research. In this study, we aim to shed light on this matter by providing insights that might help in assessing whether OEMs can achieve their targets, particularly eliminating adverse intra-brand price competition, through shifting to a direct-to-consumer sales model.

Related literature from the field of economics, marketing, and industrial organization has so far been mostly theoretical and has focused primarily on more general vertical manufacturer-retailer relationships and restraints (e.g., Brenkers & Verboven, 2006), intra-brand competition (e.g., Beard et al., 2021), and the trade-off between price and non-price competition (e.g., Stigler, 1968). To the best of our knowledge, we are the first study to empirically assess

potential effects of direct-to-consumer sales model transformations on both intra-brand competition and agents' price and non-price differentiation tactics in the context of new car retailing. Particularly, we first aim to evaluate whether this sales model transformation might effectively eliminate intra-brand price competition and lead to relevant shifts in the competitive focus between intra- and inter-brand as well as between price and non-price competition. Second, we seek to examine whether direct sales agents, compared to traditional dealers, adapt their price and non-price intra-brand differentiation efforts. Specifically, we want to assess whether customer-individually negotiated price discounts effectively vanish, and if so, whether they might be replaced by other price-related differentiating activities or by non-price-related measures such as enhanced customer targeting or service offering.

To address these research questions, we leverage a natural experiment, the direct sales model transformation of Mercedes in Germany in June 2023, and telephone survey data from two separate samples of German new car dealers. We capture perceived competitive intensity along four domains, divided into intra- and inter-brand as well as general and price competition, and self-reported use intensities of eight distinct price- and non-price-based differentiation tactics.

We find that direct sales agents perceive intra-brand price competition as statistically significantly less intense than traditional wholesale dealers, suggesting that introducing a direct-to-consumer sales model might indeed eliminate or at least reduce price competition within the brand. This might help manufacturers to prevent intra-brand price wars and to increase sales margins (Buzzavo, 2023). Further, we show that implementing an agency model might lead to important rebalancing effects in the competitive dynamics of new car retailing for the affected brands. As such, competitive focus potentially shifts from intra- to inter-brand competition, and within the intra-brand dimension, the relative importance of non-price compared to price competition might increase for direct sales brands. On the other hand, we find that while direct sales agents indeed appear to be reducing their price-related intra-brand differentiation tactics, they do not compensate for this by intensifying non-price or quality differentiation.

The remainder of this study is structured as follows: First, we present the related literature, our contribution, and the theoretical framework with the expected observations in *Section 3.2*. After that, we describe our data and methodology in *Section 3.3* before discussing our results and robustness checks in *Section 3.4*. To conclude, we provide a discussion with concluding remarks and implications for theory and practitioners in *Section 3.5*.

3.2 Related Literature, Contribution, and Theoretical Framework

With this study, we contribute to prior literature in the fields of economics, marketing, and industrial organization, particularly to research on vertical relationships between manufacturers and retailers, vertical restraints, intra-brand competition, and price and non-price (quality) competition. There are several, mostly theoretical, studies examining vertical integration, vertical restraints, and their effects on price and non-price competition. Vertical integration describes a manufacturer's strategic approach of expanding its control over the supply chain, for instance by adopting distribution activities from retailers (Donna et al., 2024). Vertical restraints are contractual arrangements between different levels of the supply chain, such as agreements between manufacturers and retailers on retail prices or exclusive territorial distribution rights (Mathewson & Winter, 1984). However, so far there is no empirical evidence on the implications of a transition from a wholesale to a direct-to-consumer (agency) model on both competitive intensity and retailer differentiation tactics. This shift is structurally similar to vertical restraints or integration, as it alters the vertical relationship between manufacturers and retailers by transferring pricing authority to the manufacturer (Johnson, 2017).

Specifically, this study contributes to three strands of literature. First, we add to the research on vertical restraints and competition by empirically analyzing the effect of transferring pricing authority from retailers to manufacturers (by introducing an agency model) on competition among same-brand dealers. Second, this study adds to the literature on vertical restraints and the trade-off between price and non-price competition, as we assess whether regulating (intra-brand) price competition shifts competitive intensity and retailer differentiation efforts from price to non-price competition. Last, we contribute to prior, mostly empirical, research on intra-brand competition and (car) dealers' service offerings by empirically analyzing dealers' usage intensities of non-price-related intra-brand differentiation tactics.

3.2.1 Vertical restraints and competition

Competitive effects of vertical restraints such as exclusive territories, exclusive dealing, and resale price maintenance (RPM) have been investigated using theoretical models for more than 30 years. Such contractual arrangements impact the competitive interactions of manufacturers and retailers, affecting both retail price-setting and the extent of competition among same-brand retailers. Rey and Stiglitz (1995) assess manufacturers' incentives to launch exclusive territory rights to retailers in imperfectly competitive environments using a theoretical model. They find that these rights, which allow retailers to act as sole distributors for a manufacturer in a specific geographic area, effectively reduce both intra- and inter-brand competition and potentially lead to higher retail prices. Desiraju (2004) analyzes a manufacturer's optimal choice between

exclusive and non-exclusive territory rights depending on the risk of retailer free-riding regarding their effort levels and depending on whether limited liability constraints are binding. Mycielski et al. (2000) develop a structural model that includes manufacturers' incentives to introduce exclusive territory and exclusive dealing rights, which grant retailers the authority to exclusively distribute the manufacturer's brand. They prove that exclusive dealing reduces inter-brand competition by eliminating "head-to-head" product competition within the same retail location, and exclusive territories reduce intra-brand competition through regional separation of same-brand retailers. They further identify conditions with respect to product differentiation under which reducing intra-brand and inter-brand competition is beneficial for manufacturers and show that this is particularly the case for almost homogenous products. Li and Luo (2020) compare exclusive and non-exclusive dealing for different market conditions, such as market penetration effects from a manufacturer's perspective. Several other theoretical studies examine the competitive effects of manufacturers introducing resale price maintenance (RPM), a practice where manufacturers set either a fixed or a minimum retail price at which retailers must sell their products. For example, Wang (2005) studies a perishable goods market with a manufacturer and competitive retailers with heterogenous distribution costs. The author shows that RPM removes intra-brand competition by preventing low-distribution-cost retailers from undercutting prices and thus helps higher-cost distributors to remain competitive. It further enables manufacturers to set optimal, increased retail prices. Although buyers can save some transportation costs due to a higher retailer market coverage, the overall welfare effect of RPM for buyers and society is found to be negative, as it increases retail prices and total distribution costs due to higher-cost retailers remaining in the market. Bang and Jin (2015) examine the effects of two manufacturers simultaneously introducing RPM on inter-brand competition and market outcomes, considering the brand-specificity of pre-sale retailer services and free-riding risks of retailers. Free-riding potential arises for retailers when products require special services such as pre-sale demonstrations or information that can be provided by one retailer and be exploited by another. This can occur when buyers can benefit from such services of one retailer (e.g., test driving a car) but purchase the product from another, often lower-cost, retailer that does not offer this costly service (Sewell & Bodkin, 2009). Several studies of the next section discuss this free-riding issue related to retailers in more detail. Bang and Jin (2015) show that RPM prevents retailer free-riding and leads to higher retail prices, and that brand-specific pre-sale services reduce buyer price sensitivity and reduce inter-brand competition. When pre-sale services are not brand-specific, RPM fails to sustain increased prices due to stronger inter-brand competition. Johnson (2017) explores the dynamics and welfare effects of vertical restraints such as revenue-sharing and retail price-parity restrictions in online retailing using a theoretical

model. He further compares an agency model (where suppliers set retail prices) to a wholesale model (where retailers set retail prices). Revenue-sharing is a contractual arrangement that determines the fixed split of sales revenues between suppliers and retailers, which is an inherent part of the agency model. Retail price-parity restrictions are optional clauses forcing suppliers under an agency model to maintain retail price consistency across different retailers. The author shows that retail price-parity restrictions raise prices by limiting price competition and that shifting from a wholesale to an agency model with revenue-sharing benefits the firms setting the revenue share, in his case the retailers (platforms), and harms those determining retail prices, in this case the suppliers. In our research context, the retailers' revenue share (i.e., commission) is set by the supplier (i.e., manufacturer) (Köhnen, 2024). Brenkers and Verboven (2006) theoretically and empirically assess the effect of liberalizing selective and exclusive distribution systems on intra-brand competition and total welfare in the European car market in the early 2000s. Liberalizing selective distribution by softening the OEMs' selection criteria for authorized dealers and exclusive distribution by terminating exclusive territory rights can be considered as a removal of vertical restraints. As a result, they find stronger intra-brand competition in most of the affected countries and total welfare gains for all respective countries.

3.2.2 Vertical restraints and price versus non-price competition

The trade-off between price competition and non-price (quality) competition has been a central topic in economic research for decades, particularly in the context of vertical restraints and market regulation. Theoretical studies dating back to Telser (1960) and Stigler (1968) examine how regulations of price competition, can shift competitive dynamics towards quality differentiation and service provision. They consider exclusive territory rights, resale price maintenance, or other price controls. Telser (1960) investigates manufacturers' preferences for RPM and its impact on retailer incentives. He shows that for products requiring special services, RPM prevents retailer free-riding and encourages them to provide enhanced services. Manufacturers benefit from RPM when service investments increase demand and when they have monopoly power. Stigler (1968) presents a general model for the way firms react when price competition is regulated, showing that regulating price competition can shift competitive focus towards non-price (quality) competition. However, relative to price competition, non-price competition, such as advertising, may not be as effective in increasing output and reducing monopoly profits. Mathewson and Winter (1984) develop a broad structural model to examine vertical restraints in imperfectly competitive markets with bilateral relationships between manufacturers and retailers. They identify externalities affecting retailers' decisions and efforts, which lead to the failure of unconstrained wholesale contracts between manufacturers and

retailers. Further, they show that vertical restraints, such as territorial protection or RPM, shift competition away from price and toward service provision, thereby neutralizing these externalities and coordinating retailers' incentives to maximize joint profits under uncertainty. Winter (1993) examines how vertical restraints affect price versus non-price competition depending on customer opportunity costs and monitoring costs. He shows that higher customer opportunity costs make price competition less effective as a differentiator between retailers, as buyers are less likely to compare prices across retailers. In such environments, manufacturers prefer shifting competition from price to non-price competition through vertical restraints such as RPM. Further, monitoring costs influence the ability of firms to enforce vertical restraints. Hatfield et al. (2016) investigate the effects of price controls on non-price (quality) competition through a series of experiments. They use double auctions to show that price ceilings and floors strongly impact market dynamics and lead to increased non-price competition among sellers.

3.2.3 Intra-brand competition and dealer service offering

Research on intra-brand competition, and particularly on its effects on service offerings, is more recent than the previous literature streams and has gained increasing attention from theoretical and empirical researchers. While some studies focus on broader strategic aspects related to intra-brand competition, such as implications for market dynamics and transaction prices or intra-brand sales channel conflicts, others focus on more specific effects on (car) dealers' service offering quality. Regarding the former, in one of the broader studies, Breton and Sbragia (2021) investigate the effects of intra- and inter-brand competition on market dynamics, considering product substitutability, firm efficiency, and market competition through a game theoretical model. They show that increasing intra-brand competition can positively influence firms' outputs and total welfare by mitigating the negative effects of inter-brand competition. Further, several theoretical studies examine the dynamics of within-firm sales channel conflicts and show that firms operating different direct and indirect (i.e., intermediated) sales channels in parallel are increasingly confronted with intra-brand competition (e.g., Vinhas & Anderson, 2005; Chung et al., 2012; Ronayne & Taylor, 2022). An empirical study by Beard et al. (2021) analyzes the effect of spatial intra-brand competition on final transaction prices through a data set of new car registrations in Texas from 2012. They show that same-brand dealerships' proximity significantly lowers the final vehicle prices, with discounts estimated at USD 500 or more when same-brand dealerships are located 25 miles closer to each other.

As for studies assessing the effect of intra-brand competition on car dealers' service offerings, Sewell & Bodkin (2009), for example, empirically examine how the Internet has intensified intra-brand competition and how this in turn directly exacerbates free-riding among

car dealers. They use a customer survey to show that intra-brand competition leads to increased free-riding, where low-service dealerships benefit from the sales and marketing efforts provided by more service-oriented dealers. Olivares and Cachon (2009) empirically study the impact of local competition on inventory holdings of U.S. car dealerships, which they use as an indicator of service levels. Contrary to the free-riding hypothesis, they find that local competition positively impacts dealers' inventory holdings, leading to enhanced service levels. Although their focal analyses consider brand-agnostic, local competition, robustness checks isolating intra-brand competition lead to similar findings. Last, Murry (2018) empirically analyzes the effect of car dealer intra-brand competition on dealer and manufacturer local market advertising efforts. He shows that greater intra-brand competition, measured as the number of same-brand car dealers within a specific area, is associated with lower dealer advertising expenditure and, for U.S. brands, also with reduced manufacturer advertising spending. This suggests that increased intra-brand competition lowers the marginal benefit of advertising and supports the free-riding hypothesis.

3.2.4 Gap in existing literature and contribution

Prior research focused mainly on analyzing vertical restraints (e.g., resale price maintenance, exclusive territories, exclusive dealing), intra-brand competition, and the trade-off between price and non-price competition. These previous studies primarily relied on theoretical models. Related empirical studies have so far focused on examining the implications of the removal of vertical restraints on intra-brand competition (Brenkers & Verboven, 2006), the impact of price controls on non-price competition in double auctions (Hatfield et al., 2016), and the effect of local or intra-brand competition on car dealer free-riding (Sewell & Bodkin, 2009), inventory holdings (Olivares & Cachon, 2009), and advertising efforts (Murry, 2018).

However, to the best of our knowledge, there is no empirical study that examines the effects of switching from a wholesale model to a direct sales model on both intra-brand competition and agents' differentiation tactics. This move can be regarded as a form of vertical restraint or integration between manufacturers and retailers, which involves a shift from retailer-imposed, negotiable retail prices to uniform, OEM-set, non-negotiable prices. Yet, it remains unclear how these dynamics unfold in real-world industry settings. In this study, we use a natural experiment and survey data from new car dealers to investigate the effects of the shift from a wholesale to an agency model on the competitive intensity and dynamics as well as price and non-price differentiation tactics in new car retailing. Particularly, we assess competitive intensity in four dimensions, disaggregated into intra- and inter-brand as well as general and price competition.

3.2.5 Theoretical framework

Drawing on prior literature, we derive how the transition to an agency model affects competitive intensity and differentiation tactics among dealers of new cars. First, as the agency model replaces discriminatory, dealer-level price setting with uniform, manufacturer-imposed pricing, we expect intra-brand price competition to disappear based on prior research on resale price maintenance (e.g., Wang, 2005). Expectations regarding the effect on general intra-brand competition, including both price and non-price competition, remain less clear. While previous studies suggest that regulating price competition shifts retailer focus to non-price competition (e.g., Winter, 1993), it is unclear whether this compensates for or even exceeds the expected decline in intra-brand price competition. Stigler (1968) argues that price rivalry is a stronger driver of competitive intensity than non-price competition. Overall, this might indicate a reduction in general intra-brand competition related to the agency model introduction.

Second, prior research suggests that intra- and inter-brand competition are inversely related for industries with an intermediate degree of product substitutability (Breton & Sbragia, 2021). If the agency model reduces intra-brand price competition, inter-brand price competition is likely to increase, assuming sufficient product substitutability. Further, Wang (2005) proves that softening intra-brand price competition increases retail prices, which might incentivize competing brands that still allow discriminatory dealer-level price setting to undercut the prices of the direct sales brand, thereby also increasing inter-brand price pressure. Analogous to the intra-brand dimension, the expected effect on general inter-brand competition, comprising both price and non-price competition, remains more ambiguous.

Third, with respect to price-related intra-brand differentiation tactics, we expect customer-individually negotiated discounts to disappear under the agency model, as dealers no longer control pricing (e.g., Heuser et al., 2023; Wang, 2005). For other price-related differentiation tactics, two important effects are conceivable. On the one hand, manufacturers could prohibit any form of price measures under a direct sales model. On the other hand, it could be that either the manufacturer itself compensates for the absent price negotiations through targeted, uniform, and centrally steered rebates, such as seasonal discounts (e.g., Demirag et al., 2010), or the dealers do so through “hidden” discounts, such as free or discounted extras (e.g., Mishra & Mishra, 2011). Such extras could function as indirect price reductions, helping dealers to differentiate while formally still complying with the manufacturer’s uniform pricing policy.

Last, drawing on several prior studies, we expect agents under a direct-to-consumer sales model to increase their non-price-related intra-brand differentiation efforts as a reaction to the expected decline in intra-brand price competition (e.g., Stigler, 1968; Bang & Jin, 2015).

3.3 Data and Methodology

3.3.1 Data collection and research approach

We collect the data for this study through two separate surveys of authorized new car dealers from Germany. Through a cooperation with an international strategy consultancy and a German market research company, we were able to retrieve data from a first survey of German new car dealers, conducted in February 2022, and to repeat a similar survey design with a comparable sample between August and October 2024. For both surveys, 15 professional interviewers conducted 10 to 15-minute telephone interviews. Both surveys comprised 400 car dealers from Germany. Importantly, the direct sales model (i.e., the treatment) was introduced in June 2023 and thus almost exactly between the two survey periods. This change affected only part of the sample, namely all Mercedes dealers, while the remaining dealers continued to operate under the traditional wholesale model (Seyerlein, 2023).¹ This enables us to study the treatment effect both over time, through our repeated cross-sectional data from 2022 and 2024, as well as within time, through our 2024 cross-sectional data. Although both samples cover the same population of dealers, we cannot track individual dealers over time. Thus, our data follows a *repeated cross-sectional* rather than a *panel structure*. We further discuss the methodology in *Section 3.3.5*. While our treatment group comprises all Mercedes dealers of our 2024 sample, the full control group includes all non-Mercedes dealers of the 2024 sample and, additionally, for our repeated cross-sectional data analyses, all dealers of our 2022 sample. The 2024 sample includes a targeted oversampling of Mercedes dealers ($N = 54$) to enable more robust analyses with respect to the treatment group.

The aim of the first survey was to provide a detailed understanding of the impact of general business trends (e.g., electrification, digitization, semiconductor crisis) for dealers as well as their perceptions of competitive intensity, agency models, and uniform prices. The research objective of our second survey is more focused, as we seek to examine the treatment effect of a direct sales model introduction more closely here. To do so, we follow a twofold approach in our second survey: First, by repeatedly asking some of the first survey's questions, the *repeated cross-sectional data approach*, we additionally leverage the first sample as our control group to study the effect of the treatment. Second, by adding several new questions, we aim to understand perceived competitive intensity and dealer differentiation tactics in more detail.

¹ There are three brands (out of 22) in our sample for which the manufacturer has already introduced an agency model for parts of its portfolio: Audi (01/2024) and Volkswagen (06/2020) for all electric vehicles and Seat for its sub-brand Cupra (10/2021). However, we explicitly ask the respective respondents in our survey to limit their assessments to the new car business with combustion vehicles of their main brand only. We provide a (preliminary) list of the direct sales model implementation plans of the OEMs of our sample in *Table B.1* in the *Appendix*.

Our two samples were both drawn from a proprietary contact list of the market research firm. Participation was not incentivized and voluntary. The samples consist of German dealerships that sell new cars and have a sales contract with at least one manufacturer, i.e., are not brand independent. *Ex ante*, we further restrict our sample to respondents who work in leading roles at their respective dealerships. In our 2024 survey, we also require respondents to be able to evaluate the private new car sales business, including sales volumes, competition, and customer interactions, and explicitly ask them to answer our survey questions solely based on their private new car sales business perspective, thereby excluding used car sales (among other aspects).

3.3.2 Variable description

As part of the *repeated cross-sectional data approach*, we repeat some important questions from the first survey in our 2024 survey to capture four focal variables over time and estimate the treatment effect of introducing a direct sales model. First, to assess the effect on intra-brand competition, we measure the dealers' perception of intra-brand competition intensity by asking them how strongly they feel they are competing with other dealers (online and offline) that sell the same brand/s as they do (*REP_IntraIntensity*). Second, we capture the respondents' perceived main competitor (*REP_MainComp*) by letting them choose between different intra- and inter-brand competitors as well as independent and other competitors. In addition, to better assess potential differences in the dealers' perception of the agency model and of uniform pricing (by the OEM), we ask them to evaluate the introduction of an agency model (*REP_AgencyEval*) and of uniform pricing (*REP_UniPriceEval*) for themselves. Except for the categorical variable for the perceived main competitor, all focal variables in this study are measured using five-point Likert-type scales, with verbal anchors adapted to each question (e.g., from "not at all" to "very strongly" or from "not good at all" to "very good").

To further estimate the treatment effect on the perceived competitive intensity, we add four questions capturing different competitive dimensions in our second survey. Particularly, we ask respondents to indicate how intensely they perceive competition in the private new car sector along four dimensions. Along these dimensions, we distinguish between intra- and inter-brand competition and between price and general competition, which leads to four combinations. We define intra- (inter-)brand competition as competition with independent dealers and branches, so-called "Niederlassungen", of their own (other) brand/s as well as online direct sales channels of their own (other) brand/s (Sewell & Bodkin, 2009). We define general competition as all aspects of competitive pressure, including product quality, price, customer service, and brand image. In contrast, price competition specifically refers to competitive pressure arising from pricing and price-based tactics, particularly from market participants trying to undercut each

other through lower prices (Bang & Jin, 2015). Price competition is therefore a subset of general competition. This results in the four focal variables: *IntraPriceIntensity* (intra-brand price competition), *InterPriceIntensity* (inter-brand price competition), *IntraGenIntensity* (general intra-brand competition), and *InterGenIntensity* (general inter-brand competition).

To estimate the treatment effect on price- and non-price-related tactics employed by dealers to differentiate themselves from other dealers of the same brand/s, we add eight focal variables in our second survey (e.g., Hatfield et al., 2016). Here, we ask respondents in randomized order how strongly they use different tactics or measures to differentiate themselves from other dealers of their own brand/s. Relevant differentiation tactics were jointly prioritized together with automotive industry experts from our cooperating strategy consultancy and comprise four price-related and four non-price-related differentiation measures.

Price-related differentiation tactics encompass customer-individually negotiated discounts (*IndivDiscIntensity*), general, customer-independent price discounts (*GenDiscIntensity*), product-related extras (*ProdExtraIntensity*), and service-related extras (*ServExtraIntensity*). Our non-price related differentiation tactics comprise measures to improve sales initiation, customer approach, and digital interaction (*TargDiffIntensity*), product variety and customization options (*ProdDiffIntensity*), customer service quality (*ServDiffIntensity*), and customer loyalty and experience programs (*LoyDiffIntensity*). We provide a comprehensive list with descriptions of the focal variables of our study in *Tables B.2.a* and *B.2.b* in the *Appendix*.

In terms of control variables, we capture the respondent's position in the dealership, the (sales) business model of the dealership (new and used car sales or new car sales only), the partnering brand/s (for which sales contracts are in place) and their price segment/s, the size of the dealership (in terms of new car and total car sales in the previous year, i.e., 2021 or 2023), the online sales channel offering, and the online sales share in both surveys. In our second survey, we further include the partnering main brand (in terms of revenue share), the new car and total car sales for the pre-treatment year (2022), the sales share of electric vehicles (EVs), the extent of price negotiability for new cars, the first digit of the ZIP-code and city size of the dealership location, and the average numbers of stock vehicles and employees (both for the pre-treatment year). In addition to these self-reported control variables, we further merge additional OEM-level control variables that include the sales and service partner network size in Germany in the year of the survey (Plate & Haunschild, 2023, 2024), the market share in Germany², and

² Based on the new car sales during the half year prior to the survey (S&P Global Mobility, 2024a).

the direct sales model implementation status as of August 2024 (indicating whether the OEM has fully or partly implemented an agency model or has communicated plans of doing so).

3.3.3 Data cleaning and missing value data imputation

We employ consistency checks with respect to all survey questions with open numeric inputs and regarding an additional question that we include to assess consistency in response behavior in our second survey. Based on these checks, we correct and exclude several observations to derive cleaned data sets, which include 389 respondents for our 2024 survey and 384 for 2022.

Regarding the open numeric input questions in our 2024 survey, comprising the number of (new) car sales, employees, and stock vehicles and the sales shares of new cars, electric vehicles, and online sales, we apply a series of consistency checks. Namely, we assess the top and bottom one-percent percentiles, the development of relevant metrics over time,³ the relation between the number of car sales, new car sales, and the indicated new car sales share, and relevant ratios of different variables⁴. In total, we identify 16 evident data inconsistencies for 11 respondents (3% of all respondents). We correct these in our cleaned 2024 data set.⁵

In the additional question to check for consistency in response behavior in our 2024 survey, we ask whether and to what extent new car prices are negotiable at the respondents' dealership. We identify 11 inconsistent cases (3% of all respondents), in which respondents indicate that all new car prices are non-negotiable but later state that they (very) strongly use negotiated discounts to differentiate themselves. We exclude these cases from our cleaned 2024 data set.

We apply similar data consistency checks for the open numeric input questions in our 2022 survey. Since the set of control variables is more limited here, we are slightly more constrained. We identify two cases of missing trailing zeros for the number of car sales, which we correct in our cleaned 2022 data set. We further exclude 16 observations (4% of all respondents) due to extremely small numbers of annual new car sales (less than 10), for which we suspect that the new car sales business relevant to us cannot be meaningfully evaluated.

For our cleaned data sets, we employ non-parametric missing value imputation using random forests to impute missing data points in our samples. This approach does not rely on any distributional assumptions. It can also perform on mixed-type data (in our case, continuous and categorical variables) and is able to handle non-linear relations between variables (Stekhoven

³ I.e., new car sales and car sales as well as the new car sales shares from 2022 to 2023.

⁴ E.g., new car sales per employee, or the ratio of car sales to the average number of stock vehicles.

⁵ Of those 16 inconsistencies, 15 appear to be missing or excessive trailing zeros, where the interviewer most likely documented the answer incorrectly during the telephone interview. The remaining inconsistency is related to an inconsistent relation between the number of car sales, new car sales, and the indicated new car sales share.

& Bühlmann, 2012).⁶ For the focal variables, the shares of missing values range from 0.3% (*LoyDiffIntensity*) to 3.6% (*REP_AgencyEval*) in our 2024 sample and in our 2022 sample from 0.5% (*REP_UniPriceEval*) to 2.1% (*REP_AgencyEval*). For the control variables, the shares of missing values range from 0.0% (respondent's position) to 17.7% (number of stock vehicles) in our 2024 sample and from 0.0% (respondent's position) to 11.7% (car sales 2021) in our 2022 sample. Overall, the employed missing value data imputation leads to very reliable results with respect to the estimated out-of-bag (OOB) imputation errors (normalized root mean squared errors, *NRMSE*, are smaller than 0.05, and the proportions of falsely classified entries, *PFC*, are smaller than 0.10).

3.3.4 Data description

We provide summary statistics for our two samples in *Table 3.1*. The two samples primarily include respondents who work as sales managers or salespeople in their dealerships (79% and 72% for 2022 and 2024, respectively), as well as a larger share of owners and managing directors (15% and 19%). We can therefore assume that most respondents are able to sufficiently evaluate the sales business. Regarding the dealership characteristics, most of them sell new and used cars (both 88%) and have exclusive sales partnerships with only one brand, i.e., are mono-brand dealerships (76% and 79%). Of the sampled dealerships, 28% (27%) only sell premium-price-segment brands, 60% (64%) volume brands, and 13% (9%) both. These shares are close to the actual distribution in the German new car market with a premium share of 30% (30%) and a volume share of 65% (66%) based on new car sales in the first half of 2024 (second half of 2021) (S&P Global Mobility, 2024a). We provide detailed sample splits by the brands represented through sales partnerships in *Tables B.3.a* and *B.3.b* in the *Appendix*. In our 2024 sample, the three most represented brands in the breakdown by main brands, Volkswagen (16%), Mercedes (14%), and Ford (8%), have a combined share of 38%, which exactly corresponds to the respective market share by new car sales. In our 2022 sample, the most represented brands in the split by mono-brand dealerships, Volkswagen (14%), BMW (12%), and Audi (8%), have a combined share of 34%, which also equals the corresponding market share by new car sales volumes. Overall, the brand splits of our two samples can be considered as both close to the market shares based on sales volumes in the German new car market and very similar to each other. While Mercedes is slightly overrepresented in our 2024 sample relative to the 2022 sample, BMW is moderately underrepresented.

⁶ Following Stekhoven & Bühlmann (2012), we set the maximum number of iterations to ten (if the stopping criterion is not reached previously) and the number of trees intended to grow in every forest to 100.

We present additional summary statistics with respect to the city size and the first digit of the ZIP-code of the dealership locations, price negotiability, and the online sales channel offering for our 2024 sample in *Table B.4* in the *Appendix*. Further, for our 2024 sample, we provide an overview of the regional distribution of all dealerships in *Figure B.1.a* in the *Appendix* and of the dealerships of our treatment group (i.e., the Mercedes dealers, $N = 54$) in comparison to the actual distribution of Mercedes dealerships in Germany (as of August 2024, $N = 427$) in *Figure B.1.b*. The dealerships are well distributed across Germany, and the regional distribution of the treatment group’s agents aligns well with the actual one of the German Mercedes sales partners. We provide additional descriptive statistics for the dealerships’ (new) car sales, numbers of stock vehicles and employees, and sales shares of new cars, electric vehicles, and online sales in *Tables B.5* to *B.10* in the *Appendix* and for (OEM-level) numbers of sales and service partners and branches (“Niederlassungen”) in *Tables B.11* and *B.12*.

Full sample 2024 [N = 389]	N	Share	Full sample 2022 [N = 384]	N	Share
Position in dealership			Position in dealership		
Owner / managing director	58	15%	Owner / managing director	72	19%
Location manager / representative	20	5%	Location manager / representative	29	8%
Sales manager / salesperson	307	79%	Sales manager / salesperson	277	72%
Other position	4	1%	Other position	6	2%
Business model of dealership			Business model of dealership		
New car sales only	46	12%	New car sales only	46	12%
New and used car sales	343	88%	New and used car sales	338	88%
No new car sales	0	0%	No new car sales	0	0%
Mono- vs. multi-brand dealerships			Mono- vs. multi-brand dealerships		
Mono-brand	297	76%	Mono-brand	305	79%
Multi-brand	92	24%	Multi-brand	79	21%
Price segment			Price segment		
Premium	107	28%	Premium	104	27%
Hybrid (premium & volume)	49	13%	Hybrid (premium & volume)	35	9%
Volume	233	60%	Volume	245	64%

Table 3.1: Summary statistics for the 2024 and 2022 samples

The distributions of new car and car sales are rather widespread in both samples, with new car sales in 2022 ranging from 10 to 9,000 in our 2024 sample. However, most dealerships report annual new car sales in 2022 of 101 to 500, with a median number of 200, which is higher than both the median new car sales of 2021 in our 2022 sample (101) and the average number of new car sales per franchised sales partner in Germany 2022 (106) (ZDK, 2024a). In both our samples, the median new car sales share in 2022 (2021) equals 50%, which is again slightly

larger than the average new car sales share of franchised sales partners in Germany in 2022 (41%) (ZDK, 2024a). In our 2024 sample, we again observe widespread distributions for the numbers of stock vehicles (ranging from 2 to 1,000, median: 27) and employees (ranging from 4 to 900, median: 35). The median number of employees in our sample is also greater than the average number of 12 employees per outlet in the German automotive industry in 2022 (ZDK, 2024a). As the sizes of car dealerships in Germany are also very heterogeneous, with the largest dealerships having up to 5,500 employees and 50,000 new car sales per year (Autohaus, 2024b, 2024c, 2024d), this should not limit the representativeness of our sample. The median electric vehicle sales share of 2022 equals 15% in our 2024 sample, which is in line with the electric vehicle share of 18% in all new car registrations in 2022 in Germany (ZDK, 2024c).

We also provide detailed descriptive statistics for our treatment group, the Mercedes dealers of our 2024 sample, in *Tables B.13 to B.20* in the *Appendix*. Overall, the Mercedes dealers of our 2024 sample display rather similar characteristics to those of our 2022 sample. Compared to dealers of other brands in our 2024 sample, they exhibit higher shares of dealers selling only new cars (26% compared to 10%) and of mono-brand dealers (98% compared to 73%) and are less prevalent in cities with less than 20,000 inhabitants (24% compared to 37%). Further, they tend to be slightly larger in terms of car sales, new car sales, and stock vehicles, and substantially larger regarding the average number of employees (median: 78 compared to 30).

3.3.5 Methodology

With respect to our repeated survey questions and given the resulting data structure, consisting of two independent cross-sectional samples from 2022 and 2024, we choose an event study regression approach based on Deb et al. (2024) to estimate the effect of the treatment, which was introduced in 2023. Other methods to analyze repeated cross-sectional data, such as pseudo panels with cohorts (Wooldridge, 2010), multilevel modeling (Lebo & Weber, 2015), imputation approaches, or flexible, heterogeneous treatment effects difference-in-differences estimators (Deb et al., 2024), require either larger data sets or longer time series. A pooled regression approach, which pools all observations and estimates a single model, would be simpler but would ignore any variation over time (Lebo & Weber, 2015). Given our data constraints, an event study approach is suitable as it explicitly includes the time dimension and isolates the treatment effect with a group-by-time interaction term (Deb et al., 2024). Here, we use different specifications of the following general event study regression equation:

$$\begin{aligned}
 Y_i = & \alpha + \delta \cdot (\text{Year}_i \cdot \text{Brand_Mercedes}_i) + \mathbf{X}'_i \cdot \gamma \\
 & + \text{Year_FE}_i + \text{RespondentPosition_FE}_i + \text{OEM_FE}_i + \text{Brand_FE}_i + \varepsilon_i
 \end{aligned}
 \tag{3.1}$$

Here, Y_i denotes one of the focal variables (e.g., $REP_IntraIntensity$) of respondent i , $Year_i$ is a dummy variable indicating the 2024 sample (0 if 2022, 1 if 2024), and $Brand_Mercedes_i$ specifies whether a dealer has a sales contract with Mercedes. The coefficient δ thus estimates the respective treatment effect with respect to the direct-to-consumer sales model (i.e., $Year_i = 1$ and $Brand_Mercedes_i = 1$). X_i is a vector of dealer-level control variables (e.g., logarithmic new car sales and a dummy variable indicating whether the dealer only sells new cars or both new and used cars). $Year_FE_i$, $RespondentPosition_FE_i$, OEM_FE_i , and $Brand_FE_i$ denote fixed effects with respect to the survey year, the respondents' position, the partnering OEMs' sales and service partner network sizes, and the partnering brand/s, and ε_i the error term.

However, the validity of our event study approach relies on critical assumptions. First, the parallel trends assumption, which indicates that without the treatment, the treatment and control groups would have followed similar patterns over time, must be valid (Lechner, 2011). Second, the treatment assignment is assumed to be exogenous (Lechner, 2011). Third, we need to assume no anticipatory effects, implying that the treatment must not influence outcomes prior to its introduction (Lechner, 2011; Malani & Reif, 2015). Fourth, we assume no spillover effects, meaning that the treatment does not (indirectly) affect the control group (Lechner, 2011; Baicker, 2005). Further, to ensure valid group-by-time comparisons, we assume comparability of the treatment and control groups across the two time periods (Lechner, 2011; Miller, 2023).

For the separate analyses of our 2024 cross-section, we employ several regression models to estimate the relationship between the treatment and our focal variables in the 2024 sample. We here use different specifications of the following general, linear regression equation:

$$Y_i = \alpha + \delta \cdot Treatment_i + X_i' \cdot \gamma + \varepsilon_i \quad (3.2)$$

As in the previous equation, Y_i denotes one of the focal variables (e.g., $IntraPriceIntensity$) and $Treatment_i$ specifies whether dealer i belongs to the treatment group, i.e., has an agency sales contract with Mercedes. The coefficient δ thus estimates the respective treatment effect with respect to the direct sales model. X_i denotes a vector of dealer-level control variables (e.g., the logarithmic number of new car sales, dummy variables indicating whether the dealer only sells new cars or both new and used cars, and whether the dealership has sales contracts with multiple brands, and controls regarding the location of the dealership) and ε_i the error term.

3.4 Analysis and Results

3.4.1 Evaluation of perceived intra-brand competition intensity

Regarding our repeated survey questions, 43% (31%) of the treated dealers indicate that they perceive competition with other dealers that sell the same brand/s as rather or very weak (strong), whereas 0% (72%) of the Mercedes dealers of our 2022 sample and 17% (58%) of our full control group do so (*Figure 3.1*). This provides an initial indication that the dealers of the treatment group perceive intra-brand competition as less intense than those of the control group.

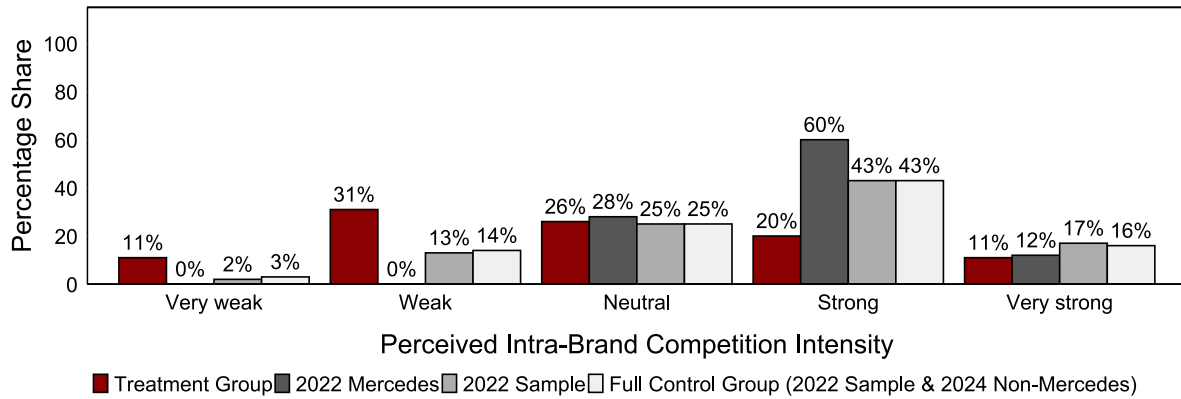


Figure 3.1: Perceived intra-brand competition intensity - frequency distribution by treatment and control groups

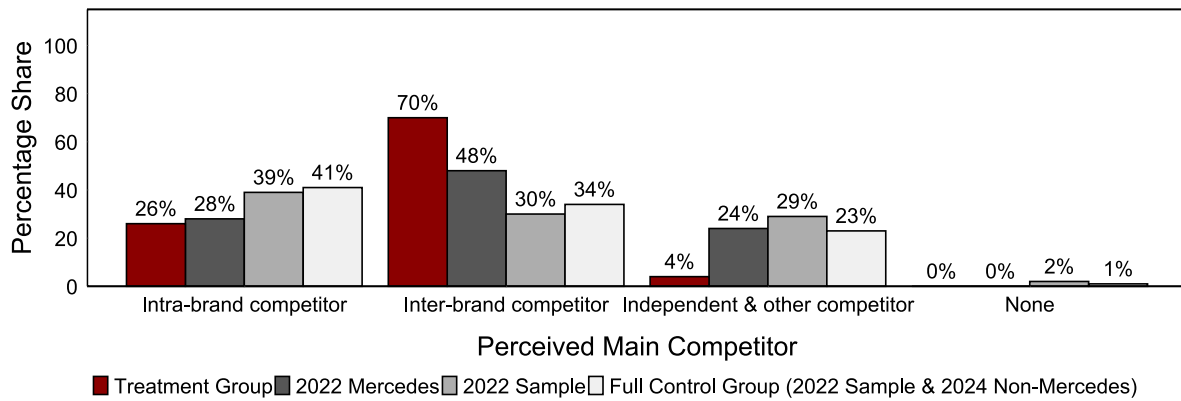


Figure 3.2: Perceived main competitor - frequency distribution by treatment and control groups

Concerning the perceived main competitor, at 70%, more dealers of the treatment group than of the Mercedes dealers of our 2022 sample (48%) and of the full control group (34%) report an inter-brand competitor (*Figure 3.2*). With 26%, a relevant share of the treatment group still states an intra-brand competitor, compared to 41% for the full control group. The remaining 4% of the treatment group perceive independent or other competitors as their main competition. However, for them, independent (mainly online) competitors can be considered inter-brand competitors, as under an agency model they are no longer authorized to sell the respective brand/s (Heuser et al., 2023). This implies that of the treatment group, 74% consider an inter-

brand and 26% an intra-brand competitor as their main competitor. From the control group's perspective, however, independent competitors might sell both the same and other brands.

Additionally, we observe that the treated dealers evaluate the agency model more positively compared to our control groups (*Figure B.2* in the *Appendix*). Specifically, 56% of the treatment group indicate that they perceive the introduction of an agency model as rather or very good (compared to 40% for the 2022 Mercedes dealers and 29% for the full control group). Regarding the evaluation of uniform pricing (*Figure B.3* in the *Appendix*), our descriptive results do not suggest substantial differences between our treatment and control groups.

In the following, we discuss our regression results for the repeated cross-sectional data, starting with the perceived intra-brand competition intensity (*REP_IntraIntensity*). To ensure robustness of results, we estimate different model specifications, which we report in *Table 3.2*. These include a simple pooled model without control variables or fixed effects (column 1), a simple event study model in which we include the time dimension (column 2), the event study model with additional control variables and respondent position fixed effects (column 3), the event study model with additional OEM sales and service partner network size fixed effects (column 4), and the event study model with partnering brand/s fixed effects (column 5)⁷. Due to the limited number of potential clusters in our cross-sectional data structure, we report robust instead of clustered standard errors and interpret inference with some caution (Colin & Miller, 2015). Clustering by partnering brand would be the only suitable choice but is not feasible, as we define the treatment assignment at the brand level and thus would not have sufficient within-cluster variation with respect to the treatment assignment (De Chaisemartin & Ramirez-Cuellar, 2024). We observe a statistically significant negative relation between the treatment and the perceived intra-brand competition intensity across all specifications. In relation to the focal variable's value range of one to five, the associated regression coefficients of -0.9 to -0.6 are also substantial. This suggests that introducing direct sales might indeed reduce the intensity of (perceived) intra-brand rivalry.

We here consider *general* intra-brand competition, which comprises both *price* and *non-price* competition. If Wang's (2005) findings hold here, OEMs' vertical restraints of dealers' pricing authority reduce intra-brand *price* competition. In this case, the observation that direct sales agents perceive *general* intra-brand competition as less intense than traditional wholesale dealers could suggest that a potential intensification of intra-brand *non-price* competition (as

⁷ To avoid multicollinearity, we here exclude the price segment/s of the partnering brand/s as well as OEM sales and service partner network size fixed effects.

postulated by Stigler, 1968) might not compensate for the reduction in *price* competition. We discuss these potential shifts in competitive intensity in more detail below.

With respect to the control variables, larger dealerships in terms of annual new car sales and dealerships that only sell new cars appear to have a statistically significant positive relation with the perceived intra-brand competition intensity.

Dependent variable:	<i>REP_IntraIntensity</i>				
	(1)	(2)	(3)	(4)	(5)
Direct-to-consumer sales	-0.660 *** (0.165)	-0.622 *** (0.170)	-0.801 *** (0.181)	-0.828 *** (0.180)	-0.916 *** (0.220)
New car sales previous year (log)			0.105 *** (0.036)	0.085 ** (0.037)	0.069 * (0.038)
Multi-brand dealership			0.105 (0.124)	0.149 (0.126)	-0.110 (0.155)
New car-only dealership			0.218 ** (0.110)	0.200 * (0.109)	0.259 ** (0.115)
Price segment premium			0.180 (0.174)	0.302 (0.183)	
Price segment volume			0.006 (0.155)	0.052 (0.157)	
<u>Fixed effects:</u>					
Year	no	yes	yes	yes	yes
Respondents' position	no	no	yes	yes	yes
OEM sales & service partner network size	no	no	no	yes	no
Partnering brand/s	no	no	no	no	yes
N	773	773	773	773	773
R ²	0.027	0.028	0.066	0.072	0.111
Note	* p < 0.10; ** p < 0.05; *** p < 0.01; robust standard errors in ()				

Table 3.2: Multiple linear regression results for different model specifications (*REP_IntraIntensity*)

Regarding the perceived main competitor, we report the regression results in *Table 3.3* and observe that treatment group dealers are related to a lower likelihood of perceiving an intra-brand competitor as their main competition compared to those of the control group. However, this is only statistically significant for the simple models (columns 1 and 3) but not for the models that include partnering brand/s fixed effects (columns 2, 4, and 5). As our categorical variable that captures the perceived main competitor (*REP_MainComp*) has four different levels (intra-brand, inter-brand, independent, and other or no competitors), we employ different approaches for our binomial logistic regression analyses.⁸ For all of them, we exclude six respondents who indicate no main competitor. First, in columns 1 and 2, we only consider

⁸ “Independent and other competitors” comprise online platforms for new cars, sellers of young used cars, leasing companies, and car subscription providers.

respondents that indicated either intra-brand or inter-brand competitors as their perceived main competition (77% of all respondents, $N = 598$). Second, we consolidate all respondents that report an independent or an inter-brand competitor as their main competition (columns 3 and 4, $N = 767$). This also results in two different levels for the *REP_MainComp* variable, namely intra-brand versus non-intra-brand competitors. Third, we consolidate independent and inter-brand competitors for the treatment group (as independent competitors are not allowed to sell the direct sales brand anymore) and exclude all control group respondents that indicate an independent competitor (as these competitors can potentially sell both the same as well as other brands). This results in a sample size of 600 (column 5).

Dependent variable:	<i>REP_MainComp</i> (intra-brand competitor)				
	(1)	(2)	(3)	(4)	(5)
Direct-to-consumer sales	-1.091 *** (0.335)	-0.062 (0.606)	-0.804 ** (0.329)	-0.195 (0.574)	-0.110 (0.605)
New car sales previous year (log)		0.126 (0.095)		0.134 (0.085)	0.126 (0.095)
Multi-brand dealership		0.581 (0.433)		0.627 * (0.364)	0.580 (0.433)
New car-only dealership		-0.300 (0.282)		-0.385 (0.255)	-0.310 (0.282)
Fixed effects:					
Year	yes	yes	yes	yes	yes
Respondents' position	no	yes	no	yes	yes
OEM sales & service partner network size	no	no	no	no	no
Partnering brand/s	no	yes	no	yes	yes
“Independent” excluded - control group	yes	yes	no	no	yes
“Independent” excluded - treated group	yes	yes	no	no	no
“Independent” consolidated - control group	no	no	yes	yes	no
“Independent” consolidated - treated group	no	no	yes	yes	yes
N	598	598	767	767	600
Residual deviance	811.7	761.9	1,029.8	971.2	763.1
AIC	817.7	823.9	1,035.8	1,033.2	825.1
Note	* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$; standard errors in ()				

Table 3.3: Logistic regression results for different model specifications (*REP_MainComp*, intra- versus inter-brand competitor)

Overall, comparing the simple models and those with partnering brand/s fixed effects suggests that Mercedes dealers might in general be less likely to perceive an intra-brand competitor as their main competition, yet the direct sales model introduction does not seem to lead to any substantial shifts. Intra-brand competitors therefore appear to continue playing a relevant competitive role under the new sales model. With respect to price competition only, they should not be relevant anymore (Wang, 2005). However, as the main competitor reflects

both price and non-price aspects of competition, this observation might indicate that the non-price dimension of intra-brand competition remains paramount under the new sales model.

With respect to the regression analyses of our variables capturing the dealers’ evaluation of the agency model (*REP_AgencyEval*) and of uniform pricing (*REP_UniPriceEval*), we find statistically significant positive associations for the treated agents in the simple models (columns 1 and 3 of *Table B.21* in the *Appendix*), but not for the full models (columns 2 and 4). This suggests no considerable post-treatment changes in the agents’ opinions regarding the transition to an agency model with uniform prices.

In the following, we focus on our 2024 sample and particularly on the perceived competition intensity along our four more granular competitive dimensions (see *Figure 3.3*).

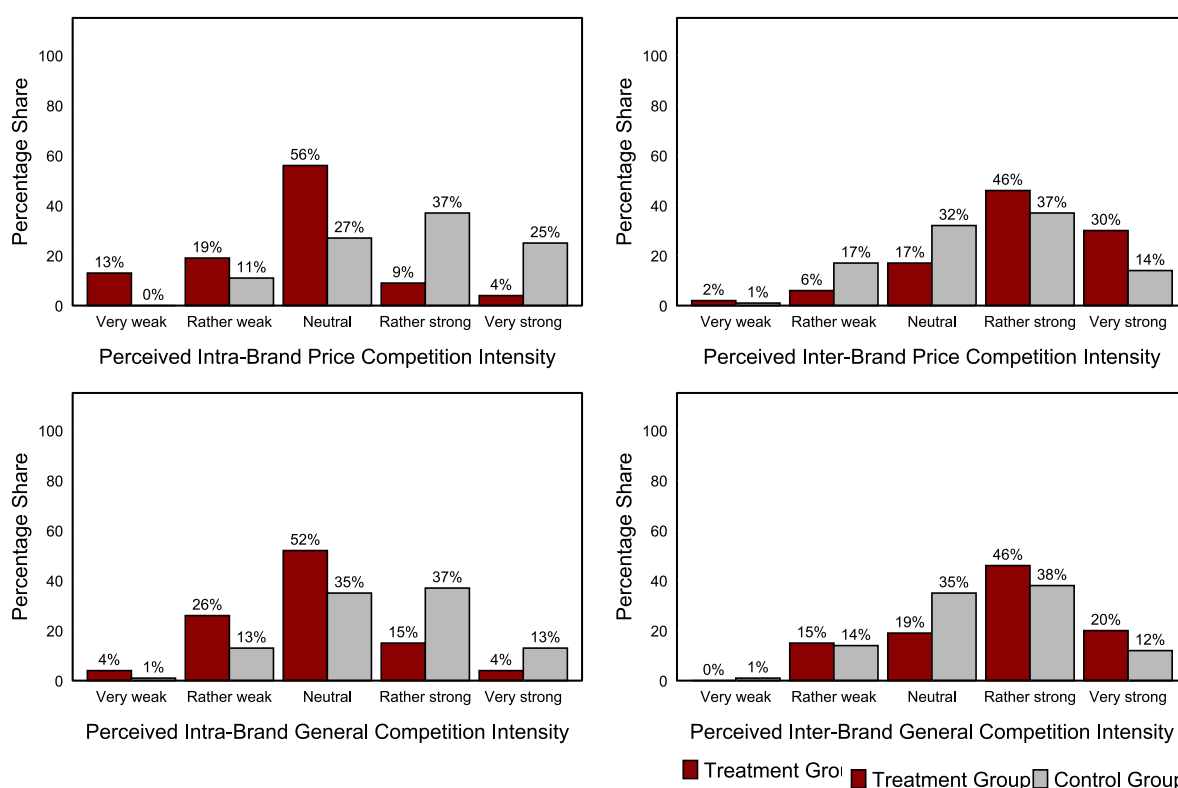


Figure 3.3: Perceived competition intensity for different competitive dimensions - frequency distribution by treatment and control group

While only 13% of the treated agents state that they perceive intra-brand price competition as rather or very strong, 61% of the control group state the same. On the other hand, at 76%, more dealers of the treatment than of the control group (51%) evaluate price competition with other-brand dealers as rather or very strong. For general competition, which includes price competition, again fewer dealers of the treatment than of the control group perceive the intra-brand dimension as rather or very strong (19% versus 51%), but more for the inter-brand dimension (67% versus 49%).

