Essays in Empirical Macroeconomics

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Introduction

The financial crisis in 2007/2008 marked the end of the Great Moderation in economies across the globe. Since then, many different new macroeconomic realities have emerged pertaining in particular to the euro area (EA). This dissertation studies three of them, all distinct, but equally important for policy making.

First, the financial crisis had significant impact on public finances both in emerging and advanced economies such as the EA. Credit conditions have diverged and interest rate spreads on sovereign bonds increased in particular in advanced economies potentially leading to real macroeconomic effects. We examine this issue more rigorously in Chapter 1 of this dissertation. Furthermore, the financial crisis has hit economies differently, not only with respect to public finances but also regarding real macroeconomic effects like unemployment, compare for instance the EA. In this context, in Chapter 2 we analyze whether and how labor migration can mitigate these adverse effects of business cycle fluctuations and thereby contribute to risk sharing in a currency union such as the US or the EA. Lastly, advanced economies have experienced a decade of low and stable inflation after the financial crisis in contrast to what economists and policy makers expected. Thus, in Chapter 3, we take a closer look at inflation, particularly in the EA, and revisit the well-known Phillips curve. In doing so, we study whether the trade-off between inflation and unemployment still exists and what this means for the current high-inflation environment. The remainder of this introduction provides a short summary over each chapter including an overview of the main results.

Chapter 1 is based on a joint research project with Benjamin Born, Johannes Pfeifer and Gernot Müller. In this project, we document that interest-rate spreads fluctuate widely across time and countries. We characterize their behavior using some 3,200 quarterly observations for 21 advanced and 17 emerging economies since the early 1990s. We show that, before the financial crisis, spreads were 10 times more volatile in emerging economies than in advanced economies. Since 2008, the behavior of spreads has converged across country groups, largely because it has adjusted in advanced economies. We also provide evidence on the transmission of spread shocks and find it similar across sample periods and country groups. Spread shocks have become a more important source of output fluctuations in advanced economies after 2008.

Chapter 2 is based on a joint research project with Wilhelm Kohler and Gernot Müller. In this study, we analyze migration in the context of risk sharing in currency unions. It is well documented that international risk sharing insulates consumption from country-specific business-cycle fluctuations. This matters for countries in currency unions who lack monetary autonomy. In the spirit of Mundell (1961), we formally integrate migration as a distinct channel into the standard framework of Asdrubali et al. (1996) used to quantify risk sharing. Comparing the EA and the US, we find that migration contributes significantly to risk sharing across US states, but not across the EA. The overall amount of risk sharing in the US is higher by a factor of two. We also present descriptive evidence showing that migration rates are about 15 times higher in the US.

Chapter 3 analyzes inflation in the EA in the context of the Phillips curve. We study whether the trade-off between inflation and unemployment still exists in EA. Using country-level data for member states of the EA, we estimate a refined specification of the Phillips curve in the spirit of Hazell et al. (2022) deploying a non-tradable price index to measure inflation. We find that the slope of the Phillips curve is small and hence the Phillips curve is flat but robust in the EA, similarly to the US. Moreover, reference estimates based on aggregate data overstate the steepness of the Phillips curve considerably. Our findings imply that the insensitivity of inflation with respect to unemployment over the last decade is a result of firmly anchored inflation expectations.

In sum, this dissertation highlights three distinct but intertwined new macroeconomic realities that have emerged in the aftermath of the financial crisis over the last decade. Hopefully, the findings presented here can contribute to a better understanding of each phenomenon individually as well as their joint macroeconomic significance.

Chapter 1

Different no more: Country spreads in advanced and emerging economies

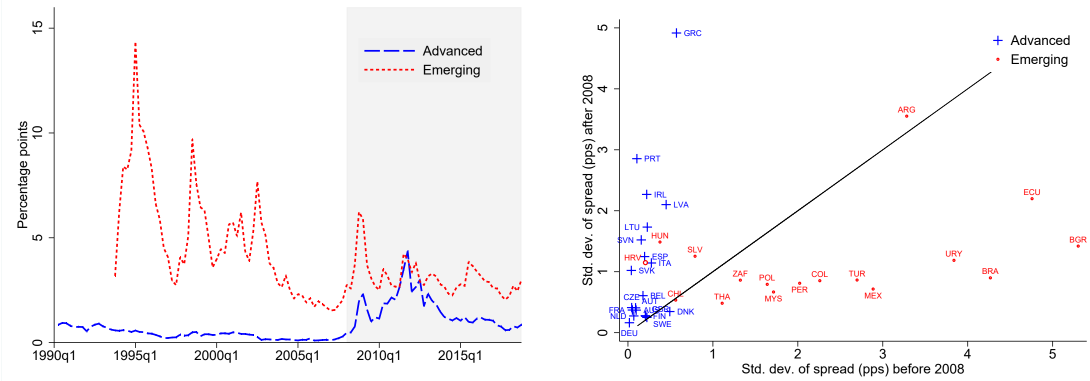
Joint with Benjamin Born, Gernot J. Müller and Johannes Pfeifer

1.1 Introduction

The global financial crisis is having a lasting impact—on many economies but also on economics as a science. The crisis gave rise to new ideas about what drives the business cycle and revived old ones. Perhaps unsurprisingly, a major research effort during the last decade has been directed towards appropriately capturing the role of financial frictions (for instance, Gilchrist and Zakrajšek 2012; Jermann and Quadrini 2012; Schularick and Taylor 2012). Still, prior to the crisis, a specific type of financial disturbance had already been well-established as an important source of the business cycle in emerging market economies: interest-rate shocks (Neumeyer and Perri 2005; Uribe and Yue 2006). According to this earlier research, interest-rate shocks and, in particular, shocks to the "country spread" matter a great deal for emerging markets but are negligible in case of advanced economies. This difference across country groups is plausible because, prior to the crisis, business cycles in emerging markets have been considerable more volatile than in advanced economies (Aguiar and Gopinath 2007).

In this chapter, we ask whether country spreads still behave differently in emerging and advanced economies. We tackle this question on the basis of a uniquely suited data set. It covers a broad range of countries and a large number of observations for the period before and after the global financial crisis. A first look at the data motivates the focus of our investigation: the left panel of Figure 1.1 shows the average country spread for 21 advanced economies (blue dashed line) and 17 emerging economies (red dotted line). For the period up to 2007Q4, we observe that the average spread is very low and stable in advanced economies and very high and volatile in emerging economies. In contrast, the average spread behaves much more similar across country groups in the period since

Figure 1.1: Average country spread and country-specific standard deviations



Notes: Left panel: Average country spread for 21 advanced economies (blue dashed line), and 17 emerging economies (red dotted line). Shaded area denotes period since 2008Q1. Right panel: country-specific standard deviations for advanced (blue plus signs) and emerging (red circles) economies before 2008 (x-axis) and after 2008 (y-axis). Black line indicates 45 degree line.

2008Q1, that is, "after 2008" in what follows.

Our data set includes about 3,200 quarterly observations for the spread, output, as well as a number of key macroeconomic and political indicators. In order to classify the 38 economies in our sample as "advanced" and "emerging" we follow IMF (2015). In the first part of the chapter, we explain the construction of our data set and establish new facts. First, before 2008 the mean, the median, and the standard deviation of the spread are at least 10 times higher in emerging economies than in advanced economies. Second, after 2008, both the mean and the median of the spread in emerging economies are only twice as large as in advanced economies. Moreover, the volatility of the spread has fully converged across country groups and this convergence is broad-based and not driven by individual countries. The right panel of Figure 1.1 displays the standard deviation of the spread before 2008 (horizonal axis) against the one after 2008 (vertical axis) on a country-by-country basis. Blue crosses (red circles) indicate observations for advanced (emerging) economies: the volatility of the spread has increased in almost all advanced economies—not only in euro area countries—and it has declined in most emerging economies.

Third, before 2008 the spread is counter-cyclical in emerging economies and a-cyclical in advanced economies. After 2008 it is counter-cyclical for both country groups. Fourth, the variation of spreads is not systematically related to the level of public debt, neither before nor after 2008. Fifth, and last, we observe that while before 2008 the variation of spreads is not systematically related to the exchange-rate regime, after 2008 it is systematically higher the less flexible the exchange rate regime is. We verify that these facts are insensitive to the particular break date in 2008Q1. They also obtain once we drop the observations for years 2007–2008 from our sample.

These patterns raise interesting questions regarding causality. The country spread is certainly endogenous to the fundamentals of a country—a central theme in the literature on sovereign default (e.g., Arellano 2008; Eaton and Gersovitz 1981). Yet spreads also vary for reasons that are exogenous to country-specific developments. One possibility is that global factors cause the spread to vary such as, for instance, changes in risk aversion or the global financial cycle (Longstaff et al. 2011; Rey 2015). This has been documented in particular in the context of emerging market economies (Mauro et al. 2002). A second source of spread variations unrelated to fundamentals is the possibility that spreads shift due to market sentiment or coordination failure as a result of which changes in expectations may become self-fulfilling (e.g., Calvo 1988; Cole and Kehoe 2000; Lorenzoni 2014; Lorenzoni and Werning 2019). Either way, the notion of a "spread shock" is economically meaningful: movements of the spread that are exogenous to the fundamentals of the specific economy under consideration.

In order to identify the dynamic effects of spread shocks, we pursue two distinct approaches. First, we rely on the causal model by Rosenbaum and Rubin (1983), recently popularized in macroeconomics (e.g. Acemoglu et al. 2019; Angrist and Kuersteiner 2011; Kuvshinov and Zimmermann 2019). In a nutshell, the idea is to measure the causal effect of a "treatment" by appropriately controlling for the fact that the probability of treatment may be endogenous. For our application, we consider the possibility that countries are treated with a large spread increase and define as treatment an increase of the spread by more than one standard deviation and, at the same time, by at least 25 basis points. There are 230 such treatments in our sample. Because they involve large increases in the spread, they are more likely to be caused by shifts in market sentiments or global factors. However, such treatments may still be an endogenous, possibly non-linear, response to changes in fundamentals. To account for "selection into treatment", we follow Angrist et al. (2016) and estimate a logit model which provides us with the propensity score, that is, the probability of a country to be treated, given its fundamentals at a specific point in time. The propensity score estimator allows the use of a conditioning set including a large number of variables, not only conventional macroeconomic indicators, but also indicators capturing the political stability of a country, as well as forward-looking financial market variables. In a final step, we follow Jordà and Taylor (2016) and employ the augmented inverse propensity score weighted (AIPW) estimator that uses the propensity score to re-randomize observations in order to establish the causal effect of spread shocks. To shed light on the transmission of spread shocks we consider the ATE on a large set of outcome variables, both for emerging and advanced economies and for the period before and after 2008.

Our main finding is that the transmission of a given spread shock is fairly similar in advanced and emerging economies—both before and after 2008. The spread increases by about 40 basis points in response to a "treatment". Output and its components contract gradually over a two-year period. The maximum effect on output is a contraction of about 0.3 percent. Importantly, the adjustment takes place in an almost identical manner across country groups. The same holds, minor differences notwithstanding, for fiscal policy. Government consumption, in particular, is fairly unresponsive, while tax revenues decline, and the public deficit-to-GDP ratio rises somewhat. Moreover, we find that the stock market contracts sharply, the real exchange rate depreciates, and bank lending contracts again in both emerging and advanced economies. This result is consistent with the notion that positive spread shocks result in capital outflows. We find that this effect is considerably stronger in emerging economies—suggesting a higher vulnerability to international capital flows in line with the received wisdom and recent evidence by Kalemli-Özcan (2019). Consistent with this interpretation, monetary policy responds more aggressively in emerging economies.

Our results are robust across a number of specifications, including alternative break dates and a model with a larger conditioning set of variables. We also verify that our main result obtains under a second identification approach. In this case we use a more parsimonious approach to model the spread and identify the effect of spread shocks in the spirit of Uribe and Yue (2006). This approach restricts effects to be linear (as opposed to the ATE), but allows us to handle both positive and negative spread shocks simultaneously and to compute forecast error variance decompositions.

A key finding of our analysis is that there is almost no change before and after 2008 as far as the transmission mechanism is concerned. This suggests that the change in the unconditional correlation pattern reflects a change in the incidence of shocks. We explore this issue by means of a forecast error variance decomposition. For this purpose we split the sample once more into advanced and emerging economies and the sample period before and after 2008. Consistent with our earlier findings, we find that, on average across horizons, spread shocks have become more important for explaining output fluctuations in advanced economies after 2008. Before 2008 the contribution of spread shocks in advanced economies amounts to 4 percent as opposed to 11 percent in emerging economies. For the period after 2008, the corresponding values are 7 and 11 percent instead, with the largest remaining difference occurring at very short horizons. The importance of country-specific spread shocks for business cycle fluctuations has also converged across country groups after 2008.

Following Neumeyer and Perri (2005) and Uribe and Yue (2006) several studies have focused on the role of interest rate shocks for the business cycle in emerging economies. Akinci (2013) shows that country spreads are a key source of fluctuations in emerging economies and, in turn, caused by global financial risk shocks. García-Cicco et al. (2010) perform a model-based analysis and find that endogenous changes in country premiums are essential to account for business cycles in emerging market economies. Further research has looked into the importance of interest-rate uncertainty as source of business cycle fluctuation in emerging economies (Born and Pfeifer 2014; Fernández-Villaverde et al. 2011). There is also model-based work that provides microfoundations for interest-rate fluctuations (e.g. Brei and Buzaushina 2015; Fernández and Gulan 2015). Corsetti et al. (2013) and Bocola (2016) put forward models where sovereign risk spills over to the private sector, affecting financing condition adversely. Monacelli et al. (2018) investigate the effect of interest rate shocks on productivity and document differences for emerging and advanced economies. However, their data for advanced economies is limited to the period before 2008.

Furthermore, recent work by Faust et al. (2013), Gilchrist and Mojon (2018), and Gilchrist et al. (2009) has highlighted the predictive role of credit spreads for real activity in advanced economies, notably the US and selected countries of the euro area. In this case, aggregate spread measures are constructed on the basis of individual bond spreads within countries, while our analysis is based on the cross-country spread. Likewise, a recent contribution by Bocola and Dovis (2019) quantifies the role of self-fulfilling expectations during the euro area crisis. Using an estimated structural model they find that non-fundamental risk accounts for 13 percent of the variation in the Italian spread. Taking a broader historical perspective, Jordà et al. (2019) show that real interest rates exhibit enormous time-series and cross-country variability in the medium run. Miyamoto and Nguyen (2017) consider the period 1900–2013 and find that financial frictions matter not only for developing but also for small developed countries. Lastly, recent work by Passari and Rey (2015) and Miranda-Agrippino and Rey (2020) provides evidence that spread fluctuations are caused by global financial conditions. Specifically, contractionary US monetary policy shocks are shown to impact global financial conditions and, as a result, various spread measures increase around the globe. International lending contracts because of a deleveraging by global financial intermediaries.

The remainder of the chapter is organized as follows. Section 1.2 provides details on our data set and establishes basic facts about the country spread. What sets our analysis apart from earlier work is both the scope of our data and our focus on the difference across country groups and sample periods. Section 1.3 introduces the empirical strategy, while Section 1.4 presents the main results regarding the transmission of spread shocks. It also reports the results of a forecast error variance decomposition. A final section concludes.

1.2 New facts

Our analysis is based on quarterly observations for macroeconomic, fiscal, and financial market variables. Most importantly, our dataset includes country spreads of interest rates. Our sample covers 38 emerging and advanced economies and runs from the early 1990s up to the end of 2018. We build on and extend the database assembled in earlier work (Born et al. 2020). In what follows, we first explain briefly the construction of the country spread and characterize its behavior. Afterwards, we provide a number of new facts concerning the co-movement of the country spread and the fundamentals of a country.

1.2.1 Country spreads

We follow Uribe and Yue (2006) and measure the country spread as the difference between foreign-currency-denominated government or government-guaranteed bonds and risk-free bonds in the same currency. As a result, changes in the spread reflect changes in default risk and/or risk aversion (rather than expectations about inflation and/or expected

Table 1.1: Descriptive statistics of the country spread before and after 2008Q1

	Before 2008		After 2008		Before 2008		After 2008	
	Adv.	Em.	Adv.	Em.	Adv.	Em.	Adv.	Em.
	Spread level s_{it} (percentage points)				Spread change Δs_{it} (basis points)			
Mean	0.33	4.25	1.50	3.09	−0.24	−3.45	2.72	2.71
Median	0.25	2.84	0.70	2.39	−0.30	−7.38	−0.95	−4.88
Std. Dev.	0.32	3.94	2.22	2.29	12.77	160.07	69.49	98.87
Min	−0.14	0.15	−0.06	0.41	−99.08	−952.59	−314.45	−854.70
Max	2.20	24.22	24.56	19.50	97.50	1 039.00	783.21	795.84
Kurtosis	10.95	6.42	26.61	11.56	20.43	12.86	29.87	20.76
Skewness	2.34	1.74	3.93	2.46	0.10	1.13	2.66	0.91
Observations	870	719	888	737	843	698	885	735

Notes: Level of spread measured in percentage points (left panel) and quarterly change in basis points (right panel).

currency depreciation). As the construction of the spread is mostly based on liquid securities with comparable maturities, it is also unlikely to be driven by liquidity or term premia. We exclude default episodes from our sample.[1] Throughout our analysis, we focus on the spread rather than the level of the (real) interest rate, because we are interested in differential developments across advanced and emerging economies—as opposed to movements in the underlying risk-free interest rate that is common to both country groups.

As stressed by Neumeyer and Perri (2005), interest rates on government debt are not identical to those of the private sector, but there is generally a very strong co-movement. Like Uribe and Yue (2006), we rely on the JPMorgan Emerging Market Bond Index (EMBI) data set, but also on a number of additional sources, as explained in detail in earlier work (Born et al. 2020). In what follows, we pursue the same approach as in Born et al. (2020), but update the data to include observations up to 2018Q4. In total, there are 1758 country-quarter observations for advanced economies and 1456 for emerging economies. Table 1.A.2 in the appendix provides details on the sample coverage and descriptive statistics at the country level.

In what follows, we compute a number of statistics, both for the period before and after 2008. Specifically, the first sample period ends in 2007Q4, the second starts in 2008Q1, that is, it includes the year 2008. We verify that our results are qualitatively unaffected when we use 2007Q1 or 2009Q1 as alternative break dates.

In Table 1.1 we report a number of summary statistics for the spread in advanced and emerging economies. The statistics in the left panel refer to the level of the spread measured in percentage points, while the right panel refers to the quarterly change of the spread measured in basis points. A number of observations stand out. First, before 2008 advanced and emerging economies exhibited very different average levels of the spread.

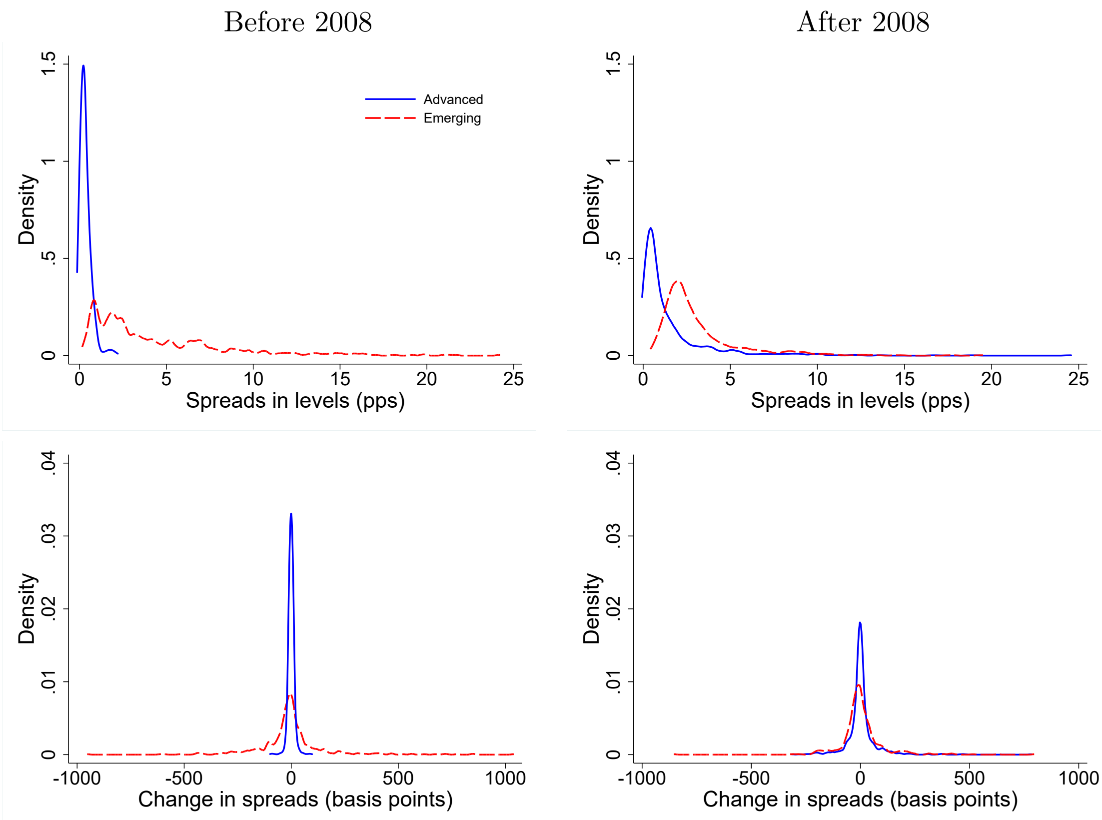
[1] Default episodes are: Greece (2012Q1-2012Q2, 2012Q4), Argentina (2001Q4-2005Q2, 2014Q3-2016Q2), Ecuador (1999Q3-2000Q3, 2008Q4-2009Q2), Uruguay (2003Q2) and Peru (2000Q3). This classification follows Standard & Poor's (see Witte et al. 2018, Table 13).

In this case, both the mean and the median are more than 10 times higher in emerging economies than in advanced economies. Likewise, the standard deviation is about 10 times higher. However, before 2008, as the mean spread change in column 6 shows, emerging market spreads were on average on a downward trajectory. Second, for the period after 2008 we find that the spread behaves much more similar in the two country groups. The mean and median spread level in emerging economies are now only bigger by a factor of 2, due to both an increase in the average spread in advanced economies and a decrease in emerging economies compared to the previous period. For the spread level, we can reject the hypothesis that the mean is the same across country groups before and after 2008, on the basis of both a parametric two-sample t-test and the non-parametric Mann-Whitney-U test. For the spread change, only the Mann-Whitney-U test rejects the null.[2] After 2008, the standard deviation and the maximum realization have largely converged to a level previously only reached by emerging economies. The same holds true for average spread changes and their standard deviation. We can reject the null of equal standard deviations for the spread level before 2008, but not after 2008 (p=0.3413). However, for the spread change we can reject the null of equal standard deviations for both sample periods. Importantly, these changes are not driven by individual countries, but are rather broad-based, as the right panel of Figure 1.1 illustrates. Tables 1.A.2 and 1.A.3 in the appendix provide additional statistics on a country-by-country basis. The maximum spread changes, for instance, increased considerably in all advanced economies. Importantly, we observe a very similar pattern once we omit the 2007/08 period in order to assess the robustness of our findings, see Table 1.A.4 in the appendix.