Theoretically, the variable of perceived intra-brand competitive intensity from the repeated survey questions (*REP_IntraIntensity*) should capture the same as the one of perceived general intra-brand competition intensity in the second survey (*IntraGenIntensity*). Yet, there are some noticeable deviations between the frequency distributions of the two variables. One explanation could be that the survey question related to *REP_IntraIntensity* is formulated less precisely, as we could not change the question compared to the first survey for consistency reasons.⁹ Although there are deviations between the two variables at the individual level, across respondents this deviation is on average zero in both the treatment and the control group.

Overall, these observations provide initial indications that the dealers of the treatment group might perceive competition in the new car industry differently than those of the control group. In the following, we examine these differences further through detailed regression analyses. We again estimate different model specifications to ensure the robustness of results with respect to included control variables and potential multicollinearity, which we report in the *Appendix*.¹⁰

For the perceived intra-brand price competition intensity (*IntraPriceIntensity*, *Tables B.22.a* and *B.22.b*), these include a simple model without control variables (column 1). In columns 2–5, we extended this simple model by adding control variables comprising different dealership size metrics,¹¹ dealership business model, respondent position, partnering main brand, partnering brands' price segment, dealership location, as well as dealership online channel and electric vehicle offerings. As the different size metrics do not lead to different results in terms of explanatory power, we henceforth use annual new car sales as our primary size metric. In column 6, we replace the partnering main brand and the price segment of the partnering brand/s by the partnering brand/s and in column 7 by the agency model implementation plans of the main brand's OEM. Since the specification with the partnering brand/s is associated with the highest explanatory power (R^2), we chose this specification as our main model. We provide an overview of the main models for our four competition intensity variables in *Table 3.4*.

Across all seven specifications, the treatment group is statistically significantly associated with perceiving intra-brand price competition as less intense than the control group (*Tables B.22.a* and *B.22.b*). Comparing our main model's treatment coefficient (-1.082) with both the

⁹ Particularly, we could not target the respondents' focus on either the new car sales business with their main brand or on a specific competitive dimension (i.e., price or general competition). This lack of specificity may have led to responses being more strongly influenced by respondents' interpretations, causing their responses to diverge.

¹⁰ In our specification, we do not accept correlation coefficients with absolute values greater than 0.40 or variance inflation factors greater than 5.

¹¹ Column 2: 2022 car sales; column 3: 2022 new car sales; column 4: average number of stock vehicles in 2022; column 5: average number of employees in 2022.

value range of our focal variable (one to five) and the control group's mean value of 3.743 shows that this difference is also substantial. This suggests that introducing an agency model might in fact reduce the (perceived) intensity of price competition among same-brand dealers, which is in line with prior theoretical research of vertical firm restraints (Wang, 2005).

Dependent variable:	<i>IntraPriceInt.</i>	<i>InterPriceInt.</i>	<i>IntraGenInt.</i>	<i>InterGenInt.</i>
	(1)	(2)	(3)	(4)
Direct-to-consumer sales	-1.082 *** (0.190)	0.670 *** (0.183)	-0.443 ** (0.182)	0.370 ** (0.181)
New car sales 2022 (log)	0.059 (0.061)	0.042 (0.057)	0.004 (0.059)	0.045 (0.061)
Multi-brand dealership	0.082 (0.183)	-0.030 (0.213)	0.313 (0.211)	0.196 (0.193)
New car-only dealership	0.218 (0.160)	0.075 (0.181)	0.265 * (0.147)	0.247 (0.158)
Additional controls:				
Respondents' position	yes	yes	yes	yes
OEM (partnering main brand)	no	no	no	no
Price segment (partnering brand/s)	no	no	no	no
Partnering brand/s	yes	yes	yes	yes
Agency model plans of OEM (main brand)	no	no	no	no
Dealership location	yes	yes	yes	yes
Dealership online and EV offering	yes	yes	yes	yes
N	389	389	389	389
R ²	0.267	0.133	0.175	0.152
Note	* p < 0.10; ** p < 0.05; *** p < 0.01; robust standard errors in ()			

Table 3.4: Multiple linear regression results for perceived competition intensity variables (*IntraPriceIntensity*, *InterPriceIntensity*, *IntraGenIntensity*, *InterGenIntensity*)

On the other hand, the dealers of the treatment group perceive price competition with dealers of other brands as statistically significantly more intense than the control group dealers (column 2 of Table 3.4). This is again statistically significant in all model specifications (Table B.23 in the Appendix). With a main model's treatment coefficient of 0.670 (compared to the control group's mean of 3.466), this difference is also considerable, albeit smaller than that for intra-brand price competition. Overall, this indicates that for the treated agents, there might be a shift in the perceived competitive intensity from intra- to inter-brand price competition. This is in line with prior theoretical research suggesting an inverse relationship between intra- and inter-brand competition for goods with intermediate substitutability (Breton & Sbragia, 2021).

With respect to general competition, we observe the same pattern as for price competition: agents of the treatment group perceive the intra-brand dimension as less intense and the inter-brand dimension as more intense than the control group (columns 3 and 4 of Table 3.4). These findings are statistically significant for all model specifications (Tables B.24 and B.25 in the

Appendix) except for perceived general inter-brand competition intensity and the specification with the status of the agency model plans of the main brand's OEM (column 4 of *Table B.25*). This inverse relationship between intra- and inter-brand competition is again in line with prior literature (Breton & Sbragia, 2021) and suggests that the observed shift in perceived price competition intensity from the intra- to the inter-brand dimension might also apply to general competition, i.e., beyond mere price competition. Per definition, general competition includes both price and non-price competition. The fact that the treatment coefficients of the general competition variables (-0.443 and 0.370 for intra- and inter-brand competition) are smaller in absolute terms than those of the price competition variables (-1.082 and 0.670, respectively) suggests that the perceived intensities of price and non-price competition might shift in opposite directions for the treated agents for both intra- and inter-brand competition. Further, price competition appears to exhibit a stronger change. Both findings are in line with prior theoretical findings by Stigler (1968). To further illustrate this, *Figures 3.4* and *3.5* compare the mean values of perceived general intra-brand and inter-brand competition intensity between the control group (first bar) and the treatment group (fourth bar). Here, we decompose the observed differences between the control and treatment groups into the two groups' delta in perceived price (second bar) and non-price (third bar) competition intensity. Since we do not explicitly capture non-price competition intensity, we implicitly derive this delta as the residual of the deltas with respect to perceived general and price competition intensity. The figures show that price and non-price competition point in opposite directions, confirming why the observed differences in the perceived intensities of intra- and inter-brand general competition are smaller in magnitude than those of price competition alone. Also, price competition seems to dominate non-price competition.

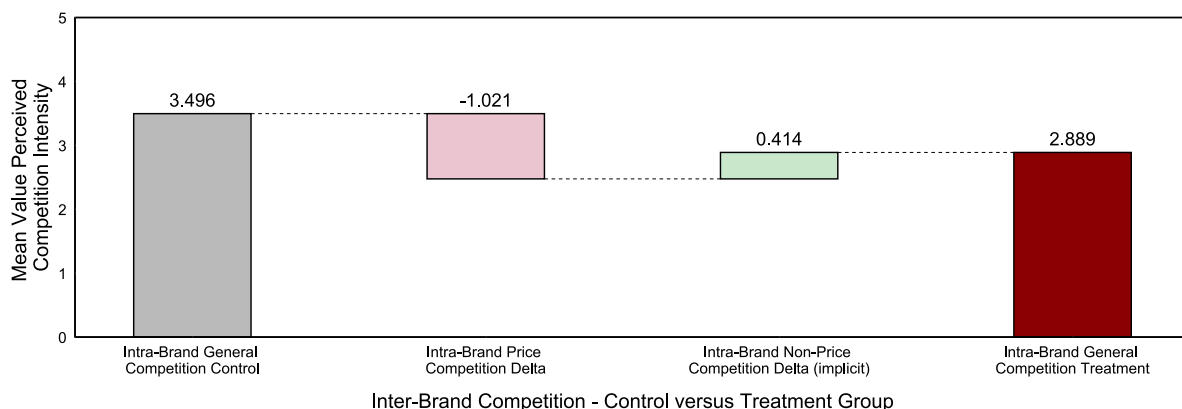


Figure 3.4: Comparison of perceived intra-brand general competition intensity between control and treatment groups (mean values; deltas in price and implicit non-price competition show differences in perceived competition intensity between treatment and control groups)

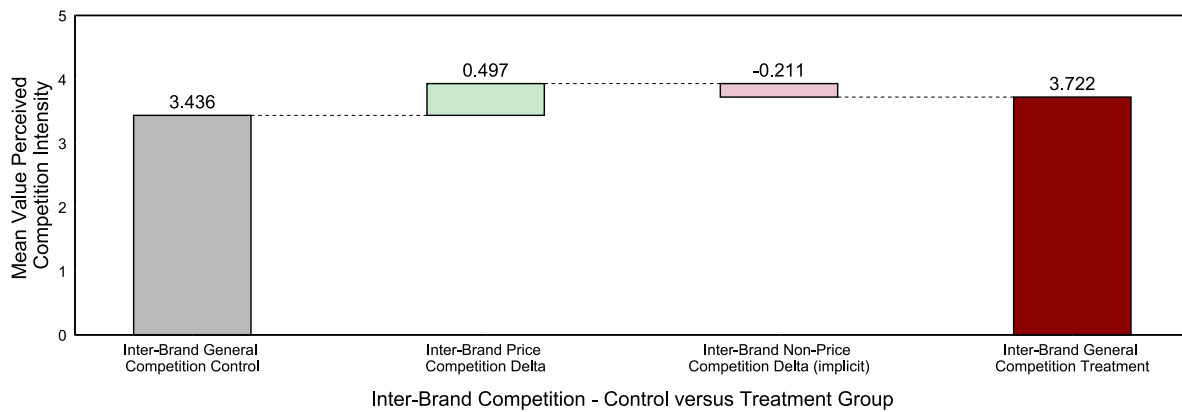


Figure 3.5: Comparison of perceived inter-brand general competition intensity between control and treatment groups (mean values; deltas in price and implicit non-price competition show differences in perceived competition intensity between treatment and control groups)

With respect to our control variables, we observe that dealerships that only sell new cars and those with sales partnerships with multiple brands tend to perceive both general intra-brand (Table B.24 in the Appendix) and general inter-brand competition (Table B.25) as more intense.

3.4.2 Analysis of differentiation tactics and efforts

With respect to our variables capturing the dealers' usage intensity of different price-related and non-price-related (intra-brand) differentiation tactics, we provide descriptive results in the Appendix. Price-related differentiation tactics comprise customer-individually negotiated and general, customer-independent discounts (Figures B.4 and B.5) as well as product- and service-related extras (Figures B.6 and B.7). Non-price-related differentiation tactics, on the other hand, encompass measures to improve customer targeting (Figure B.8), product and service offerings (Figures B.9 and B.10), and customer loyalty (Figure B.11). Overall, we observe that the treatment group uses all four price-related intra-brand differentiation tactics substantially less strongly than the control group. First, while only two percent of the treated group indicate they (very) strongly use customer-individually negotiated discounts to differentiate themselves, 64% of the control group do so. Second, 41% of the control group dealers (very) strongly use general, customer-independent discounts for differentiation, but only 7% of the treated agents do. The fact that 78% (76%) of the treatment group indicate not to use any customer-individually negotiated (general customer-independent) discounts at all for differentiation could indicate that the manufacturer's discount ban under an agency model is relatively strictly implemented or adhered to by the agents, or both.¹² Last, 22% of the treatment group state that they (very)

¹² The fact that, despite the OEM's discount ban, 22% of the treatment group still state that they use some degree of customer-individually negotiated discounts for differentiation may be due to the fact that the respective dealers also sell used cars (for which prices are negotiable). Although we explicitly ask respondents to focus only on their new car business, this may have been misunderstood or overlooked.

strongly use product-related extras for differentiation; for service-related extras, 28% do so. For the control group, on the other hand, the corresponding shares equal 48% and 54%, respectively.

For the non-price-related intra-brand differentiation tactics, the picture is less conclusive at first glance. It does not seem as if the treatment group agents tend to compensate for their lower price-related differentiation efforts by using non-price-related differentiation tactics. Overall, the response distributions for all four non-price-related differentiation variables appear similar for the control and the treatment group (*Figures B.8 to B.11*). First, 70% of the treated agents state to (very) strongly use measures to improve customer targeting to differentiate themselves from intra-brand competitors, compared to 60% of the control group. Second, 33% of the treatment group (very) strongly use measures to improve their product offering and 65% for measures to enhance their service offering. For the control group, the corresponding proportions equal 46% and 62%, respectively. Last, 65% of the treated agents state that they (very) strongly use measures to improve customer loyalty for differentiation, thereby slightly exceeding the 52% of the control group. Overall, these descriptive results reveal that the differences between the treatment and the control group are less pronounced than for price-related (intra-brand) differentiation tactics. While for both groups, measures to improve the product offering are the least strongly used non-price-related (intra-brand) differentiation tactic, for the treatment group, measures to improve customer targeting appear to be the most strongly used one.

In the following, we further examine our initial descriptive observations regarding the usage intensity of the different price- and non-price-related (intra-brand) differentiation tactics through detailed regression analyses, which we report in *Tables 3.5 and 3.6*. As alternative model specifications do not lead to any relevant deviations, we only report the main models' outputs. Overall, with respect to the price-related (intra-brand) differentiation tactics, the regression results confirm our previous descriptive observations: Treatment group agents appear to use price-related (intra-brand) differentiation tactics statistically significantly less strongly compared to the control group (*Table 3.5*). Ranging from -0.849 (service-related extras) to -2.552 (customer-individually negotiated discounts), the treatment coefficients suggest that the differences are considerable and most pronounced for individually negotiated discounts. This suggests that introducing an agency model might in fact eliminate customer-individually negotiated (retailer-imposed) discounts (e.g., Heuser et al., 2023). However, this (near) absence of price negotiations does not appear to be compensated either by the manufacturer itself through general, customer-independent rebates or by the agents through "hidden" discounts, such as free or discounted product- or service-related extras. This is not in line with prior research suggesting substitutability of these promotions (e.g., Demirag et al.,

2010; Mishra & Mishra, 2011). However, OEMs might also contractually restrict such “hidden” rebates, or their effectiveness might not be sufficiently high (e.g., Kopalle et al., 1999).

Dependent variable:	<i>IndivDisc</i>	<i>GenDisc</i>	<i>ProdExtra</i>	<i>ServExtra</i>
	(1)	(2)	(3)	(4)
Direct-to-consumer sales	-2.552 *** (0.212)	-1.660 *** (0.234)	-1.124 *** (0.271)	-0.849 *** (0.297)
New car sales 2022 (log)	-0.016 (0.065)	0.061 (0.065)	0.091 (0.077)	0.030 (0.083)
Multi-brand dealership	0.239 (0.269)	0.008 (0.260)	0.147 (0.263)	0.054 (0.298)
New car-only dealership	0.091 (0.137)	0.286 (0.201)	-0.116 (0.196)	0.239 (0.224)
<u>Additional controls:</u>				
Respondents' position	yes	yes	yes	yes
Partnering brand/s	yes	yes	yes	yes
Dealership location	yes	yes	yes	yes
Dealership online and EV offering	yes	yes	yes	yes
N	389	389	389	389
R ²	0.461	0.308	0.240	0.196
Note	* p < 0.10; ** p < 0.05; *** p < 0.01; robust standard errors in ()			

Table 3.5: Multiple linear regression results for price-related differentiation tactics variables (*IndivDiscIntensity*, *GenDiscIntensity*, *ProdExtraIntensity*, *ServExtraIntensity*)

Dependent variable:	<i>TargDiff</i>	<i>ProdDiff</i>	<i>ServDiff</i>	<i>LoyDiff</i>
	(1)	(2)	(3)	(4)
Direct-to-consumer sales	0.320 (0.240)	-0.093 (0.246)	0.160 (0.222)	0.453 ** (0.225)
New car sales 2022 (log)	0.054 (0.073)	0.079 (0.069)	0.000 (0.068)	0.152 ** (0.071)
Multi-brand dealership	0.115 (0.271)	-0.193 (0.231)	0.029 (0.199)	-0.002 (0.260)
New car-only dealership	0.326 * (0.175)	0.067 (0.186)	0.025 (0.162)	0.072 (0.178)
<u>Additional controls:</u>				
Respondents' position	yes	yes	yes	yes
Partnering brand/s	yes	yes	yes	yes
Dealership location	yes	yes	yes	yes
Dealership online and EV offering	yes	yes	yes	yes
N	389	389	389	389
R ²	0.199	0.142	0.171	0.152
Note	* p < 0.10; ** p < 0.05; *** p < 0.01; robust standard errors in ()			

Table 3.6: Multiple linear regression results for non-price-related differentiation tactics variables (*TargDiffIntensity*, *ProdDiffIntensity*, *ServDiffIntensity*, *LoyDiffIntensity*)

For our non-price-related (intra-brand) differentiation tactics, the regression results are less conclusive (Table 3.6). We find that compared to the control group, the treatment group agents

make stronger use of (intra-brand) differentiation tactics to improve customer targeting as well as service offerings and less use of measures to improve the product offerings, however, in each case, statistically insignificantly. We observe a statistically significant positive relationship only between the agents of the treatment group and the usage intensity of (intra-brand) differentiation tactics to improve customer loyalty. As this single significant relationship is associated with a relatively small regression coefficient (0.453 compared to the control group's mean of 3.448), causality inferences should be drawn with particular caution, and additional robustness tests are required. The results therefore suggest that the agency model introduction and the associated replacement of discriminatory, dealer-level pricing by uniform, manufacturer-imposed price setting do not lead agents to intensify their non-price-related (intra-brand) differentiation efforts, which is not in line with what we have expected based on prior research (e.g., Stigler, 1968). This raises the question of whether and how agents, under a direct sales model, in fact try to differentiate themselves from other agents of the same brand or also from other brands.

For our control variables, we again observe some statistically significant associations with our focal variables. Notably, dealerships selling only new cars use measures to improve customer targeting more strongly, and larger dealerships (in terms of annual new car sales) make stronger use of measures to enhance customer loyalty (*Table 3.6*).

3.4.3 Robustness check

In the following, we discuss a comprehensive series of robustness checks to further validate the results of our analyses. Particularly, we assess sensitivity to data cleaning and missing value imputation and conduct several subsample analyses and comparative analyses of brand-level regression coefficients. We also investigate within-respondent deltas in perceived competition intensities along our four competitive dimensions and test alternative methods to validate the consistency of our results on the relationship between direct sales models and perceived competition intensity. Overall, we find robust support for the main conclusions from our focal analyses, which reinforces the robustness of our findings (see *Table 3.7* for an overview).

Support of focal findings	(0)	(1)	(2)	(3)	(4)	(5)
Robustness check:	<i>Focal analyses¹⁾</i>	<i>Raw data</i>	<i>Subsample analyses</i>	<i>Brand-level coefficients</i>	<i>Relative intensities</i>	<i>Alternative methods</i>
Focal variable:						
<i>REP_IntraIntensity</i>	-0.916 ***	yes	-/-	-/-	-/-	-/-
<i>REP_MainComp</i>	-0.062	(yes)	-/-	-/-	-/-	-/-
<i>REP_AgencyEval</i>	0.180	(yes)	-/-	-/-	-/-	-/-
<i>REP_UniPriceEval</i>	-0.025	(yes)	-/-	-/-	-/-	-/-
<i>IntraPriceIntensity</i>	-1.082 ***	yes	yes	yes	yes ²⁾	yes
<i>InterPriceIntensity</i>	0.670 ***	yes	yes	yes	yes ²⁾	yes
<i>IntraGenIntensity</i>	-0.443 **	yes	yes	yes	yes ²⁾	yes
<i>InterGenIntensity</i>	0.370 **	(yes)	yes	(yes)	yes ²⁾	yes
<i>IndivDiscIntensity</i>	-2.552 ***	yes	yes	yes	-/-	-/-
<i>GenDiscIntensity</i>	-1.660 ***	yes	yes	yes	-/-	-/-
<i>ProdExtraIntensity</i>	-1.124 ***	yes	yes	yes	-/-	-/-
<i>ServExtraIntensity</i>	-0.849 ***	yes	yes	yes	-/-	-/-
<i>TargetingDiffIntensity</i>	0.320	(yes)	(yes)	(yes)	-/-	-/-
<i>ProductDiffIntensity</i>	-0.093	(yes)	(yes)	(yes)	-/-	-/-
<i>ServiceDiffIntensity</i>	0.160	(yes)	(yes)	(yes)	-/-	-/-
<i>LoyaltyDiffIntensity</i>	0.453 **	yes	yes	(no)	-/-	-/-
Detailed results	<i>Table 3.2, Table 3.3, Table B.21, Table 3.4, Table 3.5, Table 3.6</i>	<i>Table B.26, Table B.27, Table 3.8, Table B.28, Table B.29, Table B.30</i>	<i>Table 3.9, Table B.31, Table B.32</i>	<i>Figure 3.6, Figure B.12, Figure B.13</i>	<i>Table B.33, Table B.34</i>	<i>Table B.35, Table B.36</i>
Note	Does robustness check support focal findings? yes = statistically significant support; (yes) = statistically insignificant support and/or focal findings insignificant; (no) = statistically insignificant contradiction; no = statistically significant contradiction; ¹⁾ Main model regression coefficients related to treatment assignment (* p < 0.10; ** p < 0.05; *** p < 0.01) ²⁾ Includes additional insights for focal analyses					

Table 3.7: Overview of robustness checks

For our repeated cross-sectional data analyses, we repeat the main regression analyses with our raw, i.e., uncleaned and non-imputed, data sets (*Tables B.26 and B.27 in the Appendix*). Here, sample sizes differ from those in the previous analyses, firstly due to the inclusion of previously excluded, inconsistent cases and secondly due to missing values. Nonetheless, goodness-of-fit measures remain similar. Further, the regression results appear to be rather constant: The treated agents perceive intra-brand competition intensity as statistically significantly less strong than those of the control group and are (statistically insignificantly) associated with a lower likelihood of considering an intra-brand competitor as their main competitor. Regarding the evaluation of the agency model and of uniform prices, we continue to observe no considerable differences between the two groups. These results suggest that our previous findings likely do not depend on our data manipulation.

We also repeat the main regression analyses of our novel variables from the 2024 cross-section using the raw data (*Table 3.8* and *Tables B.28* and *B.29* in the *Appendix*). Due to missing values, these models are associated with lower sample sizes ($N = 278$ - 282). The share of treated agents remains almost unchanged at 11-12%, compared to 14% in our previous models. Model fit of the raw data models is slightly higher compared to our focal analyses (except column 1 of *Table B.28*). In the raw data regression models of our perceived competition intensity variables (*Table 3.8*), we find further support for our previous findings: Compared to the control group, the treated agents remain associated with perceiving both intra-brand price and general competition as less strong and inter-brand price and general competition as more intense. However, the relationship between the treatment and the perceived intensity of general inter-brand competition is statistically insignificant here. Moreover, the raw data regression models of our price- and non-price-related (intra-brand) differentiation tactics variables (*Tables B.28* and *B.29*) also provide support for our prior findings: The treatment group agents appear to use price-related differentiation tactics less intensively and measures to improve customer loyalty more strongly to differentiate themselves. For the other three non-price related differentiation tactics, we still do not observe statistically significant associations with the treatment group. Repeated regression analyses using (1) cleaned, non-imputed data, (2) uncleaned, imputed data, (3) cleaned data with only independent variables being imputed, and (4) cleaned data with independent and dependent variables imputed separately lead to the same, robust results (see *Table B.30* in the *Appendix*).

Dependent variable:	<i>IntraPriceInt.</i>	<i>InterPriceInt.</i>	<i>IntraGenInt.</i>	<i>InterGenInt.</i>
	(1)	(2)	(3)	(4)
Direct-to-consumer sales	-1.206 *** (0.263)	0.916 *** (0.204)	-0.412 * (0.212)	0.391 (0.237)
New car sales 2022 (log)	0.057 (0.066)	0.006 (0.061)	-0.002 (0.066)	0.057 (0.069)
Multi-brand dealership	0.029 (0.208)	-0.055 (0.256)	0.452 * (0.239)	0.284 (0.219)
New car-only dealership	0.267 (0.197)	0.029 (0.211)	0.228 (0.186)	0.240 (0.203)
<u>Additional controls:</u>				
Respondents' position	yes	yes	yes	yes
Partnering brand/s	yes	yes	yes	yes
Dealership location	yes	yes	yes	yes
Dealership online and EV offering	yes	yes	yes	yes
N	280	278	280	280
R ²	0.289	0.210	0.192	0.215
Note	* p < 0.10; ** p < 0.05; *** p < 0.01; robust standard errors in ()			

Table 3.8: Multiple linear regression results for perceived competition intensity variables with raw (uncleaned, non-imputed) data (*IntraPrice-*, *InterPrice-*, *IntraGen-*, and *InterGenIntensity*)

We further conduct several subsample analyses for our (perceived) competition intensity and differentiation tactics variables to validate robustness. These comprise subsample splits by agency model plans of the main brand's OEM,¹³ dealership's size,¹⁴ mono-brand dealerships, dealership business model (new car sales only versus new and used car sales), premium price segment, and dealership location.¹⁵ For our perceived competition intensity variables, we find statistically significant support for our previous findings across most subsamples (*Table 3.9*). For the perceived intensities of price competition (both intra- and inter-brand), the previously observed associations are each statistically significant for all but one subsample (mono-brand dealerships and premium price segment, respectively). For general intra-brand competition, the previously observed negative association with the treated agents is reversed in three of the subsamples. This is, however, statistically insignificant. For general inter-brand competition, the positive association is statistically insignificant for half of the subsamples and particularly for those of smaller dealerships and dealerships in smaller cities. However, this might also be due to the reduced sample sizes. Overall, these subsample regression results support our findings on the divergent intensity perceptions of our four competition dimensions between the treatment and control groups. The results for general competition appear to be slightly less robust to individual subsamples compared to those of the more specific price competition.

For our price-related differentiation tactics variables, subsample analyses again suggest very robust results of our previous analyses (*Table B.31* in the *Appendix*). Across all subsamples, agents of the treatment group use customer-individually negotiated and general, customer-independent discounts statistically significantly less strongly to differentiate themselves. For the usage intensity of both product- and service-related extras, we find statistically significant negative associations with the treated agents for most of the subsamples. With respect to our non-price-related differentiation tactics variables, on the other hand, subsample analysis results are less clear (*Table B.32* in the *Appendix*). In some, albeit less than half of the subsamples, we find statistically significant positive relations between the treatment group and the usage intensity of measures to improve both customer targeting and loyalty to differentiate. Regarding the measures to improve customer loyalty, this supports the results from our focal analysis. For the measures to enhance product and service offerings, we observe both statistically significant positive and negative associations with the treatment group across the subsamples, which does not allow for any general inferences regarding potential treatment effects at this point.

¹³ We first exclude dealerships at which the main brands' OEM has partially implemented an agency model (e.g., for selected car models) and then also those where the OEM has already communicated plans to implement one.

¹⁴ Median split by annual new car sales, average number of stock vehicles, and average number of employees.

¹⁵ Split into dealerships in locations (i.e., cities) with more or less than 20,000 inhabitants.

Dependent variable:	<i>IntraPriceInt.</i>	<i>InterPriceInt.</i>	<i>IntraGenInt.</i>	<i>InterGenInt.</i>
	(1)	(2)	(3)	(4)
Subsample:				
No partially implemented agency Subsample N = 289; Treatment group N = 54	-0.830 *** (0.170)	0.554 *** (0.151)	-0.347 ** (0.149)	0.275 * (0.164)
No partially implem. or planned agency Subsample N = 192; Treatment group N = 54	-0.686 *** (0.181)	0.499 *** (0.150)	-0.279 * (0.159)	0.135 (0.172)
Small dealerships (new car sales) Subsample N = 197; Treatment group N = 25	-0.601 * (0.332)	0.353 (0.340)	-0.300 (0.286)	0.110 (0.302)
Large dealerships (new car sales) Subsample N = 192; Treatment group N = 29	-1.742 *** (0.281)	0.716 ** (0.288)	-0.673 ** (0.284)	0.457 * (0.271)
Small dealerships (stock vehicles) Subsample N = 196; Treatment group N = 25	-1.074 *** (0.364)	0.969 *** (0.293)	-0.106 (0.326)	0.378 (0.329)
Large dealerships (stock vehicles) Subsample N = 193; Treatment group N = 29	-1.366 *** (0.295)	0.676 ** (0.305)	-0.907 *** (0.285)	0.095 (0.287)
Small dealerships (employees) Subsample N = 199; Treatment group N = 12	-0.681 * (0.375)	0.863 ** (0.354)	0.057 (0.322)	0.169 (0.329)
Large dealerships (employees) Subsample N = 190; Treatment group N = 42	-1.406 *** (0.247)	0.623 ** (0.255)	-0.736 *** (0.261)	0.520 ** (0.248)
Mono-brand dealerships Subsample N = 297; Treatment group N = 53	-0.822 (0.535)	1.004 *** (0.376)	-0.759 * (0.417)	0.162 (0.385)
New car sales only (business model) Subsample N = 46; Treatment group N = 14	-1.318 ** (0.531)	2.448 *** (0.742)	0.310 (0.714)	1.798 ** (0.698)
New & used car sales (business model) Subsample N = 343; Treatment group N = 40	-1.301 *** (0.226)	0.342 * (0.204)	-0.710 *** (0.219)	0.474 * (0.244)
Premium price segment (only) Subsample N = 107; Treatment group N = 53	-1.500 *** (0.293)	0.288 (0.305)	-0.713 ** (0.307)	0.574 * (0.337)
Small cities (dealership location) Subsample N = 136; Treatment group N = 13	-0.720 * (0.430)	0.777 ** (0.386)	0.390 (0.441)	0.535 (0.377)
Large cities (dealership location) Subsample N = 253; Treatment group N = 41	-1.196 *** (0.221)	0.662 *** (0.225)	-0.601 *** (0.200)	0.400 * (0.218)
Note	* p < 0.10; ** p < 0.05; *** p < 0.01; robust standard errors in ()			

Table 3.9: Multiple linear regression results for perceived competition intensity variables for different subsamples (*IntraPrice*-, *InterPrice*-, *IntraGen*-, and *InterGenIntensity*) – regression coefficients with respect to treatment assignment (direct-to-consumer sales)

To further examine the specificity of the estimated treatment effect for Mercedes agents, we assess the full set of brand-level regression coefficients from our main regression models (see *Tables 3.4, 3.5, and 3.6*). Each of the dealerships' partnering brands (including Mercedes) is represented in the respective model by a binary dummy variable and thus associated with its own coefficient. This comparative view helps in evaluating whether the observed differences between the treatment (i.e., all Mercedes dealers) and control (i.e., all non-Mercedes dealers) groups primarily reflect general, brand-level heterogeneity or whether they might be explained by the treatment (i.e., the direct sales model launch). If several other brands exhibit statistically

significant coefficients (or even greater ones compared to the treatment group), this might indicate brand-level heterogeneity, rendering a treatment effect for Mercedes less plausible.¹⁶

For our competitive intensity variables (*Table 3.4*) and the perceived intra-brand price competition intensity, we observe five brand-level coefficients that are statistically significant (*Figure 3.6*). However, the coefficient for Mercedes (-1.082) stands out and differs substantially from those of other brands, especially its main competitors BMW (0.182) and Audi (-0.015). The low variation (in terms of the standard deviation) of the largely insignificant coefficients among control group brands suggests a homogeneous perception within the control group. Regarding inter-brand price competition, the spread between Mercedes' coefficient (0.670) and the next largest statistically significant coefficient (Renault/ Dacia, 0.496) and the main competitors Audi (0.384) and BMW (0.360, not significant) is slightly smaller. Nevertheless, the Mercedes coefficient remains the largest, and the relatively small variation across control group brands again suggests a homogeneous perception amongst the control group. Concerning general intra-brand competition, Mercedes is the only brand with a statistically significant coefficient (-0.443). Compared to the two price competition dimensions, the variation of the (insignificant) control group brands' coefficients is even lower, again indicating a homogeneous perspective within the control group. While the difference between Mercedes and the control group brands appears less pronounced than in the price competition dimensions, the contrast to Mercedes' main competitors remains evident. Lastly, for general inter-brand competition, Mercedes again exhibits a statistically significant coefficient (0.370) and clearly differs from most coefficients of the control group brands, including its main competitors BMW (-0.162) and Audi (-0.139). Among all competitive dimensions, this one shows the least variation in brand-level regression coefficients, suggesting high homogeneity within the control group. However, Ford (0.392) also exhibits a statistically significant coefficient of comparable size to Mercedes and thus represents an exception within the control group.

¹⁶ *Note:* Our regression models include dummy variables for all brands without a reference brand, as some of the dealers in our sample are multi-brand dealers (24%; 2% for the treatment group). This enables us to account for each brand while avoiding (perfect) multicollinearity. None of the brand dummies exhibit correlation coefficients with absolute values exceeding 0.40 or variance inflation factors greater than 5. While the presence of multi-brand dealers may add complexity to interpreting individual coefficients, this mainly affects the control group brands.

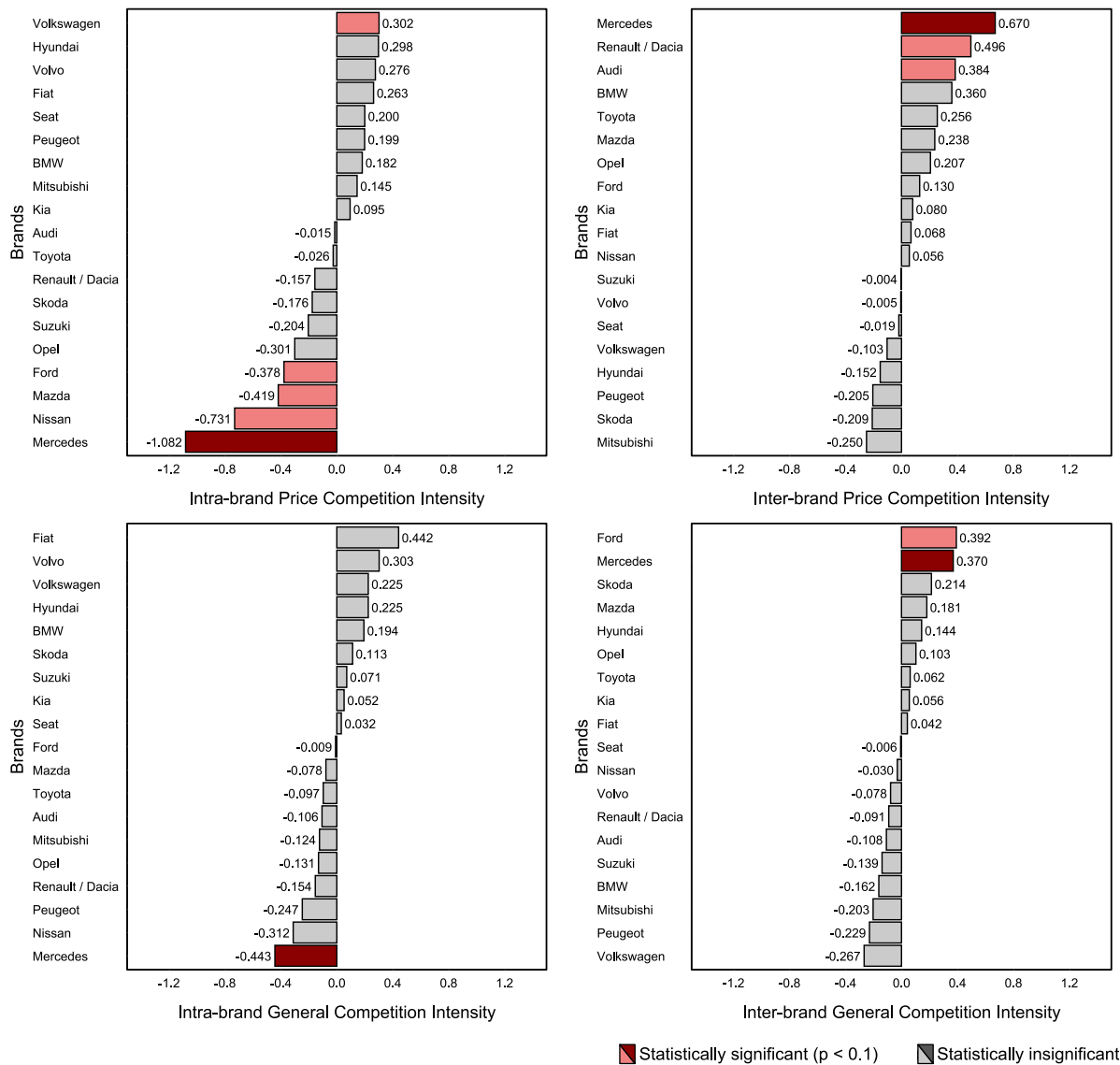


Figure 3.6: Brand-level coefficients from multiple linear regression analyses of perceived competition intensity variables (main models; exclusion of three brands with $N < 10$; *IntraPriceIntensity*, *InterPriceIntensity*, *IntraGenIntensity*, and *InterGenIntensity*) – regression coefficients with respect to treatment assignment (direct-to-consumer sales)

Overall, Mercedes consistently exhibits statistically significant and distinct regression coefficients in all four competitive intensity dimensions. It thus clearly differs from a relatively homogeneous control group, including its main competitors BMW and Audi. These observations suggest that the observed differences between Mercedes and the control group are unlikely to stem from general brand-level heterogeneity in competitive perceptions.

Regarding our price-related (intra-brand) differentiation tactics variables (*Table 3.5*), all four regression coefficients related to Mercedes are statistically significantly negative and each consistently the lowest coefficient of all brands (*Figure B.12* in the *Appendix*). Compared to the competition intensity variables, the variation within the control group is slightly higher, and some other brands also exhibit significant coefficients. Notably, two coefficients of Fiat are

also significant (-0.960 for the usage intensity of individually negotiated discounts; -0.918 for product-related extras), however, less pronounced than those of Mercedes. Still, the variation within the control group remains relatively low across all price-related differentiation tactics, thus again indicating homogeneity. Moreover, Mercedes' coefficients are consistently greater than those of any other brand and differ strongly from those of its main competitors. Altogether, these observations support the robustness of our previous findings, again suggesting that the differences in the usage intensities of price-related (intra-brand) differentiation tactics between the treatment and control groups are unlikely to reflect general brand-level heterogeneity.

Lastly, for our non-price-related (intra-brand) differentiation tactics variables (*Table 3.6*), the regression coefficient of Mercedes is statistically significant only for the usage intensity of measures to improve customer loyalty (0.453; *Figure B.13* in the *Appendix*). However, here, both main competitors exhibit significant and similar coefficients (Audi 0.496, BMW 0.447), suggesting that these differences are more likely attributable to market- or price-segment-level differences rather than to the treatment related to Mercedes. Across all four measures, the variation in brand-level coefficients, particularly within the premium price segment (comprising Audi, BMW, Mercedes, and Volvo), complicates drawing clear inferences about potential treatment effects and reduces their plausibility. We further present brand-level mean values for all focal variables in *Figure B.14* in the *Appendix*.

To complement our previous analyses, we investigate within-respondent deltas in the perceived competition intensities, focusing on four relative comparisons: (1) intra- versus inter-brand price competition, (2) intra- versus inter-brand general competition, (3) intra-brand general versus price competition, and (4) inter-brand general versus price competition. By analyzing these deltas, we control for absolute levels and examine the relationship between the treatment and the hierarchical structure of the perceived competitive intensities. As general competition per definition comprises price and non-price competition, (3) and (4) essentially reflect intra- and inter-brand non-price competition by excluding the price dimension. The regression results consistently show statistically significant coefficients for the treated agents related to all four competition intensity deltas (*Tables B.33* and *B.34* in the *Appendix*).

Compared to the control group, the treated agents perceive intra-brand competition as relatively less intense than inter-brand competition. This applies to price (*IntraVsInterPrice*) and general competition (*IntraVsInterGen*) and suggests that the treatment might be associated with a shift in perceived competitive intensity from intra- to inter-brand competition. Further, the treated agents seem to perceive intra-brand non-price competition (i.e., *IntraGenVsPrice*) as stronger and inter-brand non-price competition (i.e., *InterGenVsPrice*) as less intense

compared to the control group. Combined with their perception of a higher intensity of intra- and a lower intensity of inter-brand price competition, this is in line with theoretical predictions suggesting an inverse relation between price and non-price competition (e.g., Stigler, 1968).

Overall, these findings suggest that the treatment is not only related to differences in the absolute perceived competition intensities but also with shifted relative relationships between the perceived intensities of the different competitive dimensions. As such, this could reflect a new arrangement of the perceived competitive structure for the treated agents.

As a last check to validate the robustness of our results with respect to the perceived competition intensity variables, we test two alternative methods that more explicitly account for the inherently ordinal nature of the variables. Namely, we use proportional odds logistic regressions and binomial logistic regressions by transforming the variables into binary terms.¹⁷ Thereby, we aim to validate that our previous results do not depend on the specific modeling assumptions of our focal analyses but rather remain consistent across different methods. The proportional logistic regression results robustly support those of our focal analyses, with statistically significant treatment coefficients in the previously observed directions for all four competitive dimensions (*Table B.35* in the *Appendix*). The results from the binomial regression analyses further support our findings, with statistically significant treatment coefficients for the two intra-brand competition dimensions (*Table B.36*). The treatment coefficients of the two inter-brand dimensions confirm the direction of our previous results but are statistically insignificant. However, this could also result from the simplification of the variables associated with the reduction of the five-point Likert-type scales to binary outcomes, which loses some of the variables' information.

Altogether, our comprehensive set of robustness checks consistently supports the validity and reliability of our findings across various additional tests, specifications, subsamples, and methods.

¹⁷ By differentiating the variables' values between the perception of the competition intensity as "very weak" or "rather weak" (variable value 0) versus "rather strong" or "very strong" (variable value 1) and excluding "neutral".

3.5 Discussion, Conclusion, and Implications

In this study we empirically examine perceived intra- and inter-brand competitive dynamics and differentiation tactics of dealers in the new car industry. We analyze two carefully selected samples of German car dealers to better understand important differences between agents of a direct-to-consumer sales brand with uniform, OEM-imposed pricing (the treatment group) and dealers of brands with wholesale models and dealer-led price negotiations (the control group).

We find that direct sales agents appear to perceive price competition within their own brand as statistically significantly less strong than traditional wholesale dealers with dealer-level price setting. This is in line with theoretical predictions related to vertical restraints and resale price maintenance (e.g., Wang, 2005). In particular, while 61% of the control group state that they consider intra-brand price competition to be rather or very strong, only 13% of the treated agents do so. This could indicate that a shift to an agency model might indeed enable OEMs to achieve one of their main goals of the transformation, to eliminate (or at least reduce) within-brand price competition through uniform manufacturer-imposed pricing (e.g., Tschödrich et al., 2020).

On the other hand, the agents of the treatment group likely perceive non-price competition within their own brand as stronger than those of the control group, which is also consistent with prior theoretical research suggesting an inverse relationship between price and non-price competition (e.g., Stigler, 1968). This suggests that replacing dealer-level pricing with uniform, manufacturer-imposed price setting might shift the dealers' focus of intra-brand competition from price to non-price or quality competition. Under an agency model, aspects such as enhanced, personalized customer service could therefore play a greater role in the context of intra-brand competition (Winter, 1993). However, we find evidence indicating that the difference in the perceived intensity of price competition might exceed that of non-price competition (as predicted by Stigler, 1968). The dealers of the treatment group thus perceive general intra-brand competition as less intense than the control group. This is also supported by our repeated cross-sectional data analyses, indicating that Mercedes agents of our 2024 sample consider same-brand competition as less intense than the full 2022 sample as well as the Mercedes dealers of the 2022 sample (who were not yet operating under an agency model).

When it comes to competition with other brands, things appear to be exactly opposite, which is what we expect based on previous theoretical literature (Breton & Sbragia, 2021). At 76%, statistically significantly more dealers of the treatment than of the control group (51%) perceive inter-brand price competition as rather or very strong. A potential explanation might be that reducing intra-brand competition in theory leads to higher retail prices, which may incentivize other brands (that still allow dealer-level pricing) to undercut the direct sales brand, thus

intensifying inter-brand price competition (e.g., Wang, 2005). Conversely, the treated agents consider inter-brand non-price competition as less intense than the control group. Again, the difference in the perceived intensity of price competition exceeds that related to non-price competition, so that the treated group perceives inter-brand competition in general as stronger.

Overall, these findings suggest that introducing a direct sales model may lead to three crucial rebalancing effects in the competitive dynamics of new car retailing. First, for direct sales agents, competitive focus might rebalance from intra- to inter-brand rivalry, likely due to the elimination of dealer-level price discrimination. However, our repeated cross-sectional data analyses on the perceived main competitor indicate that same-brand competitors consistently retain high relevance for direct sales agents. Combined with our other findings, this relevance might be explained by non-price aspects of intra-brand competition, such as service quality. Second, within intra-brand competition, the relative importance of non-price compared to price competition might increase for direct sales brands. This is in line with theoretical research suggesting an increase in non-price competition due to a regulation of price competition. Third, for inter-brand competition, the opposite seems to hold. Here, the agency model appears linked to a higher relative importance of price compared to non-price competition for agents. Thus, for direct sales agents, inter-brand competition may become a more price-based rivalry, as they might face higher price pressure from competitors that continue to allow dealer-level pricing.

These potential rebalancing effects in the competitive dynamics raise the question of whether direct sales agents adapt their differentiation tactics accordingly. In this study, we focus on the intra-brand perspective and would expect that the shift in pricing authority from agents to OEMs and the rebalancing from price to non-price competition also lead direct sales agents to adjust their (intra-brand) differentiation tactics accordingly (e.g., Winter, 1993). As expected, dealer-imposed, customer-individually negotiated discounts seem to vanish. However, this does not appear to be offset by either the OEM via general, customer-independent rebates or by agents through “hidden” discounts such as free or discounted product or service extras. Overall, this suggests a general decrease in the direct sales agents’ price-related intra-brand differentiation tactics, which is in line with their perception of less intense intra-brand price competition.

On the other hand, our findings do not support the theoretical prediction that the direct sales agents intensify their non-price related intra-brand differentiation efforts as a response to the price regulation (e.g., Stigler, 1968). Although we observe a statistically significantly higher usage intensity of measures to improve customer loyalty among the treated agents, a causal effect due to the treatment is rather unlikely, as the two untreated main competitors exhibit similar patterns. With respect to measures to enhance customer targeting as well as product and

service offerings, we do not find significant differences between the treatment and control groups. A potential explanation for this omission of greater non-price intra-brand differentiation efforts might be that intra-brand non-price competition is not increasing sufficiently to put pressure on direct sales agents to differentiate themselves more strongly. Furthermore, agents might not necessarily distinguish between intra- and inter-brand differentiation activities. Since inter-brand non-price competition appears to soften, the total effect of intra- and inter-brand non-price competition combined might not be strong enough to trigger substantial increases in differentiation efforts. Moreover, from the direct sales agents' perspective, investing more into non-price differentiation might not be attractive if such measures are perceived as ineffective or if financial constraints limit their ability to do so (e.g., Kopalle et al., 1999).

Overall, our findings suggest that introducing an agency sales model might effectively eliminate or at least reduce intra-brand price competition, which helps OEMs to prevent costly intra-brand price wars that lead to reduced sales margins (Buzzavo, 2023) and thus to increase prices (Wang, 2005). Beard et al. (2021), for instance, show that spatial intra-brand competition reduces final vehicle prices by roughly 4–5% per 25 miles in same-brand dealer proximity.

Furthermore, the potential rebalancing in the agents' competitive focus from intra- to inter-brand competition might lead agents to focus more strongly on the "true rival", dealers of other brands. However, particularly the perceived increase in inter-brand price competition intensity raises the question of its origin. For instance, this might reflect that other brands in fact compete more aggressively or that direct sales agents are more aware of competition from other brands due to the softened intra-brand price competition. Alternatively, it could also be due to agents finding it more difficult to compete due to the restriction of price differentiation measures.

The suggested rebalancing effect from price to non-price competition within intra-brand competition might indicate that under an agency model, within-brand competition centers more around product and service offerings rather than new car prices and rebates. For OEMs and agents, this might lead to enhanced service quality and increased demand (Yan & Pei, 2009).

Our results further suggest that manufacturers might be effective in restricting agents in their use of price-based promotions. However, these measures do not seem to disappear entirely, potentially requiring ongoing OEM monitoring (Winter, 1993). From the agents' perspective, losing these tools might imply less leeway in sales activities. In combination with increasing price pressure from other brands, this could ultimately lead to losses in sales volumes. Related to the seemingly unchanged non-price related differentiation efforts of the direct sales agents, the question arises as to how agents ultimately attempt to differentiate themselves under the new sales model. The combination of expected higher retail prices, fewer price-based

promotions, and unchanged non-price differentiation efforts may pose substantial sales volume risks for agents and manufacturers. Manufacturers might therefore want to consider creating stronger incentives and training for their agents, particularly to improve their service offering.

We acknowledge the following limitations of this study, which might inspire future research. First, generalizability of our results might be limited to the German new car retail market and not necessarily to other industries or markets. Our data stems from a voluntary, uncompensated telephone survey, inheriting a risk of self-selection, and we derive our focal variables from self-reported, Likert-type scaled questions, which may not capture real-world competitive dynamics and might reflect subjectivity or social desirability in response behavior. To address this, future research could aim at capturing actual competitive dynamics (e.g., through dealer-level sales volumes and transaction prices) or dealer differentiation tactics and day-to-day sales activities (e.g., via mystery shopping or case studies). Future research may also capture non-price competition intensity or inter-brand differentiation tactics explicitly, as we can only implicitly do so. For the latter, we focus on intra-brand differentiation, while it could be that agents shift differentiation focus on inter-brand competitors. However, it is rather unlikely that agents adopt specific measures more strongly or exclusively related to buyers that are undecided between brands and less related to buyers who already decided on the brand but not on the point of sale.

In this study, we cannot draw on panel data. Instead, we need to rely on repeated cross-sectional data and focus on a one-time cross-section for our in-depth analyses, which might limit causal interpretation and understanding of dynamic effects. It is important to acknowledge that our design might be vulnerable to spillover effects (Baicker, 2005), and particularly for the repeated cross-sectional data analyses, to anticipatory effects (Malani & Reif, 2015).

Despite these limitations, we extend research on vertical restraints, intra-brand competition, price and non-price competition, and retailer differentiation. We provide valuable empirical evidence on how transitioning from a wholesale model with discriminatory, dealer-level pricing to a direct-to-consumer sales model with uniform, manufacturer-imposed price setting might impact competitive dynamics and dealer differentiation tactics, particularly in new car retailing.

4 Shifting Gears – Evaluating the Sales Volume Impact of Direct-to-Consumer Sales Model Transformations

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Statement of contribution: This is a single-authored paper. Julian Feldhäuser confirms sole responsibility for the development of the research idea and study design, the literature review, data preparation and analysis, presentation and interpretation of results, as well as for writing and finalizing the manuscript.

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Abstract

Several automotive manufacturers have already transitioned from indirect, dealer-based sales models with negotiable prices to direct-to-consumer sales models with uniform, non-negotiable prices in selected markets or product segments. Others are currently planning such transitions. While this transformation promises greater pricing control, better customer experience, and direct access to valuable customer data, some manufacturers have reported implementation and operational challenges. Other manufacturers have meanwhile postponed or even reversed their respective transformation plans. Despite the strategic relevance, there has been limited empirical evidence on the sales volume effects of these transformations. This paper investigates how the transition to a direct sales model with fixed prices affects manufacturers' new car sales volumes. I analyze two real-world case studies in which BMW and Mercedes introduced direct-to-consumer sales models in their South African and Austrian regional markets, respectively. By using monthly regional market-level sales volume data and the synthetic control method (SCM), I construct counterfactual sales volume trajectories based on other untreated regional markets of the same manufacturer. My results indicate that both transitions to direct sales models are followed by a decline in monthly new car sales volumes compared to their synthetic controls. For BMW South Africa, I observe an average sales volume decline of 25.3% over two years, and for Mercedes Austria, an average decrease of 9.5%. This suggests that switching to a direct sales model with fixed prices may entail substantial sales volume risks for manufacturers.

4.1 Introduction

In recent years, the way vehicles are marketed and sold has begun to fundamentally change in the new car industry. Inspired by the direct sales approach of greenfield manufacturers such as Tesla, traditional original equipment manufacturers (OEM) have embarked on rolling out direct sales models in selected regions or car segments (Hoeft, 2021; Schmidt et al., 2020).¹ Such shifts to direct sales models usually involve two overarching transformations for OEMs, dealers, and customers: First, the *sales model transformation*, which is the structural shift from an indirect, retailer- or dealer-based system to a direct sales model where the OEM sells vehicles directly to its customers, often through *agents* who facilitate transactions for the manufacturer (Buzzavo, 2023). Second, the *pricing model transformation* from discriminatory prices that are usually individually negotiated between dealers and customers to fixed, non-negotiable prices that are centrally set by OEMs and consistent across buyers and channels (Schmidt et al., 2020).

Manufacturers aim to realize various benefits from such strategic shifts. These include direct access to customer data (Wirtz, 2021), customer experience improvements (McKee et al., 2023), distribution cost reductions (Buzzavo, 2023), and better and more direct pricing control to remove price competition and price undercutting within the brand itself (Heuser et al., 2023).

However, real-world implementations of direct sales models by OEMs have proven difficult. Recent media reports highlight several technical, operational, and organizational issues, such as IT system failures (Seyerlein, 2025), legal and tax challenges (Plate, 2023), dealer complaints (Seyerlein, 2023), or complicated frictions throughout the customer journey (Seyerlein, 2025). Moreover, OEMs such as Stellantis in Belgium (Rehberg, 2024) or BMW's sub-brand Mini in Germany (Seyerlein, 2025) have reported sharp sales volume declines following the regional move to a direct sales model. In light of these developments, some manufacturers have already postponed or even reversed their planned direct sales model launches. For instance, Ford has stopped its entire rollout in Europe (Bäuchle, 2024), Stellantis and Skoda have delayed their launches in Germany (Rehberg, 2024; Autohaus, 2024a), and Volkswagen is actively reviewing the model in core European markets, where it had already adopted the direct sales model for electric vehicles (Seyerlein, 2024). These industry developments emphasize the uncertainty associated with the transition to direct sales models and the need for systematic, empirical evidence on how such transformations impact manufacturers' sales performances. Could it be that incumbent manufacturers have been too quick to follow what appeared to be a disruptive success story? Have they been lured into direct sales transformations by Tesla and the promising

¹ I provide a (non-exhaustive) list of direct sales model introductions by OEMs in *Table A.1* in the *Appendix*.

forecasts of consulting reports such as Schmidt et al. (2020) and Tschödrich et al. (2020), without fully accounting for the operational and market risks involved?

While the anecdotal evidence regarding the sales developments after adopting direct sales is insightful, it lacks analytical and causal validity. It remains unclear whether and to what extent the observed sales declines are due to the direct sales model. In general, despite the strategic relevance of these shifts to direct sales and fixed pricing, academic and especially empirical research in this field is both limited and inconclusive. Relevant studies are mainly theoretical (e.g., Johnson, 2017; Wang, 1995), focus on dual sales channel settings, in which direct and indirect sales channels coexist (typically without fully replacing traditional dealers or retailers; e.g., Yan & Pei, 2009), and/or assess sales or pricing model transformations solely in isolation (e.g., Park et al., 2018; Zeng et al., 2016). So far, no empirical study has examined sales volume effects of manufacturers' full-scale transitions to direct sales with fixed, non-negotiable prices.

In this paper, I empirically analyze the effect of two car manufacturers' regional market-level transformations from indirect, dealer-based sales models with negotiable prices to direct sales models with fixed prices on monthly new car sales volumes. Specifically, I assess BMW's switch in their South African market in January 2020 and Mercedes' (MB) move in Austria in August 2021. Company representatives of the two OEMs described the transition as efforts to remove the price negotiation process and the associated uncertainty for customers (Venter, 2021), to better understand customer needs (Automotive World, 2020), and to offer enhanced customer experiences (Smyth, 2020). Following Abadie (2021), I employ a synthetic control method to develop counterfactuals based on weighted combinations of other untreated regional markets of the respective OEMs to estimate the sales volume effects of the two transformations.

The empirical results of this study suggest that the two manufacturers' transformations into a direct sales model with fixed, non-negotiable prices are followed by a decline in monthly new car sales volumes relative to the respective synthetic control groups. For BMW, monthly sales volumes in South Africa are on average 25.3% lower than for its synthetic replica over the two-year period after the transition to direct sales. For Mercedes Austria, the results indicate a moderate monthly sales volume decline of 9.5% on average over the same period after the direct sales transition. While the post-treatment pattern in the monthly sales volume gaps relative to the synthetic twin is robust to alternative specifications of the model, I cannot entirely exclude chance as a potential explanation for Mercedes Austria's sales development. These results suggest that transitioning to a direct sales model with fixed, non-negotiable prices might involve substantial sales volume risks for automotive manufacturers. As sales volumes remain a crucial performance metric for OEMs, such implications should be carefully considered in the strategic

assessment of full-scale direct sales model transformations. This study thus provides an important empirical foundation for evaluating the trade-offs associated with switching to a fixed price direct sales model. Furthermore, it suggests that in the context of these transformations, optimal pricing strategies, product and service offering improvements, a quick development of retail operations capabilities, and effective transition management are likely to play an important role for manufacturers in mitigating potential sales volume risks.

The remainder of this paper proceeds as follows: In *Section 4.2*, I provide an overview of related literature, my contribution, and the theoretical framework. In *Section 4.3*, I describe data and methodology before discussing results in *Section 4.4* and comprehensive robustness checks in *Section 4.5*. I provide a discussion, conclusion, and implications in *Section 4.6*.

4.2 Literature Review, Research Contribution, and Theoretical Framework

The transition from a traditional retailer-based wholesale model to a direct-to-consumer sales model represents a fundamental shift in both sales and distribution structures as well as pricing models. From a distribution perspective, this switch replaces intermediated, indirect sales through independent retailers or dealers with direct sales by manufacturer-employed agents to customers. At the same time, from a pricing angle, it involves a shift from retailer-imposed, negotiable pricing to uniform, non-negotiable prices set by manufacturers (Heuser et al., 2023).

With this study, I contribute to two distinct strands of research in the fields of marketing, economics, and industrial organization, which I review in the following: studies on (1) sales models and their transformations and (2) pricing models and their transformations. Previous studies in these areas have explored crucial aspects of both domains. They selectively analyze the trade-offs between indirect and direct sales models as well as between negotiable and fixed pricing strategies. However, to the best of my knowledge, so far, none has empirically examined the impact of a simultaneous transformation of the sales and the pricing model – resulting from the shift to direct sales with fixed prices – on manufacturers’ sales volumes. This study addresses this gap by empirically applying a sophisticated event study methodology to real-world data from two direct sales model transformations in the automotive new car industry.

4.2.1 Studies on sales models and their transformations

So far, related studies on sales models and their transformations have mainly focused on three areas: (1) vertical restraints, (2) vertical integration and manufacturer encroachment, and (3) so-called dual sales channel systems. Vertical restraints are contractual agreements between supply chain stakeholders, often limiting retailer flexibility (Motta, 2004). On the other hand, vertical integration or manufacturer encroachment, which are often used interchangeably, are

more profound, as they involve the manufacturer taking control of supply chain activities, such as sales and distribution operations (Donna et al., 2024). These are thus more similar to direct sales models, where OEMs sell directly to customers. However, these studies often focus on settings where retailers continue to operate alongside manufacturer-led channels instead of retailers being fully replaced. Dual sales channel systems involve the coexistence of different channels, often involving a direct sales channel and an indirect retail channel (Yan & Pei, 2009).

Prior studies on vertical restraints address arrangements such as exclusive sales territory rights or brand-exclusive dealing that restricts retailers to only sell one brand (Mycielski et al., 2000). Research in this area has so far mainly focused on competitive dynamics (Rey & Stiglitz, 1995), welfare effects (Winter, 1993; Brenkers & Verboven, 2006), and retail prices (Li & Luo, 2020). While these studies differ in terms of context and approach, they generally conclude that vertical restraints can have crucial effects on price levels, competitive dynamics, and overall welfare, often depending on contextual parameters. However, unlike under a direct sales model, under such vertical restraints, the existence and role of retailers are usually maintained. Vertical restraints preserve the retailer's role as an intermediary and only limit its autonomy. Research on vertical integration and manufacturer encroachment extends this notion by examining settings in which manufacturers take direct control over downstream sales activities (Donna et al., 2024). These studies often assess the effects of manufacturer encroachment into retailing but usually in the context of coexisting manufacturer and retailer sales channels rather than fully replacing retailers. This has led to a large body of research on dual sales channel systems in which firms operate both direct and indirect (i.e., intermediated) sales channels in parallel.

In this domain, several, mostly theoretical studies address the competitive implications of manufacturers introducing a direct sales channel in addition to existing indirect retail channels. Among others, these include the examination of channel conflicts between direct and indirect sales channels (Ronayne & Taylor, 2022) or the implications for bargaining dynamics between manufacturers and retailers (Donna et al., 2024). Hendershott and Zhang (2006) use a theoretical model to assess welfare implications. They show that adding a direct online sales channel can benefit firms due to opportunities for price discrimination and customers due to lower prices resulting from increased retailer competition but generally harms intermediaries.

Another crucial body of theoretical literature on dual sales channel systems focuses on manufacturers' incentives to establish their own direct sales channel as well as the implications for them. Chiang et al. (2003) show that firms can add a direct to an existing retail channel to mitigate inefficiencies resulting from "double marginalization". This term describes the retail price inflation that occurs when manufacturers and retailers both aim to enhance their own profit

margins and retailers do not face direct competition from the manufacturer. Lee and Ono (2024) demonstrate that firms should establish a dual sales channel system to increase profits if their cost of sales is sufficiently small. A theoretical study by Dumrongsiri et al. (2008) examines conditions under which manufacturers benefit more from a dual rather than a single, indirect sales channel system. Arya et al. (2007) show that adding a direct sales channel intensifies downstream price competition, reduces retail prices, and leads to pareto improvements for firms and retailers. Furthermore, Yan & Pei (2009) find that channel competition in a dual-channel system can enhance retailers' services and increase individual profits for firms and retailers.

Empirical evidence in this domain remains scarce. Homburg et al. (2014), for instance, study the firm value reactions to channel expansion announcements. Vinhas and Anderson (2005) use a marketer survey to examine the extent to which firms simultaneously employ direct and intermediated sales channels as well as circumstances that foster channel conflicts.

While these studies provide valuable insights into dual sales channel strategies, none of them investigate either the full transition from an indirect wholesale to a direct sales model or the sole presence of a direct sales channel. To date, only a few studies have done so. For instance, Bei and Gielens (2023), in the context of brands selling products through online platforms, empirically compare the market share impact of two different governance models, which are similar to indirect and direct sales channels. They observe a positive market share effect for brands after starting third-party platform operations, where they directly sell to customers on the platform, compared to one-party operations, where they wholesale products to the platform, which then resells them. However, they only focus on an e-commerce context and specifically do not consider the option of brands managing their own online direct-to-consumer operations. Also in the e-commerce domain, Gielens and Steenkamp (2019) conduct a literature review on different types of (dis)intermediation. They find that digital transaction disintermediation and direct-to-consumer websites enable brands to regain control of pricing and customer interactions, improve profitability through lower transaction costs, and enhance brand equity. Johnson (2017) analyzes the profit impact of wholesale models compared to agency models in the context of e-commerce using a theoretical model. He shows that an agency model, where the supplier sets retail prices, generally leads to lower retail prices and benefits retailers but harms suppliers. Yet, in this model, retailers can set the contractual arrangements that determine the revenue sharing between suppliers and retailers. In my setting, on the other hand, both prices and retailers' revenue shares (i.e., commissions) are set by the supplier (i.e., manufacturer) (Köhnen, 2024). Lastly, and most closely to my own research, Park et al. (2018) empirically investigate the sales volume impact of direct sales model choices of U.S. farmers. They use an annual survey of farmers to assess the effect of farms voluntarily adopting an (exclusively)

direct sales model on farm-level sales. As a result, they find a strong decline of 71.3% in annual sales. However, their data is derived from a highly specific context: U.S. farm-level data collected between 2008 and 2010. It thus focuses on small-scale local food systems instead of industrial manufacturers. Further, their analysis is based on survey data and relies on self-reported, voluntary marketing choices. In contrast, I focus on full-scale transformations of large manufacturers' sales and pricing models and rely on actual monthly sales volume panel data.

In summary, while prior research provides insights into vertical restraints, dual sales channel strategies, and selectively into the adoption of direct sales channels, no study to date has empirically assessed the impact of a manufacturer's full-scale direct sales model transformation based on market-level sales data. This study addresses this gap by applying an event study methodology to two real-world transitions from a wholesale to a direct sales model of two different, globally operating manufacturers in the automotive industry.

4.2.2 Studies on pricing models and their transformations

One of the most profound changes accompanying a car manufacturer's transition from an indirect wholesale model to a direct sales model is the shift from prices that are negotiated between dealers (retailers) and customers to manufacturer-set, non-negotiable prices (Heuser et al., 2023). While only one study empirically analyzes a full transformation from negotiable to fixed pricing (Zeng et al., 2016), several others offer relevant insights for my research.

There are several studies using theoretical models to investigate the effects of resale price maintenance (RPM), where manufacturers impose fixed or minimum retail prices on retailers. Enforcing fixed prices resembles the situation of fixed, non-negotiable prices under a direct sales model. Telser (1960), for instance, shows that manufacturers can use minimum retail prices to avoid destructive price wars and to encourage retailers to provide improved services, which could boost customer demand. Wang (2005) argues that establishing fixed retail prices allows manufacturers to impose optimal retail prices and to increase profits, but that overall effects for buyers and society are detrimental. Bang and Jin (2015) also show that RPM results in higher prices but at the same time in improved retailer service quality and increased manufacturers' profits. However, while resale price maintenance often still assumes retailer-level pricing autonomy, the direct sales model implies direct price setting by the manufacturer.

Another pertinent strand of literature deals with discounts and promotions. Although these studies do not directly compare negotiable and fixed pricing, they provide relevant insights for settings where prices vary across customers and/or time. In the traditional wholesale model, retailers often apply tactical price reductions and individual discounts to impact purchase decisions (Schmidt et al., 2020), thus studies on discounts and promotions may also be relevant

in the context of my research. Kopalle et al. (1999) empirically show that increased discounting generally raises customer price sensitivity and diminishes baseline sales, that is, normal sales volumes in the absence of a promotion. Jedidi et al. (1999) and Blattberg et al. (1995) demonstrate that discounts can damage brand equity and reduce sales at regular prices. Demirag et al. (2010) use a theoretical model to compare two types of promotions: retailer incentives, where a lump sum incentive is offered from manufacturers to retailers who can then use it to flexibly pass it on to buyers, and customer rebates, which are promotions offered directly from manufacturers to buyers, such as fixed per-unit discounts. The former is conceptually similar to the traditional automotive wholesale model, where OEMs sell new cars to dealers who independently resell them at higher prices. The latter is more akin to the direct sales model, in which OEMs centrally steer sales and promotion operations (Buzzavo, 2023). They show that in case of high demand uncertainty and strong competition, OEM-controlled customer rebates are more efficient in increasing sales than retailer incentives if they result in market expansion. Overall, these studies suggest that excessive or uncontrolled discounting can affect customer price sensitivity, sales volumes, and brand equity and can have adverse effects for OEMs.

Slightly closer to my own research, several theoretical studies examine firms' optimal choices between fixed and negotiable pricing schemes and respective optimality conditions. Wang (1995) shows that fixed pricing (or posted-price selling) is optimal for a monopolist when negotiations are too expensive, seller bargaining power is low, or buyer product valuations are homogeneous. Similarly, Arnold and Lippman (1998) demonstrate that fixed posted prices are preferable for monopolists when average buyer bargaining abilities are sufficiently high. Desai and Purohit (2004) find that when the share of "non-hagglers" (buyers who dislike negotiations) is sufficiently high, negotiable pricing is optimal from a seller's perspective. For a monopoly setting, Kräkel and Schöttner (2022) study the interaction of pricing delegation and fixed prices and argue that firms should choose fixed prices to avoid unnecessary price discounts when intermediaries are not better informed about buyers' willingness to pay. Bester (1994) shows that under perfect competition, firms should adopt fixed pricing when buyer search costs are sufficiently high. While these studies provide valuable insights into the trade-offs between fixed and negotiable pricing schemes, they focus on theoretical, predominantly monopolistic models and do not examine the implications of pricing model transformations empirically.

So far, empirical evidence on pricing model choices or transformations remains scarce. DellaVigna and Gentzkow (2019) examine nearly uniform pricing of large U.S. retail chains. They find that, despite large variation in competition and buyer demographics, these chains tend to set nearly uniform prices across their stores, which suppresses price adjustments and

hurts firm profits. Although not focused on pricing model shifts, their findings highlight that deviations from flexible, locally profit-maximizing pricing potentially undermine firm profits.

Jindal and Newberry (2018) use transactional data on refrigerator purchases to analyze the role of customers' fixed psychological bargaining costs of initiating price negotiations and their effect on firms' optimal pricing policies. They estimate a structural model under a "hybrid" pricing scheme and simulate a counterfactual scenario with fixed, non-negotiable prices. Such "hybrid" pricing logic comprises posted prices and the voluntary option for customers to initiate price negotiations. Their results suggest that hybrid pricing leads to both higher sales volumes and profits for firms and that fixed pricing is only optimal when average customer bargaining costs are sufficiently high. However, compared to my research, this study mainly focuses on estimating bargaining costs. It uses data from 1,500 refrigerator purchases, which represents a substantially lower price category than new cars. Moreover, it simulates a fixed pricing scenario rather than using real-world pricing model transformations or actual counterfactual data.

Zhang et al. (2021) study the benefits and costs of price negotiations for sellers, buyers, and an online platform in the context of a large Chinese e-commerce marketplace. Using a structural model, transaction data, and a matched customer survey, they quantify different costs related to haggling and simulate the implications of banning price negotiations on the platform. They show that removing price negotiations can be beneficial for platforms, as it increases platform efficiency, simplifies transaction processes, and improves conversion rates. They also observe that the number and total value of transactions increase after banning price negotiations. However, their analysis is again based on simulation data and lower-priced product categories.

Most closely related to this study, Zeng et al. (2016) empirically analyze the effect of a large car manufacturers' unilateral shift to a fixed, non-negotiable pricing strategy on sales volumes in a market where the main competitor still offers negotiable prices affects sales volumes. By employing a difference-in-differences approach, they examine Toyota's unilateral transition to fixed "no-haggle" pricing in five of the six largest provinces in Canada between 2000 and 2002. They use the untreated province as their control group and analyze monthly new car transactions for two car models of the treated OEM compared to two similar models of its main negotiating rival. For the entry-level model, they find that the unilateral transition led to increased sales volumes and constant prices for both Toyota and its main competitor. For the larger model, prices rose, and sales volumes remained constant for both OEMs. Overall, their findings suggest that asymmetric pricing policy equilibria can exist and might help firms to differentiate from competitors, soften competition, and increase profits. While their study provides valuable insights on the price and sales volume effects of fixed pricing in a real-world automotive setting,

it differs from mine in important aspects. First, while Zeng et al. (2016) study a regional pricing initiative within a single national market, this paper analyzes two full-scale sales and pricing model transformations at the national level. Second, their empirical model relies on a simple difference-in-differences design with a single untreated region as the control group and no market-specific control variables and focuses on only two car models. In contrast, I apply a synthetic control group methodology, drawing on a large set of control markets and additional market-individual covariates to construct reliable counterfactuals. My set of potential control units comprises all untreated markets worldwide in which the same OEM still operates under an indirect sales model with negotiable prices, which enhances robustness and validity. Overall, my study complements and extends the study by Zeng et al. (2016) by examining direct sales model transformations at a broader scale by using a different empirical design.

4.2.3 Gap in existing literature, research contribution, and theoretical framework

As outlined above, there is a large body of research on vertical restraints, vertical integration, dual sales channel systems with coexisting direct and indirect channels, and comparative studies on negotiable versus fixed pricing. However, no prior study has empirically analyzed the effects of a full-scale sales and pricing model transformation from an indirect wholesale model with negotiable prices to a direct sales model with fixed, uniform pricing. In the context of research on direct sales channels, most studies focus on settings where direct and indirect sales channels coexist. Theoretical studies that compare fixed and negotiable pricing strategies mostly rely on monopolistic models (Wang, 1995) or assume symmetric equilibria with all firms adopting the same pricing strategy (Bester, 1994). As a result, their applicability to my research setting remains limited. Related empirical research focuses either on rather specific, lower-priced settings such as farming (Park et al., 2018) or e-commerce platforms (Gielens & Steenkamp, 2019), examines isolated regional pricing initiatives (Zeng et al., 2016), or uses simulation-based estimations of structural demand models instead of real-world data to compare negotiable and fixed pricing in lower-priced sectors (Jindal & Newberry, 2018; Zhang et al., 2021).

With this study, I address this gap by analyzing the effects of two large automotive OEMs' direct sales transformations of in two different regional markets on monthly sales volumes using a synthetic control group methodology and market-level panel data. I thus investigate the effect of a simultaneous change in the sales model (from an indirect wholesale model with dealers to a direct-to-consumer sales model) and the pricing model (from negotiable to fixed pricing).

While the managerial relevance of this research becomes evident in *Section 4.1*, predictions regarding its sales volume effects remain ambiguous based on prior research. Existing empirical

and theoretical studies suggest that conflicting mechanisms might be at play, which could either positively or negatively affect sales volumes following a direct sales model transformation.

To understand how the transition from a wholesale model to a direct sales model might affect manufacturers' sales volumes, it is crucial to examine how this structural change might affect demand-side mechanisms. As the transformation is mainly a shift in the sales, distribution, and pricing structures (e.g., Buzzavo, 2023), I assume that there are no meaningful changes in supply-side production constraints and physical product offerings (e.g., technical specifications or model configurations). To structure the analysis of demand-side effects, I build on prior literature and focus on three specific mechanisms through which a direct sales model transformation could potentially affect customer behavior (e.g., Buzzavo, 2023): (1) pricing-related, (2) service-related, and (3) purchase process-related mechanisms. These mechanisms address the most salient changes that might affect demand and thereby overall sales volumes. While all three might ultimately affect and reshape the customer experience, they represent distinct areas of structural change resulting from the transformation.

Pricing-related mechanisms. One of the most immediate and visible changes resulting from the direct sales transformation is the shift from customer-individually negotiated to fixed prices, which entails important implications. First, the move to fixed pricing is expected to result in higher average transaction prices. This is particularly true in markets where heavy discounting and price competition between retailers of the same brand are common, such as new car retailing (Beard et al., 2021). Under traditional dealer-based models, retailers often try to undercut each other through price negotiations and tactical discounts, which creates downward pressure on prices (e.g., Beard et al., 2021; Brenkers & Verboven, 2006). In fact, steep discounts of up to 15–20% are common in most new car markets globally (Gissler et al., 2021). The elimination of price negotiations and the expected reduction in same-brand price competition are thus expected to increase average prices (e.g., Winter, 1993; Beard et al., 2021). From a microeconomic perspective, higher average prices should, *ceteris paribus*, lead to reduced demand quantities (Varian, 2016). Second, fixed pricing restricts the flexibility for price discrimination based on individual customer attributes or willingness to pay at the point of sale (Desai & Purohit, 2004). Sacrificing this flexibility may limit the ability of firms to capture surplus from buyers with high willingness to pay (e.g., Herweg & Müller, 2016; Zeng et al., 2016) and to retain customers who are only willing to purchase at lower or discounted prices (Jindal & Newberry, 2018). This limitation may also lead to lower demand quantities. Third, fixed pricing leads to greater price transparency and consistency across customers and channels (Abhishek et al., 2016), which is generally perceived as fairer by customers (DellaVigna & Gentzkow, 2019). Furthermore, Gonzales et al. (2020) empirically show that customers have a

stronger sense of price fairness when they buy directly from the manufacturer, even if the manufacturer charges higher prices, as they value the manufacturer's activities more than those of retailers. These improved perceptions of fairness could have a positive impact on demand volumes (Kahneman et al., 1986). Overall, the transition to fixed pricing is expected to lead to higher price levels and less price discrimination, both of which can reduce demand. At the same time, it can improve price transparency and perceived fairness, which can have a positive effect on conversion rates and customer demand. The net impact on sales volumes is thus ambiguous based on the theories discussed and depends on the relative strength of these opposing forces.

Service-related mechanisms. While I assume the physical product offering to remain unaffected by direct sales transformations, the transition could have an impact on the intensity and focus of service-related activities at the point of sale. Under an indirect wholesale model, dealers often use price negotiations and tactical discounts to attract customers. Since under fixed pricing, these price-based differentiation tools are banned for dealers, theory suggests that dealers may shift their focus and activities to non-price differentiation, such as improved customer service (Stigler, 1968; Yan & Pei, 2009) or increased advertising efforts (Desiraju, 2004). *Ceteris paribus*, these potential improvements in service quality and marketing should, increase purchase likelihoods and thus positively affect demand (Dumrong Siri et al., 2008).

Purchase process-related mechanisms. Shifting to a direct sales model likely also affects the purchase process, most notably by eliminating individual price negotiations (Schmidt et al., 2020). Empirical research suggests that many customers find price negotiations emotionally stressful, tedious, and time-consuming (Zhang et al., 2021). By removing this friction from the customer journey, fixed pricing could increase conversion rates, particularly among negotiation-averse buyers. This would then increase demand. OEMs often frame transformations to direct sales as broader efforts to improve the customer experience, for instance, through direct access to customer data (Buzzavo, 2023). However, it remains unclear if, to what extent, and when such targets are realized. Buzzavo (2023) emphasizes that car manufacturers generally lack the operational expertise to directly manage the retail process and that so far, customer satisfaction and advocacy scores tend to be lower when manufacturers are responsible for retail operations. However, the findings of Gielens and Steenkamp (2019) indicate that a direct sales model might help brands to increase control over customer interactions, enhance brand equity, and raise market share. Overall, while eliminating price negotiations likely removes a crucial friction from the buying process, the true impact of direct sales transformations on the overall customer experience remains ambiguous and strongly depends on the implementation efforts and quality.

Previous empirical studies. Beyond that, previous empirical studies on sales volume effects of direct sales or fixed pricing transformations remain limited and inconclusive. Park et al. (2018), on the one hand, find a significant decline in farm sales after the adoption of a direct sales model. On the other hand, Zeng et al. (2016) observe constant to growing sales volumes after moving from negotiable to fixed pricing. Last, Zhang et al. (2021) show that banning price negotiations improves online platform efficiency and raises transaction numbers and volumes.

Overall, theoretical reasoning and prior empirical studies provide conflicting conclusions about the potential sales volume impact of direct sales and fixed pricing transformations. Negative sales volume effects are possible due to potentially increasing prices, less flexibility for price discrimination, and unfamiliar new operational responsibilities for OEMs. On the other hand, enhanced customer service quality and the removal of frictions due to unpleasant price negotiations may positively impact sales volumes. This ambiguity, combined with a lack of conclusive market-level evidence, indicates that there is a need for an empirical investigation based on real-world direct sales model transformations and a rigorous event study methodology.

4.3 Data and Methodology

4.3.1 Overview and justification of methodology

An important challenge in empirical research lies in estimating the causal effects of policy interventions or structural changes when randomized experiments are not feasible. For almost a century, applied researchers have been employing event studies and comparative case studies to address this issue (Miller, 2023). They often leverage natural experiments, which refer to situations in which external factors or policy changes create conditions resembling controlled experiments but without intentional randomization (Rosenzweig & Wolpin, 2000). Most of these approaches are based on the idea that if only a part of the population is exposed to a treatment, an untreated control group is used as an assumed counterfactual to identify temporary variation in outcome variables that are unrelated to the treatment exposure and thus to isolate residual effects that might be attributable to the treatment (Abadie, 2005). One of the most used approaches in this context is difference-in-differences (DID) estimation. This method, however, requires strong identifying assumptions and particularly the parallel trends assumption, which supposes that the outcomes of both the treatment and control groups would have continued to follow the same trajectory over time in the absence of the treatment (Lechner, 2011). The parallel trends assumption is often violated in settings with only one or a small number of treated units, as in my research setup (Arkhangelsky et al., 2021).

Methodological advances have led to the development of more robust methods, such as the synthetic control method (SCM), proposed by A. Abadie in several articles (e.g., Abadie & Gardeazabal, 2003; Abadie et al., 2010). SCM represents a substantial refinement of traditional comparative case study approaches by constructing a weighted combination of untreated units that most closely resembles the pre-intervention characteristics of the treated unit through data-driven minimization of pre-treatment discrepancies. Specifically, optimal weights are derived to minimize the outcome variable's mean square prediction error (MSPE) over a specified pre-treatment period. This weighted control group is used to construct a synthetic counterfactual, against which outcome variables are compared (Abadie et al., 2011). The method was introduced in the context of estimating the economic impact of terrorist activity in the Basque country (Abadie & Gardeazabal, 2003) and has been applied to a variety of policy evaluations, including the economic consequences of the German reunification (Abadie et al., 2015) or the effect of large-scale rapid SARS-CoV-2 testing on Covid-19 case rates (Diederichs et al., 2022).

A primary benefit of SCM is its ability to address some of the main limitations of DID estimation. While the parallel trends assumption of the DID estimator is often violated in settings with a small number of treated units and/or where the treated units structurally differ from the control group, SCM mitigates this issue by explicitly optimizing the pre-treatment fit between the treated unit and a weighted combination of untreated units (the synthetic control group). This approach reduces the risk of biased estimates resulting from non-parallel trends (Abadie, 2021). SCM is thus particularly useful for settings with one treated unit (Arkhangelsky et al., 2021). Further benefits include transparency with respect to control group composition and pre-treatment similarities between the treated unit and the synthetic control group, as well as the reduction of model-dependent extrapolation biases (Abadie et al., 2010). Despite its benefits, SCM is not without limitations. A key requirement for its validity is selecting the right comparison units (the donor pool) and ensuring that the synthetic control resembles the treated unit prior to the intervention. Without a suitable weighted combination of control units, SCM may fail to provide credible counterfactuals, which leads to poor estimates (Abadie et al., 2010).

Overall, given my research focus on evaluating the sales volume effect of direct-to-consumer sales model introductions in the automotive industry, SCM constitutes a highly suitable method for estimating causal effects in a setting where randomized experiments are not feasible. By constructing a synthetic counterfactual for a regional market in which a manufacturer has implemented the new sales model based on a weighted combination of comparable markets for which the same OEM has not yet done so, I can more accurately isolate the treatment effect from confounding factors. In the following, I detail my methodological SCM framework.

4.3.2 Empirical model

In this study, I empirically examine the impact of two direct-to-consumer sales model implementations by two different automotive manufacturers on their monthly new car sales volumes in the respective markets. Specifically, I consider BMW's introduction in their South African market in January 2020 (Schmidt et al., 2020; Venter, 2021) and Mercedes' launch in Austria in August 2021 (Achter, 2021; Schmidt et al., 2020). For BMW, South Africa marks the first regional market for which they have implemented this new sales model for their entire model range, and for Mercedes, the third, following earlier launches in South Africa in 2017 and Sweden in 2019 (Schmidt et al., 2020).² The dependent outcome variable of this study is the monthly new car sales volume in the respective geographic market. The monthly granularity allows us to capture short-term fluctuations and seasonality effects in sales volumes. As in Zeng et al. (2016), I use other non-treated regional markets of the same manufacturer as control units. Particularly, the donor pools (i.e., the sets of potential control units) for the two events to be studied comprise all other regional markets (in this case, countries) of the same OEM for which monthly sales volume data is available and which have not yet transitioned to a direct sales model at the time of the analyzed event or shortly after. By restricting the donor pool to the same manufacturer, I ensure that all potential control units operate under comparable brand positioning, firm strategies, and product portfolios. This might mitigate confounding factors related to OEM-specific distribution, marketing, and pricing policies. The event date of the treatment corresponds to the month in which the direct sales model is officially introduced. To construct a robust synthetic control group through the weighting algorithm of SCM, I define a pre-treatment period of 12 months prior to the introduction. The choice of this 12-month period appears sufficient to me, as seasonal fluctuations should be captured as such. In the case of the BMW launch in South Africa, however, it is also due to data availability constraints, as monthly sales data are only available as of January 2019. To maintain methodological consistency, I apply the same pre-treatment period definition to Mercedes' introduction in Austria in August 2021. Further, following Zhang et al. (2024), I incorporate a transition period around the event date, symmetrically spanning from two months prior to two months post-treatment, to account for potential anticipatory effects, gradual launch processes, and initial market reaction, which could bias the treatment effect estimation. Consequently, I only use 10 of the 12 pre-treatment

² Since monthly sales volume data has only been available to me as of January 2019 and a sufficiently long pre-treatment period is required to develop the synthetic control group, I cannot analyze the first two launches of Mercedes in more detail. To avoid potential bias, I exclude these two markets as well as two others in which Mercedes introduced a direct sales model shortly after Austria from the donor pool of potential control units (United Kingdom in January 2023, Neves, 2023; Germany in June 2023, Hubik, 2023). Sales volumes of BMW include its sub-brand Mini, and for Mercedes, its sub-brand Smart.

months for determining optimal weights for the synthetic control group units. For the post-treatment period, I particularly consider the interval until two years after the transition period.

I use a set of predictor variables to develop the synthetic control groups by ensuring that the weighted combinations of control units closely mimic the treated units during the pre-treatment period (Abadie et al., 2011). These variables comprise the monthly sales volumes themselves, demographic market characteristics of the countries, general features of the new car markets, and OEM-specific market attributes, which I describe in the following section.

Lastly, following Abadie et al. (2010), I apply comprehensive placebo-in-space tests by estimating pseudo-treatment effects for all donor pool units to rule out that potential changes in outcome variables are due to chance. Here, I treat each control unit of the donor pool as if it had been subject to the treatment on the event data instead of the actual treated unit.

4.3.3 Variable selection, data collection, and data description

After filtering out other markets with direct sales model launches before our event dates or during the post-treatment periods, my donor pool for BMW South Africa consists of 71 regional markets (i.e., countries) with monthly sales data and for Mercedes Austria of 69 markets. I use monthly light vehicle sales volume data from S&P Global Mobility (2024a), which comprises both business-to-consumer (B2C) and business-to-business (B2B; e.g., corporate fleet vehicles) sales and excludes heavier commercial vehicles, such as trucks.

I select my demographic predictor variables based on similar prior event studies using SCM. All data points are collected at the regional market (i.e., country) level. Particularly, I include annual data on the number of inhabitants (Abadie et al., 2010), old- and young-age dependency ratios, the share of females in the population, population density (all from Diederichs et al., 2022), and unemployment rates (Abadie et al., 2010). Additionally, I use quarterly data on real GDP per capita and inflation rates.³ Further, based on Das et al. (2022), I expect that local Covid-19 protection measures could affect customer behavior and demand and thus include daily data from an index measuring a country's stringency of Covid-19 policies, including nine response indicators such as school and workplace closures or travel bans (Roser, 2021).⁴

³ The old-age dependency ratio is calculated as the ratio of persons aged 65 years or older per 100 of the population aged 15-64 years, and the young-age dependency ratio as the ratio of persons aged 14 years or younger per 100 of the population aged 15-64 years (Diederichs et al., 2022). Population density is measured as inhabitants per km². Real GDP per capita is based on purchasing power parity (expressed in 2015 USD).

⁴ Data on inhabitants, young- and old-age dependency ratios, female population share, and population density is extracted from the World Bank Group (2023a, 2023b, 2023c, 2023d). GDP per capita and inflation rate data are obtained from Oxford Economics (2023a, 2023b), and unemployment rate from Macrotrends (2023). Covid-19 stringency index data is downloaded from Our World in Data (2023) and based on Hale et al. (2021).

Lastly, I include several additional market- and OEM-specific variables from S&P Global Mobility (2024a). These comprise monthly data on average, volume-weighted manufacturer's suggested retail prices (MSRP) for the overall new car market (i.e., all OEMs) and specifically for the OEM of interest. I further include the OEM's (volume-based) monthly market share for each market as well as product portfolio splits by car type and the share of electric vehicles.⁵

I provide detailed summary statistics for both considered manufacturers and their donor pools with respect to all predictor variables during the 10-month pre-treatment period in *Tables C.1* and *C.2* in the *Appendix*. It can be seen that South Africa represents a somewhat larger market for BMW than most of the donor pool markets. With an average of 1,304 sales per month, South Africa is above the median value of the donor pool (337) and the 19th largest out of the 72 markets. South Africa's population of 58.1 million inhabitants is also larger than the donor pool's median (11.5 million). On the other hand, South Africa is a market with a lower price level in the new car market, both in terms of the overall market (average MSRP of USD 22,485 compared to the donor pool's median of USD 31,734) and the vehicles sold by BMW itself (USD 42,512 versus USD 58,301). BMW's sales volume-based market share in South Africa (3%) is similar to the donor pool's median value (2%). Moreover, the market is characterized by high unemployment rates and a low real GDP per capita.

With respect to Mercedes, Austria represents its 14th largest out of 70 markets, with an average of 1,612 monthly new car sales during the pre-treatment period (compared to the median value of the donor pool of 249). With 8.9 million, the number of inhabitants, on the other hand, is below the donor pool's median of 12.0 million. Compared to the donor pool markets, Mercedes has a relatively higher sales volume-based market share in Austria (6%) and a higher sales share of electric vehicles (6%). The price level of the overall Austrian new car market (average MSRP of USD 41,166) is somewhat higher than that of the donor pool markets (donor pool median of USD 33,840), but the Mercedes-specific price level in Austria (average MSRP of USD 61,166) is almost in line with the donor pool markets' median (USD 66,916).

⁵ All data from S&P Global Mobility (2024a) is again based on new car sales data for the respective regional market. Car type categorization is based on car size, with "A" being the smallest and "F" the largest car type.

4.4 Analysis and Results

4.4.1 Initial monthly sales volume analyses

Before discussing the results of the synthetic control method, I first analyze raw normalized monthly sales volumes for the two treated units and their respective donor pool units to provide an initial assessment of the sales volume trend before and after the direct sales model launch.

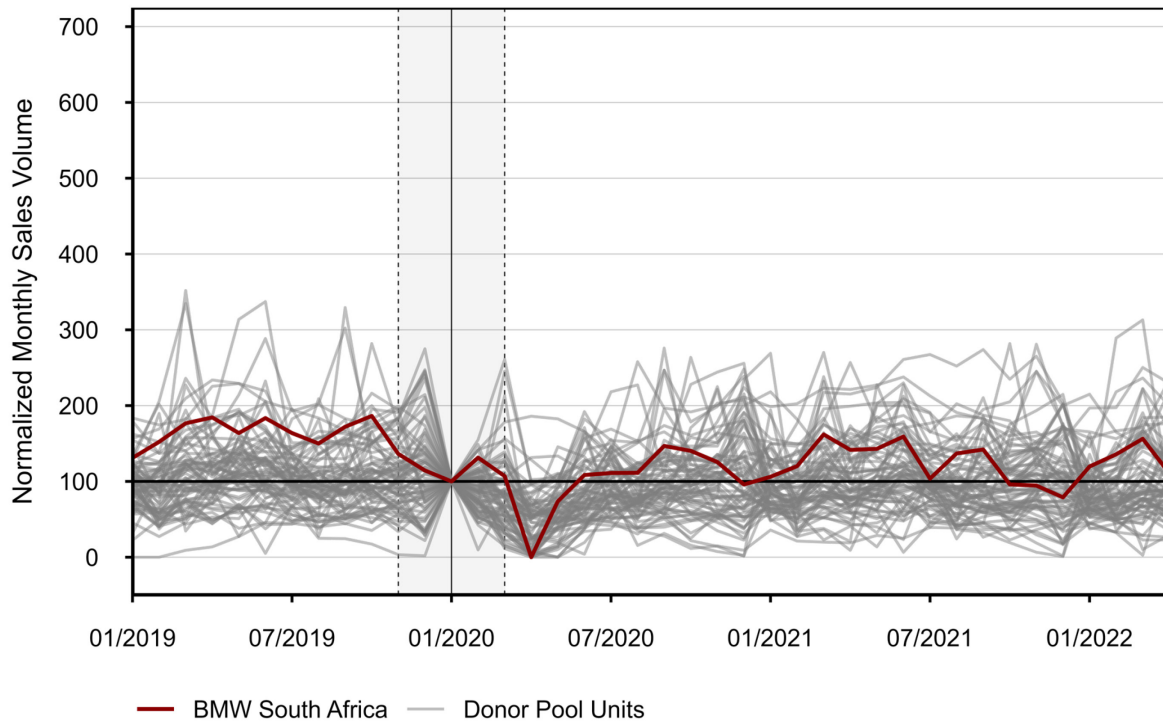


Figure 4.1: Normalized monthly sales volume of BMW South Africa versus control group units (event date: 01/2020; four-month transition period around the event date indicated in gray)

Figure 4.1 exhibits the normalized monthly sales volumes for BMW South Africa (in red) and the donor pool's other regional markets of BMW (in gray). The normalization sets monthly sales volumes in the event month (January 2020) to 100 for each unit, which allows me to compare market-level sales trends over time. During the pre-treatment period (01/2019 until 10/2019), normalized monthly sales in South Africa are relatively stable, fluctuating between 130 and 186 with an average of 166. This indicates a considerably high baseline level prior to the direct sales model launch. The donor pool markets display a broad distribution of trends, and some units exhibit strong volatility. The fact that normalized sales volumes already decline to 136 and 114 in the two months prior to the launch could indicate potential anticipatory effects and supports the use of the two-month pre-treatment transition phase for determining the control units' weights. In later robustness checks, I remove the transition period. After the four-month transition period around the event date, BMW's monthly sales temporarily decline to zero in South Africa and other markets in April 2020. This is likely due to Covid-19-related effects,

which led to temporary market shutdowns in many markets, such as South Africa, which recovered in the following month (CAR magazine, 2020; MarkLines, 2021). During the post-treatment period (04/2020 until 03/2022), normalized monthly sales volumes in South Africa mainly remain above 100, with an average of 117 (or 122 excluding April 2020). However, these sales volumes do not reach pre-treatment levels, initially indicating a potentially sustained decline in monthly sales volumes after the introduction of the direct-to-consumer sales model.

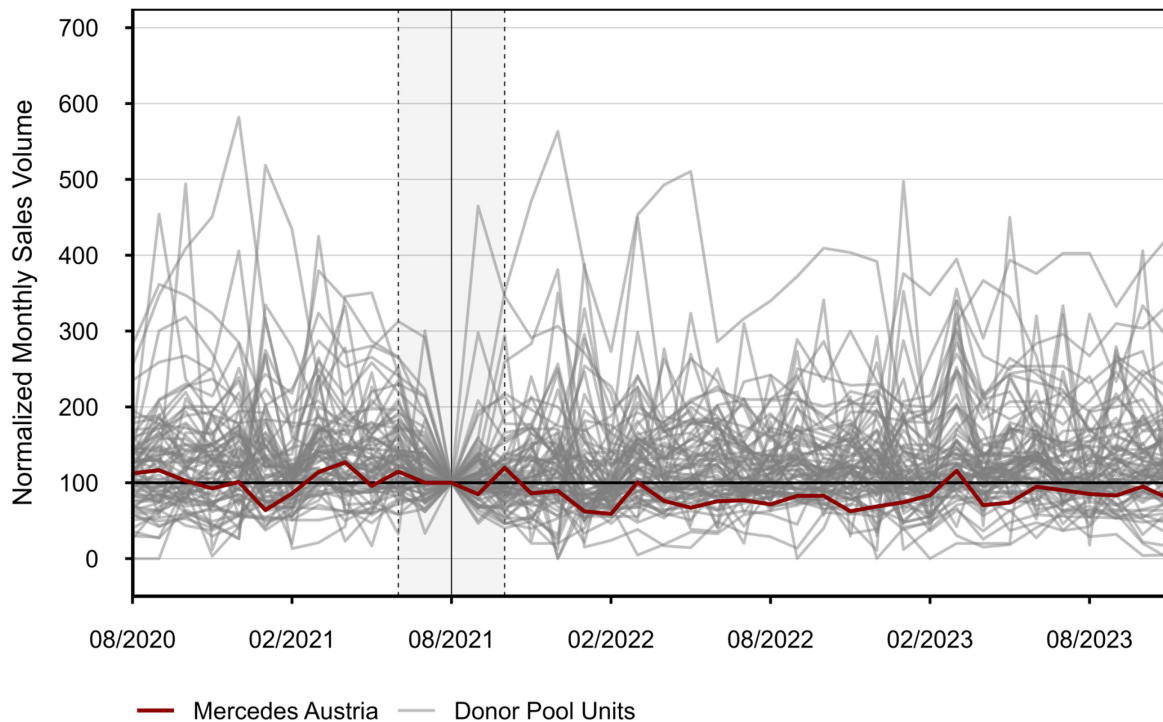


Figure 4.2: Normalized monthly sales volume of Mercedes Austria versus control group units (event date: 08/2021; four-month transition period around the event date indicated in gray)

Figure 4.2 depicts the normalized monthly sales volumes for Mercedes Austria (in red) and its donor pool's markets (in gray). During the pre-treatment period (08/2020 until 05/2021), Mercedes' monthly sales volumes remain relatively stable, fluctuating around an average normalized volume of 101 with only one sharper decline to 64 in January of 2021. Compared to the assessment for BMW, the donor pool markets exhibit an even wider distribution of trends with some even more pronounced fluctuations. Normalized monthly sales volumes remain rather constant during the four-month transition period. During the post-treatment period (11/2021 until 10/2023), Mercedes Austria's monthly sales volumes appear to stabilize below a normalized level of 100, with relatively low volatility, an average value of 80, and only one month (03/2023) above the pre-treatment average. This could indicate a sustained moderate decline in monthly sales volumes compared to the pre-treatment period. The donor pool markets continue to exhibit strong variation during the post-treatment phase.

However, overall, these initial observations emphasize the necessity of a more sophisticated methodology to further aim to disentangle the effects of the direct sales transformation from potential other external effects. In the following sections, I construct a synthetic counterfactual to examine the impact of the two direct sales model launches more closely.

4.4.2 Construction and composition of synthetic control groups

Following Abadie et al. (2011), I use the R package *Synth* (version 1.1-8; Hainmueller & Diamond, 2023) to construct the convex combination weights for the synthetic control units for the two manufacturers' direct sales model launches of interest. In my main models, I include both the full donor pool of potential control markets as well as the full set of predictor variables. I later conduct comprehensive sensitivity analyses by testing alternative compositions of the donor pool and varying predictor variable sets to validate the robustness of the results.

Following Diederichs et al. (2022), I include the individual monthly pre-treatment sales volumes as time-varying predictor variables to ensure that the treated unit and the synthetic control unit follow a similar trend during the pre-treatment period. This is supposed to enhance the validity of the counterfactual comparison. The remaining predictors, such as demographic and manufacturer-specific variables, are integrated as time-constant predictors, calculated as their average values over the pre-treatment period. For BMW's direct sales model launch in South Africa in January 2020, I exclude the Covid-19 stringency index as a predictor variable since the Covid-19 pandemic and associated policy measures started in the first quarter of 2020, and my pre-treatment period used for determining the control unit weights ends in October 2019. For Mercedes' launch in Austria in August 2021, I include the Covid-19 stringency index as a monthly time-varying predictor, as it was likely an important factor dynamically impacting market conditions (Das et al., 2022).

I provide the individual weights of the control markets of the two donor pools, as optimized by the SCM algorithm, in *Tables C.3* and *C.4* in the *Appendix*. The weights are distributed across a limited number of units. For BMW South Africa, the synthetic control primarily draws from Morocco (relative weight of 25.7%), Switzerland (22.9%), Turkey (17.9%), Brazil (16.2%), and Mexico (7.5%). The synthetic twin of Mercedes Austria is mainly composed of Hungary (50.8%), Switzerland (28.6%), and Canada (20.4%). Given the geographic proximity of Hungary and Switzerland to Austria, we cannot entirely rule out potential spillover effects, such as cross-border shopping (Asplund et al., 2007; Baicker, 2005). To assess the robustness of our findings, we examine alternative donor pool compositions in *Section 4.5*.

Table 4.1 presents balancing properties for BMW South Africa and Mercedes Austria, their respective synthetic twins, and their full donor pool mean values regarding all predictor

variables. It appears evident that the simple donor pool means (columns 3 and 6) do not serve as adequate control groups for my two OEM markets, as they fail to replicate crucial attributes of the treated units. The two synthetic control groups, on the other hand, are much more similar to the markets considered. Specifically, the monthly sales volumes prior to the treatment show a strong similarity for both OEM events. This suggests that the synthetic twins effectively replicate the sales dynamics of the treated markets before the direct sales model introduction.

While the synthetic control units successfully resemble key characteristics of the treated units, some deviations persist. For BMW South Africa, the market appears to be characterized by a smaller population size and density, a lower GDP per capita, a higher unemployment rate, and a lower price level (in terms of average MSRPs) than its synthetic counterpart. Regarding Mercedes Austria, the synthetic replica also seems to have a greater population size and a higher Mercedes-specific price level. However, despite these discrepancies, the synthetic control units remain considerably more suitable counterfactuals than the simple donor pool means. More importantly, the synthetic twins closely resemble monthly sales trends of the treated units in the pre-treatment period, providing a valid counterfactual trajectory. I therefore do not expect the discrepancies described to strongly impact the validity of my inferences. Furthermore, I conduct additional sensitivity analyses, testing alternative predictor variable specifications to ensure that my findings are not driven by specific model choices.