As a way to visualize the change in the spread distribution over time, we show kernel density estimates in Figure 1.2. Here, the top panels show the distribution of the spread measured in levels, the bottom panels show the distribution of the quarterly change. We once more contrast data for the period before and after 2008, shown in the left and right column, respectively. In each panel, the solid line displays the distribution for advanced economies and the dashed line represents the distribution for emerging economies. We again note that the two country groups are very different before 2008 and much more similar in terms of their distribution after 2008. Before 2008, the mass of the observations for advanced economy spreads is close to zero, both in terms of the level and the change. This changes considerably after 2008: the distribution becomes wider and less concentrated around zero—a feature formerly characterizing the distribution for emerging economies. Turning to higher moments, we find the distribution to be right-skewed for all time periods, country groups, and both spread measures. Given that spreads are bounded from below, this is unsurprising. But it is noteworthy that the skewness has increased after 2008 and more so for advanced economies (see also Table 1.1). We also find the distribution of spread changes to be leptokurtic, that is, the mass of observed changes is clustered around 0 with more extreme observations in both tails of the distribution (compared to a Gaussian distribution with the same first two moments).

[2] The t-test with its clearly violated assumption of normality cannot reject the null of equal means for both sample periods. This is unsurprising given the large underlying standard deviations.

Figure 1.2: Distribution of the spread in levels and in changes before 2008 and after 2008.



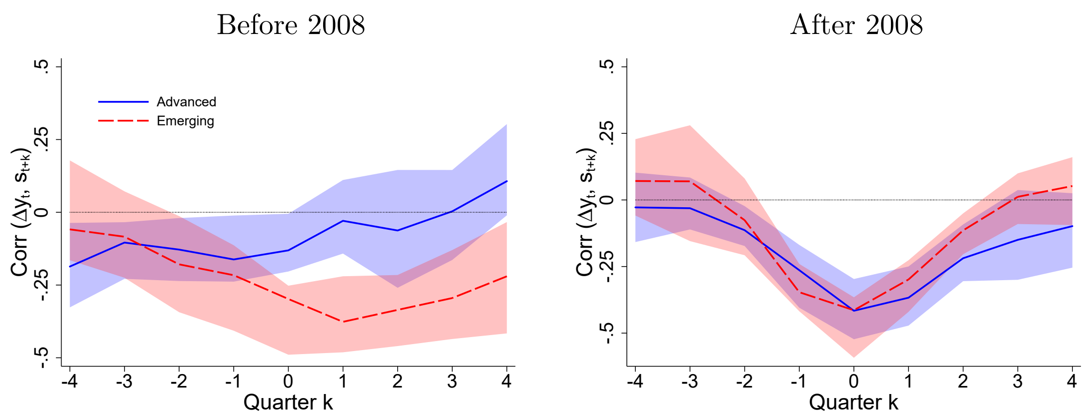
Notes: Distribution of the spread in levels (top) and in changes (bottom) before 2008 (left) and after 2008 (right). Kernel density estimate for advanced economies (blue solid line) and emerging economies (red dashed line); spread level measured in percentage points, change of spread in basis points. The kernel density estimate employs an Epanechnikov kernel with bandwidth 8 for the spread change and 0.15/0.25 (before/after 2008) for the spread level.

While positive excess kurtosis (that is >3) is pervasive for both country groups in both sample periods, it is larger to begin with and also increased more for advanced economies (see also Table 1.1).

1.2.2 Country spreads and fundamentals: co-movement

Neumeyer and Perri (2005) highlight a striking pattern regarding the cyclicality of interest rates. On the basis of data for the period up to the early 2000s for five emerging and five advanced economies, they show that the contemporaneous co-movement of output and real interest rates at business cycle frequencies is negative for emerging economies, but zero to positive for advanced economies. Fernández and Gulan (2015) consider data up to 2010Q3 and report similar results. We revisit these findings for the spread component of interest rates on the basis of our data set, which includes more countries and more recent observations after the global financial crisis. Figure 1.3 displays the cross-correlation

Figure 1.3: Cross-correlation functions for output growth Δy_t and spread s_{t+k}



Notes: Cross-correlation functions for output growth Δy_t and spread s_{t+k}, measured in levels at lead/lag $k = 0, \ldots, \pm 4$ before 2008 (left panel) and after 2008. The blue solid line depicts the average correlation for advanced economies, the red dashed line for emerging economies. Shaded areas indicates 25% and 75% interquartile range in the respective country group.

between output growth and the spread.[3]

Again, we show results for the period before 2008 in the left panel and results for the period after 2008 in the right panel. For the period before 2008 (left panel), the contemporaneous correlation for emerging economies is counter-cyclical, with the strongest (negative) correlation at lead 1. For advanced economies, the correlation is slightly negative, and more or less acyclical at all leads and lags. This pattern changes after 2008, when the contemporaneous correlation turns strongly counter-cyclical for advanced economies as well. As the right panel of the figure shows, the cross-correlation function now exhibits a similar U-shaped pattern for both emerging and advanced economies. We observe a very similar picture once we omit the 2007/08 period, see Figure 1.A.1 in the appendix.

In Table 1.2, we report more details on a country-by-country basis. For each advanced economy (left panel) we report standard deviations of output growth and the spread (in levels) for the period before and after 2008. The same statistics are reported for each emerging economy in our sample (right panel). The table shows that the convergence in the correlation pattern is not driven by specific countries: the contemporaneous correlation of output and the spread declined in all advanced economies, except for Germany and Slovenia.

Next, we turn to the co-movement between the spread and the debt-to-GDP ratio shown in Figure 1.4. As before, the left and right panels display data for the periods

[3]In contrast to the previous two papers, we use growth rates of output instead of deviations from an HP-filtered trend. The use of a one-sided filter instead of a two-sided one preserves the temporal ordering of the time-series. We report results for HP-filtered series in the Appendix. For the period before 2008 (left panel), we obtain a similar pattern as Neumeyer and Perri (2005) and Fernández and Gulan (2015) for output and real interest rates: counter-cyclical spreads for emerging economies and slightly pro-cyclical ones for advanced economies. This pattern only changes after 2008, when the contemporaneous correlation turns counter-cyclical for advanced economies as well.

Table 1.2: Unconditional relationship between output and spread

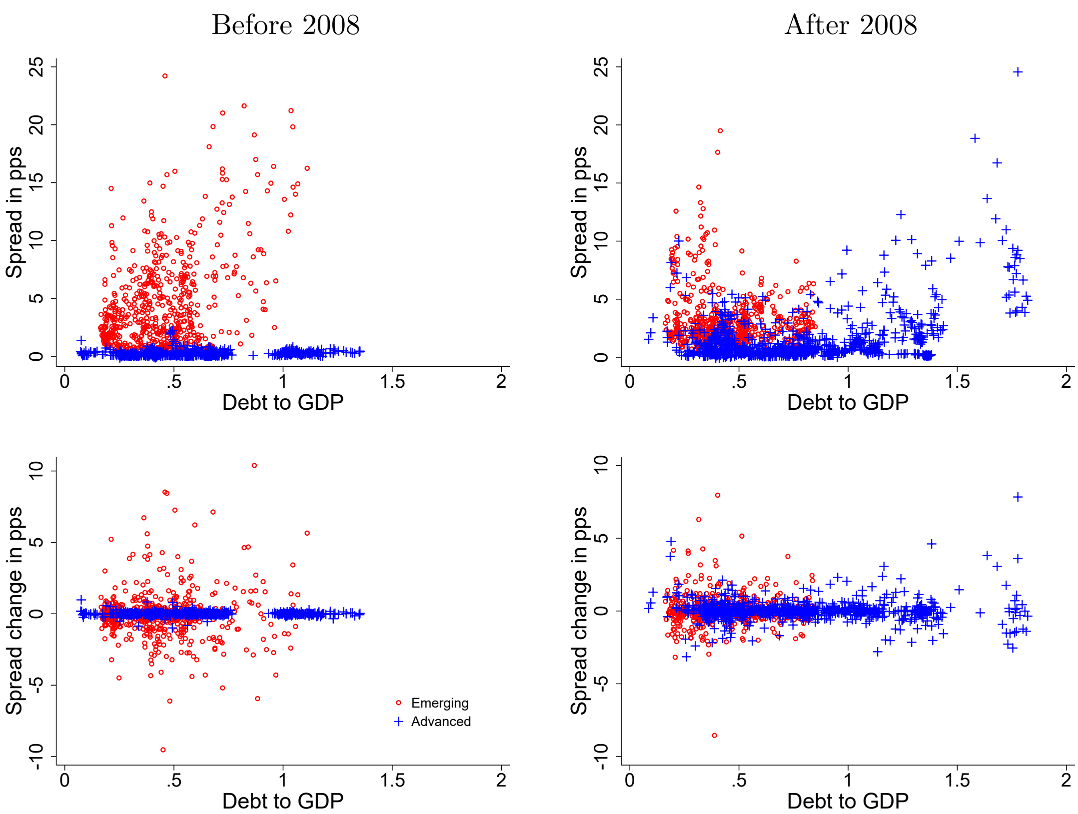
Advanced economies					Emerging economies				
	Before 2008		After 2008			Before 2008		After 2008	
	$\sigma(Y)$	$\rho(Y,s)$	$\sigma(Y)$	$\rho(Y,s)$		$\sigma(Y)$	$\rho(Y,s)$	$\sigma(Y)$	$\rho(Y,s)$
Australia	0.80	−0.02	0.43	−0.23	Argentina	2.30	−0.62	2.41	−0.38
Austria	0.44	−0.15	0.70	−0.36	Brazil	0.96	−0.25	1.30	−0.63
Belgium	0.61	−0.18	0.53	−0.29	Bulgaria	0.47	0.36	1.04	−0.44
Czech Republic	0.68	−0.43	0.93	−0.72	Chile	1.02	−0.38	0.95	−0.41
Denmark	0.99	−0.18	0.92	−0.38	Colombia	1.03	−0.53	0.68	−0.37
Finland	1.19	−0.23	1.40	−0.47	Croatia	1.18	0.03	1.22	−0.44
France	0.41	−0.09	0.51	−0.23	Ecuador	1.40	−0.51	1.06	−0.17
Germany	0.66	−0.41	0.98	−0.30	El Salvador	0.56	−0.58	0.58	−0.43
Greece	0.88	−0.07	1.54	−0.44	Hungary	0.58	0.06	1.14	−0.61
Ireland	1.74	0.18	4.05	−0.17	Malaysia	0.80	−0.48	1.21	−0.68
Italy	0.56	−0.10	0.77	−0.34	Mexico	1.41	−0.36	1.19	−0.59
Latvia	1.86	−0.66	1.88	−0.67	Peru	1.45	−0.30	0.95	−0.27
Lithuania	1.33	0.24	2.37	−0.53	Poland	1.41	0.08	0.69	−0.11
Netherlands	0.52	0.00	0.75	−0.62	South Africa	0.86	−0.47	0.58	−0.62
Portugal	0.67	−0.14	0.83	−0.45	Thailand	1.62	−0.49	2.21	−0.40
Slovakia	1.56	0.07	1.67	−0.18	Turkey	2.45	−0.33	2.49	−0.43
Slovenia	0.77	−0.46	1.25	−0.38	Uruguay	2.56	−0.36	1.41	−0.05
Spain	0.25	0.10	0.69	−0.52					
Sweden	0.61	−0.08	1.11	−0.59					
United Kingdom	0.65	−0.01	0.67	−0.40					
United States	0.71		0.67	−0.47					
Total	0.85	−0.13	1.17	−0.42	Total	1.30	−0.30	1.24	−0.41

Notes: Standard deviation of output growth ΔY_t and contemporaneous correlation with the spread level s_t in advanced and emerging economies before 2008 and after 2008. In the last line we report the equally-weighted country average.

before and after 2008, respectively. The top row refers to the level of the spread, the bottom row to the change. Blue plus signs indicate observations for advanced economies, while red circles refer to observations for emerging economies. For the period before 2008, depicted in the left panels, we observe distinct patterns for emerging and advanced economies. The debt-to-GDP ratio varies considerably in both country groups, from 7 to 135 percent in advanced economies and from 17 to 111 percent in emerging economies. Yet, even though the range of the debt-to-GDP ratio observed in both country groups is similar, the spread in levels (top left panel) seems to be positively associated with the level of debt in emerging economies, but not much in advanced economies. Again, we observe a notable change for the period after 2008 (top right panel): debt-to-GDP ratios in advanced economies now reach considerably higher levels (of up to 182 percent). The opposite holds true for emerging economies, where the largest observation now only reaches 85 percent of GDP. Moreover, after 2008, the spread in levels exhibits a positive comovement with debt in advanced economies as well. For spread changes (bottom panels) we observe that they differ systematically across country groups, but hardly with the level of debt. After 2008, the range of spread changes appears still largely unrelated to the level of debt.

Finally, we investigate how spread changes vary across exchange rate regimes. For

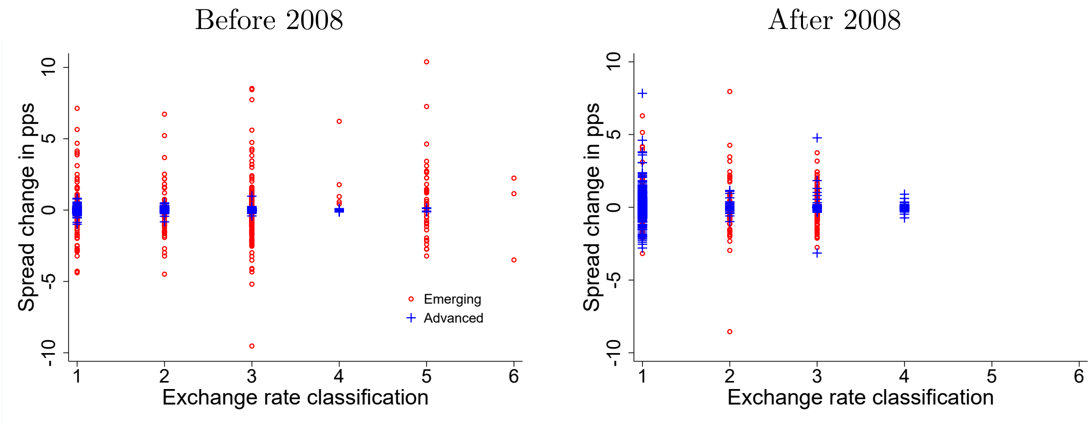
Figure 1.4: Spread, spread change and debt-to-GDP ratio



Note: Top: spread measured in levels (percentage points). Bottom: quarterly spread changes (in percentage points). Blue plus signs indicate observations for advanced economies and red circles indicate observations for emerging economies. Public debt-to-GDP ratio refers to general or central government (external) debt relative to GDP/GNI.

this purpose, we rely on the coarse regime classification of Ilzetzki et al. (2019). It allows for six categories, which feature increasingly flexible exchange rate regimes: an exchange rate peg (1), a crawling peg (2), a managed float (3), a freely floating exchange rate (4), a freely falling exchange rate (5), and a dual market (6). We order these categories from left to right on the horizontal axis in Figure 1.5, again for the period before 2008 (left panel) and after 2008 (right panel). We measure the quarterly change in the spread along the vertical axis and use red circles for observations for emerging economies and blue plus signs for advanced economies. Again, we observe that the basic patterns in the data change across the two sample periods. Prior to 2008 there is no apparent systematic relation between spread changes and exchange rate regimes. While spreads generally vary little for advanced economies, the variation in spread changes does not differ much across exchange rate regimes in emerging economies. In contrast, after 2008 variation in spread changes is systematically higher, the less flexible the exchange rate regime. This finding is consistent with the notion that some of the variation in spreads is due to self-fulfilling expectations which, in theory, are more likely to take place if monetary policy is lacking autonomy (Bianchi and Mondragon 2018; De Grauwe 2012; Lorenzoni

Figure 1.5: Spread change versus exchange rate classification



Note: Spread change versus exchange rate classification before 2008 (left panel) and after 2008 (right panel). Blue plus signs indicate observations for advanced economies and red circles indicate observations for emerging economies. The exchange rate regime classification follows the coarse classification of Ilzetzki et al. (2019): 1 denotes peg, 2 crawling peg, 3 managed float, 4 freely floating, 5 freely falling, and 6 denotes dual market. After 2008, there are no observations of categories 5 and 6 in our sample.

and Werning 2019).[4] The notion that spreads vary for reasons unrelated to fundamentals, for instance, because expectations become self-fulfilling, provides the rationale for the strategy that we use to identify exogenous variation in the spread. We take up this issue in the next section.

1.3 Measuring the effects of spread shocks

In the remainder of the chapter we focus on spread shocks and how they impact both emerging and advanced economies before and after 2008. As argued in the introduction, there are strong reasons to expect that the country spread fluctuates partly for reasons which are exogenous, either because of global developments or shifts in market sentiment. Our identification strategy is based on the causal model by Rosenbaum and Rubin (1983), which permits estimation of a "treatment effect". In the context of our analysis a treatment boils down to being exposed to a large spread increase, as we explain in some detail in what follows. In Section 1.3.2 we present a measure of how likely it is for a country to be treated at a particular point in time, that is, its propensity score. In Section 1.3.3 we explain how we rely on the propensity score as we employ an augmented inverse propensity score weighted (AIPW) estimator in order to establish the causal effect of sovereign spread shocks. Last, we also discuss an alternative strategy to measure spread shocks.

[4]This effect should be less important in case of foreign currency debt. However, even in this case self-fulling runs may be more likely the less flexible the exchange rate regime. For if monetary policy is able to act as a lender of last resort for domestic debt, this may free up resources to satisfy the claims of foreign-currency debt holders. See, e.g., Bocola and Lorenzoni (2020).

1.3.1 Treatment

In our baseline, we focus on large increases of the spread in order to capture events that are potentially more disruptive than garden-variety changes of the spread. Moreover, large changes are also more likely to be caused by exogenous factors, to the extent that country-specific fundamentals change only gradually. Still, large changes of the spread may also reflect an endogenous response to fundamentals. We account for this possibility once we control for selection into treatment on the basis of a large set of fundamentals as well as for potentially non-linear selection effects. In our baseline, we consider only spread increases rather than spread changes, because their effect is not necessarily symmetric. In our robustness analysis we pursue an alternative approach for which we no longer restrict our analysis to spread increases. Instead, we consider both positive and negative spread shocks.

To operationalize the notion of a treatment with a large spread increase, we define a dummy variable that assumes a value of one whenever the change of the spread for a given country-quarter observation is larger than one standard deviation and, in addition, at least 25 basis points. Otherwise, the dummy is zero:

$$D_{i,t} = \mathbb{1}(\Delta s_{i,t} >= \sigma_i \wedge \Delta s_{i,t} >= 25\text{bp}) \ . \tag{1.1}$$

Here and in what follows the subscripts t and i refer to the quarter and the country of an observation, respectively. $\Delta s_{i,t}$ is the change in the spread, as measured at the end of a quarter, and σ_i is the country-specific standard deviation of spread changes.[5]

On the basis of this definition, 229 observations in our sample qualify as treatments. This amounts to 7.25 percent of the observed spread changes.[6] Table 1.A.5 in the appendix reports the maximum spread change along with the number of treatments for each country in the sample.[7] Table 1.A.6 in the appendix lists all the countries which have been treated in a specific quarter. We find that treatments are fairly evenly distributed across time and countries. In 49 out of 156 quarters there is at least one treatment. Each country in our sample has been treated at least once. Still, perhaps unsurprisingly, treatments also bunch in quarters associated with major crises: 1998Q3, 2008Q3, 2008Q4, 2010Q2, and 2011Q3. For all countries in our sample we find that the spread increases by more than one standard deviation at the time of the treatment, suggesting that we indeed capture episodes of exceptionally large spread increases.

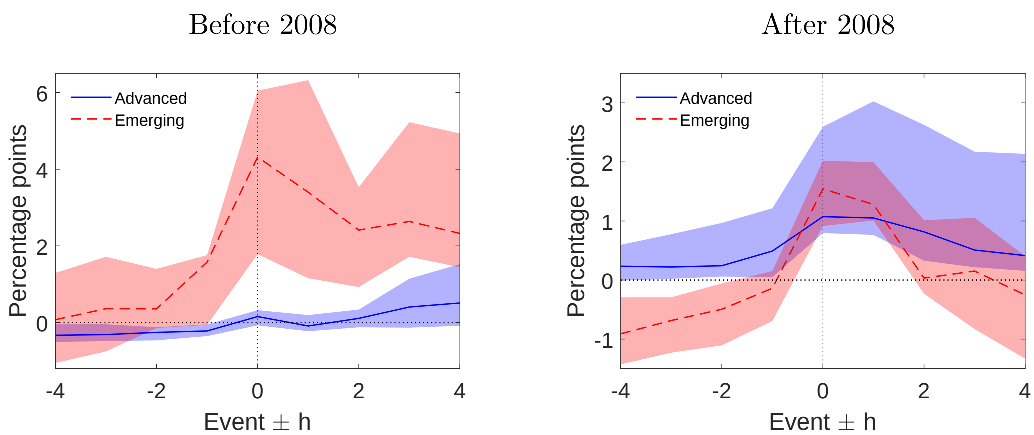
Figure 1.6 illustrates how spreads evolve in an event window centered around the quarter in which a treatment takes place. To account for the fact that the level of the spread differs across countries, we first express the country-specific spread in terms of

[5]Mauro et al. (2002), in their emerging market economy analysis, consider a spread increase large if it exceeds two standard deviations.

[6]This is well below the 16 percent of observations we would expect outside of the one-sigma interval of a normal distribution. The reason is that spread changes are not normally distributed (see Table 1.1) and because we require a treatment to raise the spread by at least 25 basis points. When dropping the latter requirement, 8.16 percent of the observations qualify as treatments.

[7]Recall that we exclude country-quarter observations for which countries are in default.

Figure 1.6: Spread deviations from country-mean around treatments



Note: Spread deviations from country-mean around treatments, before (left) and after 2008 (right) in advanced (solid line) and emerging economies (dashed line). Country-specific spread movements around treatments are measured as the average of spread deviations from the respective country mean over all events in the country in the event window $t \pm h$. Lines indicate the median of country-specific spread movements, shaded areas indicate the 25% and 75% interquartile range across countries. Time is measured in quarters. For definition of treatment, see main text, equation (1.1).

deviations from the country mean. We then compute the country-mean of these spread deviations over all events in the respective country. The left panel represents data for the period before 2008, the right panel for the period after 2008. The solid line represents the median over the individual mean-country-spreads for advanced economies around treatments. The dashed line represents the median for emerging economies. The shaded area represents the 25%-75% interquartile range across countries. The horizontal axis captures four quarters before to four quarters after treatment.