Variable	BMW ZAF	Synthetic	Mean	MB AUT	Synthetic	Mean
Monthly new car sales T-12	1,027	1,042	2,720	1,790	1,574	2,125
Monthly new car sales T-11	1,193	1,168	1,952	1,857	1,761	2,478
Monthly new car sales T-10	1,385	1,411	3,455	1,633	1,723	2,259
Monthly new car sales T-9	1,446	1,413	2,776	1,474	1,628	2,338
Monthly new car sales T-8	1,284	1,328	2,948	1,610	1,667	2,485
Monthly new car sales T-7	1,439	1,411	3,210	1,019	1,241	2,485
Monthly new car sales T-6	1,284	1,283	2,606	1,368	1,343	1,803
Monthly new car sales T-5	1,176	1,162	2,423	1,819	1,878	2,547
Monthly new car sales T-4	1,349	1,345	3,190	2,021	1,820	2,395
Monthly new car sales T-3	1,461	1,479	2,803	1,526	1,507	2,313
New car sales T-12 - T-3	13,044	13,042	28,083	16,117	16,142	23,229
Inhabitants (in millions)	58.1	73.7	75.5	8.9	15.1	76.5
Old-age dependency ratio	0.09	0.16	0.21	0.29	0.30	0.21
Young-age dependency ratio	0.44	0.32	0.29	0.22	0.23	0.30
Female share in population	0.51	0.49	0.49	0.51	0.51	0.49
Population density	48	116	376	108	119	378
GDP per capita (PPP, real)	11,251	26,204	30,149	41,375	37,012	28,515
Inflation rate	0.04	0.04	0.04	0.02	0.02	0.03
Unemployment rate	0.26	0.09	0.06	0.06	0.05	0.07
Covid-19 stringency index	-	-		66.2	61.3	61.5
Market share treated OEM	0.03	0.03	0.03	0.06	0.05	0.03
Share car types A & B	0.09	0.08	0.08	0.01	0.01	0.01
Share car types C & D	0.73	0.68	0.63	0.67	0.61	0.57
Share car types E & F	0.17	0.24	0.29	0.31	0.38	0.42
Electric vehicle share	0.01	0.01	0.02	0.06	0.04	0.03
Average treated OEM MSRP	42,512	50,703	60,641	61,166	77,479	69,949
Average total market MSRP	22,485	27,831	31,210	41,166	45,597	33,382

Table 4.1: Balancing properties of main models' predictor sets for BMW South Africa and Mercedes (MB) Austria (compared to donor pool mean; GDP and MSRP in USD; market-level averages over 10-month pre-treatment period except for GDP, which is the total over the period)

4.4.3 Detailed monthly sales volume analyses

I provide the monthly sales comparison between BMW South Africa and its synthetic control group in *Figure 4.3* and the resulting relative monthly sales gaps between the two groups in *Figure 4.5*. Over the 10-month pre-treatment period, monthly sales of the treated unit and its synthetic twin visibly follow a highly similar trend. The pre-treatment root mean square prediction error (RMSPE), which measures the monthly sales volume distance between the treated and the synthetic control unit (Diederichs et al., 2022), equals 24.2, which corresponds to only 17.2% of the standard deviation of the treated unit's monthly sales volumes during the pre-treatment period. Consistently, the relative monthly sales gaps between BMW South Africa and its synthetic twin remain very close to zero, averaging only 0.02% per month (*Figure 4.5*). The good pre-treatment fit suggests that the synthetic control constitutes a valid counterfactual.

After the transition to the direct sales model, BMW South Africa's monthly sales volumes decline notably relative to its synthetic control. The likely Covid-19-related collapse in monthly sales in April 2020 is once again more pronounced for the South African market than for its synthetic twin. After recovering from this initial shock, monthly sales volumes in South Africa remain consistently and substantially below those of its synthetic control. On a monthly average, over the 24-month post-treatment period, the treated unit's sales are 28.4% lower compared to the synthetic twin (25.3% lower excluding April 2020). This effect is even more pronounced in the first 12 months after the transition. Here, the relative sales gap averages -33.4% per month (-27.3% excluding April 2020). Beyond that, there seem to be two distinct end-of-year declines in BMW South Africa's monthly sales volumes (end of 2020 and of 2021). These dips could indicate a seasonal pattern in South Africa that differs from that of the top-weighted control units. As South Africa is located in the southern hemisphere, while most of the top-weighted controls (except for Brazil) belong to the northern hemisphere, it is plausible that different seasonal effects contribute to the observed deviations. I later examine this in more detail through an alternative donor pool consisting only of southern hemisphere markets.

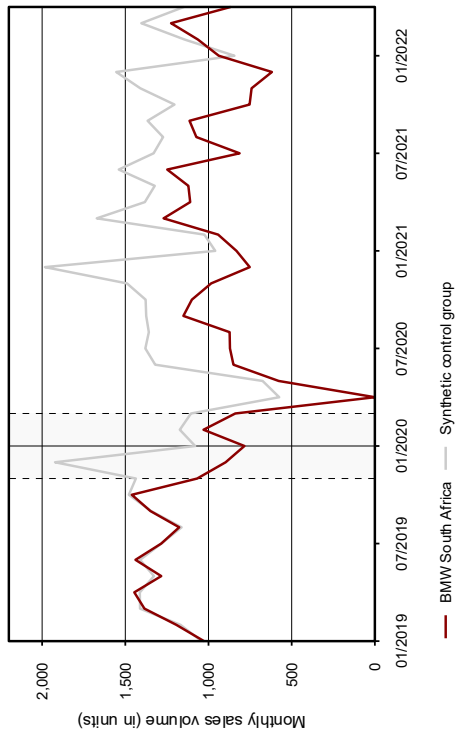


Figure 4.3: Monthly absolute sales volume comparison between BMW South Africa and its synthetic control group

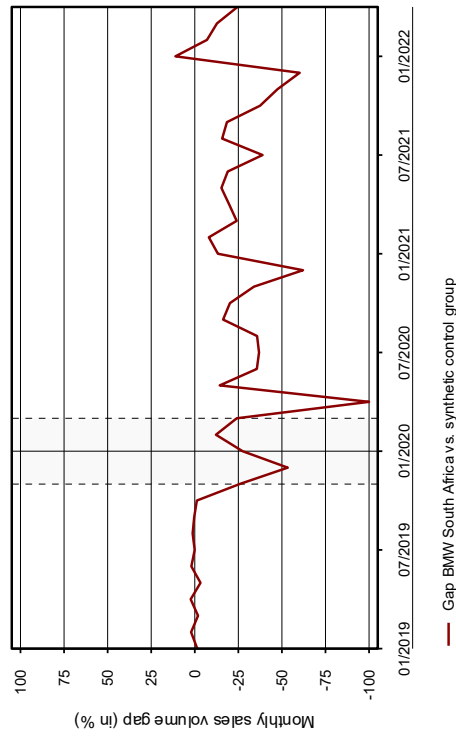


Figure 4.5: Monthly relative sales volume gap between BMW South Africa and its synthetic control group

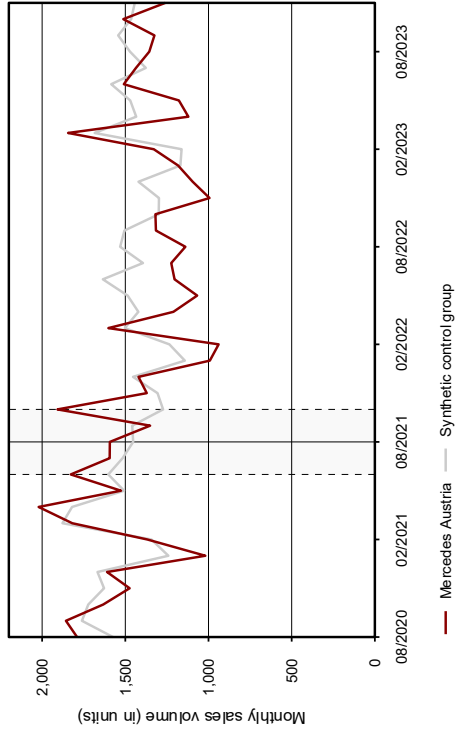


Figure 4.4: Monthly absolute sales volume comparison between Mercedes Austria and its synthetic control group

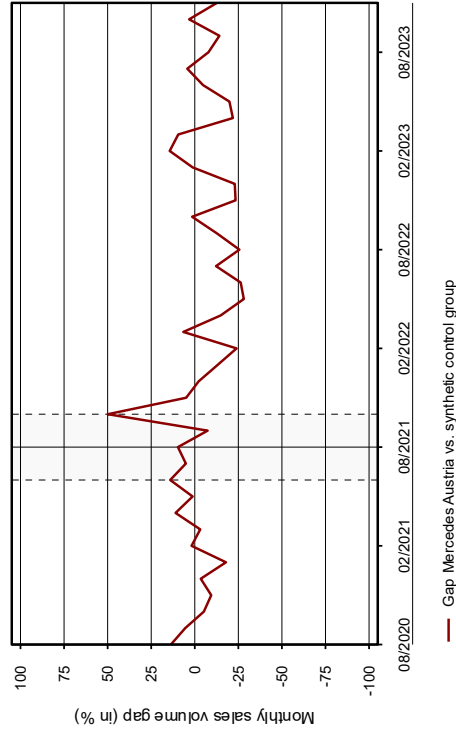


Figure 4.6: Monthly relative sales volume gap between Mercedes Austria and its synthetic control group

The persistent sales gaps suggest that the observed post-treatment decline is likely not explained by the Covid-19 pandemic. While Covid-19 affected all markets, the synthetic control group does not exhibit a decline in sales volumes compared to the pre-treatment period. Comparing the Covid-19 stringency index of South Africa and (1) its donor pool units (*Figure C.1* in the *Appendix*) as well as (2) the top-weighted control units (*Figure C.2*) further shows no substantial deviations in the stringency of Covid-19 safety measures over the post-treatment phase. Overall, this suggests that discrepancies in Covid-19 safety measures are unlikely to confound the observed sales volume gaps.

Relative to BMW South Africa, the pre-treatment fit for Mercedes Austria is slightly weaker but still acceptable for valid counterfactual analyses (*Figures 4.4* and *4.6*). During the pre-treatment period, monthly sales volumes of Mercedes Austria and its synthetic twin exhibit slightly greater deviations compared to the case of BMW, with an average relative monthly gap of -0.58% and stronger variation. The pre-treatment RMSPE of absolute sales volumes amounts to 136.0, corresponding to 47.5% of the standard deviation of the treated unit's monthly pre-treatment sales volumes. Following the transition to the direct sales model in August 2021, Mercedes' sales volumes in Austria are lower than those of its synthetic twin for most months of the post-treatment period, in particular for 16 out of the 24 months. The average relative sales volume gap is -12.2% over the first 12 months and -9.5% over the full 24-month post-treatment period. However, in contrast to BMW South Africa, the deviations appear less pronounced and more erratic, fluctuating more strongly around zero. Overall, monthly sales of Mercedes Austria and its synthetic twin do not seem to develop as parallelly as those for BMW South Africa.

Here, again, the potential impact of Covid-19 restrictions on sales volumes must be considered when interpreting these results. Unlike for BMW South Africa, I can control for differences in the stringency of Covid-19 safety measures during the pre-treatment period for Mercedes Austria. *Figures C.3* and *C.4* in the *Appendix* show that the Covid-19 stringency index for Austria and for the donor pool units (particularly the top-weighted ones) follow a similar trend before the event date, although at a slightly higher level for Austria. However, in the post-treatment phase, the differences between Austria and the most heavily weighted control units in terms of the stringency of Covid-19 safety measures become more apparent. While the overall trend of the stringency index remains similar, *Figure C.4* shows that Austria maintained stricter safety measures compared to the respective control units between March 2022 and December 2022. This raises the question of whether the observed monthly sales gaps of Mercedes Austria compared to its synthetic twin, which are on average negative, might be attributable to Covid-19 effects rather than to the sales model transformation. If stricter safety measures negatively impact new car sales volumes, the true effect of the direct sales model

launch could be less negative than suggested by *Figures 4.4* and *4.6*, or at the extreme even positive when controlling for Covid-19-related distortions.

To better understand the potential impact of Covid-19-related restrictions on the observed sales volume gaps of Mercedes Austria, I conduct additional regression analyses. First, I assess the relationship between monthly new car sales and the Covid-19 stringency index, including quarterly time interaction effects to understand the impact of pandemic-related restrictions over time (*Table 4.2*). Second, I apply subsample regressions for 2020, 2021, and 2022 to estimate the effect of the stringency index separately for each year (*Table 4.3*). For both, I estimate three model specifications with respect to the inclusion of demographic and OEM-specific controls.

Dependent variable:	<i>Log(sales + 1)</i>	<i>Log(sales + 1)</i>	<i>Log(sales + 1)</i>
	(1)	(2)	(3)
Covid-19 stringency index	0.028 * (0.017)	-0.012 (0.008)	-0.010 (0.007)
Covid-19 stringency index x Q1/2020	-0.025 (0.018)	0.006 (0.009)	0.003 (0.008)
Covid-19 stringency index x Q2/2020	-0.074 *** (0.019)	-0.016 (0.010)	-0.019 ** (0.009)
Covid-19 stringency index x Q3/2020	-0.036 * (0.019)	0.009 (0.009)	0.004 (0.008)
Covid-19 stringency index x Q4/2020	-0.003 (0.020)	0.012 (0.009)	0.010 (0.008)
Covid-19 stringency index x Q1/2021	0.012 (0.019)	0.013 (0.009)	0.011 (0.008)
Covid-19 stringency index x Q2/2021	-0.024 (0.020)	0.007 (0.009)	0.003 (0.008)
Covid-19 stringency index x Q3/2021	-0.032 * (0.019)	0.008 (0.009)	0.003 (0.008)
Covid-19 stringency index x Q4/2021	-0.017 (0.021)	0.003 (0.010)	0.004 (0.009)
Covid-19 stringency index x Q1/2022	-0.019 (0.020)	-0.002 (0.010)	-0.001 (0.009)
Covid-19 stringency index x Q2/2022	-0.015 (0.022)	-0.001 (0.010)	-0.002 (0.009)
Covid-19 stringency index x Q3/2022	-0.009 (0.024)	-0.002 (0.011)	-0.002 (0.010)
<u>Additional controls:</u>			
Demographic controls	no	yes	yes
Manufacturer-specific controls	no	no	yes
N	4,410	4,410	4,410
R ²	0.021	0.806	0.842
Note	Q = quarter * p < 0.10; ** p < 0.05; *** p < 0.01; robust standard errors in ()		

Table 4.2: Multiple linear regression results of logarithmic monthly sales volumes with respect to Covid-19 stringency index for Mercedes Austria and its donor pool units (consideration of quarterly time interaction effects)

The results suggest that the relationship between Covid-19 restrictions and new car sales varies over time. The quarterly time interaction effects indicate that the Covid-19 stringency index was statistically significantly negatively related to monthly new car sales in the second quarter of 2020. This seems consistent with the short-term economic impact of the initial lockdowns. For the simple model without additional controls (column 1 of *Table 4.2*), this also applies for the third quarters of 2020 and 2021. For the specifications with controls (columns 2 and 3), the associations are not consistently negative and mostly statistically insignificant.

Dependent variable:	<i>Log(sales + 1)</i>	<i>Log(sales + 1)</i>	<i>Log(sales + 1)</i>
	(1)	(2)	(3)
2020 Subsample:			
Covid-19 stringency index	-0.008 *** (0.003)	-0.008 *** (0.001)	-0.008 *** (0.001)
N	840	840	840
R ²	0.009	0.758	0.802
2021 Subsample:			
Covid-19 stringency index	0.011 ** (0.004)	0.000 (0.002)	0.001 (0.002)
N	840	840	840
R ²	0.008	0.818	0.853
2022 Subsample:			
Covid-19 stringency index	0.010 * (0.005)	-0.010 *** (0.002)	-0.008 *** (0.002)
N	840	840	840
R ²	0.007	0.823	0.868
Additional controls:			
Demographic controls	no	yes	yes
Manufacturer-specific controls	no	no	yes
Note	Q = quarter * p < 0.10; ** p < 0.05; *** p < 0.01; robust standard errors in ()		

Table 4.3: Subsample multiple linear regression results of logarithmic monthly sales volumes with respect to Covid-19 stringency index for Mercedes Austria and its donor pool units (consideration of subsamples for the years 2020, 2021, and 2022)

The subsample regression results (*Table 4.3*) indicate statistically significant negative relations between the stringency of Covid-19 safety measures and monthly new car sales for 2020 (all specifications) and 2022 (specifications with controls). For the specification with no controls (column 1), the associations are even statistically significantly positive for 2021 and 2022. These results might thus have implications for the interpretation of the (predominantly negative) sales volume gaps for Mercedes Austria. Austria maintained stricter Covid-19 measures than its top-weighted control units, Hungary, Switzerland, and Canada, between

March 2022 and December 2022.⁶ Since during this time, the subsample regression results indicate a negative relationship between the stringency index and monthly new car sales, it is conceivable that a part of the observed negative sales volume gap of Mercedes in Austria after the direct sales model launch might be attributable to pandemic-related distortions rather than the sales model transformation itself. To further assess this, I later conduct a robustness check in *Section 4.5* in which I restrict the donor pool to markets with similar Covid-19 restrictions during the post-treatment period.

Overall, my results suggest that the introduction of the direct sales model is likely not related to an increase in manufacturers' new car sales volumes. For the first event, the direct sales launch of BMW in South Africa in January 2020, monthly sales volumes decline substantially and persistently relative to the synthetic control over the post-treatment period. For the second event, Mercedes' introduction in Austria in August 2021, the situation remains less clear, as sales volume gaps compared to the synthetic twin are smaller, fluctuate more strongly, and could be impacted by Covid-19-related factors. Nevertheless, a positive sales volume impact remains rather unlikely. To validate the robustness of these findings, I next perform a series of robustness checks, comprising alternative donor pool and predictor set specifications, placebo-in-space tests, and leave-one-out analyses with respect to the top-weighted control units.

4.5 Robustness check and model validation

4.5.1 Alternative model specifications

To ensure that my results are not overly driven by specific modeling choices, I conduct a series of robustness checks by varying central parameters. Following prior applications of the synthetic control method (e.g., Diederichs et al., 2022), I systematically modify the composition of the donor pool and predictor set and manipulate other model parameters. Should minor deviations in the choice of model specifications result in distinctly divergent outcomes, the estimated effects might stem from modeling assumptions rather than reflecting causal effects. I provide an overview of all model specifications in *Table 4.4*. In addition to the main model (model 01), these include a simple specification that uses the full donor pool but only individual monthly sales volumes during the pre-treatment phase as predictors (model 00). One critical aspect of SCM is the choice of appropriate control units (Abadie et al., 2015). To assess whether my results depend on the specific markets included in the donor pool, I estimate alternative SCM specifications restricting the donor pool to markets from Europe (model 02), the rest of

⁶ During this time Austria's Covid-19 stringency index amounted to 36.1 on average, while it equaled 11.4 for Hungary, 9.0 for Switzerland, and 17.7 for Canada, on average.

the world (i.e., non-Europe, model 03), and the northern and southern hemispheres (models 04 and 05). Given the potential impact of Covid-19-related restrictions on sales volumes (particularly related to Mercedes Austria), I further estimate a model restricted to donor pool units with a post-treatment average Covid-19 stringency index within $\pm 20\%$ of the treated unit's average value (model 11). This ensures that the control markets face similar pandemic-related policy measures, allowing me to better isolate the impact of the direct sales model transition from Covid-19 effects. Following Diederichs et al. (2022), to further validate the robustness of my SCM estimations, I use alternative predictor specifications, altering the set of covariates used to construct the synthetic control unit. These comprise a model that excludes monthly sales volume predictors to test the sensitivity to these predictors (model 06). Further, I estimate a model without OEM-specific predictors (i.e., monthly sales volumes, OEM's average MSRP and market share, and sales shares of different car types and electric vehicles; model 07) and one with only demographic predictors (which therefore also excludes the total new car market's average MSRP; model 08). Following Diederichs et al. (2022), I also estimate a specification that alters the pre-treatment period, in my case, by removing the two-month transition period before the treatment, thus also using values from these two months for constructing the control unit (model 09). Lastly, to control for large variations in absolute monthly sales volumes and to mitigate heteroscedasticity, I also specify an SCM version using the logarithm of the monthly sales volumes as outcome variables and predictors (model 10; Curran-Everett, 2018).

Number	Donor Pool	Predictor Set	Additional specifications
ZAF/AUT 00	Full	Only monthly sales volumes	-/-
ZAF/AUT 01	Full	Full	-/-
ZAF/AUT 02	Europe	Full	-/-
ZAF/AUT 03	Rest of the world	Full	-/-
ZAF/AUT 04	Northern hemisphere	Full	-/-
ZAF/AUT 05	Southern hemisphere	Full	-/-
ZAF/AUT 06	Full	No monthly sales volumes	-/-
ZAF/AUT 07	Full	No OEM-specific predictors	-/-
ZAF/AUT 08	Full	Only demographic predictors	-/-
ZAF/AUT 09	Full	Full	No transition period
ZAF/AUT 10	Full	Full	Logarithmic monthly sales volumes
ZAF/AUT 11	Covid-19-restricted*	Full	-/-

Note: * Only donor units with average post-treatment Covid-19 stringency index of $\pm 20\%$ of the treated unit's average post-treatment value

Table 4.4: Overview of alternative model specifications for BMW South Africa (ZAF) and Mercedes Austria (AUT) for the respective main models (ZAF01/ AUT01)

I report the goodness-of-fit of the different model specifications in terms of the root mean square prediction error (RMSPE) during the pre-treatment period in *Table C.5* in the *Appendix*. For both OEM direct sales launches, the simple specification (model ZAF00) exhibits a lower RMSPE than the main model (ZAF01), which is reasonable as the RMSPE is calculated based on the monthly pre-treatment sales volume differences between treated and control units, and the simple model only considers monthly sales to derive the optimal control unit. Further, for both OEM events, the model with logarithmic monthly sales volumes (ZAF10) has the lowest RMSPE of all specifications. Regarding BMW South Africa, two model specifications exhibit an RMSPE exceeding the standard deviation of the treated unit's monthly sales volumes during the pre-treatment period (140.6): the model without OEM-specific predictors (ZAF07) and the one with only demographic predictors (ZAF08). This suggests that these models may fail to adequately mirror pre-treatment sales trends, reducing their validity as reliable counterfactuals. For Mercedes Austria, there is one such specification, namely the one with only southern hemisphere donors (AUT05; RMSPE of 336.0 compared to a standard deviation of 286.7).

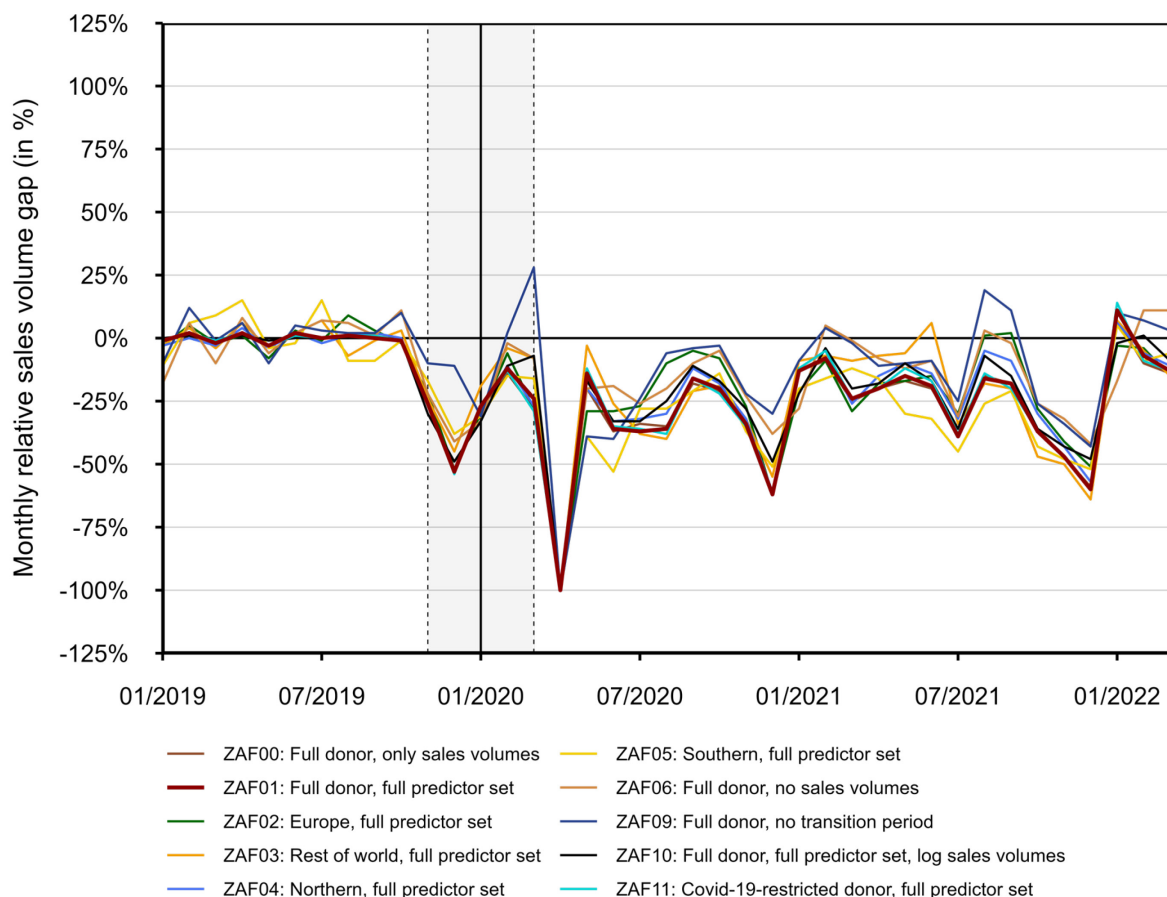


Figure 4.7: Monthly relative sales volume gap between BMW South Africa and its synthetic control for different model specifications with respect to donor pools and predictor variables

Figure 4.7 depicts the monthly relative sales volume gaps between BMW South Africa and its synthetic twin for the different model specifications, excluding those with poor pre-treatment

goodness-of-fit. Here, the alternative specifications appear to support the main model and its overall trend. BMW South Africa exhibits persistently negative monthly sales volume gaps after the direct sales model launch, with average monthly sales gaps ranging from -12.4% (ZAF09) to -28.0% (ZAF05) over the 24-month post-treatment period (excluding April 2020).

For Mercedes Austria, monthly sales volume gaps relative to its synthetic control for the different model specifications with adequate pre-treatment fit are shown in *Figure 4.8*. Again, the alternative specifications seem to confirm the main model’s overall trend. Monthly sales volume gaps moderately fluctuate but are predominantly negative, with average values ranging from -7.5% (AUT02) to -12.8% (AUT11) over the first 24 post-treatment months. Interestingly, the model including only control units with similar post-treatment Covid-19 stringency index values (AUT11) leads to the most negative average monthly sales gaps, which challenges the initial presumption that the lower sales volumes of Mercedes Austria relative to its synthetic control could be caused by different levels of pandemic-related restrictions. The development of the Covid-19 stringency index of Austria and its top-weighted controls in model AUT11 (*Figure C.5* in the *Appendix*) confirms similar post-treatment trends for the different markets.

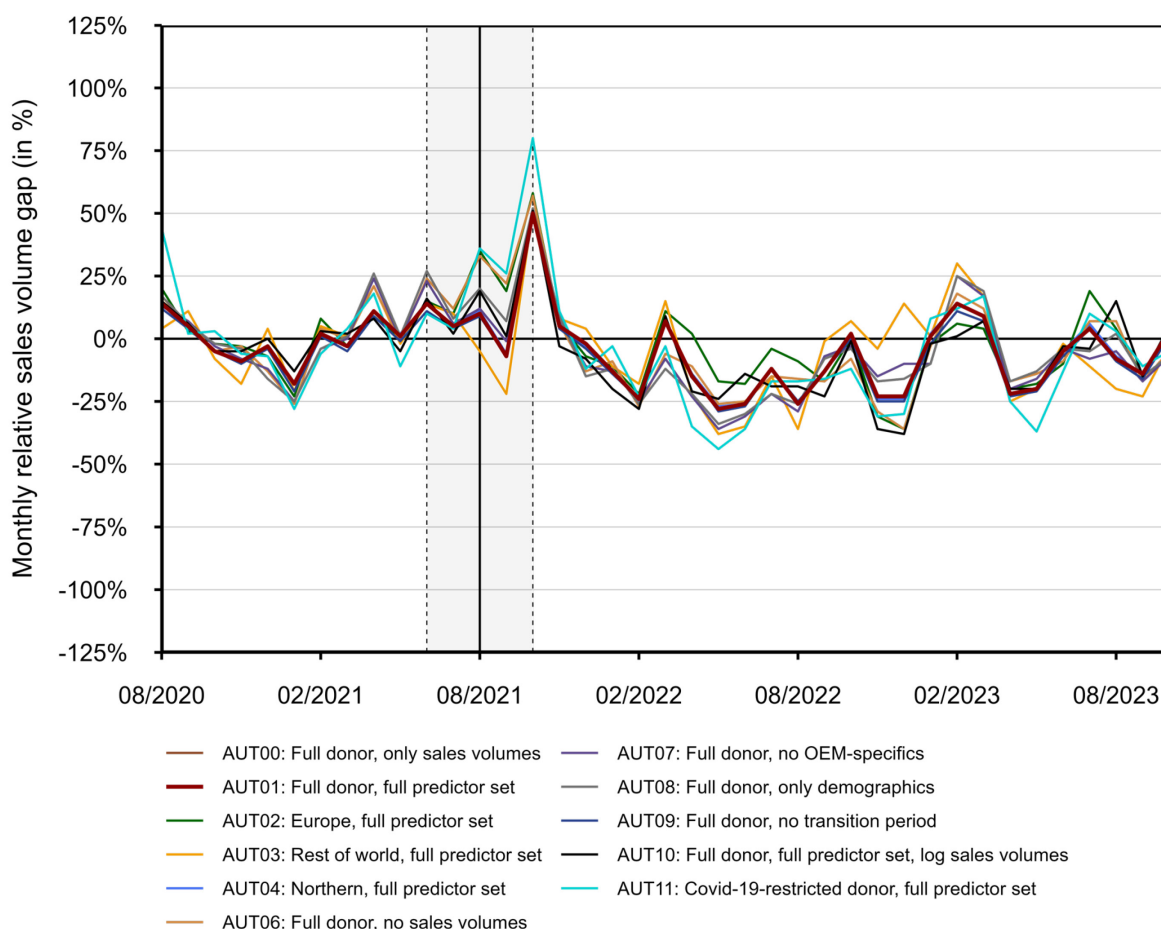


Figure 4.8: Monthly relative sales volume gap between Mercedes Austria and its synthetic control for different model specifications with respect to donor pools and predictor variables

Overall, these robustness checks show that the main SCM results remain stable across different model specifications. This suggests that the observed effects are likely not driven by specific modelling choices. The persistence of negative sales volume gaps for BMW supports the conclusion that the direct sales launch might be associated with a sustained decline in new car sales. For Mercedes, the mostly negative post-treatment sales gaps also suggest that the switch does not lead to sales gains. The results of the Covid-19-restricted donor pool challenge the notion that the observed sales gaps mainly reflect differences in pandemic-related restraints.

4.5.2 *Leave-one-out analyses*

One of the concerns in synthetic control models is that results may be affected by a small subset of control units with relatively high weights. If estimated effects change strongly when a single top-weighted control unit is excluded, findings might be driven by a specific market rather than a general pattern (Abadie et al., 2015). Following Abadie et al. (2015), to test the sensitivity of my SCM results to individual controls, I employ leave-one-out analyses in which I iteratively re-estimate my main synthetic control models while omitting one top-weighted control unit each time. For BMW South Africa, these are Morocco (weight: 25.7%), Switzerland (22.9%), Turkey (17.9%), Brazil (16.2%), and Mexico (7.5%), and for Mercedes Austria Hungary (50.8%), Switzerland (28.6%), and Canada (20.4%). I show the leave-one-out results in *Figures C.6* and *C.7* in the *Appendix*, illustrating monthly sales volume gaps across the different specifications. For both events, pre-treatment goodness-of-fit as well as monthly sales volume gap trends are relatively consistent across all specifications.⁷ These results provide additional support for the robustness of the previous findings, suggesting that the observed differences in post-treatment sales volumes are not disproportionately dependent on specific donor units but rather show a more general trend.

4.5.3 *Placebo-in-space tests*

Lastly, to assess whether the estimated treatment effects for BMW South Africa and Mercedes Austria are statistically distinct from random variation, I conduct placebo-in-space tests (following e.g., Abadie et al., 2010). In these tests, I iteratively reassign the treatment to each donor pool unit instead of to the actual treated unit and estimate synthetic control models for each pseudo-treated market. If the observed sales volume gaps for the actual treated units

⁷ For BMW South Africa, RMSPE values range between 24.2 (main model) and 37.1 (without Switzerland), and for Mercedes Austria, between 136.0 (main model) and 159.5 (without Canada). Average monthly sales gaps over the 24-month post-treatment period vary between -22.3% (without Turkey) and -28.3% (without Brazil) for BMW (excluding April 2020) and between -6.9% (without Canada) and -11.7% (without Switzerland) for Austria.

are systematically larger than those for the placebo-treated units, this would be an indication that the estimated effects are unlikely due to random variation (Abadie et al., 2015).

I provide the results for the pseudo-treatment effects in *Figures 4.9* and *4.11*. They show the distribution of the monthly relative sales volume gaps for the actual treated units (in red) and all donors (in gray). As in Diederichs et al. (2022), I restrict the placebo analyses to donor units with sufficient pre-treatment match quality to ensure suitable counterfactual data. Particularly, I exclude donors with pre-treatment RMSPEs exceeding five times the RMSPE of the actual treated unit. For BMW South Africa, out of 25 remaining donor units, only four exhibit larger average monthly sales volume gaps than South Africa. This implies that 84% (21 out of 25) of the donor units display smaller gaps, which underlines the uniqueness of the observed effects for South Africa. However, even for the four units with larger gaps, further analyses suggest questionable validity as counterfactual comparisons. First, the four donor units exhibit notably worse pre-treatment goodness-of-fit than South Africa. Their pre-treatment RMSPE values for the relative sales gaps are between 3.2x and 4.9x higher than that for South Africa, indicating that their synthetic twins fail to accurately mirror pre-treatment sales trends, rendering them unreliable counterfactuals. Second, the patterns of the sales gaps for the four donor units differ substantially from that of South Africa. One of the units exhibits positive gaps in six out of 24 post-treatment months, indicating a strongly volatile pattern rather than a systematic trend. Another unit has extremely positive sales volume gaps of up to +65%, also suggesting strong fluctuation. The only one of the four units that has exclusively negative monthly sales gaps has an RMSPE of 131% of its own pre-treatment standard deviation, making it an unreliable comparison due to its poor pre-treatment match. Third, and most crucially, South Africa has an exceptionally high ratio of post- to pre-treatment mean square prediction error (MSPE). Indeed, Abadie et al. (2015) argue that large post-treatment deviations between treated and synthetic control units are only meaningful if the pre-treatment prediction error is small, as a poorly fitting pre-treatment model can artificially inflate post-treatment errors. *Figure 4.10* shows that South Africa, compared to all 71 donor units, has the highest post-/pre-treatment MSPE ratio at 391. If the treatment were randomly assigned, the probability of obtaining a ratio as extreme as South Africa's would be $1/72 \approx 0.014$. Overall, this highlights the distinctiveness of the findings for South Africa, suggesting that South Africa is a statistical outlier in the placebo distribution and that the observed sales gaps are unlikely due to random chance (Abadie et al., 2010). Further, 80% of the donor units have a post-/pre-treatment MSPE ratio below 25. The second largest ratio equals 379. However, for this unit (Malaysia), the RMSPE for the relative sales gaps is 1.7 times higher than for South Africa and amounts to 34% of its respective pre-treatment standard deviation, indicating weaker pre-treatment fit. In addition, Malaysia exhibits positive

sales volume gaps in 15 out of 24 months (+53% on average) and negative gaps in the remaining 9 months (-40% on average), suggesting strong volatility rather than systematic differences. Together, these findings further underline the distinctiveness of the results for South Africa.

For Mercedes Austria, the placebo-in-space analyses provide less conclusive results. As shown in *Figure 4.11*, the distribution of placebo-treated donor units indicates that random variation cannot be ruled out for the post-treatment sales volume gaps observed for the Austrian market. The post-/pre-treatment MSPE ratio (*Figure 4.12*) of Austria ranks only 25th out of 70 markets, suggesting that a substantial number of placebo-treated units are related to similar or even larger pseudo-treatment effects. Overall, this means that, while the direct sales model launch might have contributed to the observed negative sales volume gaps of Mercedes in its Austrian market, random factors cannot be ruled out as a potential explanation.

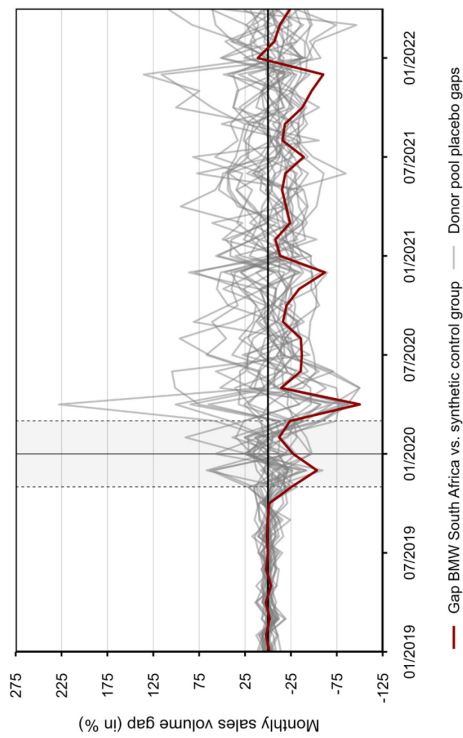


Figure 4.9: Placebo in-space analyses of pseudo-treatment effects for donor pool units of BMW South Africa

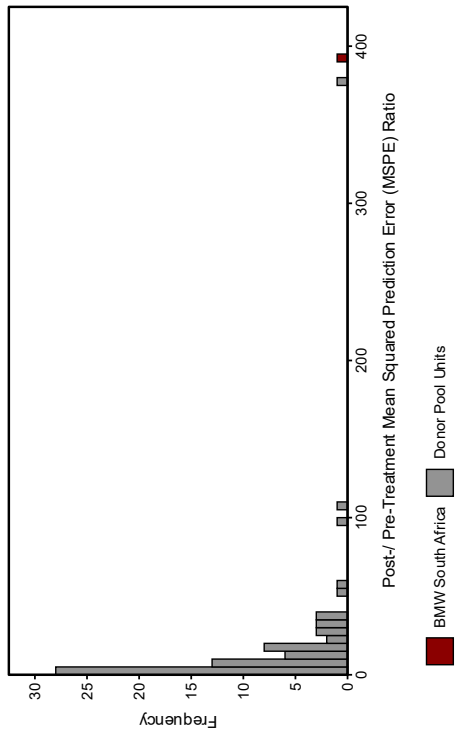


Figure 4.10: Post-/ pre-treatment MSPE ratios for placebo analyses for donor pool units of BMW South Africa

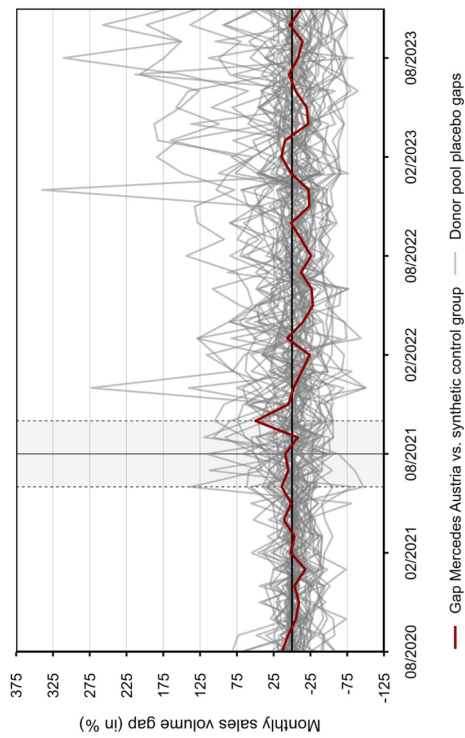


Figure 4.11: Placebo in-space analyses of pseudo-treatment effects for donor pool units of Mercedes Austria

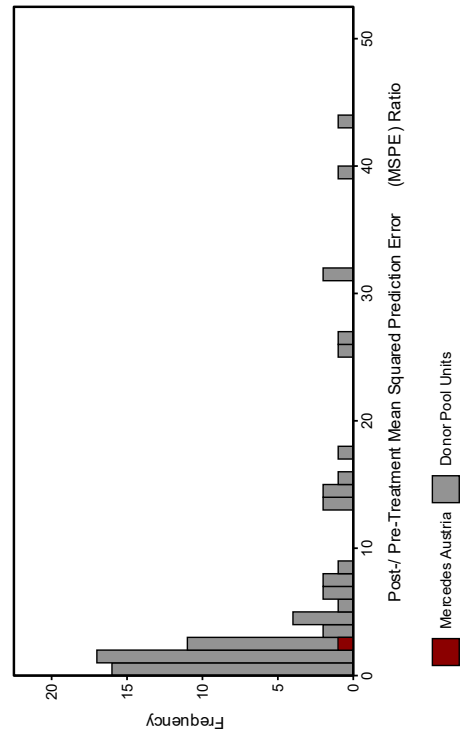


Figure 4.12: Post-/ pre-treatment MSPE ratios for placebo analyses for donor pool units of Mercedes Austria

4.6 Discussion, Conclusion, and Managerial Implications

This study empirically analyzes the monthly new car sales volume effect of two automotive OEMs' full-scale sales and pricing model transformations from indirect wholesale models with negotiable pricing to direct sales models with fixed, non-negotiable prices. I use a synthetic control methodology to develop robust counterfactuals to assess the treatment effects for the transitions of BMW South Africa in January 2020 and Mercedes Austria in August 2021 and use other untreated regional markets of the two manufacturers as control units.

Main findings. My results reveal that both transformations are followed by notable declines in monthly new car sales volumes relative to the respective synthetic control. For BMW South Africa, I observe sustained and substantial sales declines that average -27.3% per month over the first year and -25.3% per month over the first two years after the transition compared to the synthetic twin (both excluding suspected Covid-19-related extraordinary effects in April 2020). This is consistent across several robustness checks, such as alternative model specifications, leave-one-out analyses, and placebo-in-space tests, suggesting that my findings are unlikely due to poor model specification or chance. For Mercedes Austria, the estimated sales volume reduction is less pronounced and persistent than for BMW. Monthly sales volume gaps relative to the synthetic control are on average -12.2% over the first year after the transition and -9.5% over the first two years. However, while this pattern is robust to alternative specifications of the model, placebo-in-space tests show that I cannot rule out chance as a potential explanation.

Explanation through theoretical framework. Overall, my findings indicate a negative sales volume impact of the two direct sales model transformations considered in this study. With respect to my theoretical framework and the three conceptual mechanisms through which the shift to a direct sales model with fixed pricing might affect sales volumes (*price-, service-, and purchase process-related*; Section 4.2.3), this suggests that the arguments pointing to negative demand implications might dominate those indicating a positive effect on demand. While my empirical design precludes isolating individual contributions of the mechanisms and arguments, my findings indicate that potentially higher average transaction prices, reduced flexibility for price discrimination, and insufficient OEM experience in retail operations might dominate potential positive implications such as improved customer perceptions of price fairness and transparency, service and advertising quality, brand equity, and customer experience.

As for the unclear individual contributions of the mechanisms, prior empirical studies might offer further insights. Zeng et al. (2016) and Zhang et al. (2021), both focusing exclusively on pricing model transformations, find neutral to positive sales volume effects after moving from negotiable to fixed prices. Assuming that their results are transferable to my research setting

with simultaneous transformations of sales and pricing models, this would suggest that the effects directly related to banning price negotiations alone are unlikely to explain the observed sales volume declines. Instead, this might imply that other mechanisms, such as the mechanisms related to the change in the sales model, could be the dominant cause of the negative sales volume developments after moving to direct sales with fixed prices. This interpretation would be consistent with Park et al. (2018), who find a sharp decline in farm-level sales for farmers who voluntarily operate a direct sales model in a setting that does not involve a change in the pricing logic. Regarding those sales model-related mechanisms, it might thus be that potential benefits of direct sales models, such as improved service and advertising quality (Stigler, 1968; Yan & Pei, 2009; Desiraju, 2004) or enhanced brand equity (Gielens & Steenkamp, 2019) and customer experience (Buzzavo, 2023), have not materialized (sufficiently) to compensate for other challenges and downsides faced by OEMs. Particularly, the direct sales model transition requires OEMs to adopt new responsibilities in retail operations and thus an area in which they may lack experience and capabilities (Buzzavo, 2023). If OEMs are not capable of coping with this, a negative effect on the quality of supply and thus on customer demand is conceivable.

However, the results of Zeng et al. (2016) and Zhang et al. (2021) may not be fully transferable to my research setting, since both studies examine pricing model transformations in isolation. Further, I am unable to observe transaction prices and revenues prior to and after the transition to direct sales and thus cannot assess actual price changes. It is possible that the OEMs in my study have failed to implement and set the new, non-negotiable fixed prices at optimal levels. If average transaction prices are increased excessively while also limiting price discriminatory flexibility (Desai & Purohit, 2004), the resulting negative demand effects may exceed potentially positive effects due to enhanced price transparency and perceived price fairness (DellaVigna & Gentzkow, 2019; Gonzales et al., 2020) and the removal of price negotiation-related frictions in the purchase experiences (Zhang et al., 2021).

Managerial and strategic implications. The results of this study suggest that sales volume declines are a realistic and relevant risk for manufacturers following the transition to a direct sales model with fixed, non-negotiable prices. Thus, OEMs should carefully weigh this volume risk against anticipated benefits such as greater pricing control (Buzzavo, 2023), access to customer data (Wirtz, 2021), or an enhanced customer experience (Gielens & Steenkamp, 2019) as motives of the transition. To mitigate potential volume losses, manufacturers could consider several strategic responses. First, they might improve pricing strategies, lower price levels, and introduce standardized purchase incentives, such as trade-in bonuses for used cars (Demirag et al., 2010) or customer loyalty bonuses (Tschödrich et al., 2020), to stimulate demand (Schmidt et al., 2020). With the switch to fixed prices and the removal of individual price negotiations,

pricing strategies and precise price setting will likely become more critical for manufacturers. As they eliminate customer-individual discounts and restrict flexibility for price discrimination across customers at the point of sale, OEMs face higher sensitivity to pricing errors (Desai & Purohit, 2004). It may thus become ever more crucial for OEMs to understand price elasticities, willingness to pay, and heterogeneity of customers to set prices at profit-optimizing levels.

At the same time, OEMs could think beyond pricing and consider improving their product and service offerings to stimulate demand. The latter could be achieved in particular by building up retail operations capabilities (e.g., employees, processes, or customer interactions) to improve service quality and customer experience (Buzzavo, 2023; Tschödrich et al., 2020).

Moreover, a successful shift to a direct sales model requires effective transition management and communication. Poor transition management could lead to confusion, resistance, and the loss of customer relations, so it is crucial that customers and agents (i.e., employees) understand and accept the new sales model (Heuser et al., 2023). Seyerlein (2025), for instance, reports about transition challenges of manufacturers such as IT system shutdowns, overly complicated purchase processes for customers, or poor equipment of agents with demonstration vehicles.

Overall, in terms of manufacturer profits, sales volume is only one strategic objective along with price realization and cost efficiency, yet it remains a crucial factor. Monthly sales volume declines of up to 25% are substantial and cannot easily be compensated for by price increases or cost reductions alone. Decision makers should thus be aware of these potential trade-offs of transitioning to direct sales models and explicitly consider them in their strategic decisions.

Potential alternative explanations. While my findings for BMW South Africa suggest robust negative sales volume trends after the direct sales model introduction, and a positive effect can also confidently be ruled out for Mercedes Austria, some alternative explanations should nevertheless be considered when interpreting the results. First, as I cannot distinguish between private (B2C) and corporate (B2B) transactions in the sales volume data, structural differences in the B2B sales volume share between treated and control markets cannot be ruled out. Business customers, such as corporate or fleet buyers, typically purchase directly from manufacturers and are potentially less affected by the direct sales transformations, as they receive individual commercial terms and negotiated volume discounts (Simon Kucher, 2021; Heuser et al., 2023). If this unobserved share of B2B sales differs structurally between markets or was tactically increased by the OEM to support sales volumes in the treated market after the direct sales switch, this may confound our results. However, even if B2B sales remain constant over time, the true relative sales volume decreases among B2C customers – who are directly affected by the new sales model – would be even greater than the observed declines. Second,

OEMs might have adopted short-term tactical measures to stabilize sales in the treated market after the direct sales model launch that are not directly attributable to the sales and pricing model transformation itself. These may include temporary price-related measures, such as centrally steered per-unit discounts, trade-in rewards for used cars (Demirag et al., 2010), or customer loyalty rewards (Tschödrich et al., 2020) to support demand without violating the fixed price logic. Further, the OEMs may have temporarily intensified marketing, sales, and advertising efforts to support the transition (Zeng et al., 2016). They might also have tactically enhanced their product offering by earlier or extraordinary model launches or updates to stimulate demand (Zayer et al., 2025). As these measures are not directly observable in the available data, they cannot be explicitly controlled for. Yet it remains questionable whether such measures were structurally used by OEMs to mitigate frictions during the transition, and if so, whether they were employed over such a long period as the two-year post-treatment phase. However, if such tactics were indeed used, they were likely aimed at stimulating demand. This in turn would suggest that, without them, the underlying sales volume trends might have been even more negative. Third, implementation dynamics and enforcement stringency of the new sales and pricing model remain uncertain. While the transition formally eliminates individual price negotiations, it is not observable whether agents strictly adhere to this pricing policy or if they may have continued to use informal discounting, for instance, by “hidden” discounts, such as free or discounted product or service extras (Mishra & Mishra, 2011). As such, the observed sales volume developments might not fully reflect the pure effects of a strict fixed price policy. However, I again assume that such tactics would have been employed to stimulate demand. Therefore, if this was indeed the case, this should again tend to improve sales volumes, which would thus suggest that the true underlying sales volume developments after the transition might have been even more negative. Finally, broader external market factors might also have affected the observed sales trends. For instance, I cannot observe competitive behavior and responses to the direct sales model launches. In addition, specific macroeconomic factors or regulatory changes may have also affected sales (Sagaert et al., 2018). While the synthetic control method accounts for observable pre-treatment covariates, omitted variable bias, time-specific shocks, or asymmetric market-level developments cannot be entirely ruled out. However, when considering the robustness and the magnitude of the observed sales volume declines, particularly for BMW South Africa, it seems unlikely that these sales trends can be explained by such factors alone.

Limitations and directions for future research. The potential alternative explanations already link to the limitations of this research, which point to important avenues for future research. First, future studies could seek to analyze the described potential alternative explanations, such as corporate (B2B) sales dynamics, possible short-term tactical measures by manufacturers, implementation dynamics and stringencies, as well as competitive responses and additional external market factors. Second, the underlying mechanisms of the theoretical framework could empirically be tested in greater detail. While this study focuses on the aggregate outcome in terms of sales volume, future research could examine individual dimensions such as transaction prices, discounting patterns, service quality, customer experience, or brand perceptions to disentangle which underlying effects might be attributable to the transformation of the sales and distribution model and which to that of the pricing model. Analyzing alternative explanations and underlying mechanisms could entail using additional data sources, survey data, expert interviews, qualitative case studies, or mystery shopping. Third, the generalization of my results might be limited to the new car retail market, two manufacturers, and two regional markets. Studies extending my research to other industries, manufacturers, and regions could increase external validity. In addition, longer post-treatment periods of up to 10 years could provide insights into long-term sales volume dynamics. Finally, future research could extend my analysis to other strategic outcomes, such as cost structures, profitability, or customer satisfaction, to obtain a more comprehensive understanding of the trade-offs and other business implications of the transformation into a direct sales model with fixed, non-negotiable prices.

5 Conclusion

Over the past century, the general architecture of new car retailing has essentially remained unchanged. Despite the increasing technological complexity of the vehicles, changing customer needs, and profound effects due to digital technologies, the prevalent sales models of incumbent manufacturers have continued to be based on indirect structures and the outsourcing of sales and distribution activities to independent car dealers (Buzzavo, 2023). These dealers maintain important customer relationships and thereby collect valuable customer data. In addition, they usually set the transaction prices and negotiate them with potential buyers (Heuser et al., 2023).

Recently, however, this established system has come under increasing pressure and scrutiny (Schmidt et al., 2020). New market entrants such as Tesla have proven the feasibility and advantages of direct sales models with fixed, non-negotiable prices and are thereby challenging the status quo (Tschödrich et al., 2020). At the same time, incumbent manufacturers have also started to transform their sales structures into direct sales models in selected regional markets (Schmidt et al., 2020). These attempts reflect a broader strategic objective by OEMs to regain pricing control, end price wars within the same brands, reduce overall marketing and sales costs, and directly access customer data to enable enhanced customer experiences across increasingly digital sales channels (e.g., Tschödrich et al., 2020; Buzzavo, 2023). Under a direct sales model, OEMs directly sell their new cars to customers instead of indirectly through dealers. Dealers are transformed into manufacturer-employed *agents* who handle transactions and other services on behalf of the manufacturer in exchange for a fixed commission fee (Tschödrich et al., 2020). In addition, pricing authority shifts from dealers to OEMs, and prices that are individually negotiated between dealers and customers are replaced by manufacturer-determined fixed prices that are non-negotiable and consistent across all private customers and sales channels (Schmidt et al., 2020). This direct sales model has emerged as one of the most profound and controversial topics in automotive retailing in decades (Buzzavo, 2023). While industry reports have often emphasized the potential benefits for OEMs (e.g., Tschödrich et al., 2020; Schmidt et al., 2020), the broader implications of direct sales model transformations have so far received little empirical attention within academic research.

A manufacturer's transition to direct sales with fixed prices transforms its sales and distribution model as well as the way prices are set (Heuser et al., 2023). This has potentially profound implications for OEMs, retailers (i.e., former dealers, now agents), and customers. The aim of this dissertation was to investigate how such transformations affect these central stakeholders in the automotive retailing industry. Specifically, it addressed the following interrelated research questions: How do customers perceive the removal of price negotiations? What are the psychological costs they associate with price negotiations? Which personality traits explain heterogeneity in these *bargaining costs*? How does moving to a direct sales model

with fixed prices affect competition among dealers as well as their (intra-brand) differentiation tactics? And ultimately, how does the transformation affect manufacturers' sales volumes?

Collectively, these questions address critical decision domains for the automotive industry, such as customer pricing perceptions, dealer competition dynamics, and manufacturer-level sales performance. They have important implications for marketing scholars, automotive OEM managers, and potentially regulators. In the following, I synthesize the main findings of this dissertation's three empirical studies and subsequently discuss overarching implications. In *Table 5.1*, I provide an overview of the individual chapters, including their research questions, data, methodology, main findings, and implications.

In Chapter 2, we adopted the customer perspective and investigated how new car customers might perceive the removal of price negotiations under a direct sales model with fixed prices. Based on a survey of recent new car customers, we developed and analyzed a new empirical measure of the psychological *bargaining costs* that buyers assign to participating in price negotiations in the context of new car purchases. We found that the majority of customers (63%) are willing to pay a markup over the price they would expect to pay after negotiating to avoid engaging in time-consuming price negotiations. This price markup, which we interpreted as the customers' *bargaining costs*, amounts to 1.05% (or €435) relative to the initial offer price on average. We observed substantial heterogeneity in customers' *bargaining costs* and showed that the aversion toward price negotiations is mainly driven by customers' time and effort considerations, as well as by unpleasant post-purchase concerns regarding the price they managed to negotiate. The latter also includes comparisons with and envy toward other buyers.

In Chapter 3, we assessed the retailer (i.e., dealer or agent) view and examined how the shift from a traditional wholesale model to a direct sales model with fixed, manufacturer-imposed prices affects competitive dynamics and differentiation behavior among dealers and agents. We used a quasi-experimental design and repeated telephone surveys of German car dealers and compared a treatment group who had already transitioned to agency contracts with a control group that was still operating under traditional wholesale dealer agreements. Our results indicated that direct sales agents perceive both general and, particularly, price competition with other agents of the same brand (i.e., intra-brand competition) as significantly less intense than the traditional wholesale dealers. Furthermore, we observed that for direct sales agents, there appear to be important rebalancing effects in the competitive dynamics of new car retailing. For them, the competitive focus shifts from intra-brand to inter-brand rivalry (i.e., with other brands), and within the intra-brand dimension, from price to non-price competition. With respect to differentiation activities toward other dealers of the same brand, we showed that

direct sales agents make significantly weaker use of price-related tactics compared to traditional dealers. For non-price-related measures, we did not observe any conclusive differences.

Lastly, the goal of Chapter 4 was to adopt the manufacturer perspective and to examine the effect of transitioning to a direct sales model on new car sales volumes. In this study, I analyzed two real-world case studies in which BMW and Mercedes launched direct sales models in their South African and Austrian regional markets, respectively. To estimate the treatment effects with respect to monthly new car sales volumes, I applied the synthetic control method (SCM; following e.g., Abadie & Gardeazabal, 2003; Abadie, 2021) and constructed counterfactuals based on non-treated regional markets of the respective OEM. The results showed a substantial decline in sales volumes in both cases. In South Africa, BMW's monthly new car sales were on average 25.3% lower than those of its synthetic control over the first two years after the transition. In Austria, Mercedes experienced a more moderate decline of 9.5% on average over the same post-treatment period. However, I cannot entirely rule out random variation as a potential explanation for the results related to Mercedes Austria.

	Chapter 2	Chapter 3	Chapter 4
Title	<i>Who Enjoys Going to the Bargaining Table? An Empirical Analysis of Bargaining Costs in Automotive Transactions</i>	<i>Competing within the Brand – Intra-Brand Competition and Differentiation in the Automotive Direct-to-Consumer Sales Era</i>	<i>Shifting Gears – Evaluating the Sales Volume Impact of Direct-to-Consumer Sales Model Transformations</i>
Research question(s)	How do customers perceive the removal of price negotiations? What are the psychological <i>bargaining costs</i> they associate with the negotiation process? Which personality traits explain heterogeneity in these costs?	How does moving to a direct sales model with fixed prices affect competition among dealers? How does it impact dealers' differentiation tactics?	How does the transformation to a direct sales model with fixed, non-negotiable prices affect manufacturers' sales volumes?
Data (source)	Online survey of recent new car customers from Germany (N = 510)	Repeated telephone surveys of car dealers from Germany (N = 773)	Monthly new car sales volumes, (regional market- & OEM-level; S&P Global Mobility, 2024a)
Methodology	Linear regression models, Novel metric to measure these psychological <i>bargaining costs</i>	Quasi-experimental design, Event study and linear regression models	Synthetic control method (SCM), Other untreated markets of the same OEM as potential controls
Main findings	<ol style="list-style-type: none"> 1) 63% of respondents are willing to pay a higher price to avoid having to negotiate 2) Buyers on average assign a bargaining cost of 1.05% to negotiating the price 3) Consumers' negotiation aversion seems to be mainly driven by time and effort considerations as well as post-purchase concerns regarding the final price paid 	<ol style="list-style-type: none"> 1) Direct sales agents perceive intra-brand (particularly price) competition as less intense 2) Their competitive focus seems to shift from intra- to inter-brand competition and within intra-brand competition from price to non-price competition 3) While their price-related differentiation efforts decline, this does not seem to be offset by non-price differentiation 	<ol style="list-style-type: none"> 1) The transition to direct sales appears to be followed by strong sales volume declines 2) BMW's monthly new car sales volumes in South Africa on average declined by 25.3% compared to its synthetic control over the first two years 3) Mercedes' monthly sales volumes in Austria declined by 9.5% on average over the same post-treatment period
Implications	<ol style="list-style-type: none"> 1) OEMs should consider that customers prefer fixed pricing and dislike the current pricing model with negotiations 2) Switching to direct sales with non-negotiable prices appears feasible if OEMs slightly reduce their prices below current offer prices 	<ol style="list-style-type: none"> 1) Introducing direct sales might effectively eliminate or reduce intra-brand price competition, which helps OEMs to prevent costly within brand price wars 2) Dealers may need support and incentives in transitioning to intensified and effective quality differentiation tactics 	<ol style="list-style-type: none"> 1) Sales volume declines are a realistic and relevant risk for OEMs following the transition to direct sales with fixed prices 2) Manufacturers should weigh this volume risk against anticipated benefits and consider strategic responses to mitigate this risk

Table 5.1: Summary of research design, main findings, and implications across chapters

The three empirical chapters of this dissertation explored the implications of automotive manufacturers transitioning to direct sales models with fixed prices from the perspective of customers, dealers, and manufacturers. While each chapter focused on one stakeholder level, important overarching aspects and interdependencies became apparent, which may help explain the broader dynamics of such transformations. Particularly, the customer and dealer-level results might offer explanations for the sales volume evolution observed at the OEM level.

From a customer perspective, our results suggest that many buyers dislike the prevailing negotiation-based new car pricing scheme and would perceive the transition to fixed, non-negotiable prices favorably. However, customers seem accustomed to receiving considerable discounts through negotiations, so switching to fixed prices only appears feasible if OEMs slightly lower their prices below the current offer prices. Otherwise, they might risk a decline in sales volumes. Moreover, these customer preferences are not uniform. Our data indicated a strong variation in customers' negotiation preferences and in the fixed price levels that make them indifferent between the two pricing models. This heterogeneity is more difficult to address with a single, fixed price under a direct sales model than under a traditional wholesale model, where price discrimination across individual customers is feasible through price negotiations (Desai & Purohit, 2004). By switching to fixed, non-negotiable pricing, manufacturers thus risk losing customers who are less averse towards negotiations, which includes those who are used to high discount levels achieved via negotiations. Regarding the retailer perspective, we found that direct sales agents perceive intra-brand (price) competition as less intense than the traditional wholesale dealers. Further, they largely appear to abandon price-related differentiation tactics. However, they do not seem to compensate for this loss of a key value lever, particularly of negotiated price discounts, by intensifying non-price differentiation tactics such as measures to improve sales initiation, customer service quality, or customer loyalty. Overall, fewer price-based promotions and unchanged non-price differentiation efforts could plausibly contribute to considerable sales volume risks for agents and OEMs.

In the final empirical chapter, I examined the manufacturer perspective and showed that the transition to direct sales was followed by strong sales volume declines for two real-world OEM transformations. In Chapter 4, I discussed several potential mechanisms that might explain such reactions, which are likely to stem from the demand- rather than the supply-side. I concluded that potentially higher average transaction prices, less price discriminatory flexibility, and insufficient OEM retail operations capabilities might dominate potential positive effects, such as the removal of a crucial friction in the purchase process (Zhang et al., 2021) and improved buyer perceptions of price fairness and transparency (DellaVigna & Gentzkow, 2019; Gonzales et al., 2020), service and advertising quality (Yan & Pei, 2009), customer experience (Buzzavo,

2023), and brand equity (Gielens & Steenkamp, 2019). The results of Chapters 2 and 3 provide supporting evidence for this interpretation. First, customers indeed seem to dislike price negotiations, on average, and this aversion is partly explained by time and effort considerations. Their elimination might thus, in fact, imply the removal of an important friction in customers' purchase processes. Another driver of buyers' negotiation aversion is unpleasant post-purchase concerns about the negotiated price. Since under fixed pricing, every customer pays the same price at any given time, it is conceivable that customers perceive fixed prices as fairer and feel less need to compare their price paid with those of other customers. However, it is possible that the OEMs that I considered in Chapter 4 set the fixed prices at levels too close to prior, negotiable offer prices without accounting for the discounts that customers are usually used to receiving when negotiating the price. If fixed prices were not sufficiently lowered, buyers may have perceived the new pricing scheme as less attractive, potentially contributing to the observed sales volume declines. Moreover, the switch to fixed prices implies a restriction on price discriminatory flexibility. In conjunction with the strong variation in customers' aversion to negotiations and their discount expectations, this limitation might be a crucial argument explaining the observed sales declines. As such, losing this flexibility might disproportionately repel less negotiation-averse, more price-sensitive buyers and may thus constitute a decisive mechanism that reduces demand. With respect to direct sales agents' differentiation efforts, our results suggest that the positive demand effects hypothesized based on prior literature, for instance through improved customer experience as well as service and advertising quality, seem unlikely to have materialized. In addition, several news outlets point to severe implementation issues faced by OEMs (e.g., Plate, 2023; Seyerlein, 2023, 2025). This indicates that manufacturers might indeed struggle with the new, previously unfamiliar retail operations responsibilities, which may have also contributed to the observed sales volume declines. For potential brand equity improvements, no empirical conclusions can be drawn in this study.

Taken together, the integration of the customer, retailer, and manufacturer perspectives in this dissertation provides crucial empirical evidence on the broader implications of automotive manufacturers' transitions to direct sales with fixed, non-negotiable prices. It further sheds light on several underlying mechanisms that may have contributed to the observed sales volume declines in the two real-world case studies examined. However, it should be noted that at this point, I am drawing on findings from self-reported survey data of German new car customers and car dealers in combination with those related to real-world sales volume data of two specific manufacturers in their respective South African and Austrian markets. Generalizability can nevertheless not necessarily be guaranteed here. Furthermore, it is important to emphasize that sales volumes represent only one dimension of OEM performance. Other crucial metrics, such

as transaction prices, cost of sales, marketing expenditures, and profitability, were beyond the empirical scope of this dissertation but could strongly affect the overall business case for direct sales model transformations. These domains could thus be promising areas for future research. Moreover, even if manufacturers initially experience pressure on sales volumes after transitioning to the new sales model, the strategic benefits of this, such as full pricing authority (Heuser et al., 2023), strengthening of online sales (Tschödrich et al., 2020), or direct access to customer data (Heuser et al., 2023), could materialize in the longer term and potentially compensate for short- to medium-term sales volume declines.

Altogether, this dissertation provided comprehensive empirical evidence on the multi-level implications of one of the most profound changes in automotive retailing in the last decades (Buzzavo, 2023). It examined the consequences of automotive manufacturers' transitions to direct sales models with fixed, non-negotiable prices for OEMs, retailers, and customers. The empirical findings of this dissertation, particularly with respect to the customers' and the agents' perspectives, indicate important potential for the direct sales model. However, from a sales volume perspective, the results suggest that this alternative sales model does not necessarily guarantee unconditional success. For manufacturers, the road ahead might still be a bumpy one, with considerable room for improvement. As such, supporting and incentivizing differentiation activities of manufacturer-employed agents, strengthening retail operational capabilities, and optimizing pricing strategies might be critical focus areas. At the same time, it also remains possible that some OEMs were too quick to follow what appeared to be a disruptive success story. They might have been lured by greenfield entrants like Tesla and by management consultancy reports such as Schmidt et al. (2020) and Tschödrich et al. (2020) without fully accounting for the operational and market risks involved. Overall, it remains to be seen in which direction the automotive retailing industry will evolve and which sales and pricing models will ultimately prevail. I hope that with this dissertation, I have been able to fill relevant gaps in academic literature and further provide industry practitioners with practical answers as well as a profound empirical foundation for decision-making.

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A Appendix Chapters 1 and 2

A.1 List of direct sales model introductions

OEM	Region(s)	Year	Scope (models)	Source
Audi	France, Germany, Ireland, Italy, Poland, Spain, Sweden, United Kingdom	2024	Electric vehicles	<i>Bäuchle (2023), Randall (2021b)</i>
BMW	Europe	2013	BMWi	<i>Schmidt et al. (2020)</i>
BMW	Japan	2018	BMWi	<i>Schmidt et al. (2020)</i>
BMW	South Africa	2020	All	<i>Schmidt et al. (2020)</i>
BMW	Germany, Italy, Poland, Sweden	2024	Sub-brand Mini	<i>BMW Group (2023), Lulei (2024)</i>
Ford	Netherlands	2023	All	<i>Automotive News Europe (2023)</i>
Genesis	Canada	2017	All	<i>Schmidt et al. (2020)</i>
Genesis	Korea	2017	All	<i>Schmidt et al. (2020)</i>
Genesis	Europe	2021	All	<i>Randall (2021a)</i>
Honda	New Zealand	2000	All	<i>Schmidt et al. (2020)</i>
Honda	Australia	2021	All	<i>Schmidt et al. (2020)</i>
LYNK	China	2017	All	<i>Schmidt et al. (2020)</i>
Mercedes	South Africa	2017	All	<i>Schmidt et al. (2020)</i>
Mercedes	Sweden	2019	All	<i>Schmidt et al. (2020)</i>
Mercedes	India	2021	All	<i>Lidhoo (2023)</i>
Mercedes	Austria	2021	All	<i>Schmidt et al. (2020)</i>
Mercedes	Australia	2022	All	<i>Nguyen (2021)</i>
Mercedes	United Kingdom	2023	All	<i>Neves (2023)</i>
Mercedes	Germany	2023	All	<i>Hubik (2023)</i>
NIO	Global	2018	All	<i>Schmidt et al. (2020)</i>
Polestar	Europe	2019	All	<i>Schmidt et al. (2020)</i>
Polestar	USA	2020	All	<i>Schmidt et al. (2020)</i>
Polestar	China	2020	All	<i>Schmidt et al. (2020)</i>
Seat	France, Germany, Ireland, Italy, Poland, Spain, Sweden, United Kingdom	2024	Electric vehicles	<i>Randall (2021b)</i>
Stellantis	Austria, Belgium, Luxembourg, Netherlands	2023	All	<i>Reuters (2023b)</i>
Tesla	Global	2012	All	<i>Schmidt et al. (2020)</i>
Toyota	New Zealand	2018	All	<i>Schmidt et al. (2020)</i>
Volkswagen	Europe	2020	Electric vehicles	<i>Schmidt et al. (2020)</i>
Volkswagen	Ireland, Sweden	2024	All	<i>Seyerlein (2024)</i>
Volvo	India	2023	Electric vehicles	<i>Bhatia and Taumar (2023)</i>
Volvo	United Kingdom	2023	All	<i>Bleakley (2023)</i>

Table A.1: List of direct sales model introductions by OEMs (*non-exhaustive, preliminary*)

A.2 Distribution of respondents' transaction prices and leasing rates

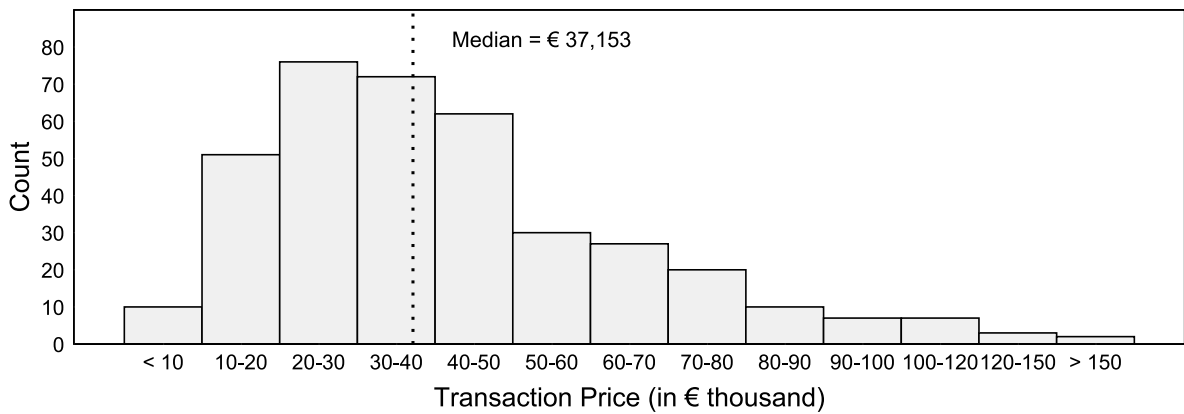


Figure A.1: Distribution of transaction prices of respondents in previous transaction (purchase and financing customers only, N = 377)

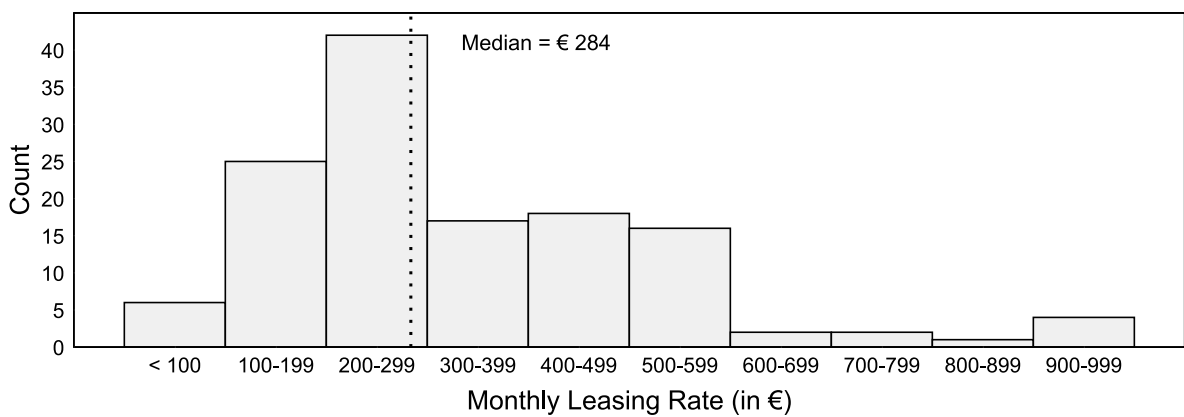


Figure A.2: Distribution of monthly leasing rates of respondents in previous transaction (leasing customers only, N = 133)

A.3 Customer survey questions

A.3.1 Screening and demographic questions (part I/II)

SC.01: Age.

How old are you?

SC.02: Gender.

Are you ...?

- 1.) Female
- 2.) Male
- 3.) Diverse
- 4.) Other
- 5.) Not specified

SC.03: Region.

Where do you live?

List of German regions to select from.

SC.04: New car indicator.

Which of the following items have you recently purchased?

Rows (randomized):

- 1.) Refrigerator (with an energy efficiency rating of at least B)
- 2.) Smart TV (with pre-installed streaming apps)
- 3.) Laptop (with at least 500 GB SSD hard drive)
- 4.) New car (including financing and leasing, but not used cars)
- 5.) Solar panels on the roof
- 6.) Portafilter coffee maker (espresso/professional) (only models with two boilers)
- 7.) Private airplane (for min. 4 passengers)

Columns:

- a) In the last 6 months
- b) In the last 7 - 12 months
- c) In the last 13 - 24 months
- d) More than 24 months ago
- e) Never

SC.05: Customer (contract) type.

How did you acquire your last new car?

- 1.) Private purchase (i.e., direct payment of the entire transaction price without financing)
- 2.) Private leasing
- 3.) Private financing through credit/ loan (at least part of the transaction price)
- 4.) Subscription model for private cars
- 5.) Company car (leasing)
- 6.) Other (please specify)

SC.06: Transaction role.

Please recall the purchase of your last new car - how would you describe your role during the decision-making process?

- 1.) I made the entire decision myself.
- 2.) I was the main decision maker, but received support (e.g., from partner or relatives).
- 3.) I gave suggestions to the main decision maker (e.g., regarding my own preferences or financial aspects).
- 4.) I was selectively informed by the main decision maker.
- 5.) I was not involved in the decision.

A.3.2 Previous transaction questions (here: example for purchase respondents)

T.01: Brand.

From which brand was the last new car you purchased?

List of the most common car brands incl. answer option “other (please specify)”.

T.02: Model.

What is the model (e.g., Golf from VW or E-Class from Mercedes) of the last new car you bought?

Text field

T.03: Financing details (*only for financing respondents*).

What share of the total transaction price of the new car did you finance through a loan/ credit?

- 1.) Less than 20%
- 2.) 20 – 39%
- 3.) 40 – 59%
- 4.) 60 – 79%
- 5.) 80 – 100%

T.04: New car experience.

How many new cars have you privately purchased, financed or leased throughout your life?

Note: Private acquisition, i.e., excluding company cars. No (young) used cars.

- 1.) None
- 2.) 1
- 3.) 2
- 4.) 3
- 5.) 4
- 6.) 5 or more

T.05: Car type.

What type of car was the last new car you purchased?

- 1.) Mini/small cars (e.g., Audi A1, VW Polo, Fiat 500)
- 2.) Medium (e.g., Audi A2/ A3, BMW 1/ 2 series, VW Golf, Toyota Corolla)
- 3.) Large (e.g., Audi A4/ A5, BMW 3 Series/ 4 Series, VW Passat, Tesla Model 3)
- 4.) Executive (e.g., Audi A6 - A8, BMW 5 Series - 7 Series, VW Crafter, Ford Transit)
- 5.) Pick-up (e.g., Ford Ranger, Toyota Hilux, Mitsubishi L200, Nissan Navara)
- 6.) Sport utility vehicle (SUV) (e.g., Audi Q2-Q7, BMW X1-X7, VW Tiguan, Skoda Kodiaq)
- 7.) Van (e.g., Hyundai HD, RAM 2500)
- 8.) Other (please specify)

T.06: Powertrain.

What type of powertrain was the last new car you purchased?

- 1.) Gas
- 2.) Diesel
- 3.) Hybrid (without external charging option)
- 4.) Plug-in hybrid (i.e., with external charging option)
- 5.) 100% electrical
- 6.) Other (please specify)

T.07: Transaction price.

What was the final transaction price of the last new car you purchased?

List of transaction price ranges to select from (from “below €10,000” to “above €150,000”).

T.08: Leasing rate (*only for leasing respondents*).

What was the final monthly leasing rate for the last new car you leased?

List of monthly leasing rate ranges to select from (from “below €100” to “above €1,500”).

T.09: Leasing duration (*only for leasing respondents*).

What contract duration did you agree on for the last new car you leased?

- 1.) Less than 6 months
- 2.) 6 – 12 months
- 3.) 13 – 18 months
- 4.) 19 – 24 months
- 5.) 25 – 36 months
- 6.) 37 – 48 months
- 7.) More than 28 months

T.10: Bargaining indicator (*here: example for purchase respondents*).

Did you negotiate the transaction price for the last new car you purchased?

- 1.) Yes, I did negotiate.
- 2.) No, I did not negotiate.
- 3.) I am not sure.

A.3.3 Search and purchase behavior-specific and general personality trait-specific questions

S.01: Willingness to search (“SEA”; Zettermeyer et al., 2006, p. 180).

For each of the following statements, please indicate how strongly you agree.

Five-point Likert-type scale (1 = “strongly disagree”, 5 = “strongly agree”)

- 1.) “I do a lot of price comparison when making larger purchases.”
- 2.) “I frequently use the Internet to obtain information about products I am interested in.”
- 3.) “I am the kind of person who gathers as much information as possible before visiting car dealers.”

S.02: Opportunity cost of time (“OPP”; Lichtenstein et al., 1993, p. 243).

For each of the following statements, please indicate how strongly you agree.

Five-point Likert-type scale (1 = “strongly disagree”, 5 = “strongly agree”)

- 1.) “I am not willing to go to extra effort to find lower prices.”
- 2.) “I will grocery shop at more than one store to take advantage of low prices.” (R, *)¹
- 3.) “The money saved by finding low prices is usually not worth the time and effort.”

¹ Note: (R) = reverse-scored item, (*) = item excluded after exploratory factor analysis

S.03: Car enthusiasm (“*CAR*”; Zettelmeyer et al., 2006, p. 180).

For each of the following statements, please indicate how strongly you agree.

Five-point Likert-type scale (1 = “strongly disagree”, 5 = “strongly agree”)

- 1.) “I read car- and/or truck-enthusiast magazines regularly.”
- 2.) “I tend to visit dealers whenever a model is introduced.”
- 3.) “I regularly read articles and/or watch video reviews of new vehicle models.” (*Newly added item*)

S.04: Patience (“*PAT*”; Schnitker, 2012, p. 280).

For each of the following statements, please indicate how strongly you agree.

Five-point Likert-type scale (1 = “strongly disagree”, 5 = “strongly agree”)

- 1.) “Although they’re annoying, I don’t get too upset when stuck in traffic jams.” (*)
- 2.) “I am patient with other people.”
- 3.) “I am able to wait out tough times.” (*)
- 4.) “When someone is having difficulty learning something new, I will be able to help them without getting frustrated or annoyed.” (*)

S.05: Information sources (*here: example for purchase respondents*).

Which of the following sources of information did you use the last time you bought a new car?

Offline information sources:

- 1.) Car dealership/workshop (e.g., showrooms, car dealers).
- 2.) Test drives (e.g., with a car from a dealer or a friend)
- 3.) Discussions with family and friends
- 4.) Test reports and reviews in print media (e.g., car magazines)
- 5.) TV or radio (e.g., reports or product advertisements)
- 6.) Product advertising in print media
- 7.) Manufacturer and dealer brochures.

Online information sources:

- 1.) Search engines (e.g., *Google*)
- 2.) Manufacturer and dealer websites (incl. vehicle configurators)
- 3.) Comparison websites and independent marketplaces (e.g., *carwow*, *MeinAuto.de*)
- 4.) Internet forums, blogs and car magazine websites
- 5.) Online advertising (e.g., banners)
- 6.) Social media (e.g., ads or influencer content on *Facebook*, *YouTube*, *Instagram*).
- 7.) Classifieds websites (e.g., *eBay Classifieds*).

S.06: Number of models informed.

Please indicate for how many different models you have researched information.

Note: For example, if you researched information for a VW Golf, an Audi A2, and an Audi A3, you researched for three different models.

- 1.) 1
- 2.) 2
- 3.) 3
- 4.) 4
- 5.) 5 or more
- 6.) 6. I am not sure

S.07: Research period (*here: example for purchase respondents*).

Overall, how long did it take from the time you started gathering initial information about vehicle models until you finally purchased your new car?

- 1.) Less than 2 weeks
- 2.) 2 – 4 weeks
- 3.) 1 – 3 months
- 4.) 3 – 6 months
- 5.) 6 – 12 months
- 6.) 12 – 24 months
- 7.) More than 24 months

S.08.a: Channel per process step (*here: example for purchase respondents*).

Which of the following channels did you use or visit throughout the purchase process for your last new car?

- 1.) Car dealership / car dealer
- 2.) Vehicle manufacturer's website
- 3.) Dealer's website
- 4.) Comparison website, independent marketplace, or classifieds website (e.g., *mobile.de, AutoScout24, carwow, eBay classifieds*)
- 5.) Other (*please specify*)
- 6.) I have not used any of these channels

S.08.b: Channel “car dealership / car dealer” (*here: example for purchase respondents*).

What exactly did you use visits to car dealerships or dealers for during the purchase process for your last new car?

- 1.) Gathering information (*e.g., about models, equipment, dealer costs, and prices*)
- 2.) Personal consultation (*e.g., presentation and explanation of different models*)
- 3.) Viewing, perceiving and test-seating models (*incl. experiencing the brand*)
- 4.) Test driving vehicles
- 5.) Configuring the vehicle (*e.g., selection of engine and equipment*)
- 6.) Negotiating the price
- 7.) Finalizing the transaction (*signing the contract*).
- 8.) Arranging the delivery

S.09: Dealer visited (*here: example for purchase respondents*).

How many car dealerships or dealers did you visit that offered the model you ultimately purchased?

Note: For example, if you purchased an Audi A1, how many dealers did you visit that offered an Audi A1?

- 1.) None
- 2.) One car dealership or dealer
- 3.) 2 – 3 car dealerships or dealers
- 4.) 4 – 6 car dealerships or dealers
- 5.) 7 or more car dealerships or dealers

S.08.c: Channel “vehicle manufacturer’s website” (*here: example for purchase respondents*).

What exactly did you use vehicle manufacturers’ websites for during the purchase process for your last new car?

- 1.) Gathering information (*e.g., about models, equipment, dealer costs, and prices*)
- 2.) Configuring the vehicle (*e.g., selection of engine and equipment*)
- 3.) Finalizing the transaction (*signing the contract*)
- 4.) Arranging the delivery

S.08.d: Channel “dealer’s website” (*here: example for purchase respondents*).

What exactly did you use dealers’ websites visits for during the purchase process for your last new car?

- 1.) Gathering information (*e.g., about models, equipment, dealer costs, and prices*)
- 2.) Configuring the vehicle (*e.g., selection of engine and equipment*)
- 3.) Finalizing the transaction (*signing the contract*)
- 4.) Arranging the delivery

S.08.e: Channel “comparison website, independent marketplace or classifieds website” (*here: example for purchase respondents*).

What exactly did you use comparison websites, independent marketplaces, or classifieds websites for during the purchase process for your last new car?

- 1.) Gathering information (*e.g., about models, equipment, dealer costs, and prices*)
- 2.) Configuring the vehicle (*e.g., selection of engine and equipment*)
- 3.) Finalizing the transaction (*signing the contract*)
- 4.) Arranging the delivery

S.10: Quality consciousness (“*QUA*”; Ailawadi et al., 2001, p. 87).

For each of the following statements, please indicate how strongly you agree.

Five-point Likert-type scale (1 = “strongly disagree”, 5 = “strongly agree”)

- 1.) “I will not give up high quality for a lower price.”
- 2.) “I always buy the best.”
- 3.) “It is important to me to buy high-quality products.”

S.11: Post-purchase price confirmation (“*PRP*”; new scale).

For each of the following statements, please indicate how strongly you agree.

Five-point Likert-type scale (1 = “strongly disagree”, 5 = “strongly agree”)

- 1.) “After I buy an expensive product, I tend to follow up on the product’s price trend.”
- 2.) “Often, after buying an expensive product, I feel that I could have gotten a better deal.”
- 3.) “After completing a purchase, I often think a lot about the price of the product.”
- 4.) “When I find that someone else paid less for the same product I bought, I get upset.”

S.12: Risk propensity (“*RIS*”; Meertens & Lion, 2008, p. 1520).

For each of the following statements, please indicate how strongly you agree.

Five-point Likert-type scale (1 = “strongly disagree”, 5 = “strongly agree”)

- 1.) “I prefer to avoid risks.” (R)²
- 2.) “I take risks regularly.”
- 3.) “I really dislike not knowing what is going to happen.” (R, *)
- 4.) “I usually view risks as a challenge.”

² Note: (R) = reverse-scored item, (*) = item excluded after exploratory factor analysis

S.13: Sale proneness (“*SAL*”; Lichtenstein et al., 1993, pp. 243-244).

For each of the following statements, please indicate how strongly you agree.

Five-point Likert-type scale (1 = “strongly disagree”, 5 = “strongly agree”)

- 1.) “When I buy a brand that’s on sale, I feel that I am getting a good deal.”
- 2.) “I have favorite brands, but most of the time I buy the brand that’s on sale.”
- 3.) “One should try to buy brands that are on sale.”
- 4.) “Compared to most people, I am more likely to buy brands that are on special.”

S.14: Regulatory focus (prevention vs. promotion focus) (“*PRE*”, “*PRO*”; Ouschan et al., 2007, p. 254).

For each of the following statements, please indicate how strongly you agree.

Five-point Likert-type scale (1 = “strongly disagree”, 5 = “strongly agree”)

- 1.) “To avoid failure, one has to be careful.” (*PRE*) (*)³
- 2.) “To achieve something, it is most important to know all the potential obstacles.” (*PRE*) (*)
- 3.) “In order to achieve something, you need to be realistic.” (*PRE*)
- 4.) “You have to take risks if you want to avoid failing.” (*PRO*) (*)
- 5.) “The worst thing you can do when trying to achieve a goal is to worry about making mistakes.” (*PRO*)
- 6.) “To achieve something, one must try all possible ways of achieving it.” (*PRO*) (*)

S.15: (Internal) locus of control (“*LOC*”; Mueller & Thomas, 2001, p. 75).

For each of the following statements, please indicate how strongly you agree.

Five-point Likert-type scale (1 = “strongly disagree”, 5 = “strongly agree”)

- 1.) “My success depends on whether I am lucky enough to be in the right place at the right time.” (R, *)
- 2.) “My life is determined by my own actions.” (*)
- 3.) “When I get what I want, it is usually because I worked hard for it.” (*)
- 4.) “I feel that what happens in my life is mostly determined by people in powerful positions.” (R, *)
- 5.) “Whether or not I am successful in life depends mostly on my ability.”

³ Note: (R) = reverse-scored item, (*) = item excluded after exploratory factor analysis

A.3.4 Bargaining costs estimation questions – adaptive version (here: example for purchase and finance respondents)

B.01: Negotiation willingness.

Situation: You want to buy a new car. A car dealer in your area offers exactly the model you want. The following information is displayed on the sales sign:

Manufacturer's suggested retail price: €55,000 (*example*)

Dealer's offer price: €50,000 (*example*)

Would you try to further negotiate down the offer price if you wanted to buy the car from this dealer?

- 1.) No, I would definitely not negotiate.
- 2.) I would probably not negotiate.
- 3.) I am not sure if I would negotiate.
- 4.) I would probably negotiate.
- 5.) Yes, I would definitely negotiate.

B.02: Best possible price.

Assuming you want to negotiate the price - what is the best possible final purchase price you think you can negotiate the dealer down to?

B.03: Likelihood best possible price.

How likely do you think it is that you can successfully negotiate this final purchase price?

B.04: Fixed price alternative (adaptive).

Situation: Another, very similar car dealer offers exactly the same model you want to buy. This dealer offers the car at a lower price. The price here is fixed and non-negotiable. Both dealers are equally far away from you, but you can visit only one of them.

Dealer A: Offer price: €50,000 (price negotiations possible) (*example*)

Dealer B: Offer price: €48,500 (no price negotiation, fixed price) (*example*)

Do you want to go to *Dealer A* and try to negotiate the price or buy the car from *Dealer B* at the fixed price?

A.3.5 Bargaining costs estimation questions – non-adaptive version (here: example for purchase and finance respondents)

B.05: Fixed price alternative (non-adaptive).

The following question is very similar to the previous one – again you are faced with the decision of which dealer to buy the car from, but this time you have received additional information about the prices customers have paid in the past for the same model at *Dealer A* (where price negotiations are possible).

Situation: You are still faced with a choice of car dealer and can still only go to one of them. In the meantime, you have found out that at *Dealer A*, about 50 out of 100 buyers have been able to negotiate a discount of €3,250 on the offer price in the past. The other 50 customers have also tried to negotiate but have only been able to negotiate a maximum discount of €520.

Dealer A: Offer price: €50,000 (50 out of 100 customers paid €46,750 after price negotiations, the other 50 paid at least €49,480 after price negotiations) (*example*)

Dealer B: Offer price: €48,500 (no price negotiation, fixed price) (*example*)

Do you want to go to *Dealer A* and try to negotiate the price or buy the car from *Dealer B* at the fixed price?

A.3.6 Demographic questions (part II/II)

D.01: Education.

What is the highest educational degree you have obtained?

- 1.) Elementary school
- 2.) Secondary school
- 3.) High school
- 4.) Vocational school
- 5.) Technical college
- 6.) Vocational academy
- 7.) University

D.02: Occupation.

What is your current employment situation?

- 1.) Full-time
- 2.) Part-time
- 3.) Self-employed
- 4.) Homemaker
- 5.) Student
- 6.) Retired
- 7.) Unemployed

D.03: Income.

What was your gross annual household income (i.e., before taxes) last year?

List of household income ranges to select from (from “below €24,000” to “above €150,000”).

D.04: Marital status.

What is your marital status?

- 1.) Single
- 2.) Married/ living with partner
- 3.) Divorced
- 4.) Widowed
- 5.) Not specified

D.05: Number of children.

How many children do you have?

- 1.) None
- 2.) 1
- 3.) 2
- 4.) 3
- 5.) 4 or more
- 6.) Not specified

A.4 Confirmatory factor analysis (CFA) methodology and results

We perform initial item analyses and purification for the 39 items included in our survey to assess the suitability and validity of the data for the subsequent factor analyses. By calculating the correlation matrix and eigenvalues, we find that there are a total of 11 eigenvalues greater than one (together explaining 64% of the total item variation), which suggests that the 39 items explain a total of 11 latent factors, as expected. We then conduct a maximum likelihood exploratory factor analysis (*EFA*) with 11 factors using *RStudio version 2023.06.1+524* and oblique rotation. Oblique rotation is reasonable, as it allows factors to correlate, which in our case is likely, since certain factors might be interrelated (e.g., willingness to search and opportunity cost of time). We only include items with factor loadings greater than 0.4 on the respective construct. We further exclude items that also load strongly on other factors, as in Wolfenbarger & Gilly (2003). After another eigenvalue analysis with the remaining items, three factors with eigenvalues less than one remain. For each of those factors, we exclude the items with the weakest factor loading. Ultimately, a total of 26 items and 11 factors (with one to four items) remain, which we use for our maximum likelihood confirmatory factor analysis (*CFA*).

Constructs & items	Standardized factor loading
Willingness to search “SEA” ($\alpha = 0.78$) (Zettermeyer et al., 2006, p. 180).	
<i>SEA.1</i> “I do a lot of price comparison when making larger purchases.”	0.817***
<i>SEA.2</i> “I frequently use the Internet to obtain information about products I am interested in.”	0.683***
<i>SEA.3</i> “I am the kind of person who gathers as much information as possible before visiting car dealers.”	0.703***
Opportunity cost of time “OPP” ($\alpha = 0.66$) (Lichtenstein et al., 1993, p. 243).	
<i>OPP.1</i> “I am not willing to go to extra effort to find lower prices.”	0.617***
<i>OPP.3</i> “The money saved by finding low prices is usually not worth the time and effort.”	0.803***
Quality consciousness “QUA” ($\alpha = 0.74$) (Ailawadi et al., 2001, p. 87).	
<i>QUA.1</i> “I will not give up high quality for a lower price.”	0.539***
<i>QUA.2</i> “I always buy the best.”	0.771***
<i>QUA.3</i> “It is important to me to buy high-quality products.”	0.803***
Sale proneness “SAL” ($\alpha = 0.81$) (Lichtenstein et al., 1993, pp. 243-244).	
<i>SAL.1</i> “When I buy a brand that’s on sale, I feel that I am getting a good deal.”	0.632***
<i>SAL.2</i> “I have favorite brands, but most of the time I buy the brand that’s on sale.”	0.669***
<i>SAL.3</i> “One should try to buy brands that are on sale.”	0.765***
<i>SAL.4</i> “Compared to most people, I am more likely to buy brands that are on special.”	0.834***
Post-purchase price confirmation “PRI” ($\alpha = 0.79$).	
<i>PRI.1</i> “After I buy an expensive product, I tend to follow up on the product’s price trend.”	0.707***
<i>PRI.2</i> “Often, after buying an expensive product, I feel that I could have gotten a better deal.”	0.693***
<i>PRI.3</i> “After completing a purchase, I often think a lot about the price of the product.”	0.803***
<i>PRI.4</i> “When I find that someone else paid less for the same product I bought, I get upset.”	0.613***
Car enthusiasm “CAR” ($\alpha = 0.87$) (Zettermeyer et al., 2006, p. 180).	
<i>CAR.1</i> “I read car- and/or truck-enthusiast magazines regularly.”	0.875***
<i>CAR.2</i> “I tend to visit dealers whenever a model is introduced.”	0.787***
<i>CAR.3</i> “I regularly read articles and/or watch video reviews of new vehicle models.”	0.826***

Note: α = Cronbach's alpha; (R) = reverse-scored; *** $p = 0.001$; CFI = 0.92; TLI = 0.90, RMSEA = 0.05; $\chi^2 = 606.456$, degrees of freedom (df) = 248, $p = 0.000$

Table A.2.a: Confirmatory factors analysis (CFA) results – search behavior-specific factors

We provide the main CFA results in *Tables A.2.a* and *A.2.b*. Overall, CFA model fit measures indicate good fit. The comparative fit index (CFI) equals 0.92 and the Tucker-Lewis index (TLI) 0.90, thus both are greater than or equal to the common threshold of 0.90 (Lichtenstein et al., 1993). The root mean square error of approximation (RMSEA) is 0.05 which equals the common threshold for good fit (Schnitker, 2012). The Chi-square test statistic (χ^2) equals 606.46, with 248 degrees of freedom and a p-value of 0.00. This suggests a significant difference between the model-implied and the observed covariance matrices, which, however, is typical for larger sample sizes. We therefore rely on the other metrics that indicate model fit to be adequate (Byrne, 2001). We next assess internal consistency for all multi-item constructs. For those

constructs, both the estimates for both Cronbach's alpha (0.66 to 0.87) and composite reliability (0.67 to 0.87) indicate acceptable internal consistency (Van Griethuijsen et al., 2015). Estimates for the average variance extracted (*AVE*), representing the amount of variance in the observed items that is explained by the respective latent factors, range from 0.49 to 0.69 (Lichtenstein et al., 1993). The threshold level of 0.50 is surpassed for all but one of the multi-item scales (except for quality consciousness at 0.49), indicating good convergent validity (Lichtenstein et al., 1993). Item-to-total correlation estimates are greater than the threshold level of 0.50 for all but one of the items (except for *QUA.01* at 0.48), suggesting that the items are all reasonably well related to their corresponding constructs (Lichtenstein et al., 1993). All standardized factor loadings are statistically significant ($p < 0.01$) with respect to the respective factors, and all eigenvalues are greater than or equal to one.