In the period before 2008, the median spread movement around treatments amounts to a 4 percentage point increase above the country average in emerging economies. At the same time, the average spread movement around treatments is fairly moderate in advanced economies, namely 0.15 percentage points above the country average and 36 basis points relative to the pre-treatment period. In advanced economies, the spread is flat in the year preceding the event, while it is already elevated in the quarter before the treatment in emerging economies. After treatment takes place, the spread remains high for an extended period only in emerging economies. For the period after 2008 a different picture emerges. The spread movement around treatments in advanced and emerging economies is now of about the same size. For emerging economies we observe a somewhat sharper rise of the spread at the time of the treatment. For advanced economies the spread is already elevated prior to treatment and persistently high afterwards. By and large, however, we find once more that the dynamics in advanced and emerging economies have become fairly well aligned after 2008. In the appendix, we display event windows on a country-by-country basis, see Figures 1.A.4 and 1.A.5.

1.3.2 Selection into treatment

The selection into treatment is not random, but likely to depend on fundamentals. In order to quantify how the probability of treatment varies with fundamentals, we run a logistic regression. Formally, a country's likelihood of receiving a treatment at a given point in time, $D_{i,t}$, conditional on some observable fundamentals $X_{i,t}$, that is, its *propensity score*, is given by

$$p(D_{i,t} = 1|X_{i,t}) = G(X_{i,t}\beta) \ , \tag{1.2}$$

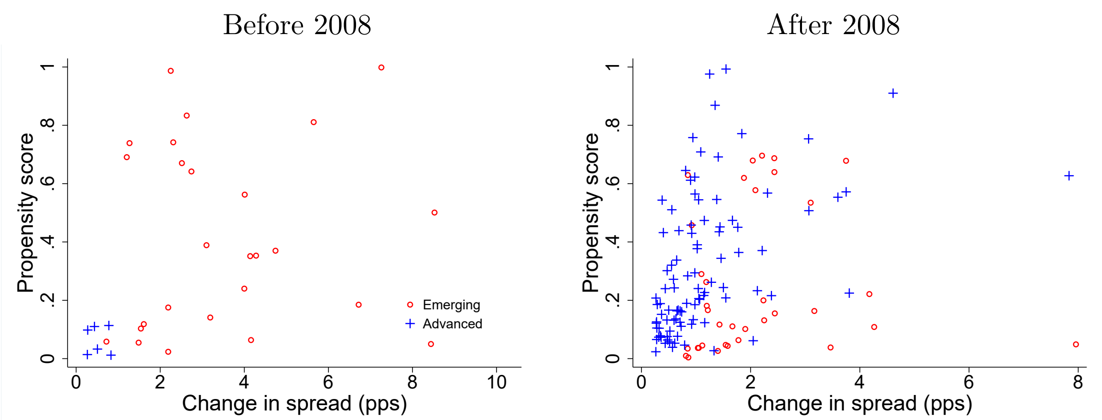
where G is a logistic cumulative density function and β denotes a vector of regression coefficients. A low propensity score p indicates that, based on the fundamentals $X_{i,t}$, experiencing a treatment is unlikely. As a consequence, the treatment is likely to be caused by exogenous factors. The vector $X_{i,t}$ in our model contains a large number of contemporaneous and lagged control variables, dummy variables, and country-fixed effects. In the baseline specification, we do not allow for time-fixed effects because we do not want to eliminate spread variation that is likely due to global economic developments and, hence, exogenous to country-specific developments. In section 1.4.2 below, we will investigate the effect of country-specific spread shocks by including time-fixed effects in order to capture common global developments.

Note that it is generally recommended to "over-model" the propensity score, that is, to include a large number of covariates because this ensures that the conditional independence assumption (CIA) (see below) is indeed satisfied. In our baseline model, $X_{i,t}$ features key macroeconomic variables such as GDP growth, public debt, and inflation, a number of indicators that capture the political stability of a country, as well as financial variables like stock prices and the exchange rate (see Table 1.A.1 in the appendix for details). The latter are particularly important due to their inherently forward-looking nature. For a subset of country-quarter observations we have an even larger conditioning set available: Additional control variables like the term spread, the short-term interest rate, a measure of credit, as well as forecasts of GDP and government spending growth are well-suited to capture potential anticipation effects. Whenever we rely on the larger set of control variables we refer to the "extended model" as opposed to the "baseline model". Given the limited availability of control variables, we estimate the logit model (1.2) on 161 treatments in case of the baseline model and 76 treatments in case of the extended model.

Figure 1.7 correlates the estimated propensity score with the change in the spread for the observations in our baseline sample for which a treatment has taken place according to definition (1.1).[8] As before, we use red circles to refer to observations for emerging market economies and blue crosses for advanced economies. The left panel refers again to the period before 2008, while the right panel refers to the period after 2008. First, we

[8]Table 1.A.7 in the appendix reports the point estimates as well as the implied average marginal effects, while Tables 1.A.8 and 1.A.9 report the means and standard deviations of the estimated propensity scores $\hat{p}$ on a country-by-country basis.

Figure 1.7: Propensity score and spread change for treatment events $D_{i,t} = 1$.



Note: Propensity score and spread change before 2008 (left panel) and after 2008 (right panel) for treatment events $D_{i,t} = 1$. Blue plus signs (red circles) indicate observations for advanced (emerging) economies.

note that there are very few treatments for advanced economies before 2008. To alleviate concerns about the small number of treatments biasing our subsequent estimation of average treatment effects, we also pursue an alternative identification strategy in Section 1.3.4. It uses a continuous spread shock measure in each single period and therefore many more observations. Still, we obtain results very similar to the baseline. Second, in the period before 2008 there are many treatments of emerging economies for which the propensity score is moderate. This suggests that the treatment cannot be well explained by fundamentals. Instead, it is likely caused by exogenous factors. Third, the same holds for the period after 2008, although in this case both for emerging and advanced economies.

Before we move on to estimating treatment effects, we formally assess the goodness-of-fit of our model. To this end, we follow Jordà and Taylor (2016) and report the Area Under the Curve (AUC)-statistic.[9] For the baseline (extended) model, we obtain a value of 0.8730 (0.9457) with a standard error of 0.0139 (0.0155). This suggests that both models are doing a good job in predicting treatments. The resulting propensity score allows us to control for selection into treatment as we estimate the ATE below. In addition, we check whether the so-called overlap condition is satisfied in the context of our analysis. It ensures that we can compute the treatment effect for all realizations of the control variables in our sample (see e.g. Imbens 2004; Wooldridge 2010).[10] We find that the distributions of the estimated propensity scores indeed show considerably overlap, see Figure 1.A.6 in the appendix.

[9]The AUC statistic summarizes the predictive ability of the estimation model to classify the observations correctly into treatment and control group. The AUC can take values between 0.5 (no predictive power) up to 1 (full accuracy). Its estimator is asymptotically normally distributed. See Jordà and Taylor (2011) and Hanley and McNeil (1982) for details.

[10]Formally, the overlap assumption is defined as $0 < p(D_{i,t} = 1|X_{i,t}) < 1$. Intuitively, for every observation with characteristic vector $X_{i,t}$, we require a strictly positive probability of being in the treatment group as well as in the control group. Otherwise, we would be trying to compare observational units that are "incomparable".

1.3.3 Estimating the treatment effect

In order to establish the causal effect of a treatment we have to account for the fact that the spread itself responds to the fundamentals of a country, that is, to macroeconomic and political factors in the economy. To address this issue, we follow Jordà and Taylor (2016) and employ the augmented inverse propensity score weighted (AIPW) estimator. Intuitively, we construct a matching-type estimator that compares a control and a treatment group. To deal with non-random allocation into the respective groups, the propensity score is used to re-randomize the observations. Observations with characteristics $X_{i,t}$ causing a high propensity score are more likely to be in the treatment group and are therefore weighted down. At the same time, observations with a low propensity score—for which the treatment is more likely to be exogenous—tend to be undersampled and receive more weight in the estimator.

We introduce some notation to fix ideas. Generally, in order to establish the causal effects of a treatment $D_{i,t} = d, d \in \{0, 1\}$, defined as in equation (1.1) above, we rely on the conditional independence assumption (CIA) (Rosenbaum and Rubin 1983):[11]

$$Y_{i,t+h}(d) - Y_{i,t} \perp D_{i,t} \quad | \quad X_{i,t} \qquad \text{for } h > 0\,, \tag{1.3}$$

where $Y_{i,t+h}(d) - Y_{i,t}$ denotes the potential outcome of variable Y at time $t + h$ relative to its baseline value. This baseline value is observed at time t and we assume it not to be affected by the treatment.[12] An exception is the spread for which we study the response to the treatment relative to its value in the pre-treatment period $t - 1$. The vector $X_{i,t}$ contains control variables as described in Section 1.3.2. Intuitively, equation (1.3) states that, conditional on the controls, the allocation of observational units to the control and treatment group, respectively, is independent of potential outcomes. We estimate the treatment effect for each variable of interest in quarters $h = 1, \ldots, 8$ after treatment.

Rosenbaum and Rubin (1983) show that if the overlap condition is satisfied and the CIA holds, then the latter will also hold if one conditions only on the propensity score:

$$Y_{i,t+h}(d) - Y_{i,t} \perp D_{i,t} \quad | \quad p(D_{i,t} = 1|X_{i,t}) \qquad \text{for } h > 0\,. \tag{1.4}$$

Intuitively, instead of effectively matching units in the treatment and control groups that are similar along all dimensions of the covariates $X_{i,t}$, it is sufficient if they have a similar propensity score. As discussed in the previous subsection, we find that condition (1.4) is satisfied in the context of our analysis. Hence, we simply use the propensity score as estimated above to compute the AIPW estimator, which provides us with the average causal effect of an exogenous increase in the spread on our outcome variables of interest.

Specifically, we employ an AIPW estimator with regression adjustment, which is the most efficient one in its class of so-called doubly-robust estimators (Lunceford and

[11]See Lunceford and Davidian (2004) and Wooldridge (2010) for a discussion.

[12]Note that as we estimate the propensity score, we permit a contemporaneous effect of the control variables on the spread.

Davidian 2004).[13] Formally, we use

$$\begin{aligned} ATE^h_{AIPW} =& \frac{1}{N}\sum_{t=1}^{N}\Bigg\{ \left[\frac{D_t(Y_{t+h}-Y_t)}{\hat{p}_t} - \frac{(1-D_t)(Y_{t+h}-Y_t)}{(1-\hat{p}_t)}\right] \\ & - \frac{D_t-\hat{p}_t}{\hat{p}_t(1-\hat{p}_t)}\left[(1-\hat{p}_t)m_1^h(X)+\hat{p}_t m_0^h(X)\right]\Bigg\}\ , \end{aligned} \tag{1.5}$$

where treatment takes place at time t and the effect on the dependent variable is captured at horizon $t+h$. In the expression above, we drop the panel index i to ease notation.

Two things are noteworthy about this estimator. First, by including propensity-score weights $\hat{p}_t$ and $(1-\hat{p}_t)$ in the denominator in the first line of Equation (1.5) we achieve a random allocation of observational units into treatment and control group. Second, the second line of Equation (1.5) features a regression adjustment component, which among other things stabilizes the estimator in case the propensity score gets close to zero or one (see Lunceford and Davidian 2004).[14] This is an issue of some concern in light of the estimated propensity scores reported in Tables 1.A.8 and 1.A.9.[15]

For inference, we use the asymptotic normality of the AIPW estimator and rely on an empirical sandwich estimator of the variance, as explained in Lunceford and Davidian (2004), to compute clustered robust standard errors.

1.3.4 An alternative approach

Our baseline approach focuses on specific treatments—defined as a large increase of the spread. As argued in Section 1.3.1 above, in this way we are more likely to capture events that are a) particularly disruptive and b) not caused by country fundamentals. In order to assess the robustness of our results, we purse an alternative strategy in the spirit of Uribe and Yue (2006), who identify spread shocks using a VAR-style recursive scheme with the spread ordered last.[16] Given this identifying assumption, the relevant regression equation for the spread change (analogous to the definition of treatment) is given by:

$$\Delta s_{i,t} = \eta_i + X_{i,t}\beta + \varepsilon_{i,t}\ , \tag{1.6}$$

where the column vector of controls $X_{i,t}$ contains current and one-period lagged values of GDP growth and net exports as well as the lag of the spread. $\varepsilon_{i,t}$ are mean zero structural innovations, that is "spread shocks", and η_i are country-fixed effects.[17] In terms of

[13] In this class, consistent estimation of the ATE is achieved as long as either the model for the conditional mean or the propensity score model are correctly specified.

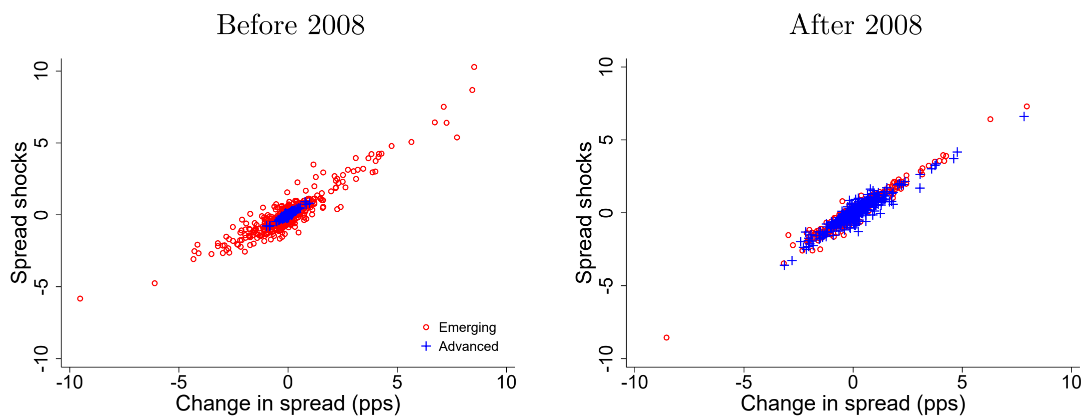
[14] The terms $m_d^h(X), d \in \{0,1\}$ are the conditional means derived from the conditional mean model. This is a regression of $(Y_{t+h}-Y_t)$ on the covariates X_t, conditional on the subsample of treatment ($d=1$) or control ($d=0$).

[15] An alternative to including a regression adjustment term is truncation. We find that our results are fairly robust as we consider a truncated propensity score at ±5%, ±10%, and ±20%.

[16] Technically, they estimate a panel VAR equation by equation and include the US interest rate and the country interest rate separately. But, as they argue, this is equivalent to including the spread directly.

[17] The R^2 of these OLS regressions (for various sample splits) ranges between 0.78 and 0.90, which indicates that around 10 to 20 percent of the variation in the spread is left unexplained by the model and hence can be attributed to non-fundamental shocks. This finding is in line with the decomposition of

Figure 1.8: Spread shocks versus changes in spreads



Note: Spread shocks (vertical axis), as captured by linear model (1.6), measured against change in spread in percentage points (horizontal axis) before and after 2008. Blue plus signs (red circles) indicate observations for advanced (emerging) economies.

identification, model (1.6) just like our baseline, allows for a contemporaneous effect of fundamentals on the spread change, but rules out that fundamentals respond immediately to spread changes. However, following Uribe and Yue (2006), model (1.6) is much more parsimonious than our baseline model for two reasons. First, with OLS regressions, "over-modeling" as in the case of propensity score estimation is not advocated. Second, because the model features fewer explanatory variables, we can estimate the OLS regressions separately for the groups of advanced and emerging economies before and after 2008. In contrast to the ATE estimator, model (1.6) does not allow for nonlinearities in the effects of spread shocks, but it has the advantage of being able to consider positive and negative spread shocks alike and allowing to compute forecast error variance decompositions.

In Figure 1.8 we correlate spread shocks, that is, the residuals from regression (1.6), $\hat{\varepsilon}_{i,t}$, and the change in the spread. As before red circles refer to observations for emerging economies, while blue plus signs refer to observations for advanced economies, the left panel shows results for the period before 2008, the right panel for the period after 2008. For the period before 2008 we again observe a different distribution between advanced and emerging economies. Shocks are small in the former and quite sizeable in the latter. After 2008, the shocks have again become much more comparable in terms of size across the two country groups. This suggests that there is considerable exogenous variation in the spread.

We use the residuals of regression (1.6) as a measure of the spread shock and estimate its dynamic effect on various outcome variables via local projections (Jordà 2005). Letting $Y_{i,t+h}$ denote the variable of interest in period $t+h$, we regress it on spread shocks in period t on the basis of the following specification:

$$Y_{i,t+h} - Y_{i,t} \;= \alpha_{i,h} + \psi_h \hat{\varepsilon}_{i,t} + u_{i,t+h} \ , \tag{1.7}$$

Bocola and Dovis (2019).

where $Y_{i,t}$ again denotes the unshocked baseline value of variable Y. In equation (1.7), the coefficients ψ_h, which we estimate by OLS, provide a direct estimate of the impulse response at horizon h to a spread shock.[18] The error term $u_{i,t+h}$ is assumed to have zero mean and strictly positive variance. $\alpha_{i,h}$ denotes country-fixed effects. We compute clustered robust standard errors.

The local projection framework also allows us to compute the contribution of the spread shocks to the forecast error variance of our variables of interest. Following Gorodnichenko and Lee (2020), we compute the variance share of the shock at horizon h as the R^2 of the following regression

$$\hat{u}_{i,t+h} = \gamma_0 \hat{\varepsilon}_{i,t+h} + \ldots + \gamma_h \hat{\varepsilon}_{i,t} + \nu_{i,t+h}\,, \tag{1.8}$$

where $\hat{u}_{i,t+h}$ is the forecast error of the local projection (1.7) at horizon h and $\nu_{i,t+h}$ is a mean 0 disturbance.

1.4 Results

We first shed some light on how spread shocks are transmitting through the economy, as we study the dynamic adjustment to spread shocks by means of impulse response functions. Second, we establish that our results are robust across a number of alternative specifications. Lastly, we report the contribution of spread shocks to output fluctuation on the basis of a forecast error variance decomposition. Throughout, we are interested in possible differences across country groups and sample periods.

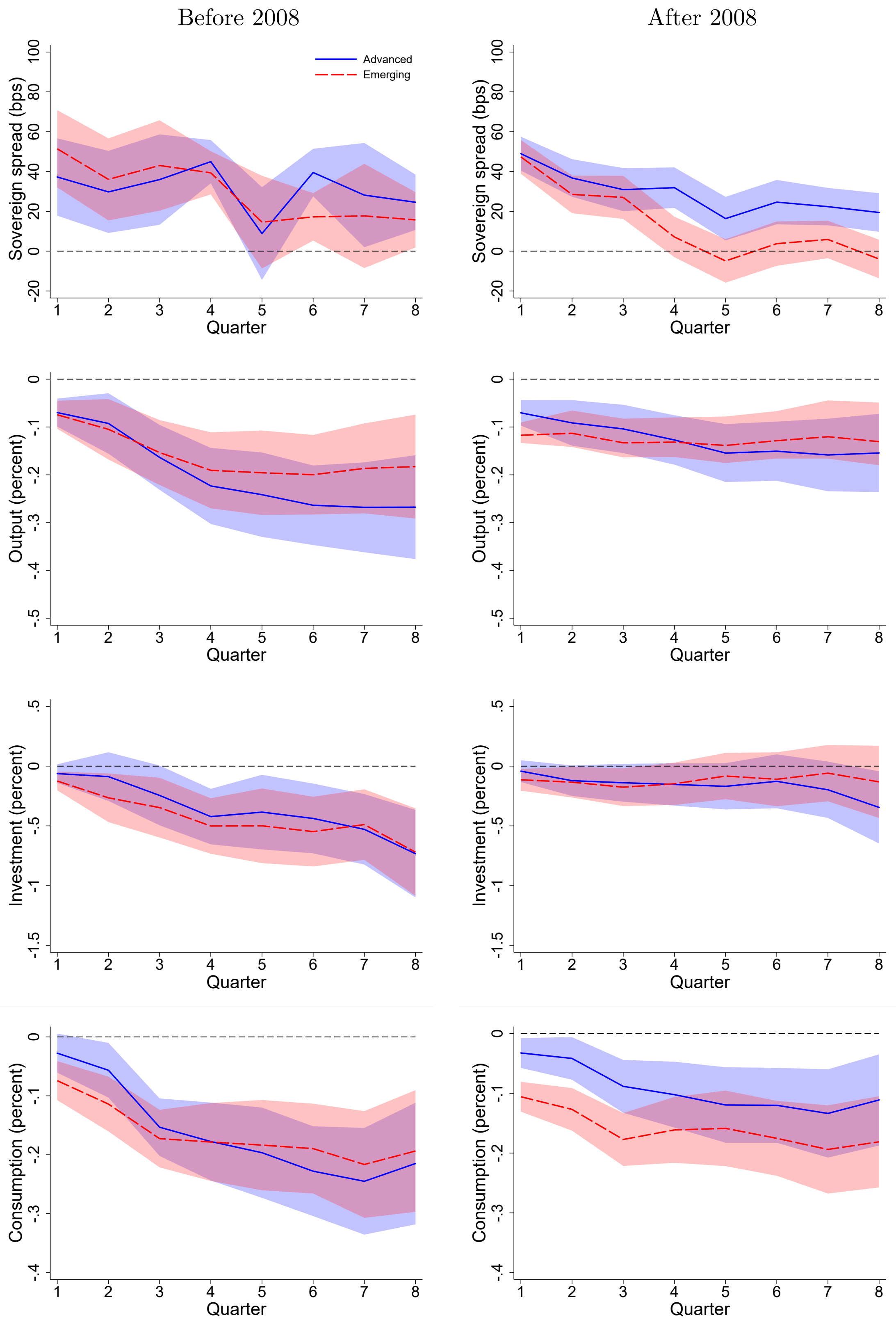
1.4.1 Shock transmission

We now show the impulse responses to a spread shock. First, we report results for the AIPW estimator in equation (1.5) with the treatment defined in equation (1.1). In Figure 1.9, the (blue) solid and (red) dashed lines represent the point estimates for advanced and emerging economies, respectively. In each instance, the shaded area indicates the 90 percent confidence interval based on clustered robust standard errors. We measure time in quarters along the horizontal axis. The vertical axis measures the deviation relative to the pre-shock level in either percent or basis points. As before, the left column shows results for the period before 2008, the right column for the period after 2008.

Our main finding is that the dynamic adjustment to a spread shock does not differ much across country groups or sample periods. We find this result particularly noteworthy in light of the facts established in Section 1.2 above. As shown in the top row, spreads remain elevated for an extended period of about four quarters. The initial increase is about 50 basis points. After three quarters, spreads are still some 20 basis points higher than prior to treatment. This pattern is remarkably similar across countries, both for

[18]The shock is thus a generated regressor in the second stage (Coibion and Gorodnichenko 2015a). Still, Pagan (1984) shows that the standard errors obtained after a regression on the shocks are asymptotically valid under the null that the coefficient is 0.