Constructs & items	Standardized factor loading
Risk propensity "RIS" ($\alpha = 0.83$) (Meertens & Lion, 2008, p. 1520).	
<i>RIS.1</i> "I prefer to avoid risks." (R)	0.670***
<i>RIS.2</i> "I take risks regularly."	0.914***
<i>RIS.4</i> "I usually view risks as a challenge."	0.767***
(Internal) locus of control "LOC" (Mueller & Thomas, 2001, p. 75).	
<i>LOC.5</i> "Whether or not I am successful in life depends mostly on my ability."	1.000***
Prevention focus "PRE" (Ouschan et al., 2007, p. 254).	
<i>PRE.3</i> "In order to achieve something, you need to be realistic."	1.000***
Promotion focus "PRO" (Ouschan et al., 2007, p. 254).	
<i>PRO.2</i> "The worst thing you can do when trying to achieve a goal is to worry about making mistakes."	1.000***
Patience "PAT" (Schnitker, 2012, p. 280).	
<i>PAT.2</i> "I am patient with other people."	1.000***

Note: α = Cronbach's alpha; (R) = reverse-scored; *** $p = 0.001$; CFI = 0.92; TLI = 0.90, RMSEA = 0.05; $\chi^2 = 606.456$, degrees of freedom (df) = 248, $p = 0.000$

Table A.2.b: Confirmatory factors analysis (CFA) results – general personality traits

A.5 Correlation matrices latent factors

	SEA	OPP	QUA	SAL	PRI	CAR	RIS	LOC	PRE	PRO	PAT
SEA		-0.52	0.28	0.20	0.16	0.23	-0.03	0.16	0.24	0.17	0.16
OPP	-0.52		0.06	-0.27	0.16	0.08	0.23	-0.05	-0.19	-0.03	-0.06
QUA	0.28	0.06		-0.18	0.12	0.54	0.38	0.30	0.17	0.28	0.20
SAL	0.20	-0.27	-0.18		0.39	-0.05	-0.09	-0.03	0.22	0.01	-0.05
PRI	0.16	0.16	0.12	0.39		0.36	0.19	-0.12	-0.03	0.06	0.03
CAR	0.23	0.08	0.54	-0.05	0.36		0.47	0.05	0.01	0.10	0.15
RIS	-0.03	0.23	0.38	-0.09	0.19	0.47		0.05	-0.14	0.15	0.07
LOC	0.16	-0.05	0.30	-0.03	-0.12	0.05	0.05		0.20	0.13	0.12
PRE	0.24	-0.19	0.17	0.22	-0.03	0.01	-0.14	0.20		0.20	0.05
PRO	0.17	-0.03	0.28	0.01	0.06	0.10	0.15	0.13	0.20		0.10
PAT	0.16	-0.06	0.20	-0.05	0.03	0.15	0.07	0.12	0.05	0.10	

Table A.3.a: Correlation matrix for latent factors with factor loading-weighted items

	SEA	OPP	QUA	SAL	PRI	CAR	RIS	LOC	PRE	PRO	PAT
SEA		-0.31	0.19	0.13	0.14	0.19	0.00	0.14	0.19	0.13	0.13
OPP	-0.31		0.02	-0.15	0.11	0.06	0.12	-0.03	-0.12	-0.01	-0.04
QUA	0.19	0.02		-0.12	0.05	0.37	0.21	0.23	0.13	0.21	0.16
SAL	0.13	-0.15	-0.12		0.30	-0.03	-0.07	-0.02	0.20	0.02	-0.03
PRI	0.14	0.11	0.05	0.30		0.26	0.08	-0.11	-0.02	0.05	0.02
CAR	0.19	0.06	0.37	-0.03	0.26		0.35	0.05	0.00	0.08	0.13
RIS	0.00	0.12	0.21	-0.07	0.08	0.35		0.05	-0.14	0.11	0.04
LOC	0.14	-0.03	0.23	-0.02	-0.11	0.05	0.05		0.20	0.13	0.12
PRE	0.19	-0.12	0.13	0.20	-0.02	0.00	-0.14	0.20		0.20	0.05
PRO	0.13	-0.01	0.21	0.02	0.05	0.08	0.11	0.13	0.20		0.10
PAT	0.13	-0.04	0.16	-0.03	0.02	0.13	0.04	0.12	0.05	0.10	

Table A.3.b: Correlation matrix for latent factors with equal-weighted items

A.6 Control variables regression analyses

Control variables	Explanation
Demographic controls	
<i>Gender</i>	Gender of the subject (female, male, diverse, other)
<i>Age</i>	Age of the subject (<i>minimum age of 18 years</i>)
<i>Education</i>	Educational level of the subject (full-time, part-time, self-employed, homemaker, student, retired, unemployed)
<i>Household income</i>	Annual gross household income of the subject
<i>Marital status</i>	Marital status of the subject (single, married/living with partner, divorced, widowed, no information)
Previous new car transaction controls	
<i>Contract type</i>	Differentiation between purchase, leasing, and financing customers
<i>Transaction time</i>	Timing of the previous new car transaction – within the past 6 months, within the past 7-12 months, or within the past 13-24 months
<i>Transaction role</i>	Differentiation between single decision makers and main decision makers
<i>Price segment</i>	Price segment of the last new car acquired – entry, mid, premium, or luxury
<i>New car experience</i>	Number of previous new car transactions
<i>Bargaining indicator</i>	Indicates whether the price/leasing rate was negotiated in the previous transaction
<i>Car type</i>	Differentiation by mini/small, medium, large, executive, pick-up, SUV, and heavy van
<i>Powertrain</i>	Differentiation by gas, diesel, hybrid, plug-in hybrid, electrical, and LPG
Search and purchase behavior controls	
<i>Number of models informed</i>	Number of models for which information was research in previous transaction
<i>Research period</i>	Length of the research period for previous transaction
<i>Online customer indicator</i>	Indicates whether the subject is classified as online of offline customer

Table A.4: Control variables multiple linear regression analyses

A.7 Overview absolute values bargaining costs (including components)

<i>in €</i>	Adaptive	Non-adaptive	Mean
Mean transaction price purchase & financing	41,976.13	41,976.13	41,976.13
Mean monthly leasing rate	342.48	342.48	342.48
Expected discount purchase & financing	2,609.41	1,476.13	2,042.77
Expected discount leasing	24.86	12.00	18.43
Indifference fixed price discount purchase & financing	1,698.04	1,516.83	1,607.43
Indifference fixed price discount leasing	16.09	13.36	14.73
Bargaining cost purchase & financing	911.37	-40.70	435.34
Bargaining cost leasing	8.77	-1.36	3.70

Table A.5: Absolute values for transaction prices/ leasing rates, expected discounts, indifference fixed price discounts, and bargaining cost

A.8 Additional figures adaptive and non-adaptive bargaining cost estimations

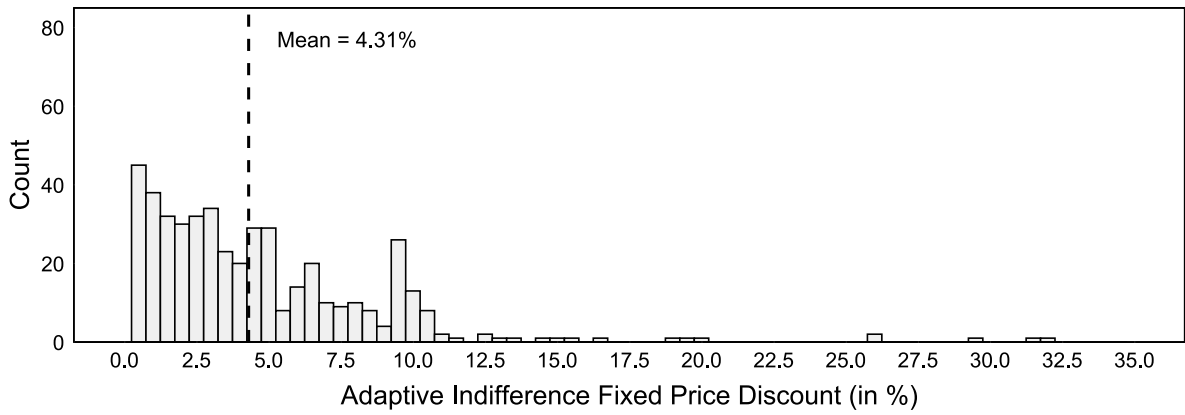


Figure A.3: Distribution of the adaptive indifference fixed price discount

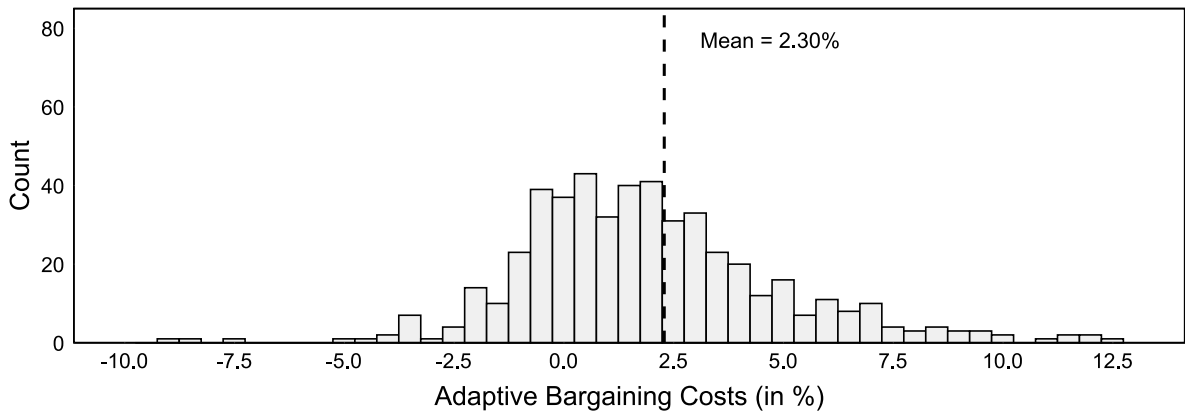


Figure A.4: Distribution of adaptive bargaining costs (exclusion of extreme outliers)

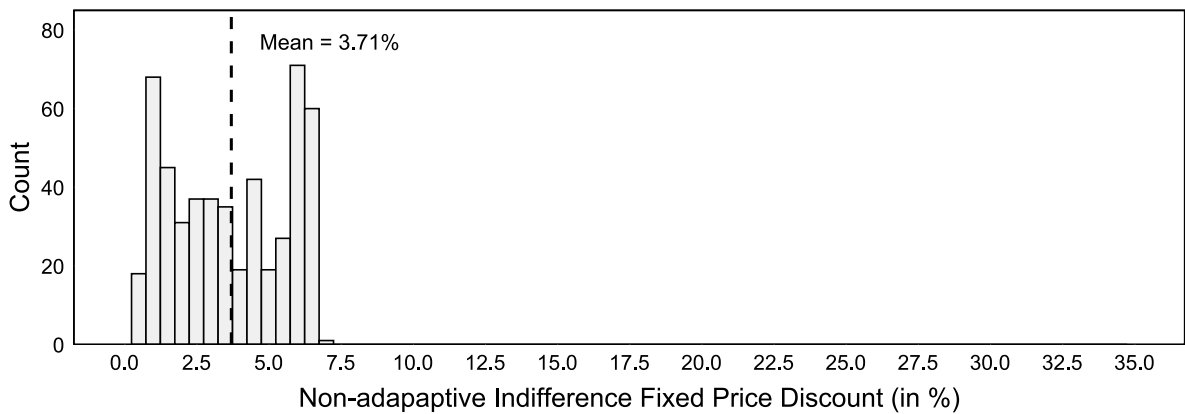


Figure A.5: Distribution of the non-adaptive indifference fixed price discount

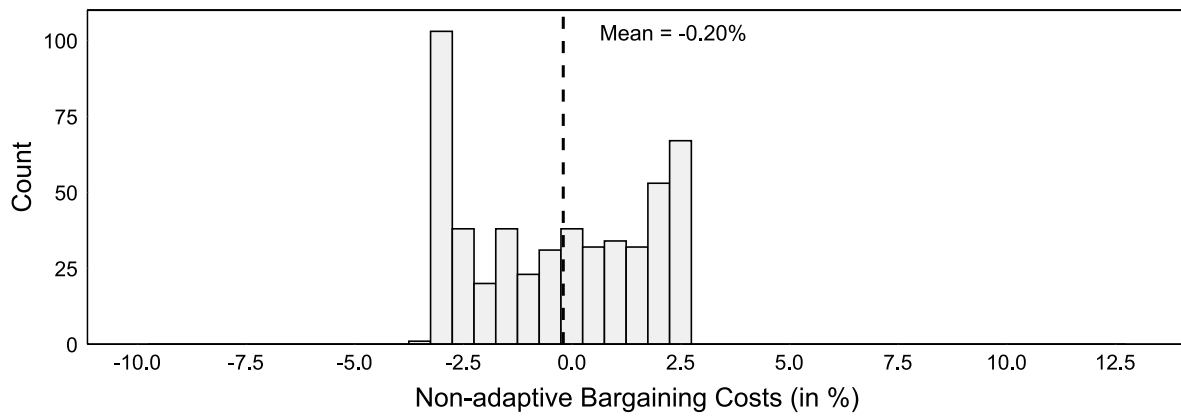


Figure A.6: Distribution of non-adaptive bargaining costs

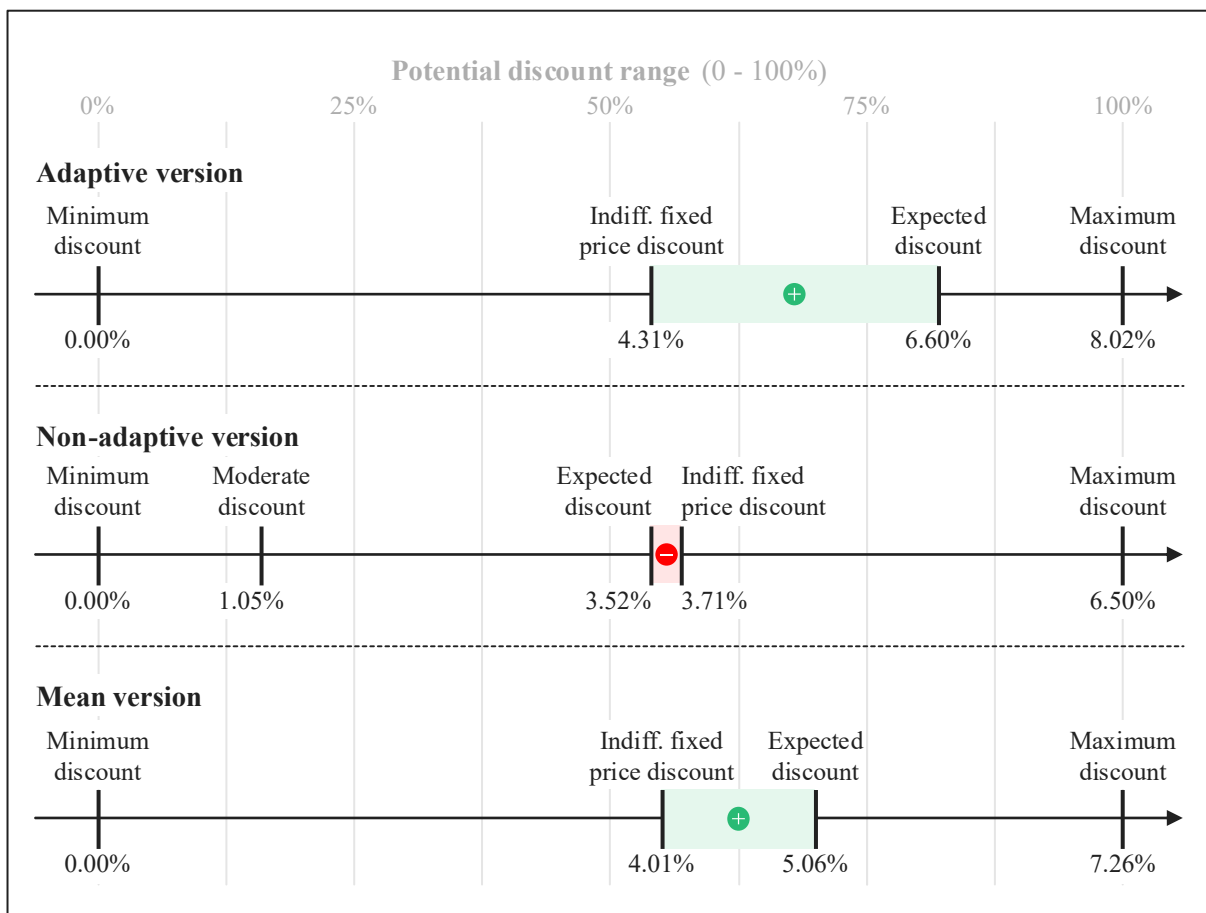


Figure A.7: Illustration of average discount ranges, expected discounts, and indifference fixed price discounts for the adaptive, non-adaptive, and mean version (the minimum discount corresponds to 0%, the maximum discount to 100%)

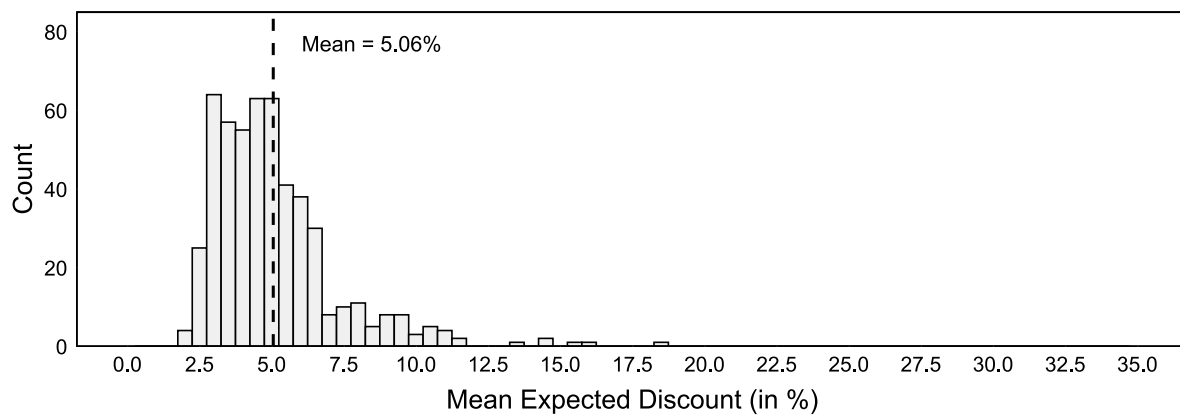


Figure A.8: Distribution of the mean expected discount

A.9 Additional regression outputs

	Dependent variable: adaptive bargaining costs - non-adaptive bargaining costs				
	(1)	(2)	(3)	(4)	(5)
Willingness to search (SEA)	-0.168 (0.200)		-0.222 (0.203)		-0.256 (0.262)
Opportunity cost of time (OPP)		0.159 (0.214)		0.139 (0.216)	0.011 (0.174)
Quality consciousness (QUA)			0.504** (0.249)	0.448* (0.242)	0.410* (0.246)
Sale proneness (SAL)	0.141 (0.212)	0.169 (0.221)	0.241 (0.215)	0.251 (0.223)	0.177 (0.227)
Post-purchase price confirmation (PRI)	0.033 (0.235)	-0.015 (0.241)	-0.026 (0.224)	-0.078 (0.228)	0.121 (0.202)
Car enthusiasm (CAR)	0.141 (0.222)	0.113 (0.220)			-0.033 (0.170)
Risk propensity (RIS)			0.075 (0.222)	0.093 (0.222)	0.137 (0.201)
(Internal) locus of control (LOC)	-0.247 (0.181)	-0.267 (0.180)	-0.341* (0.185)	-0.357* (0.185)	-0.346 (0.213)
Prevention focus (PRE)	-0.051 (0.187)	-0.064 (0.185)	-0.102 (0.190)	-0.117 (0.190)	-0.084 (0.233)
Promotion focus (PRO)	-0.099 (0.173)	-0.111 (0.173)	-0.198 (0.179)	-0.209 (0.178)	-0.164 (0.176)
Patience (PAT)	0.011 (0.171)	0.006 (0.171)	-0.029 (0.171)	-0.038 (0.171)	-0.015 (0.177)
Demographic controls (DC)	yes	yes	yes	yes	yes
Transaction controls (TC)	yes	yes	yes	yes	yes
Search & purchase behavior controls (SC)	yes	yes	yes	yes	yes
Factor loading-weighted items (CFA)	yes	yes	yes	yes	no
Equal-weighted items	no	no	no	no	yes
N	510	510	510	510	510
R ²	0.101	0.101	0.111	0.109	0.109
Note	* p < 0.10; ** p < 0.05; *** p < 0.01; robust standard errors in ()				

Table A.6: Multiple linear regression results for different model specifications (dependent variable: difference between *adaptive* and *non-adaptive relative bargaining costs*)

	Dependent variable: bargaining willingness				
	(1)	(2)	(3)	(4)	(5)
Willingness to search (SEA)	0.285 *** (0.050)		0.295 *** (0.051)		0.257 *** (0.065)
Opportunity cost of time (OPP)		-0.276 *** (0.054)		-0.286 *** (0.055)	-0.158 *** (0.043)
Quality consciousness (QUA)			-0.001 (0.062)	0.068 (0.061)	-0.010 (0.061)
Sale proneness (SAL)	0.052 (0.053)	0.003 (0.055)	0.051 (0.054)	0.006 (0.056)	0.024 (0.057)
Post-purchase price confirmation (PRI)	-0.066 (0.059)	0.017 (0.060)	-0.061 (0.056)	0.029 (0.058)	-0.008 (0.050)
Car enthusiasm (CAR)	0.033 (0.056)	0.079 (0.055)			0.024 (0.042)
Risk propensity (RIS)			0.054 (0.056)	0.050 (0.056)	0.033 (0.050)
(Internal) locus of control (LOC)	-0.060 (0.045)	-0.025 (0.045)	-0.062 (0.046)	-0.037 (0.047)	-0.049 (0.053)
Prevention focus (PRE)	0.008 (0.047)	0.030 (0.046)	0.013 (0.048)	0.028 (0.048)	0.031 (0.058)
Promotion focus (PRO)	0.005 (0.043)	0.026 (0.043)	-0.001 (0.045)	0.011 (0.045)	0.014 (0.044)
Patience (PAT)	-0.067 (0.043)	-0.060 (0.043)	-0.068 (0.043)	-0.063 (0.043)	-0.065 (0.044)
Demographic controls (DC)	yes	yes	yes	yes	yes
Transaction controls (TC)	yes	yes	yes	yes	yes
Search & purchase behavior controls (SC)	yes	yes	yes	yes	yes
Factor loading-weighted items (CFA)	yes	yes	yes	yes	no
Equal-weighted items	no	no	no	no	yes
N	510	510	510	510	510
R ²	0.354	0.346	0.355	0.347	0.363
Note	* p < 0.10; ** p < 0.05; *** p < 0.01; robust standard errors in ()				

Table A.7: Multiple linear regression results for different model specifications (dependent variable: *explicit* bargaining willingness)

	Dependent variable: bargaining indicator				
	(1)	(2)	(3)	(4)	(5)
Willingness to search (SEA)	0.076 (0.125)		0.172 (0.128)		0.016 (0.167)
Opportunity cost of time (OPP)		-0.171 (0.140)		-0.265* (0.142)	-0.180 (0.115)
Quality consciousness (QUA)			0.093 (0.162)	0.127 (0.159)	0.109 (0.162)
Sale proneness (SAL)	0.170 (0.137)	0.128 (0.143)	0.147 (0.142)	0.094 (0.148)	0.223 (0.150)
Post-purchase price confirmation (PRI)	-0.018 (0.153)	0.030 (0.158)	0.074 (0.147)	0.150 (0.152)	0.028 (0.133)
Car enthusiasm (CAR)	0.486*** (0.146)	0.497*** (0.144)			0.286** (0.112)
Risk propensity (RIS)			0.497*** (0.148)	0.514*** (0.150)	0.319** (0.135)
(Internal) locus of control (LOC)	-0.167 (0.119)	-0.154 (0.119)	-0.198 (0.122)	-0.177 (0.123)	-0.203 (0.141)
Prevention focus (PRE)	-0.092 (0.122)	-0.096 (0.121)	-0.039 (0.126)	-0.036 (0.127)	-0.077 (0.155)
Promotion focus (PRO)	0.128 (0.112)	0.132 (0.112)	0.064 (0.117)	0.067 (0.117)	0.095 (0.116)
Patience (PAT)	0.039 (0.111)	0.040 (0.111)	0.031 (0.111)	0.033 (0.111)	0.038 (0.116)
Demographic controls (DC)	yes	yes	yes	yes	yes
Transaction controls (TC)	yes	yes	yes	yes	yes
Search & purchase behavior controls (SC)	yes	yes	yes	yes	yes
Factor loading-weighted items (CFA)	yes	yes	yes	yes	no
Equal-weighted items	no	no	no	no	yes
N	502	502	502	502	502
AIC	639.250	638.110	637.480	635.740	636.640
Note	* p < 0.10; ** p < 0.05; *** p < 0.01; standard errors in ()				

Table A.8: Logistic regression results for different model specifications (dependent variable: *bargaining indicator*; note: N = 502 instead of N = 510 due to missing information for 8 respondents)

	Dependent variable: mean relative bargaining costs			
	Female	Male	Younger	Older
Willingness to search (SEA)	-0.458 (0.319)	-0.383* (0.215)	-0.638** (0.300)	-0.254 (0.215)
Opportunity cost of time (OPP)	0.440** (0.212)	0.365** (0.142)	0.374** (0.176)	0.390** (0.158)
Quality consciousness (QUA)	0.607** (0.290)	-0.240 (0.206)	0.405 (0.290)	-0.190 (0.192)
Sale proneness (SAL)	0.144 (0.250)	-0.158 (0.195)	-0.103 (0.247)	-0.036 (0.191)
Post-purchase price confirmation (PRI)	0.429* (0.233)	0.437*** (0.167)	0.432* (0.223)	0.473*** (0.168)
Car enthusiasm (CAR)	-0.244 (0.198)	0.154 (0.140)	0.078 (0.192)	0.016 (0.135)
Risk propensity (RIS)	0.466* (0.256)	0.163 (0.158)	0.081 (0.224)	0.397** (0.163)
(Internal) locus of control (LOC)	0.149 (0.250)	-0.239 (0.174)	-0.282 (0.220)	-0.037 (0.186)
Prevention focus (PRE)	0.107 (0.247)	0.063 (0.211)	0.119 (0.229)	0.198 (0.222)
Promotion focus (PRO)	-0.071 (0.235)	-0.094 (0.140)	-0.136 (0.184)	0.084 (0.157)
Patience (PAT)	0.088 (0.213)	-0.061 (0.148)	-0.104 (0.208)	-0.184 (0.140)
Demographic controls (DC)	yes	yes	yes	yes
Transaction controls (TC)	yes	yes	yes	yes
Search & purchase behavior controls (SC)	yes	yes	yes	yes
Factor loading-weighted items (CFA)	no	no	no	no
Equal-weighted items	yes	yes	yes	yes
N	187	321	246	264
R ²	0.341	0.301	0.272	0.262
Note	* p < 0.10; ** p < 0.05; *** p < 0.01; robust standard errors in ()			

Table A.9: Subsample regression results for female, male, younger (younger than median age of 49 years), and older (older than or equal to median age) respondents (dependent variable: *mean relative bargaining costs*)

	Dependent variable: mean relative bargaining costs				
	Purchase	Leasing	Financing	Low price	High price
Willingness to search (SEA)	-0.601 *** (0.209)	-0.360 (0.490)	-0.814 * (0.452)	-0.376 * (0.210)	-0.387 (0.349)
Opportunity cost of time (OPP)	0.224 (0.148)	0.360 (0.318)	0.411 (0.267)	0.280 * (0.150)	0.549 *** (0.211)
Quality consciousness (QUA)	-0.039 (0.206)	0.355 (0.429)	0.437 (0.401)	0.000 (0.198)	0.342 (0.314)
Sale proneness (SAL)	0.264 (0.213)	-0.659 (0.433)	0.324 (0.303)	0.012 (0.202)	-0.016 (0.235)
Post-purchase price confirmation (PRI)	0.126 (0.176)	0.935 ** (0.376)	1.169 *** (0.329)	0.305 * (0.169)	0.884 *** (0.261)
Car enthusiasm (CAR)	0.137 (0.145)	-0.001 (0.325)	-0.321 (0.255)	-0.002 (0.137)	0.024 (0.233)
Risk propensity (RIS)	0.108 (0.173)	0.808 ** (0.367)	-0.067 (0.285)	0.388 ** (0.177)	-0.052 (0.216)
(Internal) locus of control (LOC)	-0.038 (0.170)	-0.084 (0.362)	-0.600 * (0.347)	-0.096 (0.180)	0.030 (0.240)
Prevention focus (PRE)	-0.014 (0.194)	0.160 (0.418)	0.473 (0.388)	0.135 (0.208)	-0.008 (0.246)
Promotion focus (PRO)	0.024 (0.153)	-0.609 * (0.335)	0.002 (0.278)	0.042 (0.152)	-0.356 * (0.208)
Patience (PAT)	-0.008 (0.156)	-0.403 (0.285)	0.102 (0.276)	-0.156 (0.148)	-0.045 (0.219)
Demographic controls (DC)	yes	yes	yes	yes	yes
Transaction controls (TC)	yes	yes	yes	yes	yes
Search & purchase behavior controls (SC)	yes	yes	yes	yes	yes
Factor loading-weighted items (CFA)	no	no	no	no	no
Equal-weighted items	yes	yes	yes	yes	yes
N	268	133	109	326	184
R ²	0.305	0.436	0.507	0.236	0.456
Note	* p < 0.10; ** p < 0.05; *** p < 0.01; robust standard errors in ()				

Table A.10: Subsample regression results for purchase, leasing, financing, lower vehicle price (entry and mid-price segment according to S&P Global Mobility, 2024b classification), and higher vehicle price (premium and luxury price segment) respondents in their most recent new car transaction (dependent variable: *mean relative bargaining costs*)

	Dependent variable: mean relative bargaining costs			
	Online	Offline	Bargaining	No bargaining
Willingness to search (SEA)	-0.352 (0.290)	-0.355 (0.230)	-0.543** (0.224)	0.036 (0.300)
Opportunity cost of time (OPP)	0.718*** (0.210)	0.146 (0.136)	0.471*** (0.146)	0.118 (0.207)
Quality consciousness (QUA)	0.528 (0.337)	-0.050 (0.192)	0.290 (0.202)	-0.286 (0.305)
Sale proneness (SAL)	0.070 (0.325)	-0.089 (0.172)	0.067 (0.186)	-0.032 (0.284)
Post-purchase price confirmation (PRI)	0.390 (0.281)	0.322** (0.151)	0.374** (0.163)	0.655*** (0.248)
Car enthusiasm (CAR)	0.202 (0.241)	-0.014 (0.131)	-0.045 (0.133)	0.124 (0.225)
Risk propensity (RIS)	-0.187 (0.281)	0.392*** (0.150)	0.166 (0.165)	0.319 (0.238)
(Internal) locus of control (LOC)	-0.052 (0.270)	-0.201 (0.169)	-0.372** (0.172)	0.347 (0.261)
Prevention focus (PRE)	0.197 (0.269)	-0.182 (0.194)	0.110 (0.190)	-0.053 (0.280)
Promotion focus (PRO)	-0.283 (0.226)	0.149 (0.136)	-0.025 (0.138)	-0.253 (0.219)
Patience (PAT)	-0.538** (0.239)	0.027 (0.134)	-0.132 (0.142)	-0.111 (0.204)
Demographic controls (DC)	yes	yes	yes	yes
Transaction controls (TC)	yes	yes	yes	yes
Search & purchase behavior controls (SC)	yes	yes	yes	yes
Factor loading-weighted items (CFA)	no	no	no	no
Equal-weighted items	yes	yes	yes	yes
N	155	355	335	167
R ²	0.507	0.260	0.273	0.409
Note	* p < 0.10; ** p < 0.05; *** p < 0.01; robust standard errors in ()			

Table A.11: Subsample regression results for online and offline respondents (according to own classification logic), as well as respondents that did and did not bargain in their most recent new car transaction (dependent variable: *mean relative bargaining costs*)

	Dependent variable: mean relative bargaining costs			
	(1)	(2)	(3)	(4)
Willingness to search (SEA)	-0.420 ** (0.170)	-0.432 ** (0.172)	-0.455 *** (0.172)	-0.426 ** (0.172)
Opportunity cost of time (OPP)	0.406 *** (0.113)	0.397 *** (0.114)	0.376 *** (0.114)	0.393 *** (0.114)
Quality consciousness (QUA)	-0.232 (0.191)	-0.078 (0.248)	0.620 (0.396)	0.146 (0.714)
Sale proneness (SAL)	0.028 (0.148)	-0.005 (0.150)	0.004 (0.149)	0.004 (0.149)
Post-purchase price confirmation (PRI)	0.427 *** (0.131)	0.434 *** (0.132)	0.423 *** (0.132)	0.433 *** (0.132)
Car enthusiasm (CAR)	0.059 (0.111)	0.070 (0.112)	0.071 (0.111)	0.068 (0.111)
Risk propensity (RIS)	0.218 * (0.131)	0.204 (0.132)	0.203 (0.132)	0.208 (0.133)
(Internal) locus of control (LOC)	-0.061 (0.139)	-0.086 (0.140)	-0.091 (0.139)	-0.085 (0.140)
Prevention focus (PRE)	0.101 (0.151)	0.092 (0.153)	0.114 (0.152)	0.099 (0.153)
Promotion focus (PRO)	-0.035 (0.115)	-0.031 (0.115)	-0.034 (0.115)	-0.028 (0.115)
Patience (PAT)	-0.076 (0.116)	-0.106 (0.116)	-0.107 (0.116)	-0.105 (0.116)
Interaction QUA x female	0.673 ** (0.277)			
Interaction QUA x bargaining indicator		0.172 (0.289)		
Interaction QUA x new car experience			-0.142 * (0.086)	
Interaction QUA x price segment				-0.055 (0.306)
Demographic controls (DC)	yes	yes	yes	yes
Transaction controls (TC)	yes	yes	yes	yes
Search & purchase behavior controls (SC)	yes	yes	yes	yes
Factor loading-weighted items (CFA)	no	no	no	no
Equal-weighted items	yes	yes	yes	yes
N	510	510	510	510
R ²	0.246	0.237	0.240	0.236
Note	* p < 0.10; ** p < 0.05; *** p < 0.01; robust standard errors in ()			

Table A.12: Multiple linear regression results including different interaction effects with quality consciousness (dependent variable: *mean relative bargaining costs*)

	Dependent variable: mean relative bargaining costs			
	(1)	(2)	(3)	(4)
Willingness to search (SEA)	-0.430** (0.172)	-0.424** (0.172)	-0.427** (0.171)	-0.429** (0.172)
Opportunity cost of time (OPP)	0.389*** (0.114)	0.394*** (0.114)	0.393*** (0.114)	0.391*** (0.114)
Quality consciousness (QUA)	0.021 (0.161)	0.015 (0.162)	0.022 (0.161)	0.022 (0.161)
Sale proneness (SAL)	-0.028 (0.188)	-0.088 (0.243)	-0.070 (0.426)	0.099 (0.631)
Post-purchase price confirmation (PRI)	0.435*** (0.132)	0.430*** (0.132)	0.435*** (0.132)	0.433*** (0.132)
Car enthusiasm (CAR)	0.069 (0.112)	0.070 (0.112)	0.068 (0.111)	0.069 (0.112)
Risk propensity (RIS)	0.210 (0.132)	0.208 (0.132)	0.208 (0.133)	0.210 (0.132)
(Internal) locus of control (LOC)	-0.086 (0.140)	-0.081 (0.140)	-0.083 (0.139)	-0.083 (0.139)
Prevention focus (PRE)	0.105 (0.154)	0.100 (0.153)	0.100 (0.152)	0.100 (0.152)
Promotion focus (PRO)	-0.029 (0.115)	-0.034 (0.116)	-0.028 (0.115)	-0.030 (0.116)
Patience (PAT)	-0.105 (0.116)	-0.110 (0.116)	-0.109 (0.117)	-0.106 (0.116)
Interaction SAL x female	0.073 (0.277)			
Interaction SAL x bargaining indicator		0.141 (0.291)		
Interaction SAL x new car experience			0.016 (0.089)	
Interaction SAL x price segment				-0.040 (0.253)
Demographic controls (DC)	yes	yes	yes	yes
Transaction controls (TC)	yes	yes	yes	yes
Search & purchase behavior controls (SC)	yes	yes	yes	yes
Factor loading-weighted items (CFA)	no	no	no	no
Equal-weighted items	yes	yes	yes	yes
N	510	510	510	510
R ²	0.236	0.236	0.236	0.236
Note	* p < 0.10; ** p < 0.05; *** p < 0.01; robust standard errors in ()			

Table A.13: Multiple linear regression results including different interaction effects with sale proneness (dependent variable: *mean relative bargaining costs*)

	Dependent variable: mean relative bargaining costs			
	(1)	(2)	(3)	(4)
Willingness to search (SEA)	-0.435 ** (0.172)	-0.426 ** (0.172)	-0.419 ** (0.171)	-0.423 ** (0.171)
Opportunity cost of time (OPP)	0.392 *** (0.114)	0.393 *** (0.114)	0.369 *** (0.114)	0.387 *** (0.114)
Quality consciousness (QUA)	0.025 (0.161)	0.018 (0.162)	0.006 (0.161)	0.025 (0.161)
Sale proneness (SAL)	-0.004 (0.149)	0.002 (0.149)	0.004 (0.148)	-0.012 (0.150)
Post-purchase price confirmation (PRI)	0.435 *** (0.132)	0.434 *** (0.132)	0.424 *** (0.132)	0.425 *** (0.132)
Car enthusiasm (CAR)	0.108 (0.130)	0.102 (0.174)	0.500 * (0.266)	-0.364 (0.453)
Risk propensity (RIS)	0.207 (0.132)	0.208 (0.132)	0.202 (0.131)	0.216 (0.132)
(Internal) locus of control (LOC)	-0.086 (0.139)	-0.082 (0.140)	-0.086 (0.139)	-0.076 (0.139)
Prevention focus (PRE)	0.101 (0.152)	0.101 (0.153)	0.100 (0.152)	0.107 (0.152)
Promotion focus (PRO)	-0.025 (0.115)	-0.028 (0.115)	-0.042 (0.115)	-0.035 (0.115)
Patience (PAT)	-0.107 (0.116)	-0.104 (0.116)	-0.101 (0.116)	-0.116 (0.116)
Interaction CAR x female	-0.110 (0.185)			
Interaction CAR x bargaining indicator		-0.050 (0.190)		
Interaction CAR x new car experience			-0.098 * (0.055)	
Interaction CAR x price segment				0.190 (0.194)
Demographic controls (DC)	yes	yes	yes	yes
Transaction controls (TC)	yes	yes	yes	yes
Search & purchase behavior controls (SC)	yes	yes	yes	yes
Factor loading-weighted items (CFA)	no	no	no	no
Equal-weighted items	yes	yes	yes	yes
N	510	510	510	510
R ²	0.237	0.236	0.241	0.238
Note	* p < 0.10; ** p < 0.05; *** p < 0.01; robust standard errors in ()			

Table A.14: Multiple linear regression results including different interaction effects with car enthusiasm (dependent variable: *mean relative bargaining costs*)

	Dependent variable: mean relative bargaining costs			
	(1)	(2)	(3)	(4)
Willingness to search (SEA)	-0.426 ** (0.171)	-0.432 ** (0.171)	-0.429 ** (0.171)	-0.420 ** (0.171)
Opportunity cost of time (OPP)	0.389 *** (0.114)	0.407 *** (0.115)	0.386 *** (0.115)	0.390 *** (0.114)
Quality consciousness (QUA)	0.022 (0.161)	0.035 (0.161)	0.021 (0.161)	0.012 (0.161)
Sale proneness (SAL)	0.003 (0.149)	0.009 (0.149)	0.007 (0.150)	0.015 (0.149)
Post-purchase price confirmation (PRI)	0.434 *** (0.132)	0.427 *** (0.132)	0.435 *** (0.132)	0.433 *** (0.132)
Car enthusiasm (CAR)	0.066 (0.111)	0.060 (0.111)	0.066 (0.111)	0.059 (0.112)
Risk propensity (RIS)	0.184 (0.152)	0.180 (0.202)	0.322 (0.339)	0.830 (0.567)
(Internal) locus of control (LOC)	-0.080 (0.140)	-0.085 (0.139)	-0.085 (0.139)	-0.076 (0.139)
Prevention focus (PRE)	0.099 (0.152)	0.109 (0.152)	0.098 (0.152)	0.094 (0.152)
Promotion focus (PRO)	-0.026 (0.115)	-0.023 (0.115)	-0.032 (0.116)	-0.027 (0.115)
Patience (PAT)	-0.109 (0.116)	-0.111 (0.116)	-0.108 (0.116)	-0.111 (0.116)
Interaction RIS x female	0.085 (0.243)			
Interaction RIS x bargaining indicator		0.055 (0.239)		
Interaction RIS x new car experience			-0.026 (0.073)	
Interaction RIS x price segment				-0.260 (0.231)
Demographic controls (DC)	yes	yes	yes	yes
Transaction controls (TC)	yes	yes	yes	yes
Search & purchase behavior controls (SC)	yes	yes	yes	yes
Factor loading-weighted items (CFA)	no	no	no	no
Equal-weighted items	yes	yes	yes	yes
N	510	510	510	510
R ²	0.236	0.241	0.236	0.238
Note	* p < 0.10; ** p < 0.05; *** p < 0.01; robust standard errors in ()			

Table A.15: Multiple linear regression results including different interaction effects with risk propensity (dependent variable: *mean relative bargaining costs*)

A.10 Classification of respondents as offline and online customers

The classification of respondents as offline or online customers is based on their answers to questions related to the usage of channels (including purposes of use) and information sources. The classification logic involves several steps (*please note that steps 2.) – 6.) only apply if the previous step is not fulfilled*):

- 1.) **Dealer channel usage:** If a respondent did not indicate that she visited a dealer during the process, we classify this respondent as an online customer (*note that we filter out respondents that responded that they have not used any sales channel in our sample*).
- 2.) **Online channel usage:** If a respondent did not select any of the online channels (i.e., car manufacturer's website, dealer's website, comparison website, independent marketplace, or classifieds website), we classify this respondent as an offline customer.
- 3.) **Finalization of transaction:** If a respondent indicated that she finalized the transaction at a dealership, we classify this respondent as an offline customer (*exception: respondents who selected that they finalized the transaction through three or more channels are classified as online customers, since the dealership is the only offline channel available*).
- 4.) **Arranging of delivery:** If a respondent indicated that she arranged the delivery at a dealership, we classify this respondent as an offline customer (*exception: respondents who selected that they arranged the delivery through three or more channels are classified as online customers, since the dealership is the only offline channel available*).
- 5.) **Offline research:** If a respondent primarily used offline information sources, this respondent is classified as an offline customer. We define primary usage of offline sources based on the number of offline and online sources used. If the number of offline sources used is greater than the median number of offline sources used by all respondents, and the number of online sources used is less than the median number of online sources used, we assume that the respondent primarily used offline information sources.
- 6.) **Traditional product experience:** If a respondent used the dealership for purposes that can be considered as offline product experience (i.e., consultation, experiencing the car, test driving), we classified this respondent as an offline customer.

B Appendix Chapter 3

B.1 List of direct sales model implementation plans by sampled OEMs

OEM (sampled only)	Start	Direct sales implementation status (Germany)	Source
Mercedes	06/2023	Fully implemented	<i>Seyerlein (2023)</i>
Audi	01/2024	Partially implemented - EVs only	<i>Bäuchle (2023)</i>
Seat	10/2021	Partially implemented - sub-brand Cupra	<i>Autohaus (2020b)</i>
Volkswagen	06/2020	Partially implemented - EVs only	<i>Autohaus (2020a)</i>
BMW	10/2024	Planned - initially with sub-brand Mini	<i>Lulei (2024)</i>
Citroen	2027	Planned (start not officially communicated)	<i>Rehberg (2024)</i>
Fiat	2027	Planned	<i>Rehberg (2024)</i>
Opel	2027	Planned	<i>Rehberg (2024)</i>
Peugeot	2027	Planned	<i>Rehberg (2024)</i>
Skoda	01/2026	Planned - initially with EVs only	<i>Autohaus (2024d)</i>
Volvo	2026	Planned (start not officially communicated)	<i>Mauritz (2024)</i>
Ford	-/-	Initial plans stopped	<i>Bäuchle (2024)</i>
Hyundai	-/-	No plans (communicated)	-/-
Kia	-/-	No plans (communicated)	-/-
Land Rover / Jaguar	-/-	No plans (communicated)	-/-
Mazda	-/-	No plans (communicated)	-/-
Mitsubishi	-/-	No plans (communicated)	-/-
Nissan	-/-	No plans (communicated)	-/-
Renault / Dacia	-/-	No plans (communicated)	-/-
Subaru	-/-	No plans (communicated)	-/-
Suzuki	-/-	No plans (communicated)	-/-
Toyota	-/-	No plans (communicated)	-/-

Table B.1: List of direct sales model implementation plans for the German market by OEMs (*preliminary*)

B.2 List and description of focal variables

Focal variables	Explanation
Repeated questions (2022 and 2024)	
<i>REP_IntraIntensity</i>	Perceived degree to which they find themselves competing with intra-brand competitors <i>Five-point Likert-type scale: 1 = "not good at all", 5 = "very good"</i>
<i>REP_MainComp</i>	Perceived main competitor (in the new car sales business) <i>Selection of intra-brand, inter-brand, independent and other, or no competitors</i>
<i>REP_AgencyEval</i>	Evaluation of the introduction of an agency model for themselves as dealers <i>Five-point Likert-type scale: 1 = "not good at all", 5 = "very good"</i>
<i>REP_UniPriceEval</i>	Evaluation of the introduction of uniform pricing for themselves as dealers <i>Five-point Likert-type scale: 1 = "not good at all", 5 = "very good"</i>
Perceived competitive intensity	
<i>IntraPriceIntensity</i>	Perceived intensity of intra-brand price competition <i>Five-point Likert-type scale: 1 = "very weak", 5 = "very strong"</i>
<i>InterPriceIntensity</i>	Perceived intensity of inter-brand price competition <i>Five-point Likert-type scale: 1 = "very weak", 5 = "very strong"</i>
<i>IntraGenIntensity</i>	Perceived intensity of general intra-brand competition (including price competition) <i>Five-point Likert-type scale: 1 = "very weak", 5 = "very strong"</i>
<i>InterGenIntensity</i>	Perceived intensity of general inter-brand competition (including price competition) <i>Five-point Likert-type scale: 1 = "very weak", 5 = "very strong"</i>

Table B.2.a: List and description of focal variables (repeated survey questions and perceived competitive intensity)

Focal variables	Explanation
Price-related intra-brand differentiation tactics – usage intensity of ...	
<i>IndivDiscIntensity</i>	... customer-individually negotiated discounts to differentiate (i.e., discounts individually negotiated with customers, such as negotiated rebates, negotiated special financing or leasing conditions or individually negotiated trade-in incentives) <i>Five-point Likert-type scale: 1 = “not at all”, 5 = “very strongly”</i>
<i>GenDiscIntensity</i>	... general, customer-independent discounts to differentiate (i.e., centrally defined discounts that are not individually negotiated, e.g., seasonal or introductory discounts, special promotions, volume discounts, sales discounts or fixed loyalty discounts) <i>Five-point Likert-type scale: 1 = “not at all”, 5 = “very strongly”</i>
<i>ProdExtraIntensity</i>	... (free or discounted) product-related extras to differentiate (e.g., winter tires, accessories or insurance) <i>Five-point Likert-type scale: 1 = “not at all”, 5 = “very strongly”</i>
<i>ServExtraIntensity</i>	... (free or discounted) service-related extras to differentiate (e.g., maintenance packages or vehicle reconditioning) <i>Five-point Likert-type scale: 1 = “not at all”, 5 = “very strongly”</i>
Price-related intra-brand differentiation tactics – usage intensity of ...	
<i>TargDiffIntensity</i>	... measures to improve sales initiation, customer approach, and digital interaction (e.g., marketing campaigns, customer targeting, online appointment, and configuration options and virtual showrooms) <i>Five-point Likert-type scale: 1 = “not at all”, 5 = “very strongly”</i>
<i>ProdDiffIntensity</i>	... measures to improve product variety and customization options (e.g., offering special vehicle models, individual vehicle configurations, and special equipment options) <i>Five-point Likert-type scale: 1 = “not at all”, 5 = “very strongly”</i>
<i>ServDiffIntensity</i>	... measures to improve service quality and customer advice (e.g., personalized services and consultations, exclusive maintenance services, or VIP customer services) <i>Five-point Likert-type scale: 1 = “not at all”, 5 = “very strongly”</i>
<i>LoyDiffIntensity</i>	... measures to improve customer loyalty and experience programs (e.g., loyalty programs, exclusive customer events, VIP events, and regular contact) <i>Five-point Likert-type scale: 1 = “not at all”, 5 = “very strongly”</i>

Table B.2.b: List and description of focal variables (differentiation tactics usage)

B.3 Additional sample summary statistics

Brand	Sales Partnership		Main brand		Market share Germany 2024 (first half)	
	N	Share	N	Share	New car sales	Sales partners
Audi	49	9%	30	8%	7%	4%
BMW	32	6%	32	8%	8%	5%
Citroen	7	1%	2	1%	2%	2%
Fiat	13	2%	8	2%	3%	5%
Ford	36	7%	33	8%	5%	5%
Hyundai	31	6%	19	5%	3%	6%
Kia	12	2%	7	2%	3%	5%
Land Rover / Jaguar	6	1%	3	1%	1%	2%
Mazda	18	3%	11	3%	2%	5%
Mercedes	54	10%	54	14%	11%	5%
Mitsubishi	17	3%	14	4%	1%	5%
Nissan	14	3%	10	3%	1%	4%
Opel	33	6%	26	7%	6%	6%
Peugeot	16	3%	5	1%	3%	3%
Renault / Dacia	20	4%	17	4%	5%	8%
Seat	22	4%	9	2%	3%	4%
Skoda	29	5%	10	3%	7%	6%
Subaru	5	1%	3	1%	0%	2%
Suzuki	11	2%	5	1%	1%	4%
Toyota	17	3%	16	4%	3%	4%
Volkswagen	77	14%	61	16%	22%	8%
Volvo	20	4%	14	4%	2%	3%

Table B.3.a: Brand split 2024 sample by sales partnerships and main brands (based on revenue) compared to actual market shares (new car sales data from S&P Global Mobility, 2024b; sales partner data from Plate and Haunschild, 2024)

Brand	Sales Partnership		Mono brand		Market share Germany 2021 (second half)	
	N	Share	N	Share	New car sales	Sales partners
Audi	47	9%	25	8%	6%	4%
BMW	40	8%	37	12%	9%	5%
Citroen	15	3%	3	1%	2%	3%
Fiat	18	4%	16	5%	4%	6%
Ford	32	6%	22	7%	6%	6%
Hyundai	15	3%	7	2%	5%	5%
Kia	12	2%	2	1%	3%	4%
Land Rover / Jaguar	2	0%	0	0%	1%	2%
Mazda	22	4%	18	6%	2%	5%
Mercedes	25	5%	23	8%	11%	4%
Mitsubishi	18	4%	12	4%	2%	5%
Nissan	22	4%	11	4%	1%	3%
Opel	30	6%	16	5%	7%	7%
Peugeot	12	2%	4	1%	2%	3%
Renault / Dacia	23	5%	19	6%	7%	8%
Seat	20	4%	4	1%	3%	4%
Skoda	27	5%	8	3%	5%	6%
Subaru	6	1%	1	0%	0%	2%
Suzuki	10	2%	3	1%	1%	4%
Toyota	15	3%	13	4%	3%	4%
Volkswagen	67	13%	44	14%	19%	9%
Volvo	28	6%	17	6%	2%	2%

Table B.3.b: Brand split 2022 sample by sales partnerships and mono-brand dealerships compared to actual market shares (new car sales data from S&P Global Mobility, 2024b; sales partner data from Plate and Haunschild, 2023)

Full sample 2024 [N = 389]	N	Share	Full sample 2024 [N = 389]	N	Share
City size dealership location (number of inhabitants)			ZIP-code (first digit)		
< 5,000	23	6%	0	51	13%
5,000-20,000	113	29%	1	24	6%
20,000-100,000	167	43%	2	36	9%
> 100,000	86	22%	3	30	8%
Price Negotiability			4	30	8%
All new car prices negotiable	231	59%	5	39	10%
Some new car prices negotiable	100	26%	6	35	9%
No new car prices negotiable	58	15%	7	57	15%
Online Sales Channel Offering			8	48	12%
Own online channel	113	29%	9	39	10%
OEM-provided online channel	217	56%			
No online channel	59	15%			

Table B.4: Additional summary statistics 2024 sample (city size and ZIP-code dealership location, price negotiability, and online sales channel offering)

Full 2024 sample dealership distribution

Population distribution Germany (as of 05/2022)

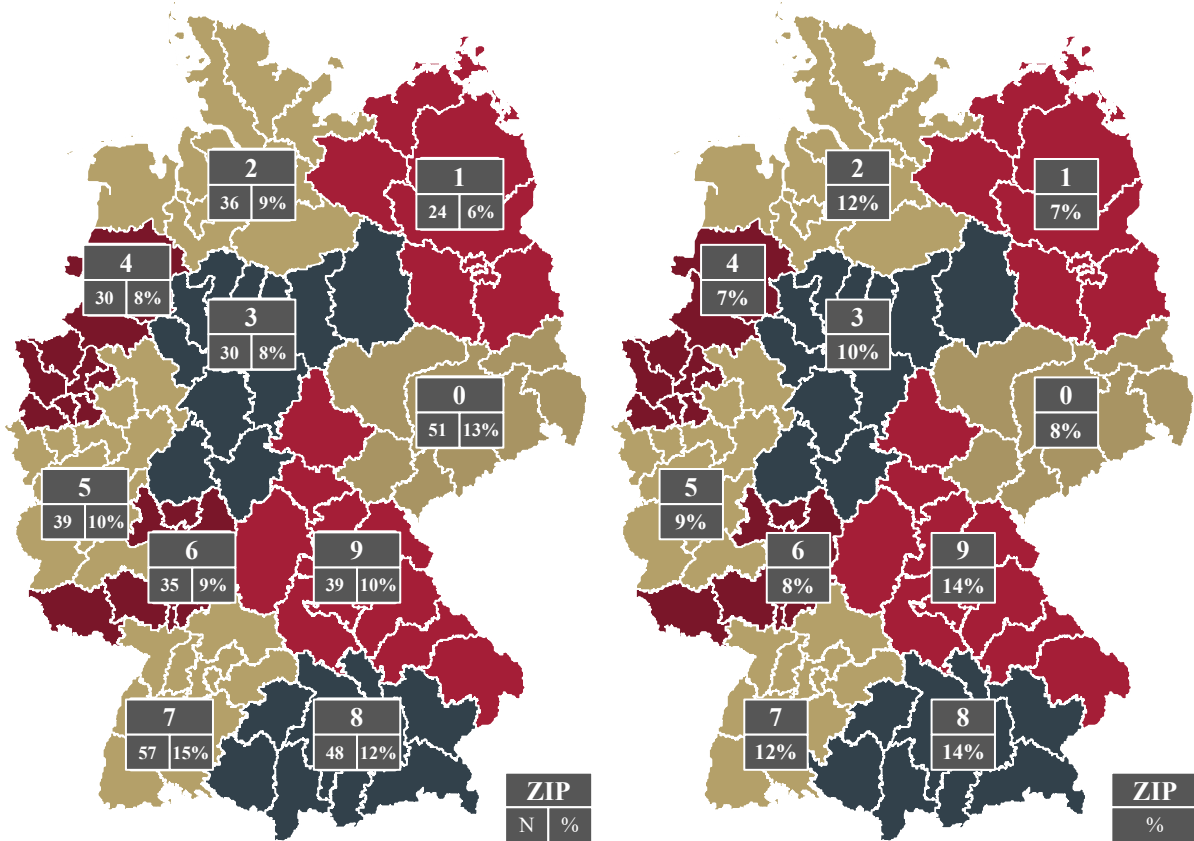


Figure B.1.a: Regional dealership distribution by first digit of ZIP-code (2024 sample) (in comparison to population distribution in Germany as of 05/2022, source: Statistisches Bundesamt, 2024)

2024 sample Mercedes dealership distribution

Mercedes dealership distribution (as of 08/2024)

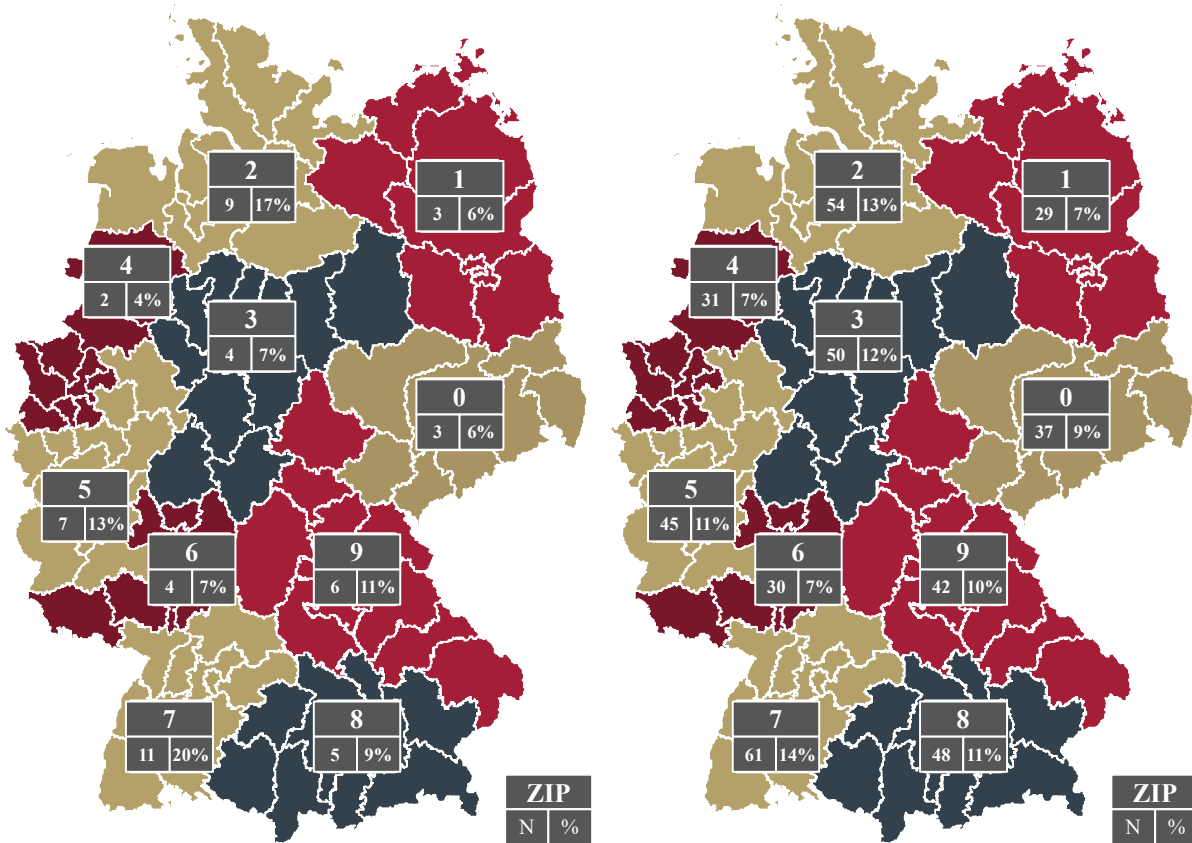


Figure B.1.b: Regional Mercedes dealership distribution by first digit of ZIP-code (2024 sample) (in comparison to Mercedes new car sales partner distribution in Germany as of 08/2024, source: Mercedes-Benz AG, 2024)

Segmentation	N	Share	Segmentation	N	Share
Car sales 2023			New car sales 2023		
0-100 cars	29	7%	0-100 cars	106	27%
101-200 cars	62	16%	101-200 cars	93	24%
201-500 cars	132	34%	201-500 cars	123	32%
501-1,000 cars	78	20%	501-1,000 cars	31	8%
1,001-2,000 cars	61	16%	1,001-2,000 cars	24	6%
> 2,000 cars	27	7%	> 2,000 cars	12	3%
Car sales 2022			New car sales 2022		
0-100 cars	26	7%	0-100 cars	94	24%
101-200 cars	56	14%	101-200 cars	103	26%
201-500 cars	129	33%	201-500 cars	125	32%
501-1,000 cars	96	25%	501-1,000 cars	31	8%
1,001-2,000 cars	55	14%	1,001-2,000 cars	29	7%
> 2,000 cars	27	7%	> 2,000 cars	7	2%

Table B.5: Distribution of annual car sales and new car sales 2022 and 2023 (2024 sample)

Segmentation	N	Share	Segmentation	N	Share
Car sales 2021			New car sales 2021		
0-100 cars	112	29%	0-100 cars	192	50%
101-200 cars	83	22%	101-200 cars	76	20%
201-500 cars	110	29%	201-500 cars	85	22%
501-1,000 cars	61	16%	501-1,000 cars	22	6%
1,001-2,000 cars	14	4%	1,001-2,000 cars	8	2%
> 2,000 cars	4	1%	> 2,000 cars	1	0%

Table B.6: Distribution of annual car sales and new car sales 2021 (2022 sample)

Segmentation	N	Share	Segmentation	N	Share
New car sales share 2022			New car sales share 2023		
0-20%	22	6%	0-20%	27	7%
21-30%	44	11%	21-30%	48	12%
31-40%	63	16%	31-40%	72	19%
41-50%	114	29%	41-50%	100	26%
51-60%	42	11%	51-60%	35	9%
61-70%	37	10%	61-70%	32	8%
71-80%	16	4%	71-80%	20	5%
81-100%	51	13%	81-100%	55	14%
Online sales channel share 2022			Electric vehicle (EV) sales share 2022		
0-10%	293	75%	0-10%	171	44%
11-20%	55	14%	11-20%	132	34%
21-30%	17	4%	21-30%	49	13%
31-40%	4	1%	31-40%	15	4%
41-50%	9	2%	41-50%	15	4%
51-60%	5	1%	51-60%	4	1%
61-70%	2	1%	61-70%	2	1%
71-80%	4	1%	71-80%	1	0%
81-100%	0	0%	81-100%	0	0%

Table B.7: Distribution of new car sales shares 2022 and 2023, online sales channel shares 2022, and electric vehicle sales shares 2022 (2024 sample)

Segmentation	N	Share	Segmentation	N	Share
New car sales share 2021			Average online sales channel share		
0-10%	3	1%	0-10%	308	80%
11-20%	6	2%	11-20%	36	9%
21-30%	45	12%	21-30%	16	4%
31-40%	71	18%	31-40%	7	2%
41-50%	96	25%	41-50%	11	3%
51-60%	44	11%	51-60%	2	1%
61-70%	41	11%	61-70%	1	0%
71-80%	22	6%	71-80%	3	1%
81-100%	56	15%	81-100%	0	0%

Table B.8: Distribution of new car sales shares 2021 and average online sales channel shares (2022 sample)

Variable	Mean	Min	1 st Qua.	Median	3 rd Qua.	Max
Car sales 2023	930	20	230	430	1,000	15,000
Car sales 2022	945	20	240	450	900	24,150
New car sales 2023	435	12	100	200	400	10,000
New car sales 2022	418	10	110	200	400	9,000
New car sales share 2023	53	5	35	49	66	100
New car sales share 2022	53	2	38	50	64	100
Stock Vehicles 2022 (average number)	55	2	15	27	50	1,000
Employees 2022 (average number)	68	4	20	35	75	900
Online channel sales share 2022 (%)	9	0	0	5	10	80
EV sales share 2022 (%)	16	0	5	15	20	75

Table B.9: Descriptive statistics for annual car sales, new car sales, and new car sales shares 2022 and 2023, stock vehicles, employees, online channel sales shares, and EV sales share 2022 (2024 sample)

Variable	Mean	Min	1 st Qua.	Median	3 rd Qua.	Max
Car sales 2021	364	20	100	200	493	5,000
New car sales 2021	213	10	50	101	250	5,000
New car sales share 2021	56	5	40	50	70	100
Online channel sales share (average, %)	8	0	0	0	10	80

Table B.10: Descriptive statistics for annual car sales, new car sales, and new car sales shares 2021, and average online channel sales shares (2022 sample)

Variable	Mean	Min	1 st Qua.	Median	3 rd Qua.	Max
Sales partners 2024 (OEM)	394	134	309	401	474	690
Service partners 2024 (OEM)	355	36	122	236	497	1,076
Branches (“Niederlassungen”) 2024 (OEM)	11	0	0	0	14	69

Table B.11. Descriptive statistics for OEM-level numbers of sales partners, service partners, and branches (“Niederlassungen”) 2024 (2024 sample) (source: Plate & Haunschild, 2024)

Variable	Mean	Min	1 st Qua.	Median	3 rd Qua.	Max
Sales partners 2022 (OEM)	421	140	325	408	522	802
Service partners 2022 (OEM)	361	39	118	251	503	1,065
Branches (“Niederlassungen”) 2022 (OEM)	10	0	0	0	13	69

Table B.12: Descriptive statistics for OEM-level numbers of sales partners, service partners, and branches (“Niederlassungen”) 2022 (2022 sample) (source: Plate & Haunschild, 2023)

Mercedes dealers 2024 [N = 54]			Mercedes dealers 2022 [N = 25]		
	N	Share		N	Share
Position in dealership			Position in dealership		
Owner / managing director	2	4%	Owner / managing director	3	12%
Location manager / representative	3	6%	Location manager / representative	2	8%
Sales manager / salesperson	48	89%	Sales manager / salesperson	20	80%
Other position	1	2%	Other position	0	0%
Business model of dealership			Business model of dealership		
New car sales only	14	26%	New car sales only	4	16%
New and used car sales	40	74%	New and used car sales	21	84%
No new car sales	0	0%	No new car sales	0	0%
Mono- vs. multi-brand dealerships			Mono- vs. multi-brand dealerships		
Mono-brand	53	98%	Mono-brand	23	92%
Multi-brand	1	2%	Multi-brand	2	8%
Price segment			Price segment		
Premium	53	98%	Premium	23	92%
Hybrid (premium & volume)	1	2%	Hybrid (premium & volume)	2	8%
Volume	0	0%	Volume	0	0%

Table B.13: Summary statistics for Mercedes dealers of the 2024 and 2022 samples

Mercedes dealers 2024 [N = 54]	N	Share	Mercedes dealers 2024 [N = 54]	N	Share
City size dealership location (number of inhabitants)			ZIP-code (first digit)		
< 5,000	1	2%	0	3	6%
5,000-20,000	12	22%	1	3	6%
20,000-100,000	30	56%	2	9	17%
> 100,000	11	20%	3	4	7%
Price Negotiability			4	2	4%
All new car prices negotiable	0	0%	5	7	13%
Some new car prices negotiable	1	2%	6	4	7%
No new car prices negotiable	53	98%	7	11	20%
Online Sales Channel Offering			8	5	9%
Own online channel	11	20%	9	6	11%
OEM-provided online channel	32	59%			
No online channel	11	20%			

Table B.14: Additional summary statistics for Mercedes dealers of the 2024 sample (city size and ZIP-code dealership location, price negotiability, and online sales channel offering)

Mercedes dealers 2024 [N = 54]	N	Share	Mercedes dealers 2024 [N = 54]	N	Share
Car sales 2023			New car sales 2023		
0-100 cars	10	19%	0-100 cars	20	37%
101-200 cars	6	11%	101-200 cars	5	9%
201-500 cars	16	30%	201-500 cars	18	33%
501-1,000 cars	10	19%	501-1,000 cars	6	11%
1,001-2,000 cars	8	15%	1,001-2,000 cars	4	7%
> 2,000 cars	4	7%	> 2,000 cars	1	2%
Car sales 2022			New car sales 2022		
0-100 cars	7	13%	0-100 cars	14	26%
101-200 cars	6	11%	101-200 cars	11	20%
201-500 cars	14	26%	201-500 cars	16	30%
501-1,000 cars	16	30%	501-1,000 cars	7	13%
1,001-2,000 cars	7	13%	1,001-2,000 cars	6	11%
> 2,000 cars	4	7%	> 2,000 cars	0	0%

Table B.15: Distribution of annual car sales and new car sales 2022 and 2023 (Mercedes dealers of the 2024 sample)

Mercedes dealers 2022 [N = 25]	N	Share	Mercedes dealers 2022 [N = 25]	N	Share
Car sales 2021			New car sales 2021		
0-100 cars	7	28%	0-100 cars	9	36%
101-200 cars	2	8%	101-200 cars	5	20%
201-500 cars	6	24%	201-500 cars	8	32%
501-1,000 cars	6	24%	501-1,000 cars	3	12%
1,001-2,000 cars	4	16%	1,001-2,000 cars	0	0%
> 2,000 cars	0	0%	> 2,000 cars	0	0%

Table B.16: Distribution of annual car sales and new car sales 2021 (Mercedes dealers of the 2022 sample)

Mercedes dealers 2024 [N = 54]	N	Share	Mercedes dealers 2024 [N = 54]	N	Share
New car sales share 2022			New car sales share 2023		
0-20%	2	4%	0-20%	1	2%
21-30%	7	13%	21-30%	9	17%
31-40%	8	15%	31-40%	9	17%
41-50%	10	19%	41-50%	10	19%
51-60%	5	9%	51-60%	2	4%
61-70%	2	4%	61-70%	1	2%
71-80%	4	7%	71-80%	3	6%
81-100%	16	30%	81-100%	19	35%
Online sales channel share 2022			Electric vehicle (EV) sales share 2022		
0-10%	50	93%	0-10%	15	28%
11-20%	1	2%	11-20%	24	44%
21-30%	1	2%	21-30%	9	17%
31-40%	2	4%	31-40%	3	6%
41-50%	0	0%	41-50%	2	4%
51-60%	0	0%	51-60%	1	2%
61-70%	0	0%	61-70%	0	0%
71-80%	0	0%	71-80%	0	0%
81-100%	0	0%	81-100%	0	0%

Table B.17: Distribution of new car sales shares 2022 and 2023, online sales channel shares 2022, and electric vehicle sales shares 2022 (Mercedes dealers of the 2024 sample)

Mercedes dealers 2022 [N = 25]	N	Share	Mercedes dealers 2022 [N = 25]	N	Share
New car sales share 2021			Average online sales channel share		
0-10%	1	4%	0-10%	22	88%
11-20%	0	0%	11-20%	2	8%
21-30%	4	16%	21-30%	1	4%
31-40%	6	24%	31-40%	0	0%
41-50%	6	24%	41-50%	0	0%
51-60%	3	12%	51-60%	0	0%
61-70%	0	0%	61-70%	0	0%
71-80%	0	0%	71-80%	0	0%
81-100%	5	20%	81-100%	0	0%

Table B.18: Distribution of new car sales shares 2021 and average online sales channel shares (Mercedes dealers of the 2022 sample)

Mercedes dealers 2024 [N = 54]	Mean	Min	1 st Qua.	Median	3 rd Qua.	Max
Car sales 2023	798	30	200	380	982	5,500
Car sales 2022	841	63	213	501	938	6,000
New car sales 2023	416	30	94	275	446	3,000
New car sales 2022	437	30	105	266	497	2,500
New car sales share 2023	63	15	36	50	100	100
New car sales share 2022	61	13	39	51	100	100
Stock Vehicles 2022 (average number)	46	3	16	30	47	390
Employees 2022 (average number)	121	16	41	78	130	850
Online channel sales share 2022 (%)	5	0	0	3	5	39
EV sales share 2022 (%)	18	0	10	17	21	60

Table B.19: Descriptive statistics for annual car sales, new car sales, and new car sales shares 2022 and 2023, stock vehicles, employees, online channel sales shares, and EV sales share 2022 (Mercedes dealers of the 2024 sample)

Mercedes dealers 2024 [N = 54]	Mean	Min	1 st Qua.	Median	3 rd Qua.	Max
Car sales 2021	546	50	100	475	800	2,000
New car sales 2021	268	18	50	188	420	1,000
New car sales share 2021	53	5	40	50	60	100
Online channel sales share (average, %)	4	0	0	0	5	30

Table B.20: Descriptive statistics for annual car sales, new car sales, and new car sales shares 2021, and average online channel sales shares (Mercedes dealers of the 2022 sample)

B.4 Additional descriptive figures for focal variables

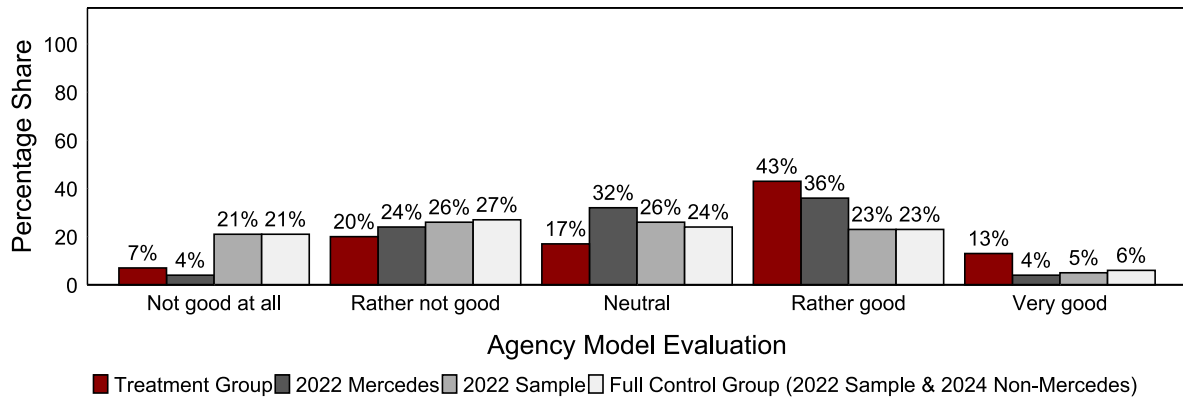


Figure B.2: Agency model evaluation - frequency distribution by treatment and control groups

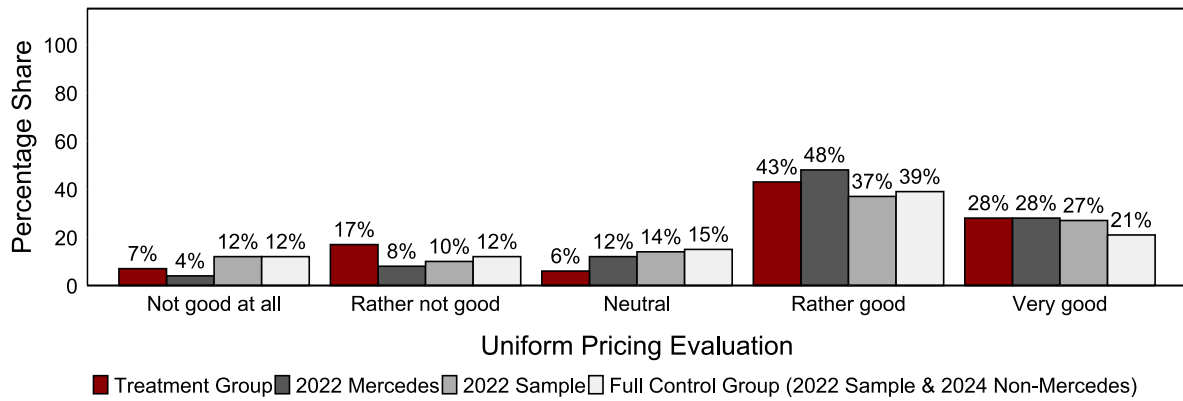


Figure B.3: Uniform price evaluation - frequency distribution by treatment and control groups

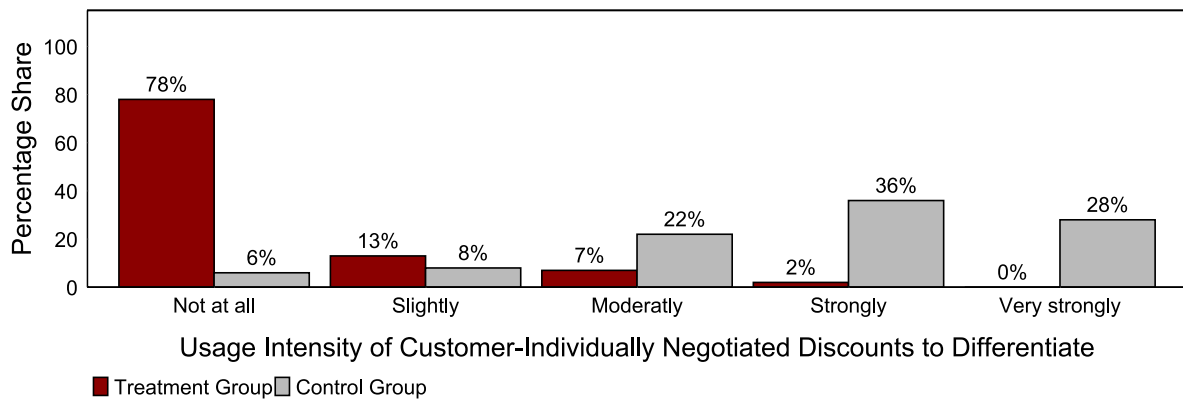


Figure B.4: Usage intensity of customer-individually negotiated discounts to differentiate - frequency distribution by treatment and control groups

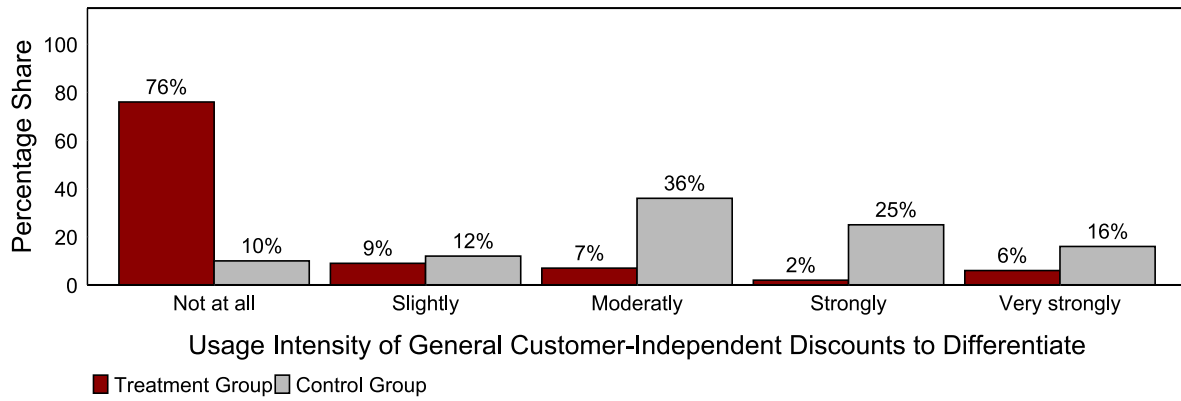


Figure B.5: Usage intensity of general, customer-independent discounts to differentiate - frequency distribution by treatment and control groups

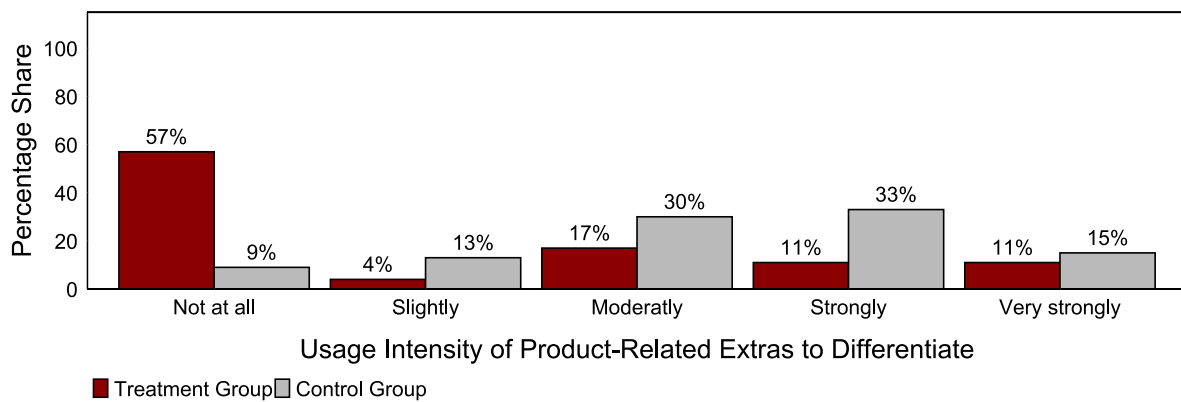


Figure B.6: Usage intensity of product-related extras to differentiate - frequency distribution by treatment and control groups

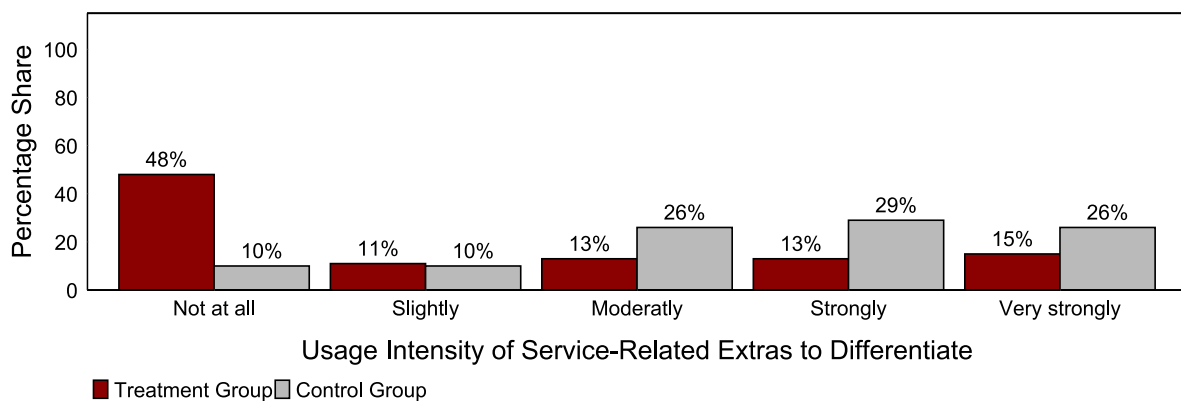


Figure B.7: Usage intensity of service-related extras to differentiate - frequency distribution by treatment and control groups

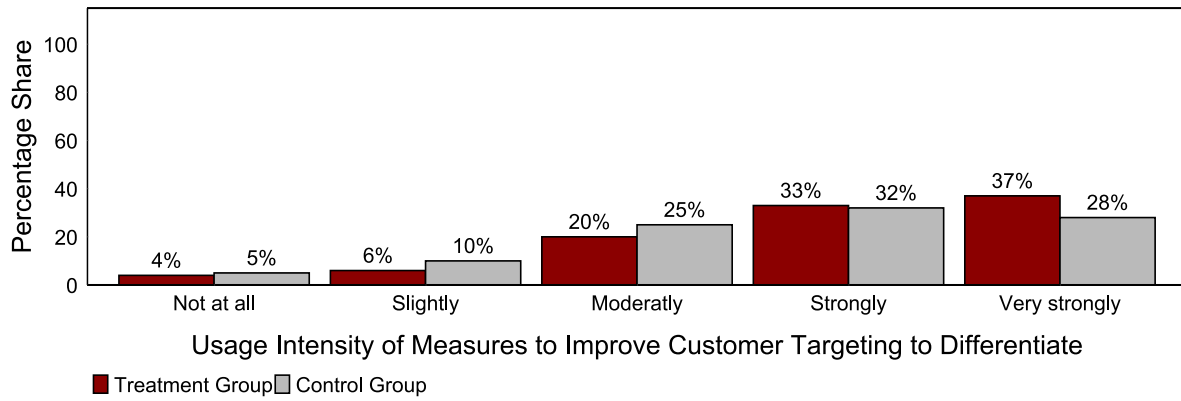


Figure B.8: Usage intensity of measures to improve customer targeting to differentiate - frequency distribution by treatment and control groups

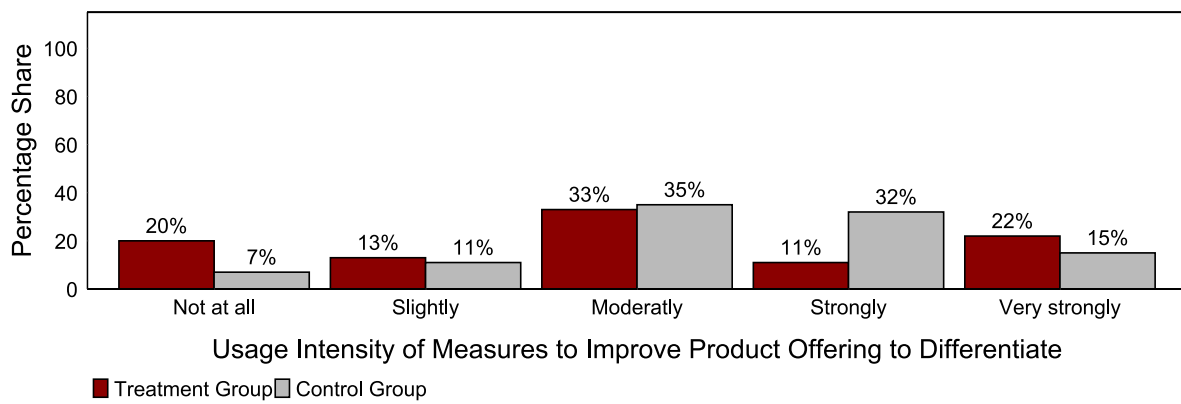


Figure B.9: Usage intensity of measures to improve the product offering to differentiate - frequency distribution by treatment and control groups

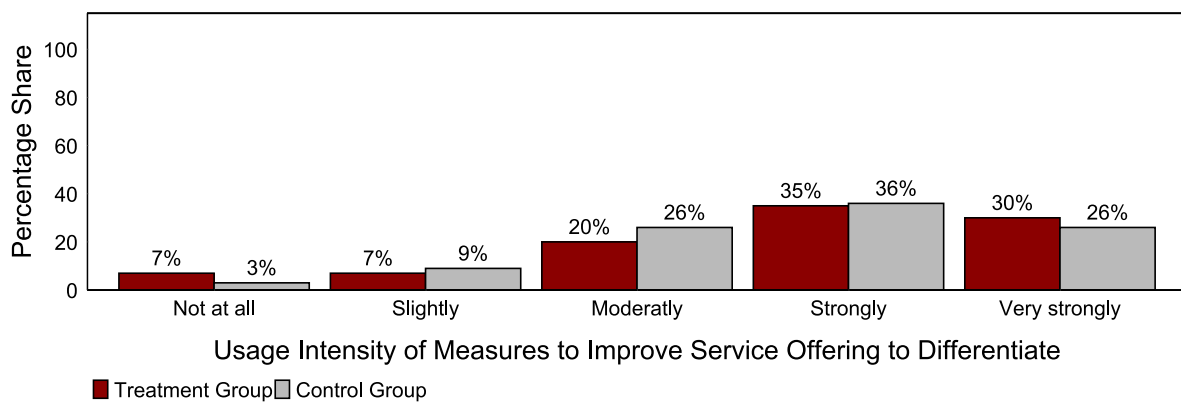


Figure B.10: Usage intensity of measures to improve the service offering to differentiate - frequency distribution by treatment and control groups

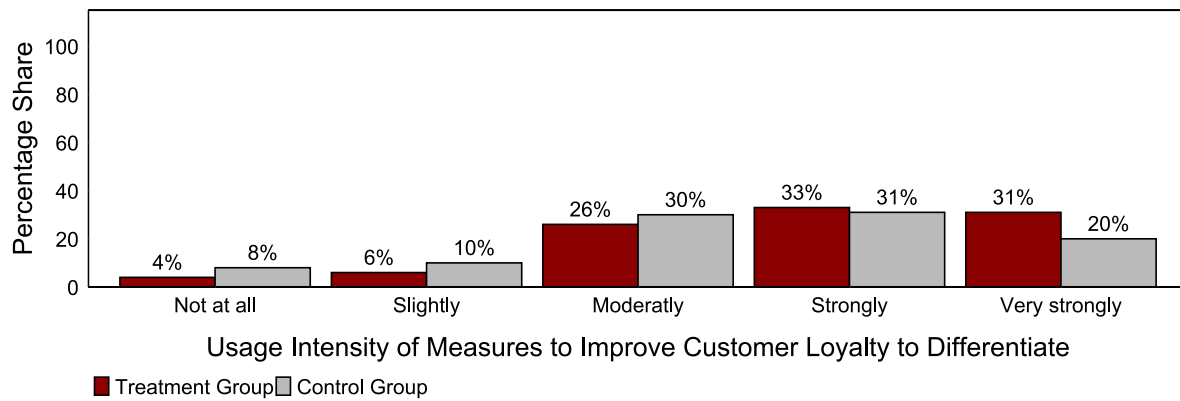


Figure B.11: Usage intensity of measures to improve customer loyalty to differentiate - frequency distribution by treatment and control groups

B.5 Additional regression outputs

Dependent variable:	<i>REP_AgencyEval</i>		<i>REP_UniPriceEval</i>	
	(1)	(2)	(3)	(4)
Direct-to-consumer sales	0.683 *** (0.171)	0.180 (0.273)	0.329 * (0.183)	-0.025 (0.305)
New car sales previous year (log)		0.070 (0.044)		-0.026 (0.048)
Multi-brand dealership		-0.138 (0.213)		0.101 (0.196)
New car-only dealership		0.081 (0.141)		0.053 (0.142)
Fixed effects:				
Year	no	yes	no	yes
Respondents' position	no	yes	no	yes
OEM sales & service partner network size	no	no	no	no
Partnering brand/s	no	yes	no	yes
N	773	773	773	773
R ²	0.020	0.109	0.009	0.080
Note	* p < 0.10; ** p < 0.05; *** p < 0.01; robust standard errors in ()			

Table B.21: Multiple linear regression results for different model specifications (*REP_AgencyEval*, *REP_UniPriceEval*)

Dependent variable:	<i>IntraPriceIntensity</i>			
	(1)	(2)	(3)	(4)
Direct-to-consumer sales	-1.021 *** (0.138)	-1.462 *** (0.205)	-1.463 *** (0.205)	-1.470 *** (0.204)
Car sales 2022 (log)		0.061 (0.054)		
New car sales 2022 (log)			0.073 (0.058)	
Stock vehicles 2022 (log, average number)				0.061 (0.052)
Employees 2022 (log, average number)				
Multi-brand dealership		0.038 (0.139)	0.033 (0.138)	0.044 (0.138)
New car-only dealership		0.244 (0.157)	0.195 (0.158)	
New car share 2022				0.094 (0.108)
<u>Additional controls:</u>				
Respondents' position	no	yes	yes	yes
OEM (partnering main brand)	no	yes	yes	yes
Price segment (partnering brand/s)	no	yes	yes	yes
Partnering brand/s	no	no	no	no
Agency model plans of OEM (main brand)	no	no	no	no
Dealership location	no	yes	yes	yes
Dealership online and EV offering	no	yes	yes	yes
N	389	389	389	389
R ²	0.119	0.233	0.234	0.232
Note	* p < 0.10; ** p < 0.05; *** p < 0.01; robust standard errors in ()			

Table B.22.a: Multiple linear regression results for different model specifications (*IntraPriceIntensity*) – part 1/2

Dependent variable:	<i>IntraPriceIntensity</i>			
	(1)	(5)	(6)	(7)
Direct-to-consumer sales	-1.021 *** (0.138)	-1.514 *** (0.205)	-1.082 *** (0.190)	-0.844 *** (0.163)
Car sales 2022 (log)				
New car sales 2022 (log)			0.059 (0.061)	0.093 (0.058)
Stock vehicles 2022 (log, average number)				
Employees 2022 (log, average number)		0.076 (0.064)		
Multi-brand dealership		0.044 (0.137)	0.082 (0.183)	-0.038 (0.118)
New car-only dealership			0.218 (0.160)	0.151 (0.157)
New car share 2022		0.111 (0.108)		
<u>Additional controls:</u>				
Respondents' position	no	yes	yes	yes
OEM (partnering main brand)	no	yes	no	no
Price segment (partnering brand/s)	no	yes	no	no
Partnering brand/s	no	no	yes	no
Agency model plans of OEM (main brand)	no	no	no	yes
Dealership location	no	yes	yes	yes
Dealership online and EV offering	no	yes	yes	yes
N	389	389	389	389
R ²	0.119	0.232	0.267	0.223
Note	* p < 0.10; ** p < 0.05; *** p < 0.01; robust standard errors in ()			

Table B.22.b: Multiple linear regression results for different model specifications (*IntraPriceIntensity*) – part 2/2

Dependent variable:	<i>InterPriceIntensity</i>			
	(1)	(2)	(3)	(4)
Direct-to-consumer sales	0.497 *** (0.136)	0.422 ** (0.206)	0.670 *** (0.183)	0.565 *** (0.148)
New car sales 2022 (log)		0.046 (0.056)	0.042 (0.057)	0.059 (0.054)
Multi-brand dealership		-0.061 (0.163)	-0.030 (0.213)	0.007 (0.135)
New car-only dealership		0.032 (0.178)	0.075 (0.181)	0.075 (0.178)
<u>Additional controls:</u>				
Respondents' position	no	yes	yes	yes
OEM (partnering main brand)	no	yes	no	no
Price segment (partnering brand/s)	no	yes	no	no
Partnering brand/s	no	no	yes	no
Agency model plans of OEM (main brand)	no	no	no	yes
Dealership location	no	yes	yes	yes
Dealership online and EV offering	no	yes	yes	yes
N	389	389	389	389
R ²	0.032	0.098	0.133	0.099
Note	* p < 0.10; ** p < 0.05; *** p < 0.01; robust standard errors in ()			

Table B.23: Multiple linear regression results for different model specifications (*InterPriceIntensity*)

Dependent variable:	<i>IntraGenIntensity</i>			
	(1)	(2)	(3)	(4)
Direct-to-consumer sales	-0.607 *** (0.124)	-0.717 *** (0.197)	-0.443 ** (0.182)	-0.359 ** (0.146)
New car sales 2022 (log)		0.007 (0.057)	0.004 (0.059)	0.026 (0.056)
Multi-brand dealership		0.315 * (0.164)	0.313 (0.211)	0.300 ** (0.121)
New car-only dealership		0.256 * (0.144)	0.265 * (0.147)	0.246 * (0.142)
<u>Additional controls:</u>				
Respondents' position	no	yes	yes	yes
OEM (partnering main brand)	no	yes	no	no
Price segment (partnering brand/s)	no	yes	no	no
Partnering brand/s	no	no	yes	no
Agency model plans of OEM (main brand)	no	no	no	yes
Dealership location	no	yes	yes	yes
Dealership online and EV offering	no	yes	yes	yes
N	389	389	389	389
R ²	0.052	0.150	0.175	0.149
Note	* p < 0.10; ** p < 0.05; *** p < 0.01; robust standard errors in ()			

Table B.24: Multiple linear regression results for different model specifications (*IntraGenIntensity*)

Dependent variable:	<i>InterGenIntensity</i>			
	(1)	(2)	(3)	(4)
Direct-to-consumer sales	0.286 ** (0.139)	0.475 ** (0.231)	0.370 ** (0.181)	0.256 (0.158)
New car sales 2022 (log)		0.048 (0.060)	0.045 (0.061)	0.044 (0.057)
Multi-brand dealership		0.305 ** (0.147)	0.196 (0.193)	0.229 * (0.130)
New car-only dealership		0.253 (0.154)	0.247 (0.158)	0.280 * (0.155)
<u>Additional controls:</u>				
Respondents' position	no	yes	yes	yes
OEM (partnering main brand)	no	yes	no	no
Price segment (partnering brand/s)	no	yes	no	no
Partnering brand/s	no	no	yes	no
Agency model plans of OEM (main brand)	no	no	no	yes
Dealership location	no	yes	yes	yes
Dealership online and EV offering	no	yes	yes	yes
N	389	389	389	389
R ²	0.011	0.133	0.152	0.124
Note	* p < 0.10; ** p < 0.05; *** p < 0.01; robust standard errors in ()			

Table B.25: Multiple linear regression results for different model specifications (*InterGenIntensity*)

Dependent variable:	<i>REP_IntraIntensity</i>	<i>REP_AgencyEval</i>	<i>REP_UniPriceEval</i>
	(1)	(2)	(3)
Direct-to-consumer sales	-0.914 *** (0.244)	0.199 (0.307)	-0.012 (0.347)
New car sales previous year (log)	0.062 * (0.036)	0.050 (0.044)	0.005 (0.046)
Multi-brand dealership	-0.094 (0.161)	-0.205 (0.233)	0.036 (0.216)
New car-only dealership	0.273 ** (0.116)	0.136 (0.152)	0.053 (0.151)
<u>Fixed effects:</u>			
Year	yes	yes	yes
Respondents' position	yes	yes	yes
OEM sales & service partner network size	no	no	no
Partnering brand/s	yes	yes	yes
N	730	713	727
R ²	0.103	0.114	0.068
Note	* p < 0.10; ** p < 0.05; *** p < 0.01; robust standard errors in ()		

Table B.26: Multiple linear regression results for repeated cross-sectional variables with raw (uncleaned, non-imputed) data (*REP_IntraIntensity*, *REP_AgencyEval*, *REP_UniPriceEval*)

Dependent variable:	<i>REP_MainComp (intra-brand competitor)</i>				
	(1)	(2)	(3)	(4)	(5)
Direct-to-consumer sales	-1.069 *** (0.326)	-0.283 (0.607)	-0.762 ** (0.321)	-0.414 (0.571)	-0.785 (0.578)
New car sales previous year (log)		0.124 (0.087)		0.076 (0.078)	0.124 (0.087)
Multi-brand dealership		0.498 (0.456)		0.573 (0.385)	0.497 (0.456)
New car-only dealership		-0.435 (0.298)		-0.518 * (0.271)	-0.447 (0.298)
<u>Fixed effects:</u>					
Year	yes	yes	yes	yes	yes
Respondents' position	no	yes	no	yes	yes
OEM sales & service partner network size	no	no	no	no	no
Partnering brand/s	no	yes	no	yes	yes
"Independent" excluded - control group	yes	yes	yes	yes	yes
"Independent" excluded - treated group	yes	yes	yes	no	no
"Independent" consolidated - control group	no	no	no	no	no
"Independent" consolidated - treated group	no	no	no	yes	yes
N	612	562	785	720	564
Residual deviance	831.7	715.6	1,055.0	913.8	716.8
AIC	837.7	777.6	1,061.0	975.8	778.8
Note	* p < 0.10; ** p < 0.05; *** p < 0.01; standard errors in ()				

Table B.27: Logistic regression results for different model specifications with raw (uncleaned, non-imputed) data (*REP_MainComp*, intra- versus inter-brand competitor)

Dependent variable:	<i>IndivDisc</i>	<i>GenDisc</i>	<i>ProdExtra</i>	<i>ServExtra</i>
	(1)	(2)	(3)	(4)
Direct-to-consumer sales	-2.557 *** (0.294)	-1.707 *** (0.285)	-1.272 *** (0.303)	-1.090 *** (0.329)
New car sales 2022 (log)	-0.026 (0.070)	0.068 (0.065)	0.107 (0.077)	0.026 (0.087)
Multi-brand dealership	0.188 (0.307)	-0.026 (0.283)	0.039 (0.282)	0.000 (0.343)
New car-only dealership	0.250 (0.174)	0.479 ** (0.236)	-0.031 (0.220)	0.637 *** (0.236)
<u>Additional controls:</u>				
Respondents' position	yes	yes	yes	yes
Partnering brand/s	yes	yes	yes	yes
Dealership location	yes	yes	yes	yes
Dealership online and EV offering	yes	yes	yes	yes
N	278	280	278	279
R ²	0.423	0.338	0.374	0.283
Note	* p < 0.10; ** p < 0.05; *** p < 0.01; robust standard errors in ()			

Table B.28: Multiple linear regression results for price-related differentiation tactics variables with raw (uncleaned, non-imputed) data (*IndivDiscIntensity*, *GenDiscIntensity*, *ProdExtraIntensity*, *ServExtraIntensity*)

Dependent variable:	<i>TargDiff</i>	<i>ProdDiff</i>	<i>ServDiff</i>	<i>LoyDiff</i>
	(1)	(2)	(3)	(4)
Direct-to-consumer sales	0.278 (0.260)	-0.401 (0.286)	0.175 (0.245)	0.533 * (0.273)
New car sales 2022 (log)	0.061 (0.072)	0.046 (0.069)	0.003 (0.072)	0.052 (0.085)
Multi-brand dealership	-0.127 (0.267)	-0.358 (0.272)	-0.170 (0.221)	-0.126 (0.290)
New car-only dealership	0.419 ** (0.204)	0.053 (0.218)	0.164 (0.179)	0.182 (0.230)
<u>Additional controls:</u>				
Respondents' position	yes	yes	yes	yes
Partnering brand/s	yes	yes	yes	yes
Dealership location	yes	yes	yes	yes
Dealership online and EV offering	yes	yes	yes	yes
N	282	281	281	281
R ²	0.297	0.220	0.182	0.202
Note	* p < 0.10; ** p < 0.05; *** p < 0.01; robust standard errors in ()			

Table B.29: Multiple linear regression results for non-price-related differentiation tactics variables with raw (uncleaned, non-imputed) data (*TargDiffIntensity*, *ProdDiffIntensity*, *ServDiffIntensity*, *LoyDiffIntensity*)

Dependent variable:	<i>IntraPriceInt.</i>	<i>InterPriceInt.</i>	<i>IntraGenInt.</i>	<i>InterGenInt.</i>
	(1)	(2)	(3)	(4)
<u>Specification:</u>				
Not cleaned, not imputed (raw data) N = 280, 278, 280, 280	-1.206 *** (0.263)	0.916 *** (0.204)	-0.412 * (0.212)	0.391 (0.237)
Not cleaned, imputed N = 400, 400, 400, 400	-1.095 *** (0.190)	0.643 *** (0.181)	-0.441 ** (0.182)	0.350 * (0.180)
Cleaned, not imputed N = 272, 270, 272, 272	-1.216 *** (0.266)	0.939 *** (0.209)	-0.493 ** (0.208)	0.369 (0.245)
Cleaned, IVs & DVs imputed separately N = 389, 389, 389, 389	-1.085 *** (0.190)	0.635 *** (0.184)	-0.455 ** (0.181)	0.356 * (0.182)
Dependent variable:	<i>IndivDisc</i>	<i>GenDisc</i>	<i>ProdExtra</i>	<i>ServExtra</i>
	(5)	(6)	(7)	(8)
<u>Specification:</u>				
Not cleaned, not imputed (raw data) N = 278, 280, 278, 279	-2.557 *** (0.294)	-1.707 *** (0.285)	-1.272 *** (0.303)	-1.090 *** (0.329)
Not cleaned, imputed N = 400, 400, 400, 400	-2.486 *** (0.219)	-1.630 *** (0.235)	-1.113 *** (0.269)	-0.835 *** (0.291)
Cleaned, not imputed N = 270, 272, 271, 272	-2.726 *** (0.271)	-1.756 *** (0.290)	-1.268 *** (0.308)	-1.125 *** (0.345)
Cleaned, IVs & DVs imputed separately N = 389, 389, 389, 389	-2.362 *** (0.242)	-1.565 *** (0.246)	-1.072 *** (0.276)	-0.829 *** (0.300)
Dependent variable:	<i>TargDiff</i>	<i>ProdDiff</i>	<i>ServDiff</i>	<i>LoyDiff</i>
	(9)	(10)	(11)	(12)
<u>Specification:</u>				
Not cleaned, not imputed (raw data) N = 282, 281, 281, 281	0.278 (0.260)	-0.401 (0.286)	0.175 (0.245)	0.533 * (0.273)
Not cleaned, imputed N = 400, 400, 400, 400	0.348 (0.232)	-0.119 (0.241)	0.233 (0.217)	0.453 ** (0.221)
Cleaned, not imputed N = 274, 273, 273, 273	0.216 (0.268)	-0.369 (0.301)	0.116 (0.255)	0.581 ** (0.276)
Cleaned, IVs & DVs imputed separately N = 389, 389, 389, 389	0.328 (0.239)	-0.098 (0.245)	0.149 (0.221)	0.456 ** (0.224)
Note	IV = independent variable, DV = dependent variable; * p < 0.10; ** p < 0.05; *** p < 0.01; robust standard errors in ()			

Table B.30: Multiple linear regression results for focal variables with different data cleaning and imputation specifications (2024 data) – regression coefficients with respect to treatment assignment (direct-to-consumer sales)

Dependent variable:	<i>IndivDisc</i>	<i>GenDisc</i>	<i>ProdExtra</i>	<i>ServExtra</i>
	(1)	(2)	(3)	(4)
Subsample:				
No partially implemented agency	-2.218 ***	-1.694 ***	-0.865 ***	-1.026 ***
Subsample N = 289; Treatment group N = 54	(0.155)	(0.198)	(0.245)	(0.264)
No partially implem. or planned agency	-2.155 ***	-1.575 ***	-0.712 ***	-0.987 ***
Subsample N = 192; Treatment group N = 54	(0.155)	(0.200)	(0.253)	(0.281)
Small dealerships (new car sales)	-2.783 ***	-2.127 ***	-1.176 **	-0.873 *
Subsample N = 197; Treatment group N = 25	(0.310)	(0.352)	(0.472)	(0.500)
Large dealerships (new car sales)	-2.793 ***	-1.360 ***	-0.768 *	-0.416
Subsample N = 192; Treatment group N = 29	(0.313)	(0.366)	(0.413)	(0.431)
Small dealerships (stock vehicles)	-3.122 ***	-1.809 ***	-1.829 ***	-1.403 ***
Subsample N = 196; Treatment group N = 25	(0.332)	(0.395)	(0.424)	(0.469)
Large dealerships (stock vehicles)	-2.293 ***	-1.689 ***	-0.483	-0.061
Subsample N = 193; Treatment group N = 29	(0.346)	(0.363)	(0.443)	(0.495)
Small dealerships (employees)	-3.219 ***	-1.828 ***	-0.974 *	-0.515
Subsample N = 199; Treatment group N = 12	(0.331)	(0.410)	(0.542)	(0.650)
Large dealerships (employees)	-2.794 ***	-1.749 ***	-1.454 ***	-1.496 ***
Subsample N = 190; Treatment group N = 42	(0.337)	(0.337)	(0.327)	(0.373)
Mono-brand dealerships	-1.612 **	-1.994 ***	-0.506	0.395
Subsample N = 297; Treatment group N = 53	(0.699)	(0.584)	(0.776)	(0.581)
New car sales only (business model)	-2.979 ***	-2.993 **	-2.983 ***	-3.149 ***
Subsample N = 46; Treatment group N = 14	(0.326)	(1.103)	(0.642)	(0.543)
New & used car sales (business model)	-2.567 ***	-1.824 ***	-0.988 ***	-1.490 ***
Subsample N = 343; Treatment group N = 40	(0.215)	(0.293)	(0.302)	(0.328)
Premium price segment (only)	-2.743 ***	-1.954 ***	-1.366 ***	-1.411 ***
Subsample N = 107; Treatment group N = 53	(0.260)	(0.344)	(0.412)	(0.431)
Small cities (dealership location)	-2.574 ***	-1.347 **	-0.719	0.157
Subsample N = 136; Treatment group N = 13	(0.435)	(0.522)	(0.632)	(0.668)
Large cities (dealership location)	-2.559 ***	-1.971 ***	-1.342 ***	-1.231 ***
Subsample N = 253; Treatment group N = 41	(0.255)	(0.244)	(0.288)	(0.317)
Note	* p < 0.10; ** p < 0.05; *** p < 0.01; robust standard errors in ()			