Figure 1.9: Impulse responses of the spread and real national accounts variables to a spread shock



Note: Impulse responses of the spread and real national accounts variables to a $h = 0$ sovereign spread shock based on the ATE estimator in equation (1.5) together with the treatment definition in (1.1). Solid (blue) and dashed (red) line represents deviation from pre-shock treatment level for advanced and emerging economies, respectively. Shaded areas correspond to 90% confidence intervals based on clustered robust standard errors. Horizontal axis measures time after treatment in quarters.

the period before and after 2008.

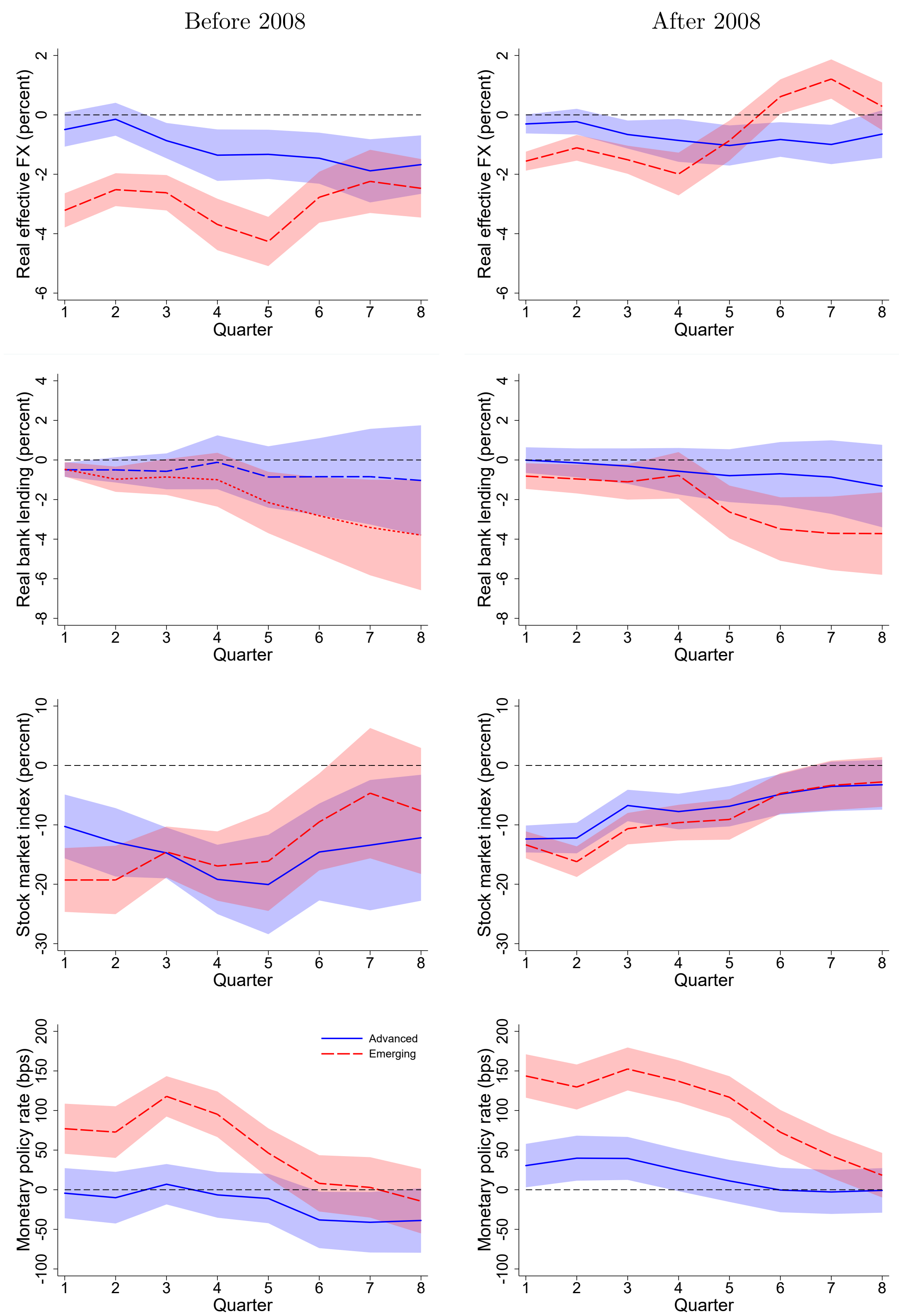
The adjustment of output is shown in the second row. It is again highly similar across country groups, in particular in the period before 2008. Output declines immediately by about 0.1 percent and continues to decline in the following one to two years. According to the point estimate, the maximum effect is about 0.3 percent in advanced economies and 0.2 percent in emerging economies. After 2008 the effect is a bit weaker. It is similar on impact, but afterwards there is less of a decline. Overall these numbers are in the same ballpark as those established by the earlier literature on the effect of interest increases due to monetary policy shocks. In a recent paper, Coibion et al. (2017), for instance, find that US output declines by about 0.6 percent in response to a US monetary policy shock that raises the Fed funds rate by 100 basis points (see their Figure 2).

The fact that the output effect is more moderate after 2008 seems to be driven by the weaker response of investment, shown in the third row of the figure. It is almost identical across country groups both before and after 2008, but generally weaker after 2008. We show the responses of private consumption in the bottom row of the figure. In emerging economies it is unchanged across sample periods. In advanced economies, it is almost identical to that in emerging economies before 2008 and somewhat weaker after 2008.

We obtain additional insights into the transmission mechanism as we consider the impulse responses of the real exchange rate and of financial variables in Figure 1.10. Here, the top row shows the response of the real effective exchange rate. It declines in response to the shock, that is, the currency depreciates in real terms in both country groups and for both sample periods. We note, however, that the response is considerably stronger in emerging economies. The depreciation is consistent with the notion that the spread shock reflects a capital outflow shock—for instance because global risk aversion increases or because there is a run on the country. Consistent with this interpretation, we find that real bank lending contracts in response to the spread shock (second row). The effect is similar across sample periods and somewhat stronger in emerging economies than in advanced economies—consistent with the notion that emerging economies are more vulnerable to a reversal of international capital flows (see, for instance, Broner et al. 2013). In the third row, we show the response of the real stock market index. It contracts strongly, but the response is again remarkably similar across sample periods and country groups.

Recent work by Miranda-Agrippino and Rey (2020) shows that a contractionary US monetary policy shock raises global risk aversion and induces a deleveraging of global financial intermediaries such that domestic credit declines. At the same time credit spreads go up. Consistent with our findings, their shock affecting spreads also appreciates the dollar in real terms against a basket of currencies and triggers a sharp decline of the FTSE and the German DAX. Miranda-Agrippino and Rey (2020) look more closely at monetary policy in the UK and the euro area and find that short-term policy rates decline in response to the shock, although the response is not significant in the UK. We show the response of monetary policy to our identified spread shock in the last row of Figure 1.10 and observe rather strong differences across emerging and advanced economies. For

Figure 1.10: Impulse response of exchange rate and financial variables to a spread shock



Note: Response of exchange rate and financial variables to spread shock. See Figure 1.9 for details.

both sample periods we find that interest rates go up in emerging economies and, in fact, strongly so. In advanced economies their response is very much muted. The difference across country groups may reflect a stronger dependency of emerging economies on capital flows such that monetary policy may respond more aggressively in order to prevent large capital outflows—in line with the notion of limited monetary policy independence in emerging economies (Rey 2015).

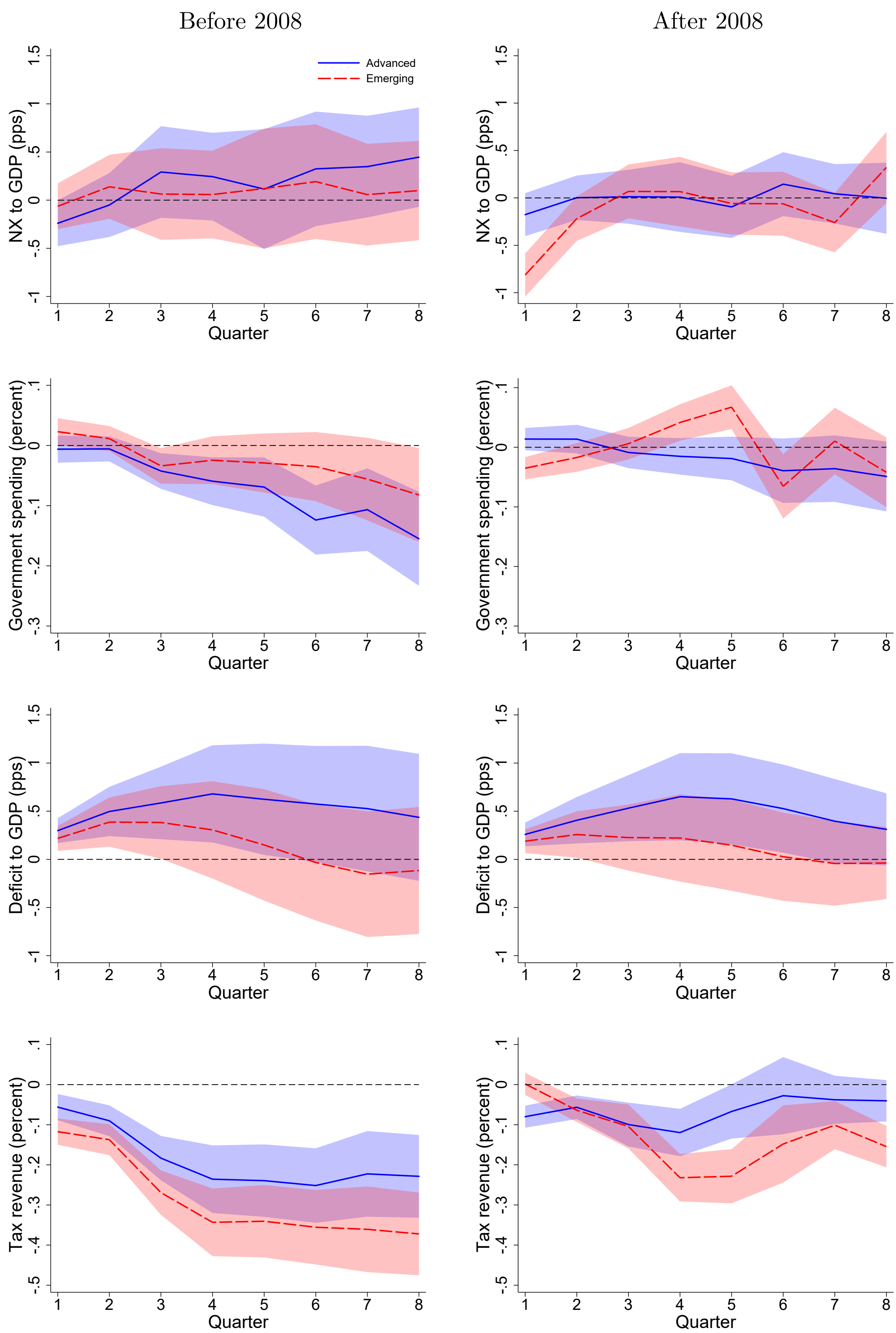
In Figure 1.11 we show the response of net exports and real fiscal variables to the spread shock. By and large, we again find a very similar adjustment pattern across country groups and sample periods. The top panels show the response of the trade balance-to-GDP ratio. In general, it is not very responsive to the shock. An exception are net exports in emerging economies after 2008, where we observe an immediate and sizable decline in response to the shock. In the second row, we show the response of real government consumption. It is fairly unresponsive on impact, before subsequently declining gradually, most notably in the period before 2008. To rationalize this finding, recall that government consumption consists largely of items that are not automatically responding to the cycle. At the same time, it takes time to adjust spending because of decision and implementation lags (Blanchard and Perotti 2002). Our results support the idea that, at least prior to 2008, there is a fiscal retrenchment if a country's financing conditions deteriorate. However, this effect takes place with a considerable delay only—in line with the evidence and arguments put forward in Born et al. (2020)

The budget-deficit-to-GDP ratio, in turn, increases persistently and somewhat more strongly in advanced economies, both before and after 2008 (third row). The increase of the deficit ratio is consistent with the decline of GDP, shown in Figure 1.9 above. But we also find that real tax revenues, shown in the last row of Figure 1.11, decline somewhat. In this case the decline is more pronounced before 2008. After 2008 the decline is considerably weaker in both country groups. However, the change across samples is more pronounced for emerging economies. This finding, in turn, is consistent with the notion that fiscal policy in emerging economies has become less pro-cyclical (Frankel et al. 2013).

Overall, we find that the transmission of spread shocks is fairly similar in advanced and emerging economies. Output and its components contract in an almost identical manner. The same holds, notwithstanding minor differences, for fiscal policy as well as for financial variables. An exception is monetary policy and the exchange rate. Here, we observe a strong contraction in emerging economies and a much weaker one in advanced economies. But throughout we find that there is almost no change before and after 2008. This suggests that any change in the correlation pattern documented in Section 1.2 reflects a change in the incidence of shocks rather than in the transmission mechanism. We assess this issue more systematically below.

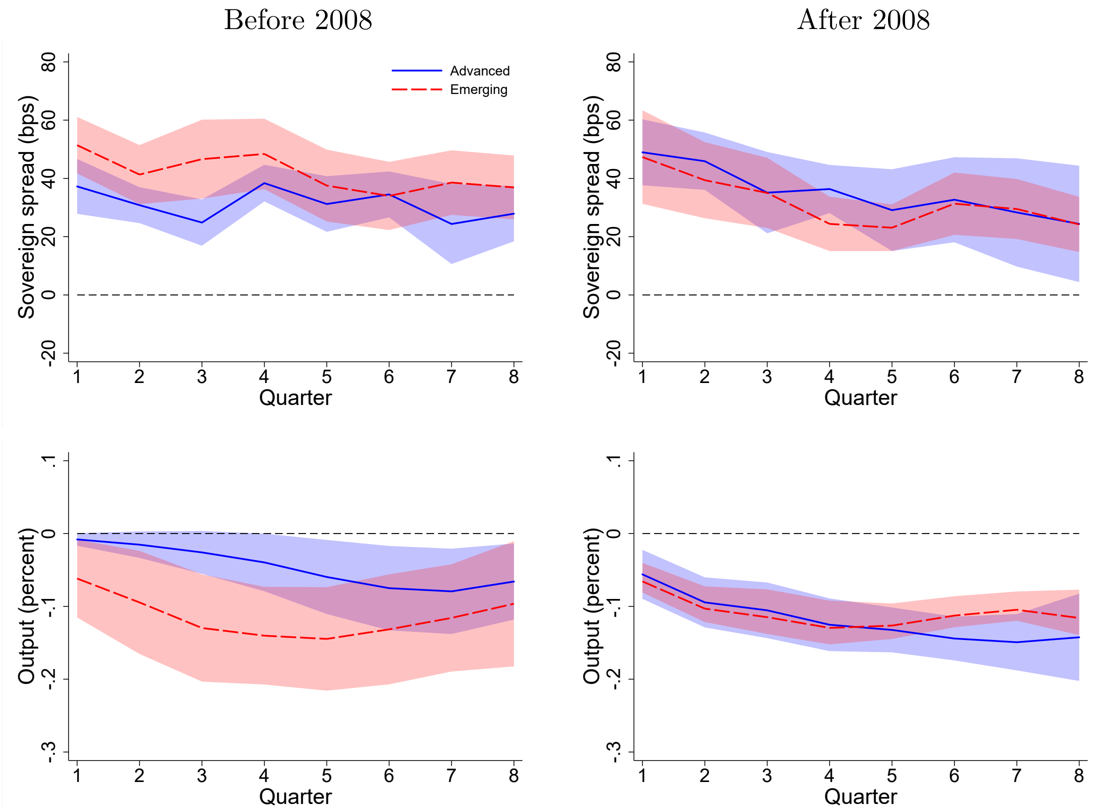
We obtain very similar results once we use an alternative framework for estimating the effect of spread shocks. In this case, as explained in Section 1.3.4, rather than accounting for the propensity score of a treatment in estimating the ATE, we rely on a more conventional recursive identification scheme in the spirit of Uribe and Yue (2006).

Figure 1.11: Impulse responses of net exports and real fiscal variables to a spread shock.



Note: Response of net exports and real fiscal variables to spread shock. See Figure 1.9 for details.

Figure 1.12: Impulse responses to a spread shock based on local projections



Note: Impulse responses to a sovereign spread shock based on the local projection in equation (1.7) together with spread shocks identified using equation (1.6). The left panel shows results for the period before 2008 and the right panel after 2008. Solid (blue) and dashed (red) line indicate point estimates for advanced and emerging economies, respectively. Shaded areas correspond to 90% confidence intervals based on clustered robust standard errors computed for advanced (blue) and emerging economies (red). All variables are expressed relative to their pre-shock level. Responses have been re-scaled to have the same $h = 1$ spread response as the ATE estimator. The horizontal axis indicates quarters.

We show results in Figure 1.12. To make results comparable to those shown in Figure 1.9 above, we re-scale the response of the impulse responses so as to match the $h = 1$ response of the spread for each sample period and country group. The organization of the figure follows Figure 1.9, except that we now only report results for the spread (top row) and output (bottom row). As before, we find that the adjustment of both variables is quite similar before and after 2008 as well as across country groups. In addition, we note that the adjustment pattern of both variables is quite similar to what we display in Figure 1.9. This is quite remarkable because the conceptual and methodological approach that we use in both instances is quite distinct. Most importantly, we note that the results in our baseline are based on a much larger set of control variables and on a more narrowly defined set of shocks. In particular, in the baseline specification we only estimate the effect of an increase in the spread, while results shown in Figure 1.12 are based on all shocks, regardless of their sign. We find our key results are largely confirmed.[19]

[19]The response of the other variables are generally also very similar to what we obtain for the baseline. They are available on request.

Table 1.3: Forecast error variance decomposition

	Advanced Economies				Emerging Economies			
	Before 2008		After 2008		Before 2008		After 2008	
Horizon h	Spread	Output	Spread	Output	Spread	Output	Spread	Output
1	0.45	0.00	0.16	0.00	0.38	0.00	0.42	0.00
2	0.51	0.01	0.21	0.01	0.48	0.02	0.53	0.05
3	0.50	0.02	0.24	0.03	0.50	0.07	0.55	0.11
4	0.46	0.03	0.24	0.05	0.50	0.11	0.52	0.14
5	0.46	0.06	0.24	0.08	0.50	0.14	0.46	0.16
6	0.43	0.06	0.24	0.09	0.45	0.13	0.42	0.14
7	0.41	0.06	0.26	0.10	0.42	0.14	0.42	0.13
8	0.39	0.06	0.28	0.10	0.41	0.14	0.42	0.12
9	0.34	0.05	0.28	0.10	0.40	0.14	0.40	0.11
10	0.33	0.04	0.28	0.09	0.38	0.14	0.33	0.11
11	0.31	0.04	0.28	0.09	0.36	0.14	0.28	0.10
12	0.28	0.04	0.29	0.10	0.35	0.15	0.29	0.10
∅	0.41	0.04	0.25	0.07	0.43	0.11	0.42	0.11

Note: Forecast error variance decomposition for the spread and output based on local projections (see Section 1.3.4).

1.4.2 Spread shock contribution to business cycle variance

In Section 1.2 above we established a new fact: that country spreads have become much more volatile in advanced economies after 2008 and indeed almost as volatile as in emerging economies. At the same time, we find little evidence for a change in the transmission of spread shocks after 2008, neither in emerging nor in advanced economies. Against this background, we ask two questions. First, does the increase in the volatility reflect an increase in the incidence of spread shocks? Second, and relatedly, does the increase in the volatility of spreads translate into a larger role of spread shocks as a source of business cycle fluctuations in advanced economies?

In order to answer these questions, we compute a forecast error variance decomposition, as detailed in Section 1.3.4. As always, we split the sample into advanced and emerging economies and distinguish the period before and after 2008. In Table 1.3 we report the contribution of spread shocks to the forecast error variance of the spread and output for a forecast horizon of 1 to 12 quarters. The bottom row reports the average across those 3 years.

In response to the first question, and focusing on the average contribution, we note that the contribution of spread shocks to the forecast error variance of the spread itself has actually declined in advanced economies after 2008. Before 2008 the contribution of shocks was about 40 percent and similar to what we find for emerging economies. After 2008, it is reduced to about 25 percent. In emerging economies there is no strong change over time.

In response to the second question, we note that before 2008 spread shocks account for only 4 percent of output variation in advanced economies and for about 11 percent in emerging economies. The latter finding is consistent with the value of 12 percent reported by Uribe and Yue (2006). After 2008, we find that the contribution in advanced economies has gone up to 7 percent, while it is still 11 percent for emerging economies. Hence, while we find that the relative importance of spread shocks for the volatility of the spread itself has declined in advanced economies after 2008, we observe that the volatility of the spread has increased by so much in absolute terms that the contribution of spread shocks to the volatility of output has actually gone up in advanced economies. For this reason, we conclude that, by and large, the role of spread shocks as a source of business cycle fluctuations has become more aligned across country groups.

Historically, spread levels in both advanced and emerging economies have spiked after global or regional events that presumably featured a significant common component. The Tequila crisis in 1994/95, the Asian financial crisis in 1997, the Global Financial Crisis in 2007/08, and the European debt crisis in 2011/12, for instance, are clearly visible in Figure 1.1. In order to isolate the effect of country-specific shocks, we include time-fixed effects in the shock identification equation (1.6) and the local project equation (1.7).[20]

Table 1.4 displays the forecast error variance contribution of the identified country-specific spread shocks to spreads and output *after* common factors have been controlled for. Put differently, here we decompose the forecast error variance of the country-specific spread and as well as output. Now a somewhat more nuanced picture emerges compared to the case with both common and country-specific shocks in Table 1.3. Advanced and emerging economies also have become more similar in terms of the variance share of output explained by country-specific spread shocks. But the reason is not simply an increase in the importance of spread shocks in advanced economies after 2008, but also that emerging economies have been less affected by country-specific spread shocks during this period. Turning to the share of the spread variance that is explained by country-specific spread shocks after accounting for the common international component, we now find a significant drop after 2008 in both groups.

[20]Figure 1.A.12 in the appendix displays the IRFs. The transmission of country-specific shocks is again similar across country groups and time periods, albeit quantitatively smaller. The same holds true when adding time-fixed effects to our logit model (1.2) and the conditional mean model employed in (1.5). The ATE results are displayed in Figure 1.A.13.

Table 1.4: Forecast error variance decomposition: country-specific shocks

	Advanced Economies				Emerging Economies			
	Before 2008		After 2008		Before 2008		After 2008	
Horizon h	Spread	Output	Spread	Output	Spread	Output	Spread	Output
1	0.44	0.00	0.05	0.00	0.39	0.00	0.15	0.00
2	0.49	0.00	0.09	0.01	0.50	0.02	0.21	0.00
3	0.51	0.01	0.15	0.02	0.53	0.07	0.25	0.02
4	0.50	0.01	0.19	0.04	0.51	0.12	0.33	0.04
5	0.52	0.03	0.23	0.05	0.51	0.15	0.38	0.07
6	0.53	0.02	0.25	0.06	0.44	0.14	0.38	0.08
7	0.55	0.02	0.27	0.07	0.41	0.15	0.38	0.08
8	0.54	0.02	0.29	0.07	0.40	0.14	0.38	0.09
9	0.52	0.02	0.29	0.08	0.38	0.13	0.40	0.10
10	0.53	0.02	0.29	0.08	0.35	0.12	0.41	0.12
11	0.55	0.02	0.28	0.08	0.32	0.11	0.41	0.12
12	0.54	0.02	0.27	0.08	0.32	0.11	0.44	0.13
∅	0.52	0.02	0.22	0.05	0.42	0.11	0.34	0.07

Note: Forecast error variance decomposition for the spread and output based on local projections (see Section 1.3.4).

1.4.3 Further robustness

We also make sure that our main result is robust across a number of specifications. First, we estimate the propensity score on the basis of a larger set of control variables, see Section 1.3.2 for details.[21] Importantly, these variables include forecasts for GDP among others and are thus potentially important to capture anticipation effects. Unfortunately, they are available for advanced economies only. For these countries, the estimated impulse responses of the spread and output to a spread shock in the extended model are very similar to the baseline results, see Figure 1.A.7 in the appendix.

Second, we consider a more conservative treatment definition. In this case, we require either the spread increase to be at least 50 basis points (alternative treatment definition 1) or the spread to increase by more than two standard deviations (alternative treatment definition 2). In this case, we obtain 196 and 113 treatments, respectively. Based on these alternative treatment definitions, we again estimate impulse responses to a spread shock and report the responses of the spread and output in Figures 1.A.8 and 1.A.9 in the appendix. They are again quite similar to the baseline.

Third, we consider alternative sample periods. Rather than distinguishing the period before and after 2008, we drop the 2007/08 period from our sample. Figure 1.A.10 in the appendix shows the impulse responses of the spread and output to the spread shock for both alternatives. The responses are very similar to what we obtain for the baseline.

Fourth, we drop the US and Germany from the sample because one could argue that

[21] The right panel of Figure 1.A.6 in the appendix displays the distribution of the estimated propensity scores for the extended model, while Table 1.A.9 reports details on a country-by-country basis.

these countries should be considered as risk-free benchmark countries that are hardly subject to spread shocks. Results, shown in Figure 1.A.11 in the appendix, are again similar to the baseline.

1.5 Conclusion

In this chapter we ask whether country spreads behave differently in emerging and advanced economies. We find that this is the case before 2008, in line with the received wisdom and much of the earlier research. However, the behavior of spreads after 2008 is no more different. We establish this result on the basis of a large data set which contains quarterly observations for 21 advanced and 17 emerging economies since the early 1990s. Our data runs up to the end of 2018. In the first part of the chapter, we document the basic facts for the period before and after 2008. We do not repeat these facts here, except for one: before 2008 the spread is about 10 times more volatile in emerging economies than in advanced economies, after 2008 the volatility is basically the same in both country groups. Other moments have converged as well and this is mostly because advanced economies have converged towards levels common in emerging economies before 2008.

In the second part, we provide evidence on the transmission of spread shocks, again allowing for differences across country groups and sample periods. Here, our main result is that the transmission of spread shocks is fairly similar in advanced and emerging economies and there is also no evidence for a significant change in the transmission mechanism after 2008. A spread shock induces a fairly persistent increase of the spread and a contraction of economic activity. Overall the response of fiscal policy is rather moderate. There are some spending cuts, tax revenues decline and the government deficit increases somewhat, but there are no large differences in the adjustment mechanism across time and country groups. We also find that the real exchange rate depreciates and that bank lending contracts in response to the spread shock. This is consistent with the notion that the spread shock reflects a capital outflow. The effect is considerably more pronounced in emerging economies and so is the response of monetary policy, which raises short-term rates in response to the shock. However, also these patterns of adjustment do not change much across sample periods.

Lastly, as we summarize our findings regarding the importance of spread shocks in accounting for the volatility of spreads and output, we highlight a tentative policy implication. We find that the relative importance of spread shocks for the volatility of the spread is rather low in advanced economies after 2008, both relative to the pre-2008 period and relative to emerging economies. This points to a relatively larger role of shocks to fundamentals and their transmission for explaining spread movements. It also indicates that advanced economies are now more vulnerable to market assessment regarding these fundamentals. Identifying the specific reasons for this is beyond the scope of the present chapter. But policy makers ignore this increased vulnerability at their own peril.

1.A Appendix

Table 1.A.1: Description of outcome and control variables

Variable	**Description**	**Source**
Consumption	Real private consumption	Eurostat, National Sources
Credit-to-GDP	Credit lending to private non-financial sector by banks at market value relative to GDP Data available except for: Croatia, Slovenia, Latvia, Lithuania, Slovakia, Bulgaria, Ecuador Uruguay, and Peru	BIS
Debt-to-GDP	General or central government outstanding debt relative to GDP. For Ecuador, El Salvador, Malaysia and Thailand: External debt stock as % of GNI (annual data interpolated to quarterly frequency). Data available except for: Chile and Uruguay	Eurostat, Worldbank QPSD, and International Debt Statistics
Deficit-to-GDP	Net lending or borrowing respectively relative to real GDP	Eurostat, IMF Government Finance Statistics
Floating	Fixed versus floating. We rely on the coarse classification of Ilzetzki et al. (2019) where codes 1 and 2 are classified as a peg, while 3 to 6 are classified as floating	Ilzetzki et al. (2019)
Real effective FX rate	Log effective real exchange rate; an increase indicates an appreciation of the economy's currency against a broad basket of currencies	BIS, complemented by Darvas (2012)
G	Government spending is exhaustive real government spending	Eurostat, National sources
G growth	First log difference of real government spending G.	
G growth forecast	Expected government spending growth at time t List of available countries, see GDP growth forecast	Oxford Economics
GDP	Real GDP	Eurostat, National sources
GDP growth	First log difference of real GDP	
GDP growth forecast	Expected GDP growth at time t. Data available for: Austria, Czech Republic Denmark, Finland, France, UK US, Germany, Greece, Ireland, Italy, Malaysia, Netherlands, Portugal, Spain, Sweden, Thailand	Oxford Economics
IMF assistance	Dummy variable which equals 1 if a country has a Standby Arrangement (with or without Supplemental Reserve Facility) or an Extended Fund Facility and 0 otherwise.	Monitoring of Fund Arrangements (MONA) database
Inflation	Inflation based on GDP Deflator	Eurostat, National sources
Investment	Real Investment	Eurostat, National Sources
Interest Rate	Policy or short term interest rate	IMF, OECD
NFA	Net financial assets	Lane and Milesi-Ferretti (2007)
NX share	Net export share of GDP	Eurostat, National sources
Political risk	Total political risk index from International Country Risk Guide (ICRG) ranging between 0 (low risk) and 100 (high risk). Composed of 12 subcomponents covering different aspects of political risk	PRS Group
Political stability	Government stability index from ICRG ranging from 0 (low risk) to 12 (high risk). Subcomponent of political risk, see above	PRS Group
Political turnover	Dummy variable indicating an ideological leadership change: 1 if new incumbent reaches office with different political orientation, 0 else	Archigos Database of Political Leadership, own classifications
Real bank lending	Credit-to-GDP multiplied by real GDP. For more information, see description and data sources for Credit-to-GDP and GDP	
Stock Market Index	Real log stock market index detrended	Datastream (Thomson Reuters)
Tax revenue	Log linearly detrended real total government revenues	Eurostat, IMF World Revenue Longitudinal Dataset (WoRLD)
Tax-to-GDP	Total government revenues relative to real GDP, linearly detrended	Eurostat, IMF World Revenue Longitudinal Dataset (WoRLD)
Term spread	10–year term spread, difference between bond market and money market rate. Data available except for: Croatia, Hungary, Latvia, Turkey, Argentina, Chile Colombia, Ecuador, Brazil, El Salvador, Uruguay, Peru	Datastream (Thomson Reuters)

Table 1.A.2: Descriptive statistics for spread changes (end of quarter) measured in basis points.

					Before 2008		After 2008	
Country	Group	First obs	Last obs	Obs	min(Δs_i)	max(Δs_i)	min(Δs_i)	max(Δs_i)
Australia	A	2003q2	2010q3	25	−14	11	−73	90
Austria	A	1994q1	2018q4	100	−15	20	−62	85
Belgium	A	1992q1	2018q4	108	−35	17	−87	104
Czech Republic	A	2004q2	2018q4	59	−4	11	−98	109
Denmark	A	1988q4	2018q4	111	−99	83	−58	98
Finland	A	1992q3	2018q4	106	−30	41	−47	73
France	A	1999q2	2018q4	79	−12	12	−54	60
Germany	A	2004q2	2018q4	59	−4	4	−30	47
Greece	A	1992q3	2018q4	101	−40	50	−254	783
Ireland	A	1992q1	2018q4	108	−25	18	−280	205
Italy	A	1989q2	2018q4	119	−20	32	−204	238
Latvia	A	2006q2	2018q4	51	−7	98	−314	477
Lithuania	A	2005q3	2018q4	54	−24	57	−240	375
Netherlands	A	1999q2	2018q4	79	−8	11	−40	59
Portugal	A	1993q3	2018q4	102	−14	14	−215	307
Slovakia	A	2004q2	2018q4	59	−7	9	−205	116
Slovenia	A	2003q2	2018q4	63	−51	31	−183	178
Spain	A	1992q4	2018q4	105	−55	22	−75	144
Sweden	A	1993q2	2018q4	92	−83	51	−35	102
United Kingdom	A	1993q1	2018q4	104	−41	25	−47	81
United States	A	2008q1	2018q4	44			−23	61
Argentina	E	1994Q1	2018q4	75	−291	565	−855	796
Brazil	E	1994q3	2018q4	98	−953	852	−165	184
Bulgaria	E	1994q4	2018q4	97	−594	468	−211	417
Chile	E	1999q3	2018q4	78	−55	89	−148	165
Colombia	E	1997q2	2018q4	87	−433	560	−208	225
Croatia	E	2004q2	2018q4	59	−24	38	−174	310
Ecuador	E	1995q2	2018q4	85	−519	1 039	−317	629
El Salvador	E	2002q3	2018q4	66	−67	90	−201	515
Hungary	E	1999q2	2018q4	79	−67	63	−190	375
Malaysia	E	1997q1	2018q4	88	−439	622	−200	221
Mexico	E	1994q1	2018q4	100	−611	726	−185	204
Peru	E	1997q2	2018q4	85	−299	368	−176	244
Poland	E	1995q1	2018q4	96	−349	224	−124	190
South Africa	E	1995q1	2018q4	96	−175	300	−157	243
Thailand	E	1997q3	2018q4	86	−253	225	−123	86
Turkey	E	1996q3	2018q4	90	−322	382	−212	188
Uruguay	E	2001q3	2018q4	68	−415	774	−276	318

Notes: "A" denotes advanced economies, while "E" denotes emerging economies following the classification in IMF (2015). US observations before 2008 are missing since CDS data is not available.

Table 1.A.3: Standard deviation of spreads and spread changes in advanced and emerging economies before 2008 and after 2008

	Before 2008		After 2008			Before 2008		After 2008	
	$\sigma(s_{it})$	$\sigma(\Delta s_{it})$	$\sigma(s_{it})$	$\sigma(\Delta s_{it})$		$\sigma(s_{it})$	$\sigma(\Delta s_{it})$	$\sigma(s_{it})$	$\sigma(\Delta s_{it})$
Advanced economies					*Emerging economies*				
Australia	0.10	6.60	0.37	41.70	Argentina	3.28	191.48	3.55	260.23
Austria	0.09	6.21	0.41	26.13	Brazil	4.27	286.38	0.90	66.93
Belgium	0.18	7.43	0.61	32.97	Bulgaria	5.30	169.72	1.42	96.43
Czech Republic	0.04	3.65	0.41	30.45	Chile	0.56	30.65	0.53	44.75
Denmark	0.47	24.68	0.35	25.02	Colombia	2.26	164.52	0.85	63.75
Finland	0.21	9.77	0.27	19.77	Croatia	0.21	16.19	1.15	84.34
France	0.05	5.18	0.37	23.54	Ecuador	4.76	274.82	2.20	186.51
Germany	0.02	1.93	0.16	12.25	El Salvador	0.79	40.09	1.25	113.37
Greece	0.57	15.90	4.92	200.48	Hungary	0.38	25.73	1.49	97.19
Ireland	0.22	7.17	2.27	87.39	Malaysia	1.71	130.96	0.67	61.20
Italy	0.28	9.68	1.14	66.24	Mexico	2.89	172.56	0.72	57.48
Latvia	0.45	35.93	2.10	112.56	Peru	2.02	124.78	0.81	63.47
Lithuania	0.23	28.94	1.73	100.57	Poland	1.64	78.10	0.79	56.41
Netherlands	0.07	5.02	0.27	18.65	South Africa	1.32	68.26	0.86	69.84
Portugal	0.11	6.27	2.85	102.10	Thailand	1.11	73.00	0.48	35.73
Slovakia	0.04	4.05	1.02	58.98	Turkey	2.70	154.77	0.86	68.49
Slovenia	0.16	19.21	1.52	70.28	Uruguay	3.84	215.05	1.19	83.92
Spain	0.20	10.08	1.25	50.28					
Sweden	0.22	18.51	0.25	19.95					
United Kingdom	0.20	11.22	0.28	18.98					
United States			0.11	11.60					
Mean	0.32	12.77	2.22	69.49	Average	3.94	160.07	2.29	98.87

Notes: Spreads are measured in percentage points and spread changes in basis points.

Table 1.A.4: Descriptive statistics of the country spread for the period before 2007Q1 and from 2009Q1 onwards

	Before 2007		After 2009		Before 2007		After 2009	
	Adv.	Em.	Adv.	Em.	Adv.	Em.	Adv.	Em.
	Spread level s_{it} (percentage points)				Spread change Δs_{it} (basis points)			
Mean	0.35	4.52	1.56	3.02	−0.74	−4.76	−1.38	−8.31
Median	0.26	3.16	0.72	2.36	−0.74	−12.88	−1.83	−8.83
Sd	0.33	4.02	2.29	2.23	12.22	167.80	67.76	84.80
Min	−0.14	0.19	−0.06	0.41	−99.08	−952.59	−314.45	−854.70
Max	2.20	24.22	24.56	19.50	82.89	1 039.00	783.21	628.69
Kurtosis	10.54	6.03	25.31	11.26	20.06	11.83	32.78	24.59
Skewness	2.28	1.65	3.83	2.44	−0.64	1.12	2.63	−0.54
Observations	792	651	804	670	767	630	802	668

Notes: Level of spread measured in percentage points (left panel) and quarterly change in basis points (right panel). The years 2007 and 2008 have been dropped from the sample.

Table 1.A.5: Number of treatments and share of treatments in total number of spread changes by country (excluding default episodes)

Country	$\sum D_i$ (>25bp)	% of nobs	$\sum D_i$(>50bp)	% of nobs	$\sum D_i$(>2σ)	% of nobs
Argentina	9	12.00	9	12.00	2	2.67
Australia	1	4.00	1	4.00	1	4.00
Austria	4	4.00	2	2.00	3	3.00
Belgium	8	7.41	2	1.85	3	2.78
Brazil	6	6.12	6	6.12	4	4.08
Bulgaria	8	8.25	8	8.25	3	3.09
Chile	10	12.82	6	7.69	3	3.85
Colombia	6	6.90	6	6.90	2	2.30
Croatia	4	6.78	4	6.78	2	3.39
Czech Republic	6	10.17	2	3.39	2	3.39
Denmark	6	5.41	4	3.60	4	3.60
Ecuador	8	9.41	8	9.41	3	3.53
El Salvador	6	9.09	6	9.09	2	3.03
Finland	3	2.83	2	1.89	3	2.83
France	4	5.06	2	2.53	3	3.80
Germany	2	3.39	0	0.00	2	3.39
Greece	9	8.91	9	8.91	5	4.95
Hungary	6	7.59	6	7.59	3	3.80
Ireland	8	7.41	8	7.41	5	4.63
Italy	8	6.72	6	5.04	5	4.20
Latvia	4	7.84	4	7.84	1	1.96
Lithuania	6	11.11	6	11.11	2	3.70
Malaysia	5	5.68	5	5.68	2	2.27
Mexico	5	5.00	5	5.00	3	3.00
Netherlands	2	2.53	1	1.27	2	2.53
Peru	7	8.24	7	8.24	4	4.71
Poland	6	6.25	6	6.25	4	4.17
Portugal	7	6.86	7	6.86	4	3.92
Slovakia	7	11.86	7	11.86	3	5.08
Slovenia	6	9.52	6	9.52	2	3.17
South Africa	10	10.42	10	10.42	3	3.13
Spain	8	7.62	7	6.67	6	5.71
Sweden	6	6.52	2	2.17	3	3.26
Thailand	7	8.14	7	8.14	3	3.49
Turkey	12	13.33	12	13.33	4	4.44
United Kingdom	3	2.88	1	0.96	3	2.88
United States	1	2.27	1	2.27	1	2.27
Uruguay	5	7.35	5	7.35	3	4.41
Total	229	mean: 7.24	196	mean: 6.20	113	mean: 3.57

Table 1.A.6: Quarters t with treatment D in country i

Quarter t	Countries with $D_t = 1$ according to Equation (1.1)
1989Q2	Denmark
1994Q1	Argentina, Mexico
1994Q4	Argentina, Bulgaria, Mexico
1995Q1	Argentina, Brazil, Bulgaria, Mexico, Poland, South Africa
1997Q3	South Africa, Thailand
1997Q4	Bulgaria, Denmark, South Africa, Thailand, Turkey
1998Q2	Brazil, Bulgaria, Malaysia, Peru, Thailand, Turkey
1998Q3	Argentina, Brazil, Bulgaria, Colombia, Ecuador, Finland, Malaysia, Mexico, Peru, Poland, South Africa, Thailand, Turkey
1999Q1	Ecuador
1999Q2	Colombia
2000Q1	Chile, Colombia, Sweden
2000Q2	Chile, Colombia
2000Q4	South Africa, Turkey
2001Q1	Turkey
2001Q3	Argentina, Brazil, Chile, Poland, Turkey
2001Q4	Denmark
2002Q1	Uruguay
2002Q2	Chile, Brazil, Peru, Turkey, Uruguay
2002Q3	Brazil, Colombia, Ecuador, Peru, Turkey, Uruguay
2003Q1	Turkey
2004Q2	Ecuador, Turkey
2005Q3	Sweden
2005Q4	Denmark, Sweden
2006Q4	Ecuador
2007Q2	Sweden
2007Q3	Chile
2008Q1	Belgium, Czech Republic, El Salvador, Lithuania, Hungary, South Africa
2008Q3	Argentina, Belgium, Chile, Czech Republic, Ecuador, El Salvador, Latvia, Lithuania, Peru, Slovakia, South Africa
2008Q4	Argentina, Australia, Austria, Belgium, Bulgaria, Chile, Colombia, Croatia, Czech Republic, Denmark, El Salvador, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Latvia, Lithuania, Malaysia, Mexico, Netherlands, Peru, Poland, Slovakia, Slovenia, South Africa, Spain, Sweden, Thailand, Turkey, United Kingdom, United States, Uruguay
2009Q1	Czech Republic, France, Ireland, Latvia, Lithuania, Portugal
2009Q4	Greece, United Kingdom
2010Q2	Austria, Belgium, Bulgaria, Croatia, Czech Republic, El Salvador, Greece, Hungary, Ireland, Italy, Lithuania, Poland, Portugal, Spain
2010Q3	Ireland
2010Q4	Belgium, Greece, Ireland, Spain
2011Q1	Ireland, Portugal
2011Q2	Belgium, Greece, Ireland, Italy, Portugal, Slovakia, Slovenia, Spain
2011Q3	Argentina, Austria, Belgium, Bulgaria, Chile, Croatia, Czech Republic, Denmark, El Salvador, Finland, France, Germany, Greece, Hungary, Italy, Latvia, Lithuania, Malaysia, Netherlands, Peru, Poland, Portugal, Slovakia, Slovenia, South Africa, Spain, Sweden, Thailand, Turkey, United Kingdom, Uruguay
2011Q4	Austria, Belgium, France, Greece, Hungary, Ireland, Italy, Portugal, Slovakia, Slovenia
2012Q2	Croatia, Italy, Slovenia, Spain
2013Q1	Argentina, Hungary, Slovenia
2013Q3	Slovakia
2014Q2	Slovakia
2014Q4	Ecuador, Greece
2015Q1	Greece
2015Q2	Italy, Spain
2015Q3	Chile, Ecuador, El Salvador, Malaysia, South Africa, Thailand
2016Q1	Portugal
2018Q2	Italy, Spain
2018Q4	Chile

Table 1.A.7: Logit model: coefficients and average marginal effects (AME) based on Equation (1.2)

Dependent Variable:	Baseline model		Extended model	
Treatment D_t	coeff	AME	coeff	AME
Debt-to-GDP$_t$	17.5430*	0.9855*	115.1179***	4.1949***
	(8.5996)	(0.4838)	(28.2418)	(1.0035)
Debt-to-GDP^2_t	-0.0006	-0.0000	-0.0054***	-0.0002***
	(0.0005)	(0.0000)	(0.0015)	(0.0001)
GDP growth$_t$	-37.7084***	-2.1183***	-71.8303**	-2.6175**
	(9.2445)	(0.5167)	(26.8157)	(0.9629)
G growth$_t$	-1.1192	-0.0629	-15.6519	-0.5704
	(5.5443)	(0.3115)	(14.1591)	(0.5164)
Tax-to-GDP$_t$	0.0121	0.0007	-0.1296	-0.0047
	(0.0949)	(0.0053)	(0.1898)	(0.0069)
Deficit-to-GDP$_t$	10.5446	0.5924	-50.4703	-1.8391
	(14.5264)	(0.8161)	(36.0059)	(1.3067)
NFA$_t$	2.6319	0.1479	-0.9824	-0.0358
	(2.6718)	(0.1502)	(5.0811)	(0.1851)
NX share$_t$	-7.4250	-0.4171	-8.8244	-0.3216
	(6.6155)	(0.3720)	(18.5801)	(0.6766)
Inflation$_t$	-22.5318**	-1.2658**	-93.6485**	-3.4126**
	(8.1768)	(0.4595)	(32.0344)	(1.1592)
FX rate$_t$	-16.7344***	-0.9401***	-24.8502**	-0.9055**
	(3.0005)	(0.1672)	(8.1644)	(0.2897)
Stock market$_t$	-1.3734	-0.1564**	22.2501**	-0.1015
	(1.2316)	(0.0532)	(6.9120)	(0.0842)
Political risk$_t$	-0.4118**	-0.0231**	-0.0242	-0.0009
	(0.1417)	(0.0079)	(0.3366)	(0.0123)
Government stability$_t$	0.4520	0.0254	-0.2159	-0.0079
	(0.2380)	(0.0134)	(0.4999)	(0.0182)
IMF assistance$_t$	0.8033	0.0451	0.6599	0.0240
	(0.4130)	(0.0232)	(1.7848)	(0.0650)
Floating$_t$	-1.5424**	-0.0866**	-4.3400**	-0.1582**
	(0.4883)	(0.0275)	(1.4333)	(0.0513)
Political turnover$_t$	0.1875	0.0105	-0.0145	-0.0005
	(0.4957)	(0.0278)	(1.0258)	(0.0374)
Debt-to-GDP$_{t-1}$	-20.8251*	-1.1699*	-91.1007***	-3.3197***
	(8.3335)	(0.4687)	(25.6742)	(0.9160)
Debt-to-GDP$^2_{t-1}$	0.0008	0.0000	0.0046***	0.0002***
	(0.0005)	(0.0000)	(0.0013)	(0.0000)
GDP growth$_{t-1}$	17.8767*	1.0043*	-18.4398	-0.6719
	(8.1544)	(0.4579)	(31.4582)	(1.1450)
G growth$_{t-1}$	-10.8099	-0.6073	-40.1146*	-1.4618*
	(6.3303)	(0.3562)	(16.7281)	(0.6058)
Tax-to-GDP$_{t-1}$	-0.0077	-0.0004	0.0177	0.0006
	(0.0952)	(0.0053)	(0.1951)	(0.0071)
Deficit-to-GDP$_{t-1}$	15.1266	0.8498	64.9080	2.3653
	(15.0660)	(0.8462)	(40.3421)	(1.4655)
NFA$_{t-1}$	-3.4585	-0.1943	2.8335	0.1033
	(2.6466)	(0.1488)	(5.2296)	(0.1903)