Table B.31: Multiple linear regression results for price-related differentiation tactics variables for different subsamples (*IndivDiscIntensity*, *GenDiscIntensity*, *ProdExtraIntensity*, *ServExtraIntensity*) – subsample splits by agency model plans of the main brand’s OEM, dealership size (median split by new car sales, stock vehicles, and employees), mono-brand dealerships, dealership business model, premium price segment, and dealership location (city size smaller or larger than 20,000 inhabitants) – regression coefficients with respect to treatment assignment (direct-to-consumer sales)

Dependent variable:	<i>TargDiff</i>	<i>ProdDiff</i>	<i>ServDiff</i>	<i>LoyDiff</i>
	(1)	(2)	(3)	(4)
Subsample:				
No partially implemented agency	0.385 *	-0.268	0.234	0.223
Subsample N = 289; Treatment group N = 54	(0.201)	(0.223)	(0.200)	(0.206)
No partially implem. or planned agency	0.474 **	-0.216	0.253	0.102
Subsample N = 192; Treatment group N = 54	(0.207)	(0.236)	(0.213)	(0.213)
Small dealerships (new car sales)	0.715 **	0.585	0.071	0.360
Subsample N = 197; Treatment group N = 25	(0.361)	(0.388)	(0.373)	(0.407)
Large dealerships (new car sales)	0.247	-0.580	0.238	0.820 **
Subsample N = 192; Treatment group N = 29	(0.370)	(0.386)	(0.328)	(0.316)
Small dealerships (stock vehicles)	0.301	-0.029	-0.435	0.446
Subsample N = 196; Treatment group N = 25	(0.403)	(0.462)	(0.387)	(0.419)
Large dealerships (stock vehicles)	0.135	-0.454	0.741 **	0.813 **
Subsample N = 193; Treatment group N = 29	(0.335)	(0.388)	(0.292)	(0.320)
Small dealerships (employees)	1.027 ***	0.560	0.255	0.238
Subsample N = 199; Treatment group N = 12	(0.321)	(0.411)	(0.444)	(0.427)
Large dealerships (employees)	0.020	-0.657 **	0.000	0.344
Subsample N = 190; Treatment group N = 42	(0.337)	(0.313)	(0.292)	(0.338)
Mono-brand dealerships	0.184	0.605	0.870	1.761 ***
Subsample N = 297; Treatment group N = 53	(0.552)	(0.662)	(0.647)	(0.495)
New car sales only (business model)	1.338	0.937	0.651	1.264
Subsample N = 46; Treatment group N = 14	(0.934)	(0.646)	(0.775)	(0.773)
New & used car sales (business model)	-0.338	-0.796 ***	-0.534 **	-0.131
Subsample N = 343; Treatment group N = 40	(0.258)	(0.280)	(0.246)	(0.262)
Premium price segment (only)	-0.143	-0.634 *	-0.536	0.119
Subsample N = 107; Treatment group N = 53	(0.272)	(0.338)	(0.333)	(0.340)
Small cities (dealership location)	1.416 ***	1.332 **	0.352	0.714 *
Subsample N = 136; Treatment group N = 13	(0.481)	(0.532)	(0.563)	(0.425)
Large cities (dealership location)	0.152	-0.427	0.136	0.381
Subsample N = 253; Treatment group N = 41	(0.260)	(0.267)	(0.240)	(0.263)
Note	* p < 0.10; ** p < 0.05; *** p < 0.01; robust standard errors in ()			

Table B.32: Multiple linear regression results for non-price-related differentiation tactics variables for different subsamples (*TargDiffIntensity*, *ProdDiffIntensity*, *ServDiffIntensity*, *LoyDiffIntensity*) – subsample splits by agency model plans of the main brand’s OEM, dealership size (median split by new car sales, stock vehicles, and employees), mono-brand dealerships, dealership business model, premium price segment, and dealership location (city size smaller or larger than 20,000 inhabitants) – regression coefficients with respect to treatment assignment (direct-to-consumer sales)

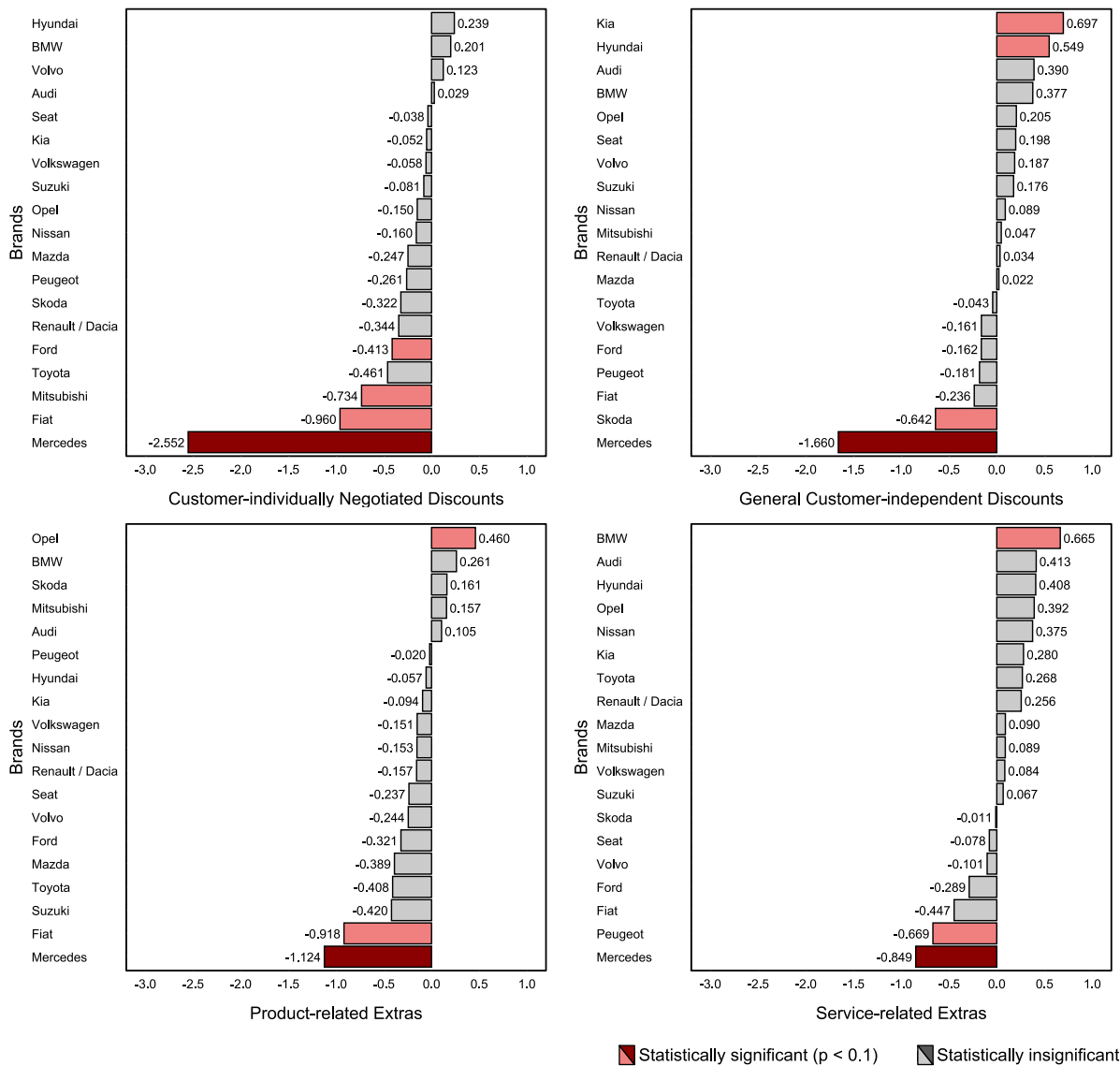


Figure B.12: Brand-level coefficients from multiple linear regression analyses of price-related differentiation tactics variables (main models; exclusion of three brands with N < 10; *IndivDiscIntensity*, *GenDiscIntensity*, *ProdExtraIntensity*, *ServExtraIntensity*) – regression coefficients with respect to treatment assignment (direct-to-consumer sales)

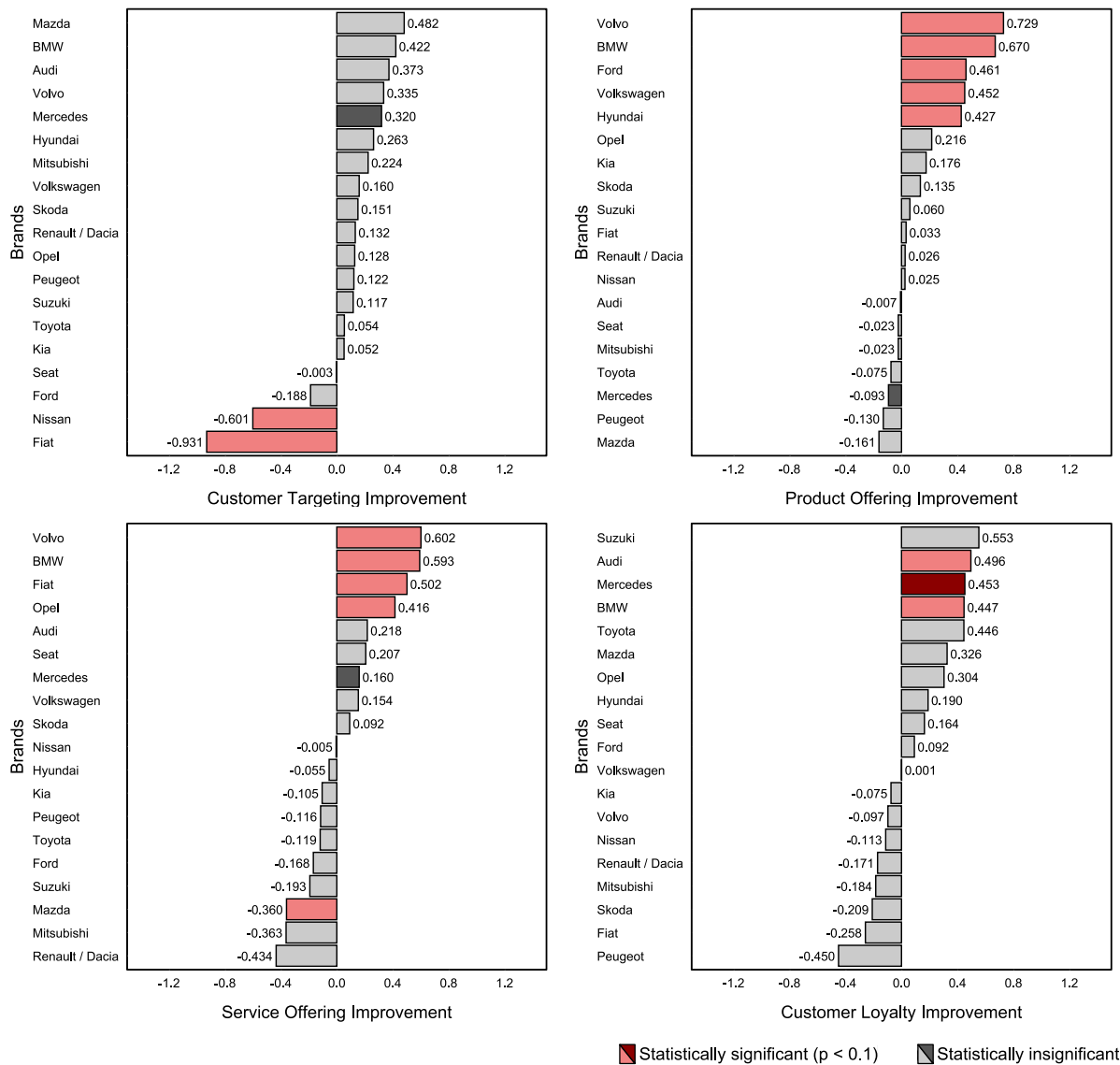


Figure B.13: Brand-level coefficients from multiple linear regression analyses of non-price-related differentiation tactics variables (main models; exclusion of three brands with $N < 10$; *TargDiffIntensity*, *ProdDiffIntensity*, *ServDiffIntensity*, *LoyDiffIntensity*) – regression coefficients with respect to treatment assignment (direct-to-consumer sales)

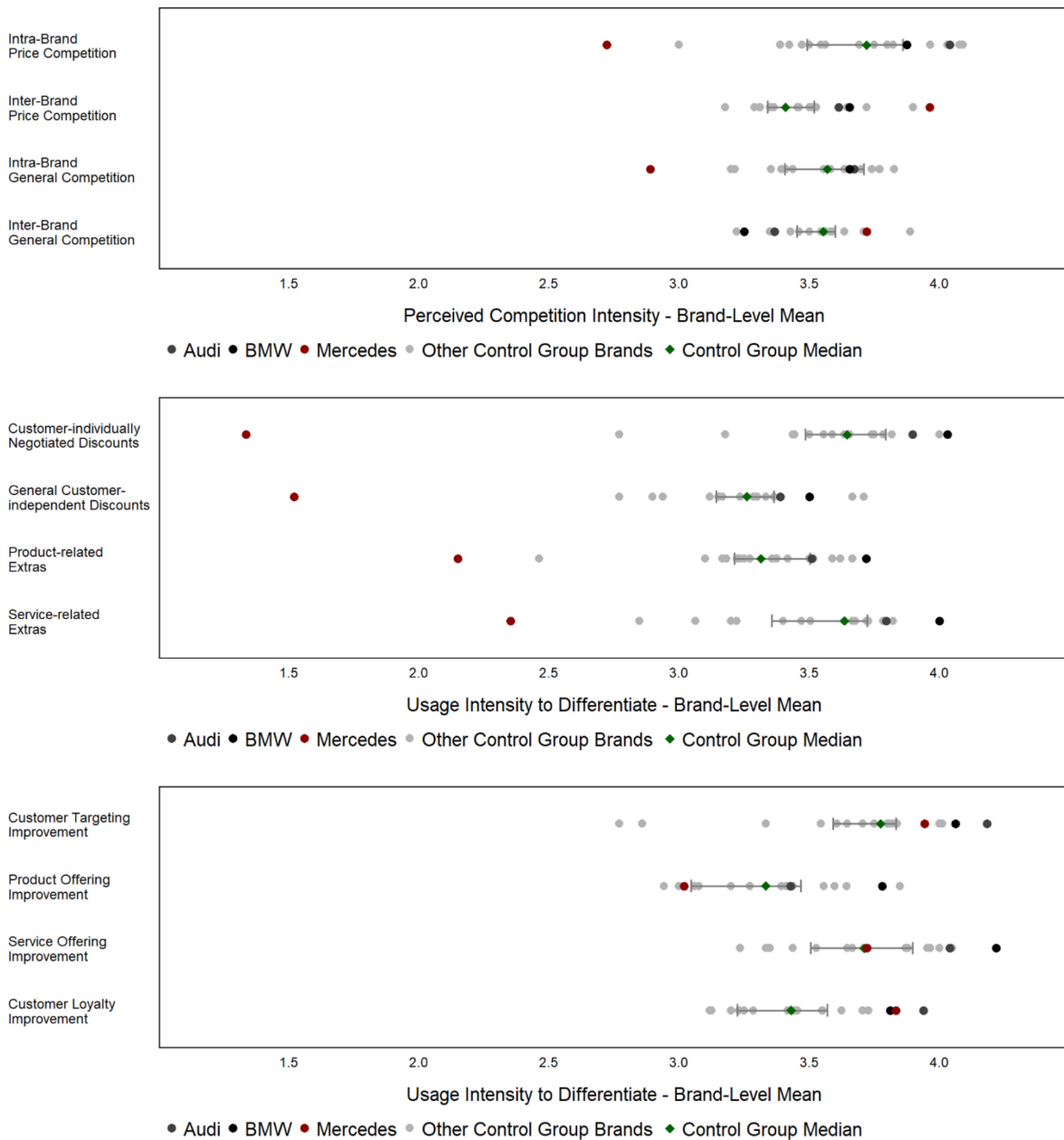


Figure B.14: Brand-level means for all focal variables with visualization of interquartile ranges and median values for brand-level means (exclusion of three brands with N < 10, highlighting the two main competitors BMW and Audi)

Dependent variable:	<i>IntraVsInterPrice</i>		<i>IntraVsInterGen</i>	
	(5)	(6)	(7)	(8)
Direct-to-consumer sales	-1.518 *** (0.214)	-1.752 *** (0.279)	-0.893 *** (0.186)	-0.814 *** (0.239)
New car sales 2022 (log)		0.017 (0.082)		-0.041 (0.067)
Multi-brand dealership		0.112 (0.272)		0.117 (0.236)
New car-only dealership		0.143 (0.222)		0.018 (0.177)
<u>Additional controls:</u>				
Respondents' position	no	yes	no	yes
Partnering brand/s	no	yes	no	yes
Dealership location	no	yes	no	yes
Dealership online and EV offering	no	yes	no	yes
N	389	389	389	389
R ²	0.146	0.281	0.078	0.191
Note	* p < 0.10; ** p < 0.05; *** p < 0.01; robust standard errors in ()			

Table B.33: Multiple linear regression results of within-respondent deltas in perceived competition intensities (simple and main regression models for: *IntraVsInterPrice*: *IntraPriceIntensity* versus *InterPriceIntensity*; *IntraVsInterGen*: *IntraGenIntensity* versus *InterGenIntensity*)

Dependent variable:	<i>IntraGenVsPrice</i>		<i>InterGenVsPrice</i>	
	(1)	(2)	(3)	(4)
Direct-to-consumer sales	0.414 *** (0.143)	0.638 *** (0.188)	-0.211 * (0.121)	-0.300 * (0.160)
New car sales 2022 (log)		-0.056 (0.058)		0.003 (0.052)
Multi-brand dealership		0.231 (0.196)		0.226 (0.189)
New car-only dealership		0.047 (0.183)		0.172 (0.142)
<u>Additional controls:</u>				
Respondents' position	no	yes	no	yes
Partnering brand/s	no	yes	no	yes
Dealership location	no	yes	no	yes
Dealership online and EV offering	no	yes	no	yes
N	389	389	389	389
R ²	0.023	0.154	0.007	0.149
Note	* p < 0.10; ** p < 0.05; *** p < 0.01; robust standard errors in ()			

Table B.34: Multiple linear regression results of within-respondent deltas in perceived competition intensities (simple and main regression models for: *IntraGenVsPrice*: *IntraGenIntensity* versus *IntraPriceIntensity*; *InterGenVsPrice*: *InterGenIntensity* versus *InterPriceIntensity*)

Dependent variable:	<i>IntraPriceInt.</i>	<i>InterPriceInt.</i>	<i>IntraGenInt.</i>	<i>InterGenInt.</i>
	(1)	(2)	(3)	(4)
Direct-to-consumer sales	-2.214 *** (0.403)	1.398 *** (0.391)	-0.992 ** (0.397)	0.876 ** (0.394)
New car sales previous year (log)	0.090 (0.120)	0.070 (0.117)	-0.063 (0.122)	0.063 (0.121)
Multi-brand dealership	0.117 (0.425)	-0.050 (0.435)	0.763 * (0.455)	0.481 (0.437)
New car-only dealership	0.090 (0.120)	0.070 (0.117)	-0.063 (0.122)	0.063 (0.121)
<u>Additional controls:</u>				
Respondents' position	yes	yes	yes	yes
Partnering brand/s	yes	yes	yes	yes
Dealership location	yes	yes	yes	yes
Dealership online and EV offering	yes	yes	yes	yes
N	389	389	389	389
Residual deviance	971.7	990.8	954.5	970.9
AIC	1,067.7	1,086.8	1,050.5	1,067.0
Note	* p < 0.10; ** p < 0.05; *** p < 0.01; standard errors in ()			

Table B.35: Proportional odds logistic regression results for perceived competition intensity variables (*IntraPriceIntensity*, *InterPriceIntensity*, *IntraGenIntensity*, *InterGenIntensity*)

Dependent variable:	<i>IntraPriceInt.</i>	<i>InterPriceInt.</i>	<i>IntraGenInt.</i>	<i>InterGenInt.</i>
	(1)	(2)	(3)	(4)
Direct-to-consumer sales	-3.059 *** (0.943)	2.039 *** (0.773)	-1.277 (0.896)	0.089 (0.821)
New car sales previous year (log)	0.405 (0.251)	0.082 (0.215)	0.322 (0.242)	-0.087 (0.235)
Multi-brand dealership	0.092 (1.059)	-0.075 (0.728)	1.110 (1.074)	0.990 (0.991)
New car-only dealership	0.346 (0.662)	-0.240 (0.474)	1.301 ** (0.612)	1.118 * (0.586)
<u>Additional controls:</u>				
Respondents' position	yes	yes	yes	yes
Partnering brand/s	yes	yes	yes	yes
Dealership location	yes	yes	yes	yes
Dealership online and EV offering	yes	yes	yes	yes
N	269	273	243	262
Residual deviance	175.9	248.1	216.7	210.1
AIC	265.9	338.1	306.7	300.1
Note	* p < 0.10; ** p < 0.05; *** p < 0.01; standard errors in ()			

Table B.36: Logistic regression results for perceived competition intensity variables (perception as “rather weak” or “very weak” versus perception as “rather strong” or “very strong”, exclusion of “neutral”; *IntraPriceIntensity*, *InterPriceIntensity*, *IntraGenIntensity*, *InterGenIntensity*)

C Appendix Chapter 4

C.1 Summary statistics and composition of synthetic control groups

Variable	South Africa	Mean	Min	1 st Qua.	Median	3 rd Qua.	Max
Monthly new car sales	1,304	2,808	8	83	337	1,267	59,851
Inhabitants (in millions)	58.1	75.5	0.4	5.0	11.5	46.0	1,407.7
Old-age dependency ratio	0.09	0.21	0.01	0.12	0.23	0.30	0.50
Young-age dependency ratio	0.44	0.29	0.16	0.23	0.27	0.34	0.54
Female share in population	0.51	0.49	0.27	0.50	0.50	0.51	0.54
Population density	48	376	3	33	93	176	7,966
GDP per capita (PPP, real)	11,251	30,149	3,558	14,440	28,979	39,881	90,769
Inflation rate	0.04	0.04	-0.02	0.01	0.02	0.03	0.54
Unemployment rate	0.26	0.06	0.00	0.03	0.05	0.07	0.17
Covid-19 stringency index	-	-	-	-	-	-	-
Market share BMW	0.03	0.03	0.00	0.01	0.02	0.04	0.12
Share car types A & B	0.09	0.08	0.00	0.04	0.08	0.12	0.27
Share car types C & D	0.73	0.63	0.20	0.56	0.66	0.75	0.84
Share car types E & F	0.17	0.29	0.03	0.16	0.23	0.37	0.79
Electric vehicle share	0.01	0.02	0.00	0.00	0.01	0.03	0.43
Average BMW MSRP	42,512	60,641	12,330	48,348	58,301	71,080	127,087
Average total market MSRP	22,485	31,210	2,761	25,478	31,734	37,397	55,453

Table C.1: Summary statistics BMW South Africa and donor pool units (N = 71, 10 months pre-treatment period from 01/2019 to 10/2019; GDP per capita and MSRP in USD; market-level average values over pre-treatment period except for GDP per capita, which is the total over the period)

Variable	Austria	Mean	Min	1 st Qua.	Median	3 rd Qua.	Max
Monthly new car sales	1,612	2,323	4	47	249	1,046	71,471
Inhabitants (in millions)	8.9	76.5	0.4	5.0	12.0	45.6	1,411.7
Old-age dependency ratio	0.29	0.21	0.02	0.11	0.21	0.30	0.51
Young-age dependency ratio	0.22	0.30	0.16	0.23	0.27	0.36	0.66
Female share in population	0.51	0.49	0.27	0.50	0.50	0.51	0.54
Population density	108	378	3	31	84	146	7,919
GDP per capita (PPP, real)	41,375	28,515	3,439	12,106	26,765	37,735	90,820
Inflation rate	0.02	0.03	-0.01	0.00	0.01	0.03	0.41
Unemployment rate	0.06	0.07	0.00	0.04	0.06	0.08	0.27
Covid-19 stringency index	65.3	61.2	28.1	55.3	62.1	69.8	82.4
Market share Mercedes	0.06	0.03	0.00	0.01	0.02	0.04	0.15
Share car types A & B	0.01	0.01	0.00	0.00	0.00	0.00	0.31
Share car types C & D	0.67	0.57	0.03	0.45	0.62	0.73	0.92
Share car types E & F	0.31	0.42	0.07	0.25	0.38	0.53	0.97
Electric vehicle share	0.06	0.03	0.00	0.00	0.01	0.04	0.40
Average Mercedes MSRP	61,166	69,949	14,409	55,267	66,916	80,333	123,325
Average total market MSRP	41,166	33,382	4,538	25,200	33,840	41,175	59,887

Table C.2: Summary statistics Mercedes Austria and donor pool units (N = 68, 10 months pre-treatment period from 08/2020 to 05/2021; GDP per capita and MSRP in USD; market-level average values over pre-treatment period except for GDP per capita, which is the total over the period)

Market	Weight	Market	Weight	Market	Weight
Argentina	0.0%	Germany	0.0%	Norway	0.0%
Australia	1.1%	Greece	0.0%	Oman	0.0%
Austria	0.1%	Hong Kong	0.0%	Peru	0.0%
Bahrain	0.0%	Hungary	0.0%	Philippines	0.0%
Belgium	0.1%	Iceland	0.0%	Poland	0.1%
Bolivia	0.0%	India	0.0%	Portugal	0.2%
Bosnia and Herzegovina	0.0%	Indonesia	0.0%	Qatar	0.0%
Brazil	16.2%	Iran	0.0%	Romania	0.1%
Brunei Darussalam	0.0%	Ireland	0.0%	Saudi Arabia	0.0%
Bulgaria	0.0%	Israel	0.1%	Singapore	0.0%
Cambodia	0.0%	Italy	0.0%	Slovak Republic	0.0%
Canada	0.0%	Japan	0.5%	Slovenia	0.0%
Chile	0.8%	Kazakhstan	0.0%	Spain	0.0%
China	0.0%	Kuwait	0.0%	Sweden	0.1%
Colombia	0.0%	Latvia	0.0%	Switzerland	22.9%
Croatia	0.0%	Lithuania	0.2%	Tunisia	0.3%
Cyprus	0.0%	Luxembourg	0.0%	Turkey	17.9%
Czechia	0.5%	Malaysia	0.1%	Ukraine	0.1%
Denmark	0.1%	Malta	0.0%	United Arab Emirates	4.2%
Ecuador	0.0%	Mexico	7.5%	United Kingdom	0.0%
Egypt, Arab Rep.	0.1%	Moldova	0.0%	United States	0.3%
Estonia	0.0%	Morocco	25.7%	Uruguay	0.0%
Finland	0.0%	Netherlands	0.1%	Vietnam	0.0%
France	0.0%	New Zealand	0.0%		

Table C.3: Control markets and their weights for the main model for BMW South Africa

Market	Weight	Market	Weight	Market	Weight
Algeria	0.0%	Greece	0.0%	New Zealand	0.0%
Argentina	0.0%	Hong Kong	0.0%	Norway	0.0%
Australia	0.0%	Hungary	50.8%	Oman	0.0%
Bahrain	0.0%	Iceland	0.0%	Peru	0.0%
Belgium	0.0%	India	0.0%	Philippines	0.0%
Bolivia	0.0%	Indonesia	0.0%	Poland	0.0%
Bosnia and Herzegovina	0.0%	Iran	0.0%	Portugal	0.0%
Brazil	0.0%	Ireland	0.0%	Qatar	0.0%
Brunei Darussalam	0.0%	Israel	0.0%	Romania	0.0%
Bulgaria	0.0%	Italy	0.0%	Saudi Arabia	0.0%
Cambodia	0.0%	Japan	0.0%	Singapore	0.0%
Canada	20.4%	Kazakhstan	0.0%	Slovak Republic	0.0%
Chile	0.0%	Kenya	0.0%	Slovenia	0.0%
China	0.0%	Kuwait	0.0%	South Africa	0.0%
Colombia	0.0%	Latvia	0.0%	Spain	0.0%
Croatia	0.0%	Lithuania	0.0%	Switzerland	28.6%
Cyprus	0.0%	Luxembourg	0.0%	Tunisia	0.0%
Czechia	0.1%	Malaysia	0.0%	Turkey	0.0%
Denmark	0.0%	Malta	0.0%	Ukraine	0.0%
Ecuador	0.0%	Mexico	0.0%	United Arab Emirates	0.0%
Estonia	0.0%	Moldova	0.0%	United States	0.0%
Finland	0.0%	Morocco	0.0%	Vietnam	0.0%
France	0.0%	Netherlands	0.0%		

Table C.4: Control markets and their weights for the main model for Mercedes Austria

C.2 Additional confounder analyses

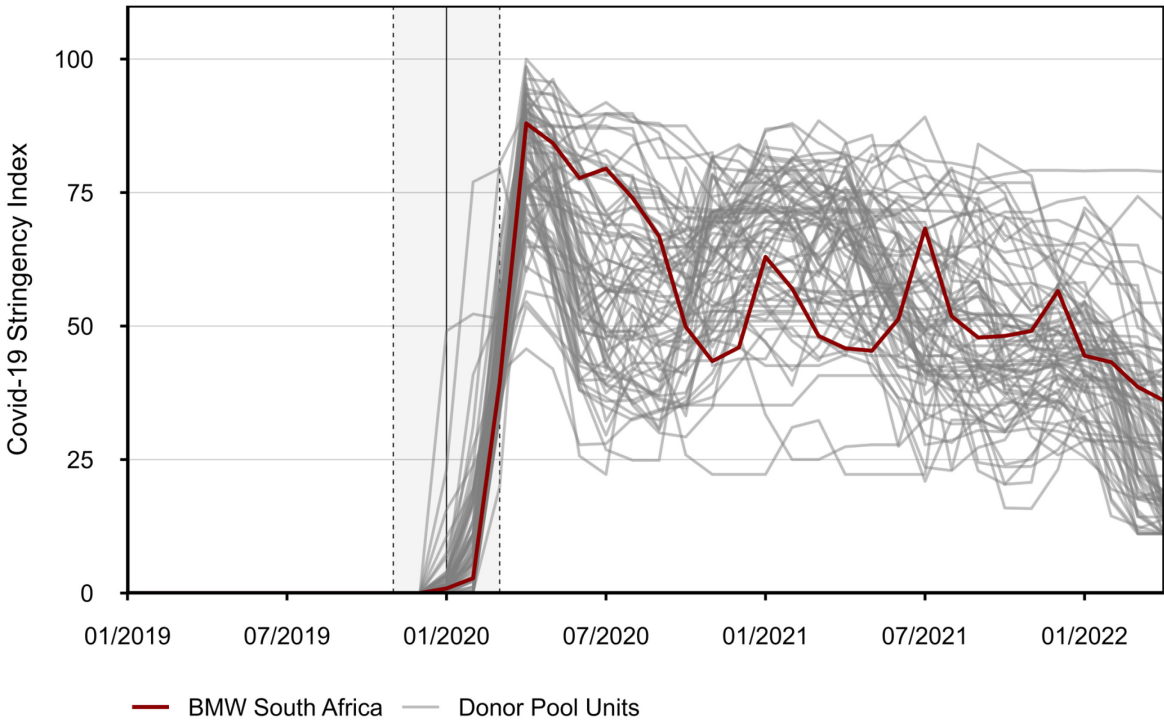


Figure C.1: Covid-19 stringency index for BMW South Africa and its donor pool units (Our World in Data, 2023)

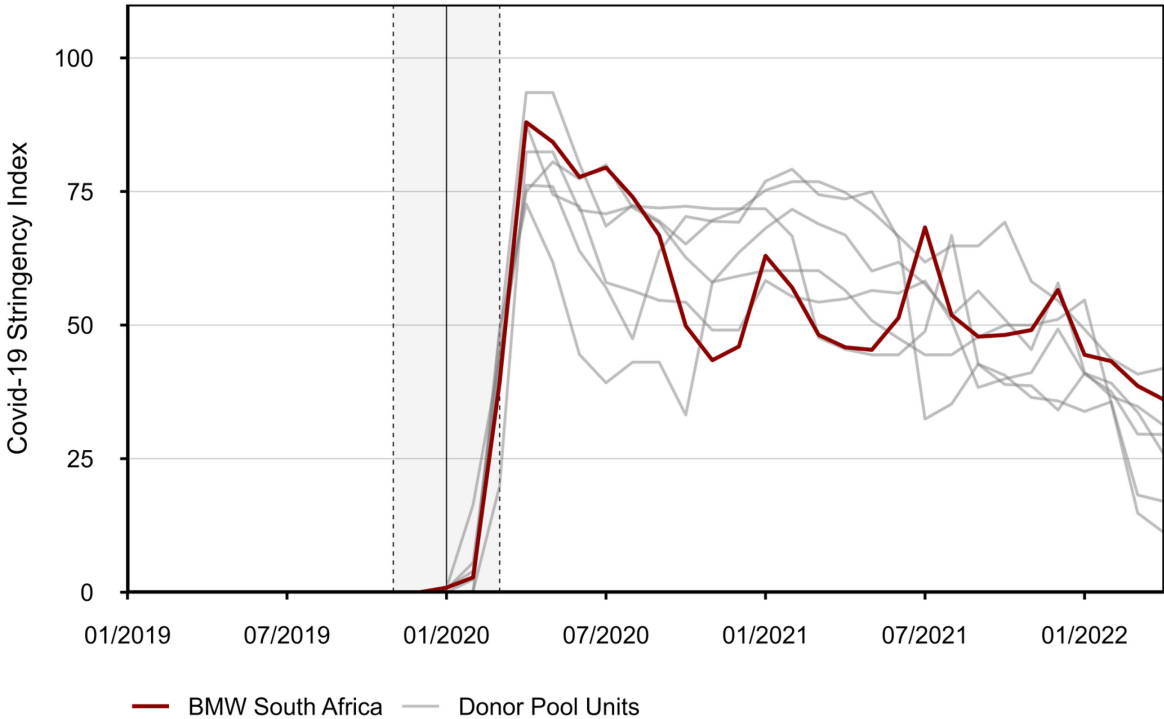


Figure C.2: Covid-19 stringency index for BMW South Africa and the top-weighted control units in its synthetic control group (Morocco, Switzerland, Turkey, Brazil, Mexico, and United Arab Emirates) (Our World in Data, 2023)

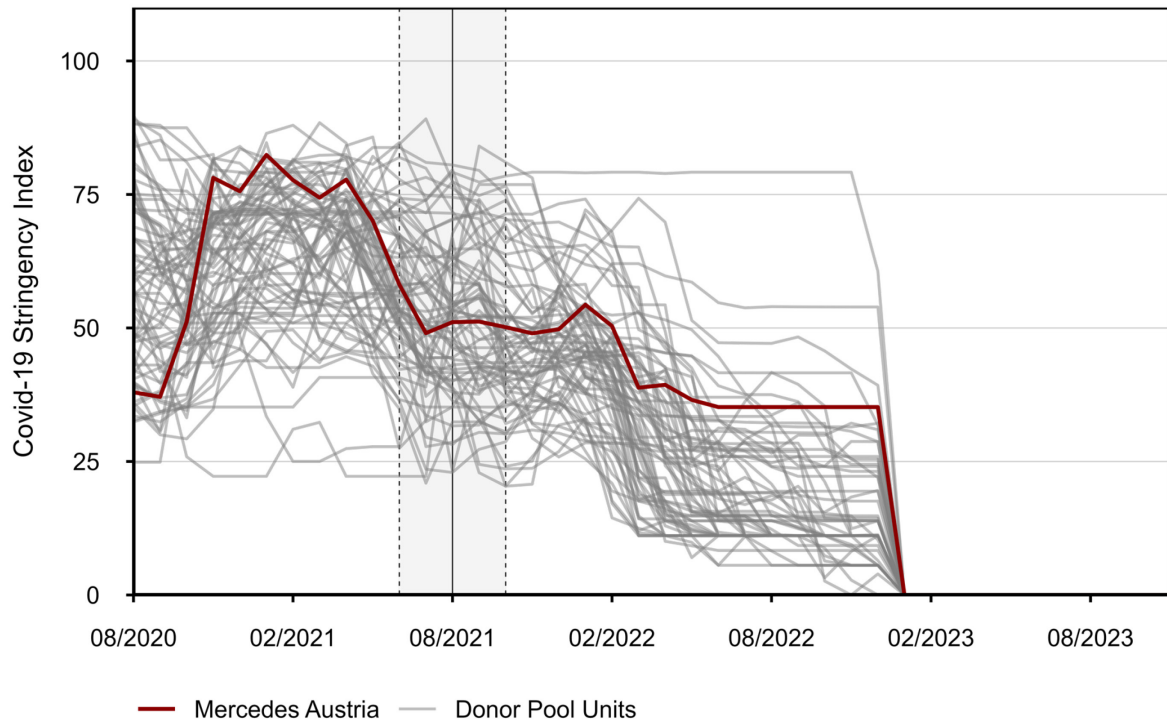


Figure C.3: Covid-19 stringency index for Mercedes Austria and its donor pool units (Our World in Data, 2023)

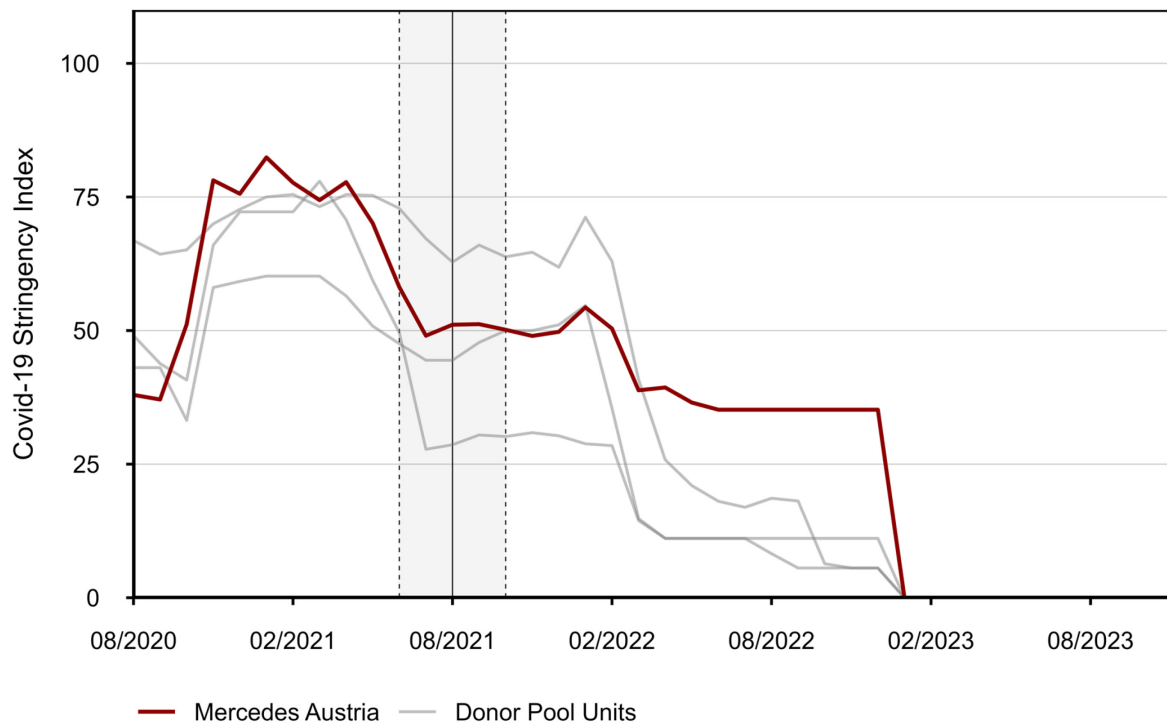


Figure C.4: Covid-19 stringency index for Mercedes Austria and the top-weighted control units in its synthetic control group (Hungary, Switzerland, and Canada) (Our World in Data, 2023)

C.3 Additional robustness checks

Number	Model specification	RMSPE ZAF	RMSPE AUT
ZAF/AUT 00	Full, only monthly sales	22.4 (N = 71)	135.9 (N = 68)
ZAF/AUT 01	Full, full predictor set	24.2 (N = 71)	136.0 (N = 68)
ZAF/AUT 02	Europe, full predictor set	54.6 (N = 33)	157.6 (N = 29)
ZAF/AUT 03	Rest of the world, full predictor set	59.5 (N = 38)	192.1 (N = 40)
ZAF/AUT 04	Northern hemisphere, full predictor set	34.4 (N = 61)	135.9 (N = 58)
ZAF/AUT 05	Southern hemisphere, full predictor set	114.5 (N = 10)	336.0 (N = 11)
ZAF/AUT 06	Full donor pool, no monthly sales volumes	111.9 (N = 71)	197.7 (N = 68)
ZAF/AUT 07	Full donor pool, no OEM-specific predictors	229.6 (N = 71)	198.9 (N = 68)
ZAF/AUT 08	Full donor pool, only demographic predictors	882.4 (N = 71)	216.4 (N = 68)
ZAF/AUT 09	Full donor pool, full predictor set, no transition period	93.7 (N = 71)	139.3 (N = 68)
ZAF/AUT 10	Full donor pool, full predictor set, logarithmic sales	10.1 (N = 71)	117.2 (N = 68)
ZAF/AUT 11	Covid-19-restricted donor pool*, full predictor set	21.4 (N = 58)	250.6 (N = 14)

Note: * Only donor units with average post-treatment Covid-19 stringency index of $\pm 20\%$ of the treated unit's average post-treatment value; donor pool sample size in parentheses

Table C.5: Overview of root mean square prediction errors (RMSPE) and donor pool sizes for alternative model specifications for BMW South Africa (ZAF) and Mercedes Austria (AUT)

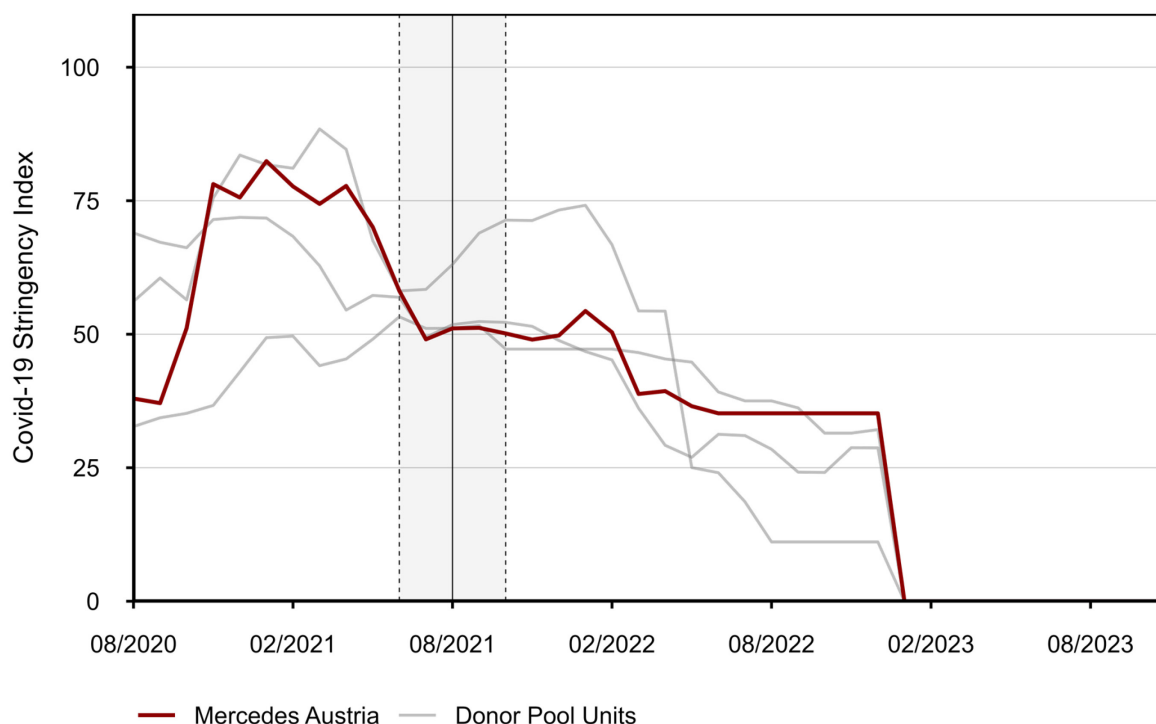


Figure C.5: Covid-19 stringency index for Mercedes Austria and the top-weighted control units in its synthetic control group for alternative model specification with Covid-19 stringency index-restricted donor pool (AUT11; Greece, Japan, United States) (Our World in Data, 2023)

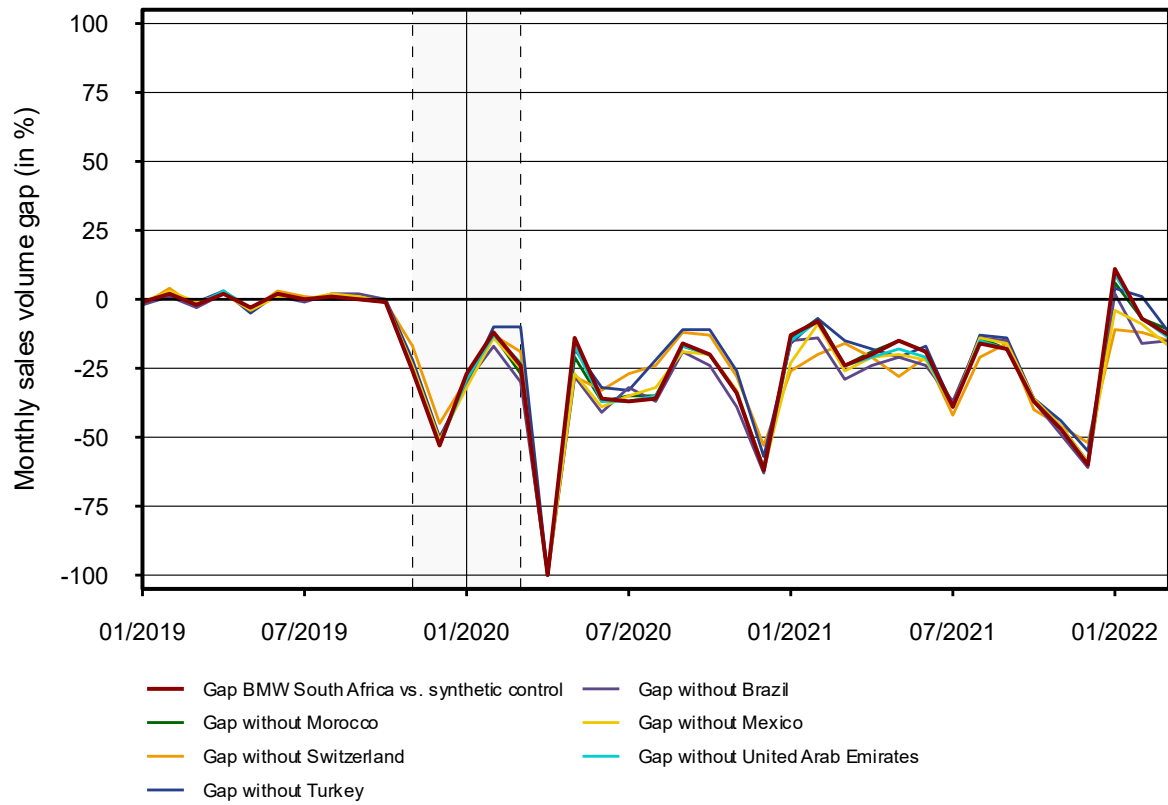


Figure C.6: Leave-one-out distribution of monthly relative sales volume gaps between BMW South Africa and its synthetic control group

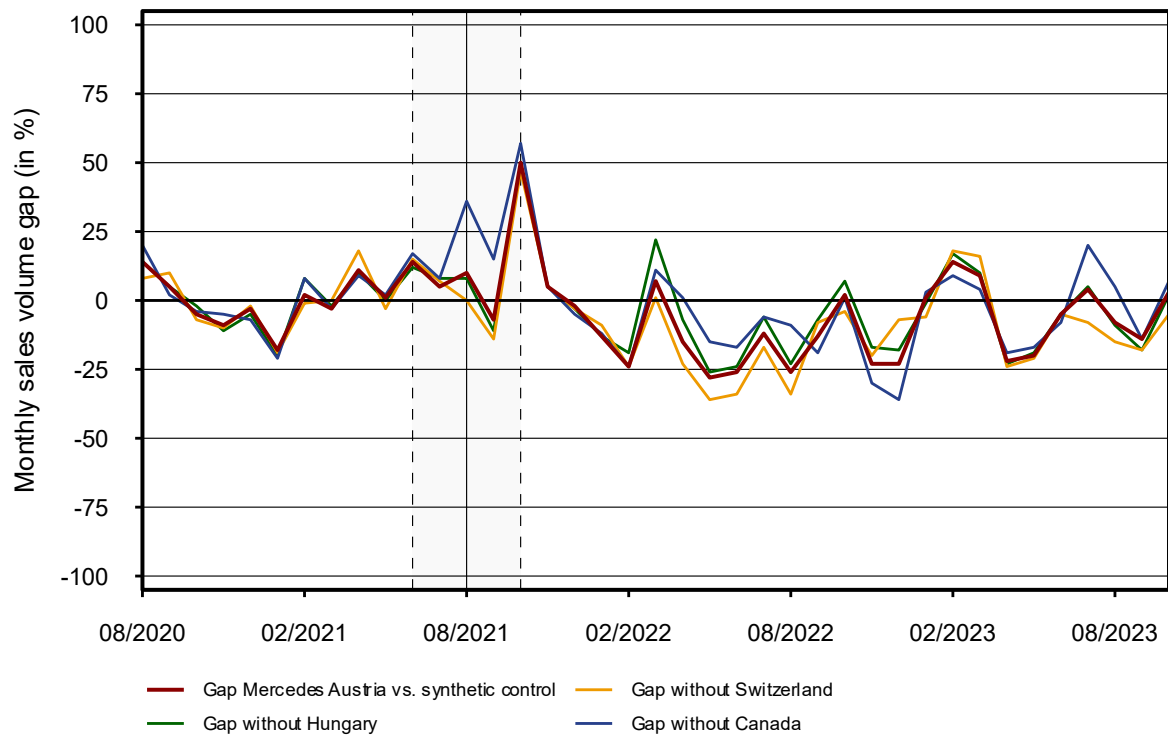


Figure C.7: Leave-one-out distribution of monthly relative sales volume gaps between Mercedes Austria and its synthetic control group