Logit model estimation results based on Equation (1.2) – continued

Dependent Variable:	Baseline model		Extended model	
Treatment D_t	coeff	AME	coeff	AME
NX share$_{t-1}$	-1.5166	-0.0852	-6.8379	-0.2492
	(6.7019)	(0.3765)	(19.2400)	(0.7012)
Inflation$_{t-1}$	11.7221	0.6585	-19.7957	-0.7214
	(8.3943)	(0.4709)	(31.0485)	(1.1299)
FX rate$_{t-1}$	14.8142***	0.8322***	28.5589***	1.0407***
	(2.9757)	(0.1656)	(8.5966)	(0.3043)
Stock market$_{t-1}$	1.6735	0.0940	6.0567	0.2207
	(1.3278)	(0.0746)	(3.4333)	(0.1249)
Δs_{t-1}	-0.0011	-0.0001	-0.0074	-0.0003
	(0.0013)	(0.0001)	(0.0054)	(0.0002)
Political risk$_{t-1}$	0.5283***	0.0297***	0.3930	0.0143
	(0.1437)	(0.0080)	(0.3094)	(0.0112)
Government stability$_{t-1}$	-0.8565***	-0.0481***	-0.8497	-0.0310
	(0.2406)	(0.0135)	(0.4597)	(0.0165)
Stock market^2_t	-0.1097		-1.8278***	
	(0.0587)		(0.4605)	
D_{t-1} × Stock market$_t$	-0.1332		0.2359	
	(0.0762)		(0.4008)	
GDP growth$_{t-2}$	7.1439	0.4013	60.4079*	2.2013*
	(8.3100)	(0.4664)	(26.4611)	(0.9593)
G growth$_{t-2}$	-13.8706*	-0.7792*	0.6169	0.0225
	(6.3529)	(0.3572)	(18.8570)	(0.6872)
G growth$_{t-3}$	-7.4643	-0.4193	25.5322	0.9304
	(6.2228)	(0.3499)	(18.5595)	(0.6740)
G growth$_{t-4}$	-12.8755*	-0.7233*	-18.6650	-0.6802
	(5.4041)	(0.3042)	(15.4221)	(0.5619)
Stock market$_{t-2}$	1.0253	0.0576	-2.7126	-0.0988
	(1.2592)	(0.0708)	(3.1649)	(0.1153)
Stock market$_{t-3}$	2.7250*	0.1531*	6.4923*	0.2366*
	(1.2150)	(0.0683)	(3.1547)	(0.1141)
Stock market$_{t-4}$	-2.5033**	-0.1406**	-7.2327**	-0.2636**
	(0.8613)	(0.0485)	(2.3299)	(0.0839)
D_{t-1}	0.5435	0.0305	-3.4780	-0.1267
	(0.5790)	(0.0325)	(2.7397)	(0.0996)
D_{t-2}	-0.1948	-0.0109	-0.2511	-0.0092
	(0.3440)	(0.0193)	(0.7783)	(0.0283)
D_{t-3}	0.3609	0.0203	-1.6442	-0.0599
	(0.3350)	(0.0188)	(0.8572)	(0.0312)
D_{t-4}	0.1982	0.0111	0.0299	0.0011
	(0.3567)	(0.0200)	(0.7408)	(0.0270)
D_{t-1}(neg)	-0.0525	-0.0030	-0.5953	-0.0217
	(0.4155)	(0.0233)	(1.0288)	(0.0375)
D_{t-2}(neg)	-0.5162	-0.0290	-1.2669	-0.0462
	(0.4002)	(0.0225)	(0.9004)	(0.0327)
Interest Rate$_t$			0.1166	0.0042
			(0.6530)	(0.0238)

Logit model estimation results based on Equation (1.2) – continued

Dependent Variable:	Baseline model		Extended model	
Treatment D_t	coeff	AME	coeff	AME
Credit-to-GDP$_t$			17.5733	0.6404
			(13.5510)	(0.4941)
Term spread$_t$			1.1042*	0.0402*
			(0.4792)	(0.0173)
GDP growth forecast$_t$			-322.8091***	-11.7632***
			(92.7298)	(3.3317)
G growth forecast$_t$			102.0260	3.7178
			(52.6013)	(1.9093)
Interest Rate$_{t-1}$			0.9404	0.0343
			(0.6814)	(0.0248)
Credit-to-GDP$_{t-1}$			-13.5219	-0.4927
			(13.1559)	(0.4797)
Term spread$_{t-1}$			-0.3922	-0.0143
			(0.4325)	(0.0157)
GDP growth forecast$_{t-1}$			231.9433***	8.4521***
			(66.3761)	(2.3742)
G growth forecast$_{t-1}$			-157.1149***	-5.7253***
			(46.7019)	(1.6768)
Observations	1965	1965	1003	1003
AUC	0.8730		0.9457	
std(AUC)	0.0139		0.0155	

Note: Dependent variable is treatment according to Equation (1.1). Clustered robust standard errors in parenthesis. Constant and country-fixed effects included but not reported. Some country-fixed effects are dropped in estimation due to perfect collinearity. For interaction terms, marginal effects cannot be computed. * p<0.10, ** p<0.05, *** p<0.01. Note that there is no one-to-one relationship between the coefficient and average marginal effects (AME) significance levels (e.g. Greene 2009).

Table 1.A.8: Descriptive statistics of the estimated propensity score by country for the baseline model specification

Country	Mean	Std. Dev.	Median	Min	Max	Obs.
Argentina	0.14	0.17	0.08	0.00	0.81	59
Australia	0.04	0.12	0.01	0.00	0.61	25
Austria	0.06	0.06	0.05	0.00	0.30	67
Belgium	0.11	0.09	0.08	0.00	0.51	75
Brazil	0.07	0.17	0.01	0.00	0.83	68
Bulgaria	0.08	0.09	0.03	0.00	0.32	39
Colombia	0.04	0.06	0.02	0.00	0.37	52
Croatia	0.09	0.11	0.05	0.00	0.53	45
Czech Republic	0.11	0.14	0.06	0.00	0.71	54
Denmark	0.07	0.09	0.05	0.00	0.62	57
Finland	0.03	0.05	0.01	0.00	0.32	71
France	0.06	0.06	0.04	0.00	0.32	71
Germany	0.04	0.04	0.02	0.01	0.19	54
Greece	0.14	0.23	0.02	0.00	0.91	63
Hungary	0.08	0.15	0.03	0.00	0.80	74
Ireland	0.13	0.25	0.01	0.00	0.99	63
Italy	0.09	0.08	0.07	0.01	0.47	75
Lithuania	0.12	0.19	0.03	0.01	0.98	49
Malaysia	0.04	0.10	0.02	0.00	0.70	52
Mexico	0.05	0.14	0.02	0.00	1.00	76
Netherlands	0.03	0.04	0.01	0.00	0.27	72
Peru	0.10	0.15	0.05	0.00	0.67	51
Poland	0.02	0.03	0.01	0.00	0.12	51
Portugal	0.10	0.12	0.04	0.01	0.57	72
Slovakia	0.16	0.16	0.12	0.03	0.93	43
Slovenia	0.10	0.13	0.04	0.00	0.56	58
South Africa	0.09	0.13	0.03	0.00	0.69	56
Spain	0.10	0.15	0.04	0.00	0.78	87
Sweden	0.08	0.09	0.04	0.00	0.49	77
Thailand	0.08	0.19	0.01	0.00	0.99	66
Turkey	0.16	0.23	0.05	0.00	0.83	56
United Kingdom	0.05	0.09	0.02	0.00	0.65	63
United States	0.04	0.03	0.04	0.01	0.10	24
Total	0.08	0.14	0.03	0.00	1.00	1965

Notes: Baseline specification includes a smaller set of control variables. Total indicates the equally-weighted country average/sum. Values have been rounded to 3 decimal places and are bounded away from zero in all instances. Robustness of the results to truncating the propensity score has been verified.

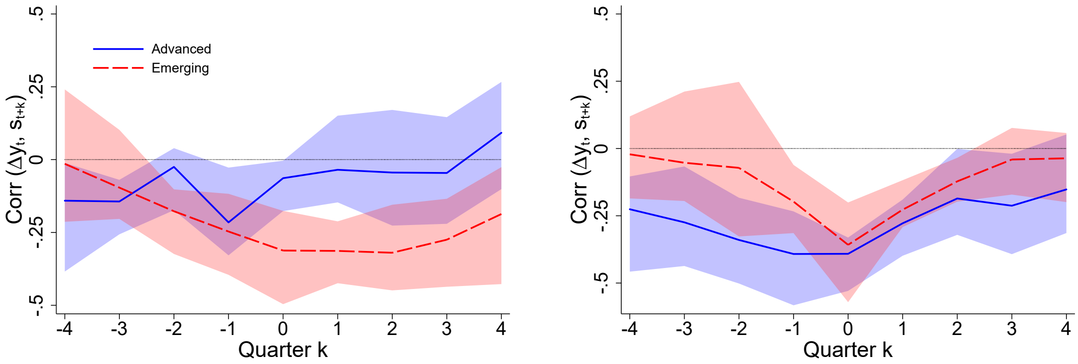
Table 1.A.9: Descriptive statistics of the estimated propensity score by country for the extended model specification

Country	Mean	Std. Dev.	Median	Min	Max	Obs.
Australia	0.04	0.13	0.00	0.00	0.60	25
Austria	0.06	0.14	0.01	0.00	0.94	63
Czech Republic	0.11	0.18	0.02	0.00	0.70	54
Denmark	0.07	0.17	0.01	0.00	1.00	55
Finland	0.03	0.09	0.00	0.00	0.57	69
France	0.05	0.13	0.01	0.00	0.65	67
Germany	0.04	0.08	0.00	0.00	0.43	52
Greece	0.16	0.30	0.01	0.00	1.00	55
Ireland	0.15	0.32	0.00	0.00	1.00	54
Italy	0.11	0.20	0.02	0.00	0.83	73
Malaysia	0.05	0.17	0.00	0.00	1.00	39
Netherlands	0.03	0.10	0.00	0.00	0.78	70
Portugal	0.10	0.23	0.00	0.00	0.98	68
Spain	0.08	0.19	0.01	0.00	0.83	80
Sweden	0.11	0.20	0.02	0.00	0.88	47
Thailand	0.04	0.12	0.00	0.00	0.61	52
United Kingdom	0.05	0.15	0.01	0.00	0.99	56
United States	0.04	0.07	0.02	0.00	0.32	24
Total	0.08	0.18	0.00	0.00	1.00	1003

Note: Total indicates the equally-weighted country average/sum. Values have been rounded to 3 decimal places and are bounded away from zero and one in all instances. Robustness of the results to truncating the propensity score has been verified.

Figure 1.A.1: Cross-correlation functions for output growth Δy_t and spread s_{t+k}

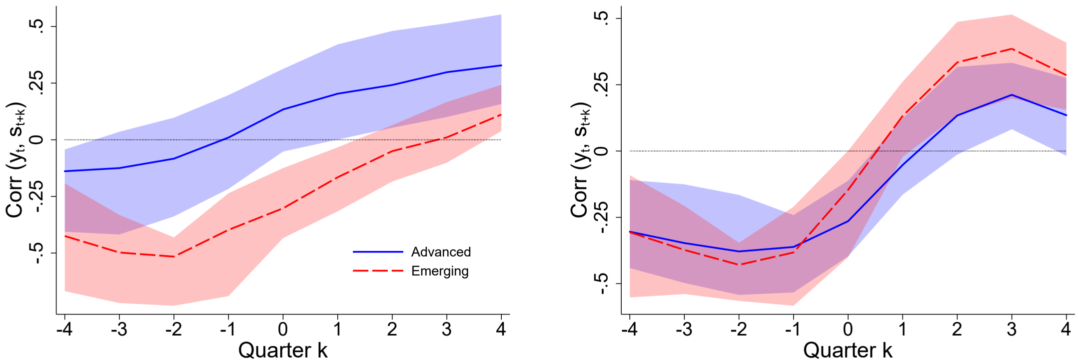
Before 2007Q1 | From 2009Q1 onwards



Note: Cross-correlation functions for output growth Δy_t and spread s_{t+k}, measured in levels at lead/lag $k = 0, \ldots, \pm 4$ for the period before 2007Q1 and from 2009Q1 onwards. For details, see Figure (1.3).

Figure 1.A.2: Cross-correlation functions for output y_t and spread s_{t+k}

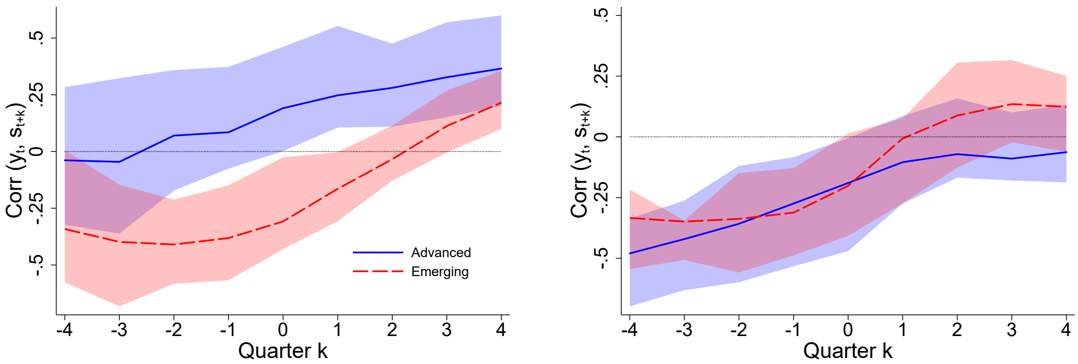
Before 2008Q1 | From 2008Q1 onwards



Note: Cross-correlation functions for output y_t and spread s_{t+k}, measured in levels at lead/lag $k = 0, \ldots, \pm 4$ before 2008 (left panel) and after 2008. For details, see Figure (1.3)

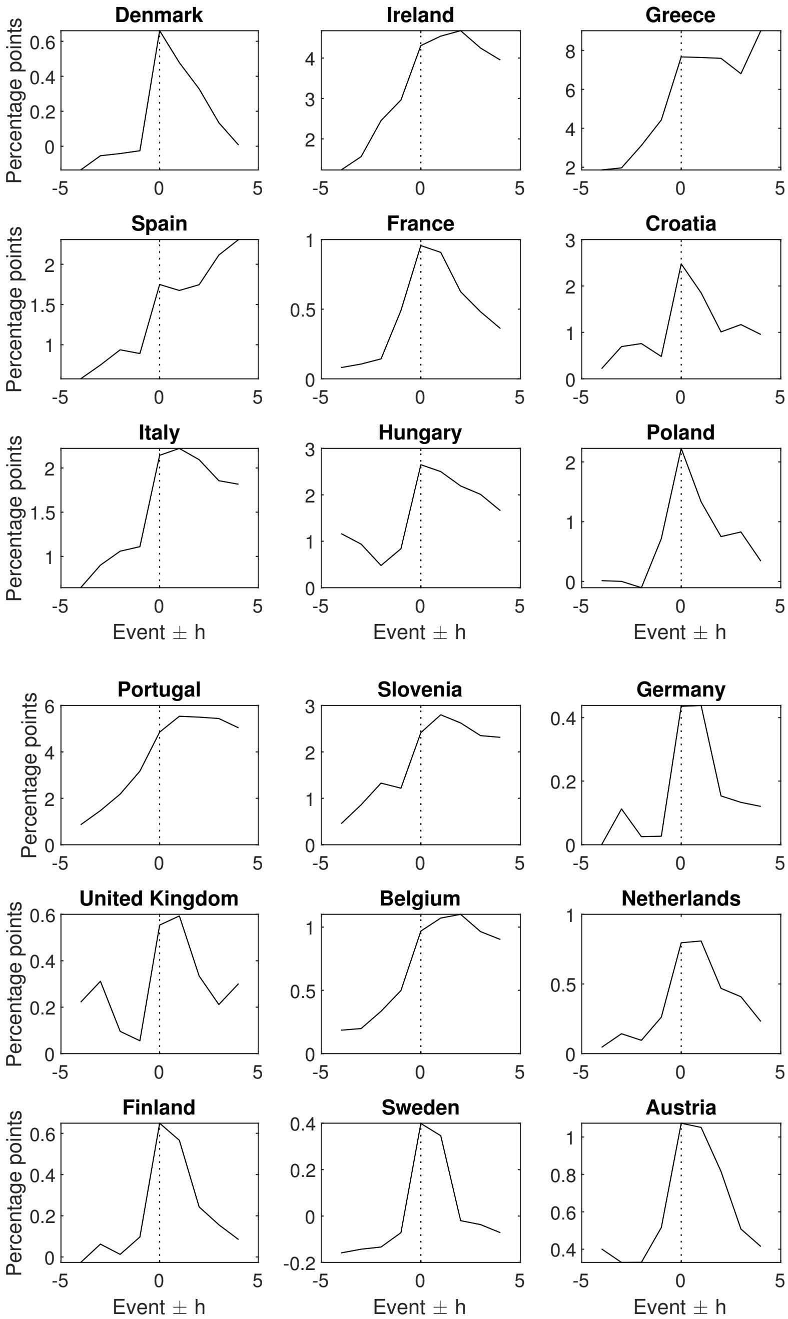
Figure 1.A.3: Cross-correlation functions for output y_t and spread s_{t+k}

Before 2007Q1 | From 2009Q1 onwards



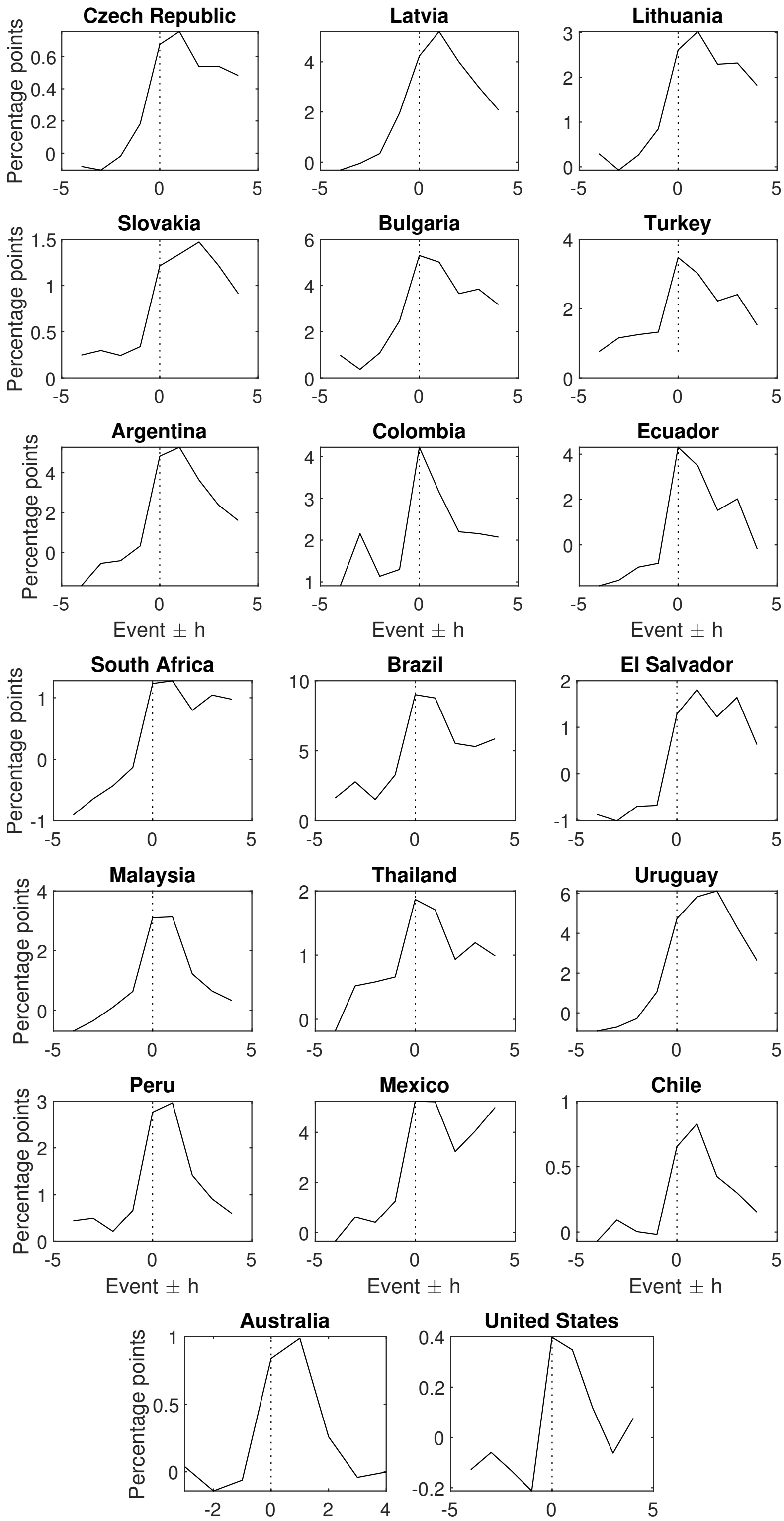
Note: Cross-correlation functions for output y_t and spread s_{t+k}, measured in levels at lead/lag $k = 0, \ldots, \pm 4$ for the period before 2007Q1 and from 2009Q1 onwards.. For details, see Figure (1.3).

Figure 1.A.4: Event windows country-by-country for the full sample



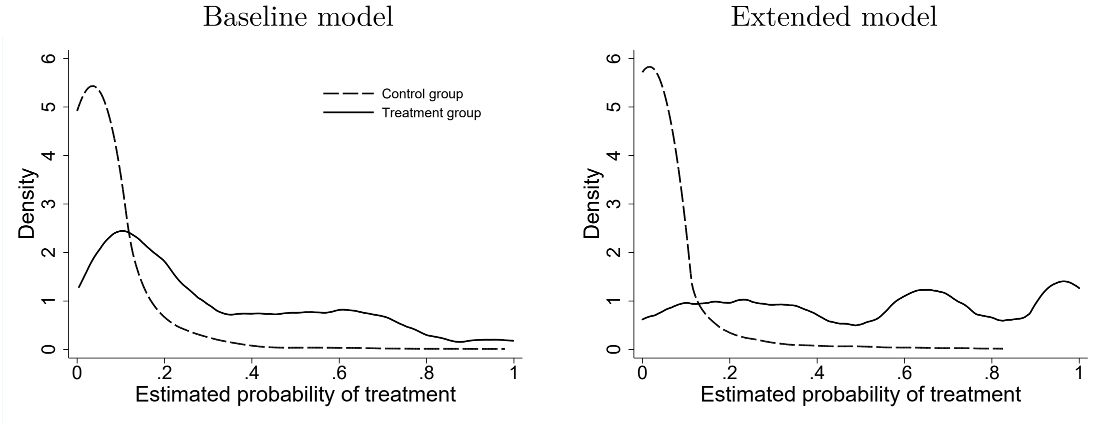
Note: Treatment in period $t = 0$ and the average spread (in pps) in period $t \pm h$. Country-specific spread movements around treatments are measured as the average of spread deviations from the respective country mean over all events in the country in the event window $t \pm h$. Time is measured in quarters. Treatment is defined according to Equation (1.1).

Figure 1.A.5: Event windows country-by-country for the full sample (continued)



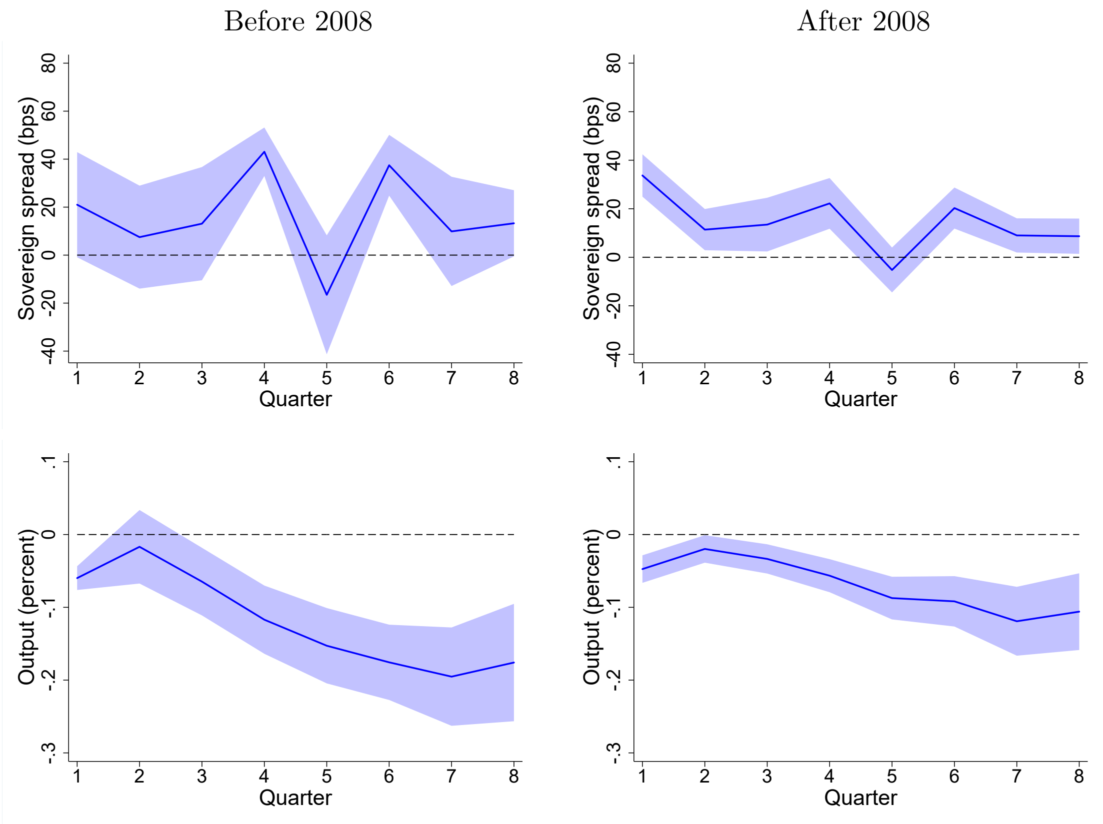
Note: Treatment in period $t = 0$ and the average spread (in pps) in period $t \pm h$. Country-specific spread movements around treatments are measured as the average of spread deviations from the respective country mean over all events in the country in the event window $t \pm h$. Time is measured in quarters. Treatment is defined according to Equation (1.1).

Figure 1.A.6: Distribution of propensity score for the baseline and the extended model



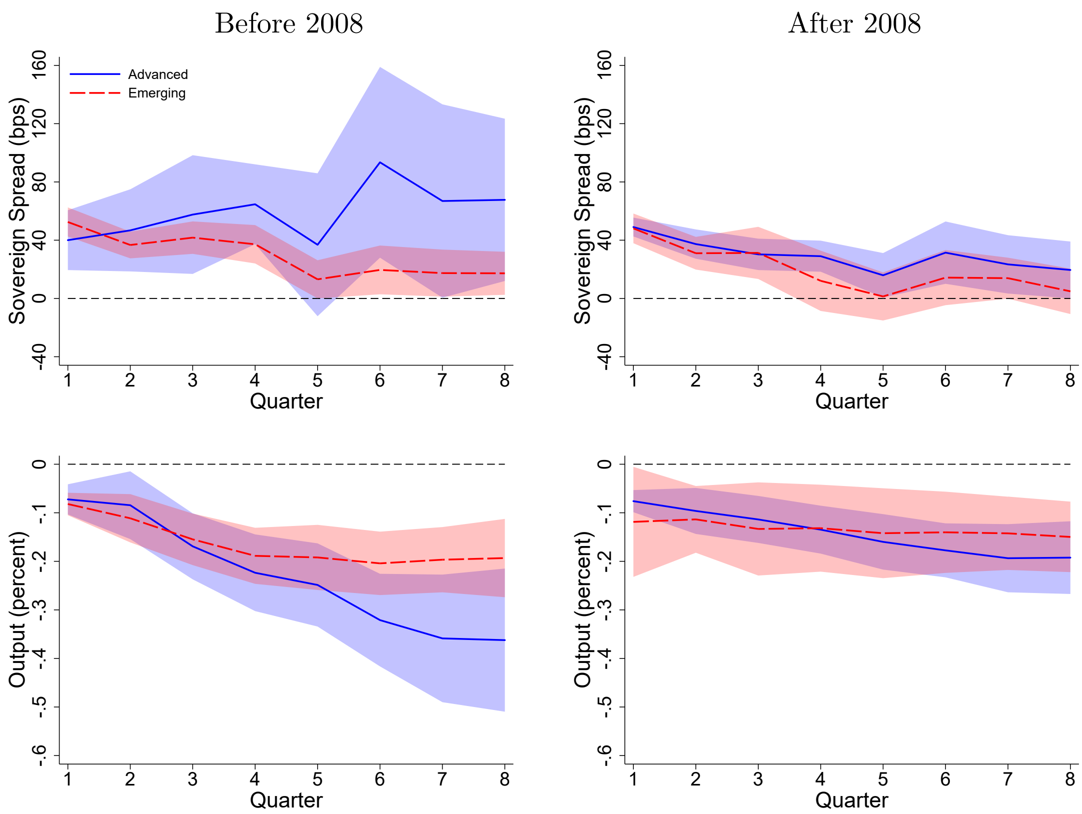
Note: Distribution of propensity score for the baseline model (left panel) and the extended model (right panel). Kernel density estimate of the predicted probabilities for treatment (solid line) and control group (dashed line) based on an Epanechnikov kernel with bandwidth 0.025.

Figure 1.A.7: Impulse responses to a spread shock: extended specification



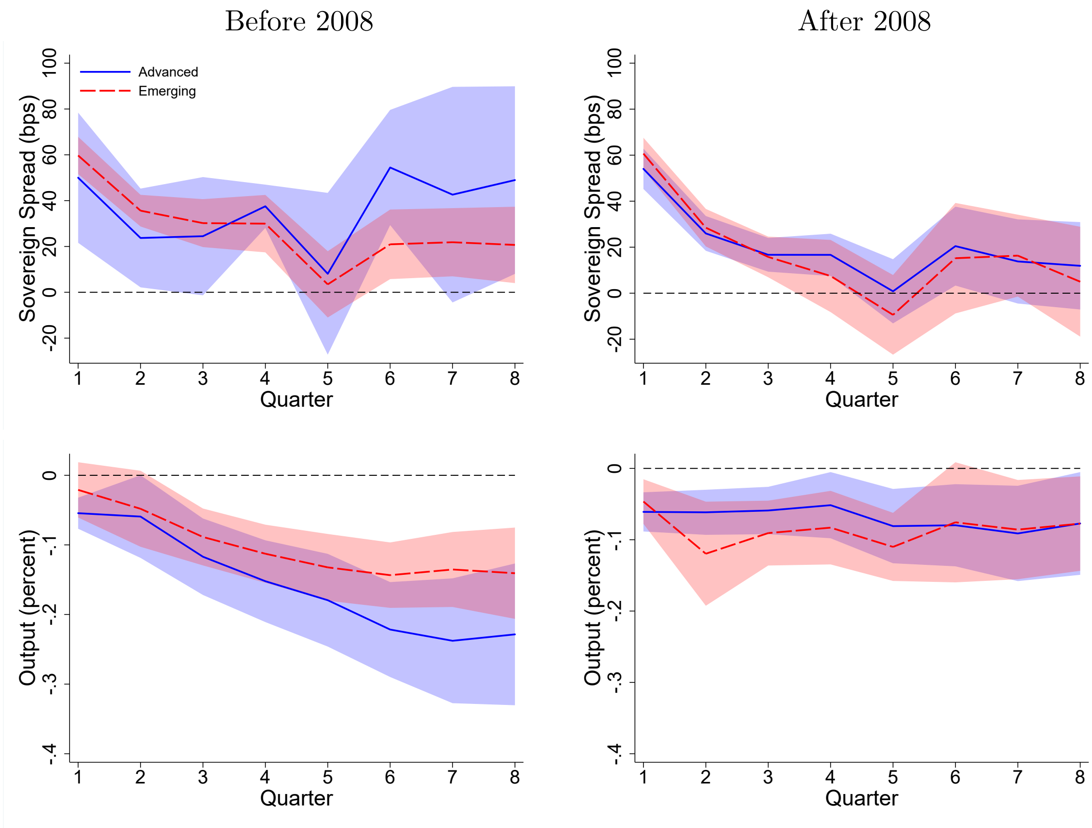
Note: ATE: responses to a sovereign spread shock (spread increase by more than one standard deviation but at least 25 bp). Extended specification of the first stage and regression adjustment. Response for advanced economies only due to data limitations. For details, see Figure 1.9.

Figure 1.A.8: Impulse responses to a spread shock: increases of at least 50bp



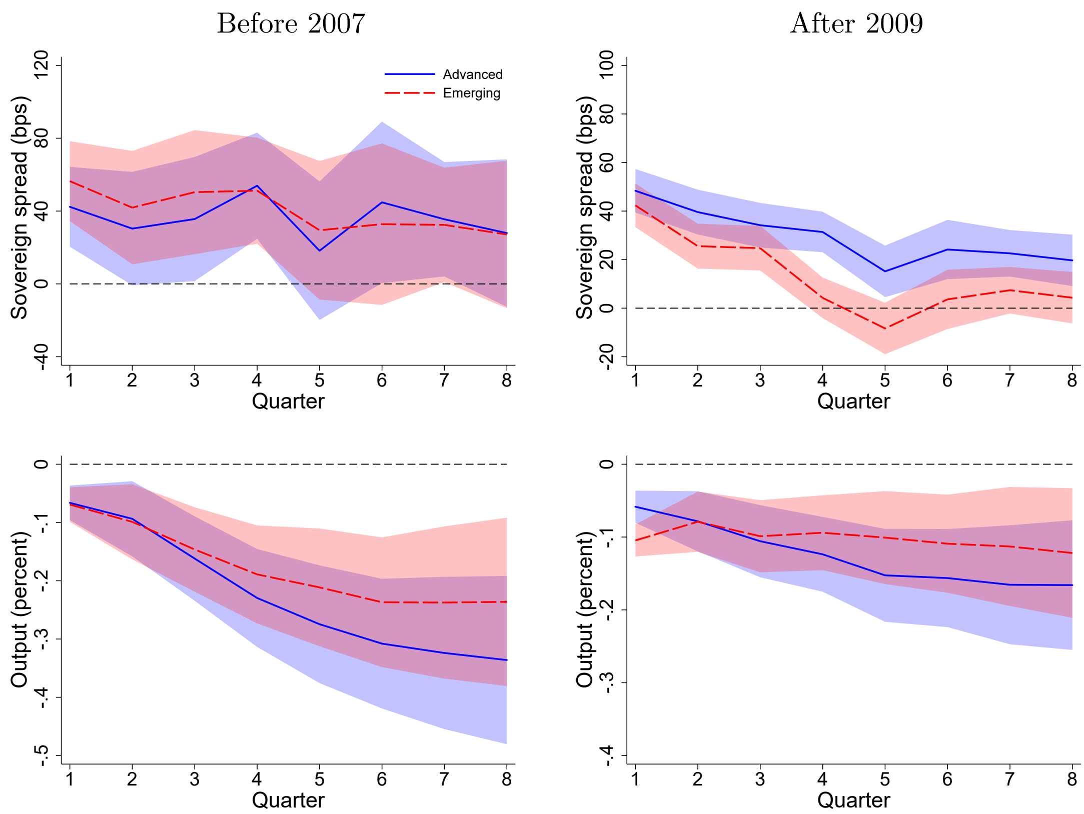
Impulse responses to a $h = 0$ sovereign spread shock based on the ATE estimator in equation (1.5) together with a conservative treatment definition of $D_{i,t} = \mathbb{1}(\Delta s_{i,t} >= \sigma_i \wedge \Delta s_{i,t} >= 50\text{bp})$, i.e. increases of at least 50bp. For details, see Figure 1.9.

Figure 1.A.9: Impulse responses to a spread shock: increases of at least 2 standard deviations



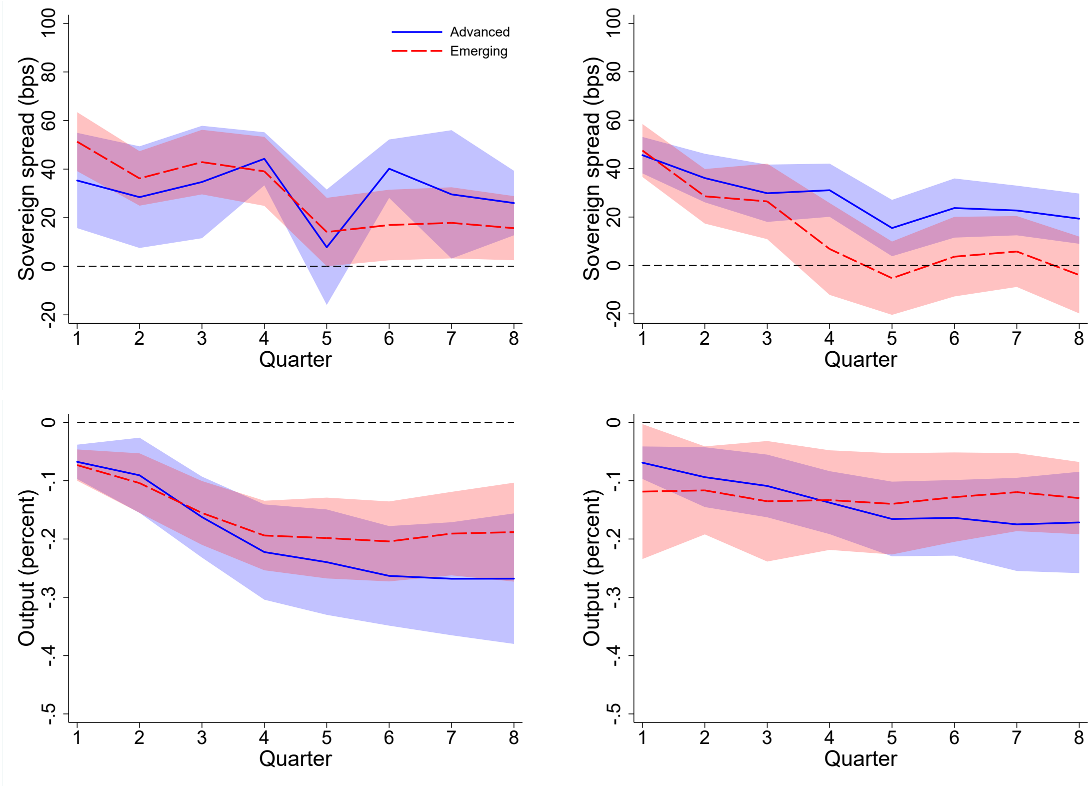
Note: Impulse responses to a $h = 0$ sovereign spread shock based on the ATE estimator in equation (1.5) together with a conservative treatment definition of $D_{i,t} = \mathbb{1}(\Delta s_{i,t} >= 2\sigma_i \wedge \Delta s_{i,t} >= 25\text{bp})$, i.e. increases of at least 2 standard deviations. For details, see Figure 1.9

Figure 1.A.10: Impulse responses to a spread shock: sample split in 2007



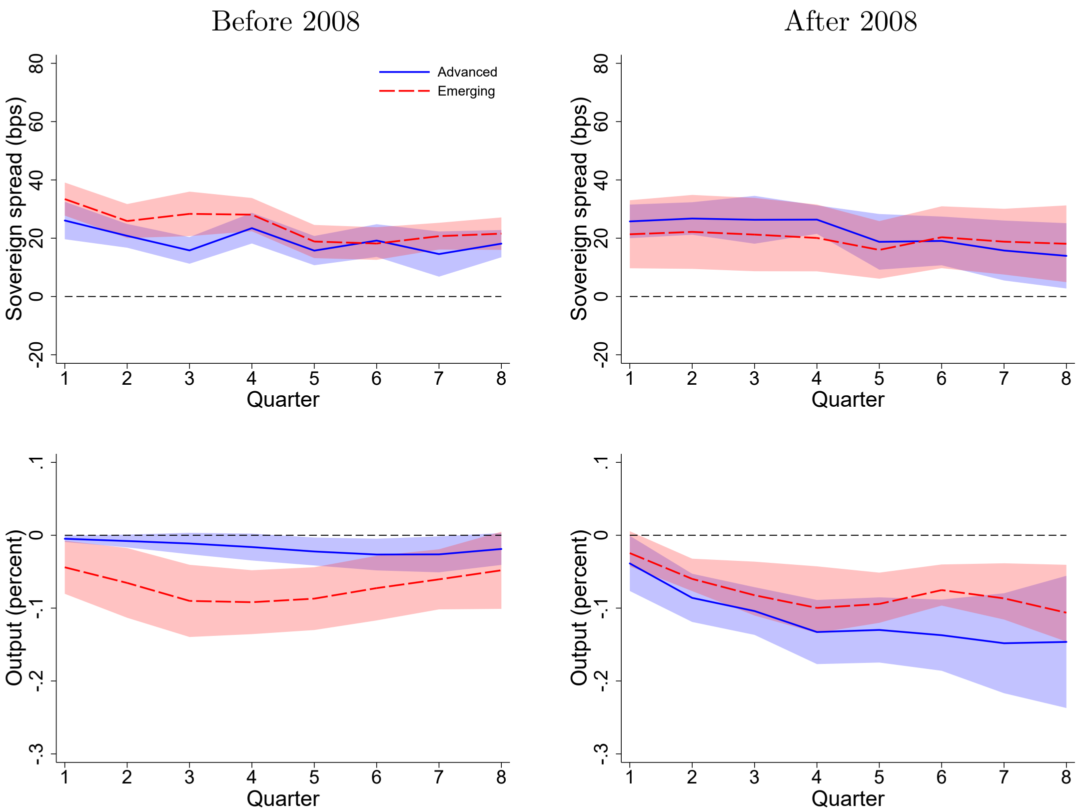
Note: Impulse responses to a $h = 0$ sovereign spread shock based on the ATE estimator in equation (1.5) together with the treatment definition in (1.1) for the sample before 2007Q1 and from 2009Q onwards. For details, see Figure 1.9.

Figure 1.A.11: Impulse responses to a spread shock: excluding Germany and US



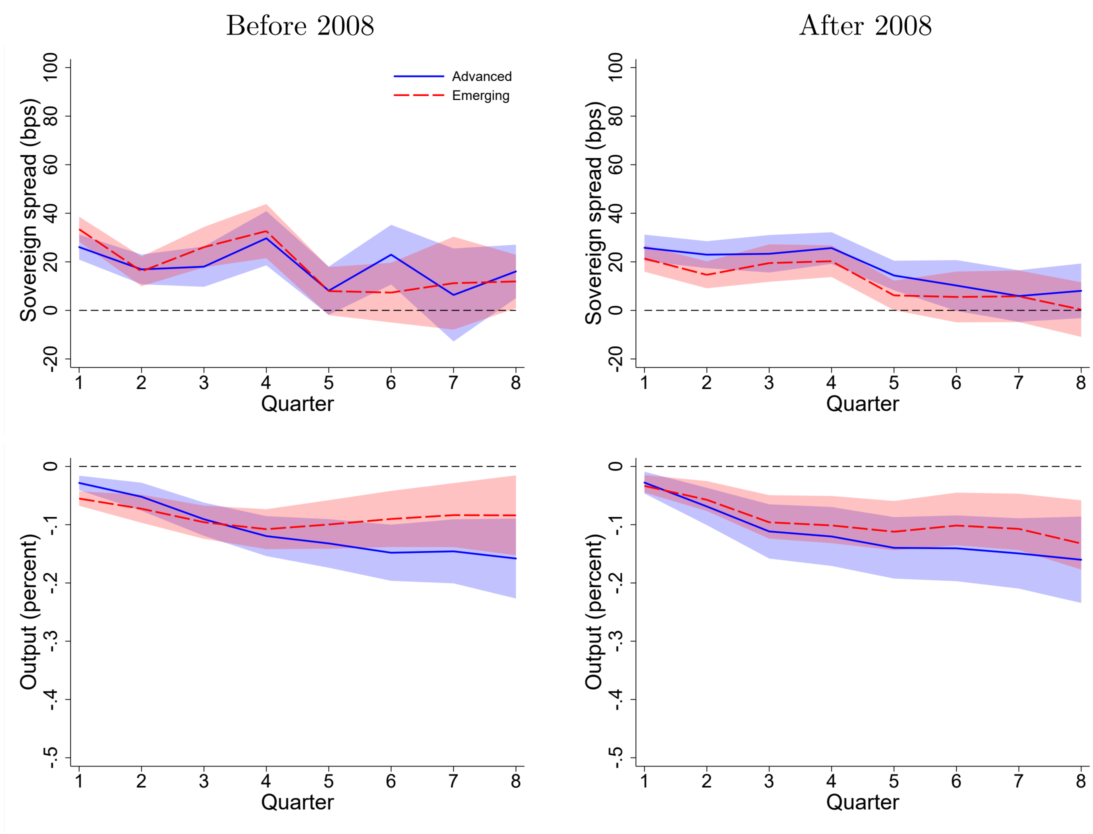
Note: Impulse responses to a $h = 0$ sovereign spread shock based on the ATE estimator in equation (1.5) together with the treatment definition in (1.1) when excluding Germany and the United States. For details, see Figure 1.9.

Figure 1.A.12: Impulse responses to a country-specific spread shock based on the local projection approach



Note: Impulse responses to a country-specific sovereign spread shock based on the local projection approach with time-fixed effect added to both estimation stages. See Figure 1.12 for details.

Figure 1.A.13: Impulse responses to a country-specific spread shock based on the ATE estimator



Note: Impulse responses to a country-specific sovereign spread shock, based on the ATE estimator in equation (1.5) together with the treatment definition in (1.1). See Figure 1.9 for details.

Chapter 2

Risk sharing in currency unions: The migration channel

Joint with Wilhelm Kohler and Gernot J. Müller

2.1 Introduction

In this chapter we quantify and compare the empirical significance of different channels of risk sharing among members of the most important currency unions currently in existence: the US and the euro area (EA). Risk sharing allows member countries of the union, by design or unintended, to smooth consumption in the face of country-specific output fluctuations. Intuitively, the type and degree of economic integration reached by the union should play a crucial role in this regard, and the extent to which market integration differs in the US and the EA is the subject of an ongoing debate. Recent estimates by Head and Mayer (2021) suggest that economic integration in Europe matches or even surpasses the level observed for US states along several metrics. However, they find that the costs of intra-European migration exceed those of intra-US migration by a factor of 10. Likewise, Dorn and Zweimüller (2021) document that migration across European countries is still much lower than interstate migration in the US. Against this background, we focus our analysis on the role of migration for risk sharing in the EA and the US.

Specifically, we use the accounting framework introduced by Asdrubali et al. (1996), hereafter abbreviated as ASY, in order to identify and contrast the patterns of risk sharing among US states and among member countries of the EA. The advantage of this approach is twofold. First, it is outcome-oriented in that it directly measures the degree of consumption smoothing relative to output fluctuations. Second, and more importantly, it allows for a decomposition of consumption smoothing into different channels of risk sharing. We consider five channels: (i) diversification of income sources (factor trade channel), (ii) borrowing or lending (credit channel), iii) the transfer channel, (iv) the migration channel and (v) the labor-market-participation channel. While channels (i) through (iii) have been explored in previous literature, our contribution lies in formally integrating the migration channel into the ASY-framework and in quantifying its importance. For this purpose, as we explain below, we also need to account for the labor-market-participation channel.

The factor trade channel allows *national* income to differ from *domestic* income because of cross-border holdings of financial wealth or because of commuting to a foreign work place. While the possibility of taking up a job across the border in case of deteriorating domestic employment perspectives offers risk-sharing potential, this potential is relevant only for a small part of the population living close enough to the border. Our channel (iv) of risk sharing is different from commuting: migration involves movement of people across countries, rather than people moving their jobs (without changing their residence). If workers avoid taking wage cuts or losing their jobs by moving to other countries where labor demand is high, this, no doubt, contributes to smoothing of consumption against asymmetric shocks. Note that this type of risk sharing is not captured by the factor trade channel since migration does not generate foreign factor income. Moreover, it is not restricted to workers living close to country borders. It may, however, generate international transfers in the form of remittances, that is, private transfer payments by migrants to their families in their country of origin. These remittances contribute to risk sharing via the transfer channel.

In exploring the migration channel, we are motivated by the Mundellian criterion of an optimum currency area. Mundell (1961) argues that labor mobility between countries serves as a powerful adjustment mechanism which can limit the adverse employment effects of asymmetric shocks if a common currency prevents exchange rate adjustments. Prior to the inception of the euro, many economists warned that a currency area including all members of the EU would face severe problems, exactly because such a currency union would fail the Mundellian criterion of labor mobility (see, for instance, Feldstein 1997). But the architects of the Economic and Monetary Union (EMU) have acknowledged the Mundellian criterion by including provisions for internal labor mobility among the so-called "four freedoms" of the Single Market, and it seemed possible that the EA would eventually fulfill the labor mobility criterion of an optimum currency endogenously through long-run behavioral adjustments to the new environment (see Mundell 1973; Frankel and Rose 1998; Warin et al. 2009). And indeed, numerous studies conclude that international labor mobility among euro area countries has increased over time (see, for instance, Basso et al. 2019). However, the extent to which migration does in fact serve as a vehicle of risk-sharing among EA member states is still an open question.

We take up the question within a suitably extended ASY-framework. The framework as originally introduced relies on a simple variance decomposition of output per person that allows measuring the extent of consumption smoothing in a regression framework. Intuitively, without any consumption smoothing, changes in consumption per person are perfectly "explained" by changes in output per person. Conversely, with perfect consumption smoothing, changes in output and changes in consumption are disconnected; consumption is perfectly insulated from output shocks. Allowing for intermediate cases and different channels, the approach by ASY offers a straightforward way to quantify the fraction of output fluctuations that is smoothed through various risk sharing channels by means of a simple regression analysis. Our extension of the ASY framework to include the migration channel is based on a very simple idea. The original framework treats shocks to certain countries' output *per person* as the primary source of volatility, and the question is to what extent channels (i) through (iii) serve as an insurance of consumption per person against these shocks. We argue that initial demand or supply shocks are, first and foremost, shocks to *aggregate* output, and the extent to which such shocks get translated into shocks to output per person is precisely the question we want to address by a suitable extension of the approach.

Under this extension, migration potentially matters for how aggregate shocks impact output per person—not only mechanically (via a change of the denominator) but also because domestic income may change as migrants move in and out of the domestic labor force. However, even in the absence of migration, the labor force will also change if aggregate shocks lead to adjustments in the labor-market participation in response to aggregate shocks. Hence, in order to measure the contribution of the migration channel to international risk sharing correctly, we also account for the participation channel. Both, the migration channel and the participation channel, provide some insulation of effective consumption in the face of aggregate shocks—be it because people move and take up new jobs elsewhere, or be it because they replace paid work by home production and leisure activities (see, e.g., Gronau 1977; Gnocchi et al. 2016; Aguiar et al. 2021).

To study risk sharing within the ASY-framework, we measure the extent to which variations in aggregate output are passed through into income and consumption, respectively, per person of the labor force. Absent any change in the labor force due to migration (or, alternatively, due to changes in domestic labor market participation), a shock to aggregate output will affect output per person of the labor force by the same percentage amount. Or, applying the same logic as above, output per person of the labor force is then perfectly "explained" by aggregate output. But an adverse shock to aggregate output is likely to generate an adjustment of the labor force—by outward migration or by a withdrawal from the labor force, and conversely for positive shocks. To the extent that such an adjustment takes place, the shocks will be absorbed by a muted reaction of output per person of the labor force.

Given our Mundellian perspective on labor mobility, we explicitly disentangle movements between the domestic and some foreign labor force (that is, migration) from changes in the domestic labor force that are due to changes in domestic participation. Arguably, a given change in employment, whether from migration or an adjustment in domestic participation, has the same effect on income per person employed, but migration is a more effective adjustment mechanism for asymmetric shocks of countries belonging to a currency union: it affects the labor force of both types of countries, those hit by positive as well as those hit be negative shocks. Disentangling these channels is thus crucial if one uses the ASY-framework to quantify different channels of risk sharing. Failing to disentangle the two channels risks falsely interpreting a muted reaction of income per person in the labor force or, for that matter, income per capita, as reflecting migration when it is actually due to a reaction in domestic participation.

We apply the extended approach to annual US-inter-state data for the period 1976–2017 as well as to EA member states for the period 1999–2020. We find that the degree of risk sharing among the latter is generally much lower: for EA members we find that only about 1/2 of output fluctuations are buffered by risk sharing. For the US it is about 4/5. More importantly still, we find that the migration channel makes a significant contribution to risk sharing in the US: it smooths up to 21 percent of output fluctuations (at a three-year horizon). In contrast, for EA members it does not contribute to risk sharing in a significant way. These results are consistent with evidence which we compile on the basis of migration data from the Internal Revenue Service's Statistics of Income and the European Labour Force Survey: interstate migration rates are about 15 times higher for US states compared to migration rates for EA members.

At the same time, we find that the participation channel is very important for smoothing the impact of aggregate fluctuations, and particularly so in the EA where it smooths roughly 20 percent of the fluctuations in aggregate output. But it turns out to be important in the US, too, at least in the short run. This is consistent with the notion of a "Great Resignation", according to which a large number of people dropped out of the labor force following the Great Recession and even more so after the pandemic. To what extent this is a temporary or permanent withdrawal is the subject of an ongoing debate and, of course, a crucial question from a risk-sharing perspective.[1] More generally, there is evidence that labor force participation declines significantly while non-market activities increase in response to contractionary shocks (Cajner et al. 2021).

The chapter is organized as follows. In the remainder of the introduction we place the chapter in the context of the literature. Afterwards, in Section 2.2, we present descriptive statistics on business cycles and migration flows, paving the ground for the subsequent analysis. In Section 2.3 we present the econometric framework of the ASY-approach, with due emphasis on our novel element which is the migration channel. Section 2.4 presents our main results. We conclude in Section 2.5 with a brief summary.

Related literature. The framework of ASY is widely used to quantify channels of risk sharing, often with a focus on Europe (see, for instance, Sørensen and Yosha 1998; Kalemli-Ozcan et al. 2004; Balli and Sørensen 2006). A robust finding is that risk sharing in Europe still falls short of the levels observed for the US (European Commission 2016; Milano 2017; Furceri et al. 2022), also once additional channels of risk sharing are brought into focus (e.g., Demyanyk et al. 2007; Evers 2015; Hoffmann et al. 2019; Cimadomo et al. 2020; Nikolov and Pasimeni 2022).

Up to now, however, migration has not been considered as a distinct channel of risk sharing despite its importance in the Mundellian theory of optimum currency areas. An exception is Parsley and Popper (2021), but their focus is different from ours as they are concerned with possible differences in risk sharing among 'red' and 'blue' states in the US. More importantly, they do not distinguish between migration and the domestic adjustments in labor-force participation, as we do below.

[1] See the recent commentary pieces by Faccini et al. (2022), Fuller and Kerr (2022) and Krugman (2022).

Following the influential work of Blanchard and Katz (1992), various studies investigate how migration and changes in labor market participation are contributing to the absorption of shocks (Decressin and Fatás 1995; Obstfeld and Peri 1998; Beyer and Smets 2015; Arpaia et al. 2016; Bandeira et al. 2019) or, instead, area genuine source of business cycle fluctuations (Furlanetto and Robstad 2019). A related but distinct strand of work focuses on the responsiveness of migration to local labor market conditions (Saks and Wozniak 2011; Jauer et al. 2019; Huart and Tchakpalla 2019; Mitze 2019). A major theme throughout this literature are differences across the US and Europe and how, if at all, these differences are changing over time, an issue which has not been settled yet (see, for instance, Dao et al. 2017; Furceri et al. 2022). Our chapter differs as it revisits the issue within the ASY variance-decomposition framework.

A third strand of literature relies on structural models to explore the adjustment of migration to business cycle shocks (Lkhagvasuren 2012; Caliendo et al. 2019; Mangum and Coate 2019; Smith and Thoenissen 2019; Monras 2020). Here, some authors explicitly share our Mundellian perspective on migration as an adjustment mechanism of particular relevance for currency unions (Farhi and Werning 2014; House et al. 2019; Hauser and Seneca 2022). Relative to these insightful analyses, the ASY approach, being a mere accounting framework, offers the advantage of "structural agnosticism": It allows us to capture the consumption smoothing effect of migration regardless of the detailed mechanisms at work.

2.2 Descriptive statistics for EA members and US states

To set the stage for our analysis of the risk-sharing channels that operate across US states (or regions) on the one hand and across EA member states on the other, we present a number of descriptive statistics. Our sample covers annual observations for the period up to 2020. It starts in 1976 for the US and in 1999 for the EA, that is, the introduction of the euro.[2] For the US, our sample covers observations for all 50 states as well as the District of Columbia. In addition, we also consider the major regions of the US as defined by the US Census Bureau which features a coarse (four regions) and a fine (nine regions) classification. For the EA, we distinguish three groupings which include a progressively larger set of countries: EA9, EA12, and EA19. Unfortunately, we have to exclude Ireland from the set of countries in the formal estimation, because we lack migration data; see Section 2.2.2. In the spirit of conventionality, we still refer to EA12 and EA19. We list our data sources and details regarding the regional classification for the US and the country groupings for the EA in the appendix (Tables 2.A.1 – 2.A.3).

[2]For some variables our observations for the US end in 2017. In particular, we lack data for components of consumption, state income and disposable state income. For this reason we present descriptive statistics and estimate our baseline model on US data for the period 1976–2017.

2.2.1 The co-movement of macroeconomic aggregates

In theory, risk sharing is about idiosyncratic shocks—common shocks impact all participants in a risk-sharing arrangement in the exact same way whence there is no scope for risk sharing. In practice, the distinction is not always clear-cut because common shocks may transmit differently across countries—the unfolding of the Covid-19 pandemic illustrates this point rather sharply: A common shock comes with an idiosyncratic component for each participant, which generates some potential for risk sharing.[3] We account for this complication as we focus directly on business cycle fluctuations and observe that there is scope for risk sharing to the extent that business cycles are not perfectly synchronized across countries and states of the world.[4] We stress that throughout this chapter fluctuations in aggregate output—rather than on output per person—are our point of departure because the extent to which these fluctuations are passed through to the per-person level is endogenous to the migration channel of risk sharing, which we focus on in the subsequent analysis.

In order to assess the extent of business cycle synchronization at the aggregate level, we compute a measure of GDP-synchronicity originally proposed by Kalemli-Ozcan et al. (2013). It is based on the growth difference of economic activity across countries. For EA members we rely on GDP, for US states we use Gross State Product (GSP) as a comprehensive measure of economic activity. For easier exposition, we use GDP when referring to the GSP of US states. Formally, we use $\phi_{i,j,t}$ to denote the negative of the absolute value of the difference of GDP growth between EA members (or between US states) i and j:[5]

$$\phi_{i,j,t} \equiv -|(\ln gdp_{i,t} - \ln gdp_{i,t-1}) - (\ln gdp_{j,t} - \ln gdp_{j,t-1})| \tag{2.1}$$

We first compute $\phi_{i,j,t}$ on a country-by-country (state-by-state) basis for each year in our sample and for all possible pairs of EA members and US states. Next, we compute ϕ_t as the (unweighted) mean of $\phi_{i,j,t}$ over all pairs in a given year.

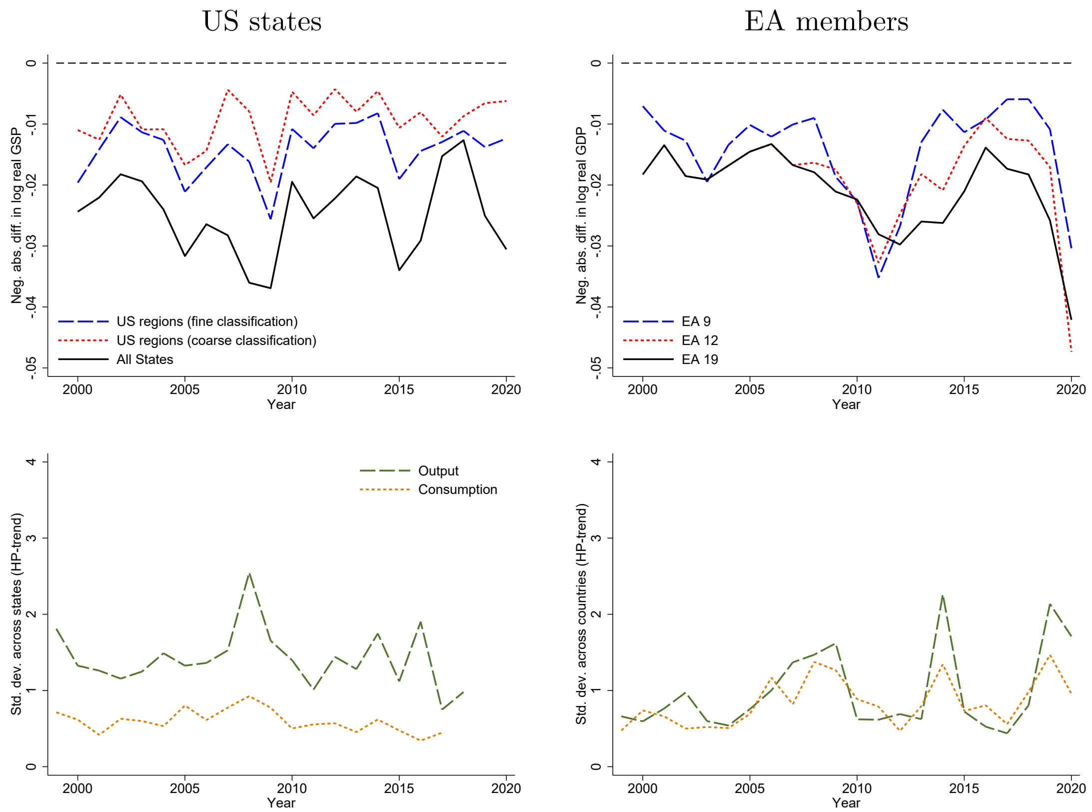
We show the time series of ϕ_t in the top panels of Figure 2.1, for the US in the left panel and for the EA in the right panel. For the sake of comparability, we report statistics for the period since 1999. For the US, we show the synchronicity measure not only across states (black solid line) but also across major regions, using both the fine (blue dashed line) and the coarse (red dotted line) classification based on GSP data aggregated to the region level. For the EA, we report the synchronicity measure for three (sub-)groups: EA9 (blue dashed line), EA12 (red dotted line), and EA19 (black solid line); see again Table 2.A.3 in the appendix for details on the classification. At first sight, the two panels look quite different, but there are striking similarities. The

[3] In response to the Covid-19 pandemic, the EU agreed on a recovery fund worth EUR750 billion within the “Next Generation EU” framework—very much in the spirit of risk sharing. By historical standards, this fund is exceptionally large and involves considerable cross-country transfers.

[4] Enders et al. (2013) document to what extent the introduction of the euro changed business cycle co-movements in the EA.

[5] Note that this measure always takes on negative values: a lower absolute value indicates a higher degree of business-cycle synchronicity.

Figure 2.1: Business cycle co-movement across US states and EA members



Notes: Top panels display synchronicity of real aggregate output growth for US states (left) and EA19 members (right), computed according to equation (2.1). Bottom panels show dispersion of real aggregate output and real consumption per person across US states/EA19 members, measured in terms of log deviation from HP-trend (smoothing parameter $\lambda = 6.25$). We dropped the observation for IRE in 2015 due to data anomalia. Data sources: see Table 2.A.1 in the Appendix.

degree of synchronicity is lowest for US states and the EA19 group. Moreover, in all instances synchronicity declines during the 2000s. For the US, it reaches a trough during the financial crisis and declines again towards the end of the sample period. In the EA, synchronicity is particularly low in the early 2010s and then again in 2020 during the pandemic. Importantly, we observe that synchronicity generally tends to be somewhat higher in the US than in the EA—suggesting that the potential for risk sharing is higher in the EA than in the US.

On a very fundamental level, risk sharing is about insulating consumption per person from *aggregate* output fluctuations. It is therefore instructive to compare the dispersion of output and consumption across countries/states. For this comparison, we de-trend real aggregate output and consumption per person with an HP-filter and compute the standard deviation across countries/states for each year. The bottom panels of Figure 2.1 show the results for the US states in the left panel and for the EA in the right panel. We find that the co-movement of consumption and output dispersions across EA members is much stronger than across US states. In particular, during the entire sample period the dispersion of consumption across US states is low, compared to the dispersion of output. This also holds true during the global financial crisis when the dispersion of output across US states picks up sharply. In contrast, no such disconnect between output and consumption dispersion is observed in the EA. Here, the dispersion of consumption tracks the dispersion of output very closely. These patterns suggest that risk sharing across US states is considerably higher than across the members of the euro area.[6] However, a simple comparison of such cross-country dispersion measures for output and consumption has limited information value when it comes to international risk sharing. Below, we therefore use a refined approach described in Section 3.

2.2.2 Migration

Our main interest in this chapter is to investigate the role of migration as a potential risk-sharing channel and to quantify its importance. For the US, we obtain migration data from the Internal Revenue Service's Statistics of Income (henceforth IRS) available on the IRS website from 1991 onwards. We expand the sample by including data for the period from 1976 to 1990 compiled by Saks and Wozniak (2011).[7] Specifically, the IRS collects year-to-year address changes reported on individual income tax returns for the entire US. Based on these address changes, the IRS compiles inflows (that is, the number of residents moving to a state) and outflows (the number of residents leaving a state) of individuals by state including origin and destination of the movers, respectively. These state-level migration figures (both in- and outflows) cover internal as well as international migration. For our analysis, we focus on migration across US states (and the District of Columbia) and ignore within-state migration as well as migration to or from outside the US, and similarly for US regions. We sum up these internal flows for each state and region, taking as a counterpart the remaining states and regions, respectively.

For the EA, we obtain migration data from the Labour Force Survey (LFS). The data for the LFS is collected by national statistical agencies on behalf of Eurostat. Data are available at an annual frequency since 1998. Across the member states of the European Union, about 1.5 million households are surveyed every quarter which amounts to about 0.3% of the total population. Based on a yearly weighting coefficient included in the LFS we scale up the survey figures to the total population of the EU. For our research question, the survey question about the residence situation one year ago is essential: respondents are asked about the country of residence in the previous year. Based on these household-level data, we compute annual migration inflows and outflows for each EA member state individually. In doing so, we limit our analysis to migration to and from the remaining countries of the EA9, EA12, and EA19 group, respectively.[8] Unfortunately,

[6] As a robustness check, we compute the same statistic using growth rates instead of HP-filtered time series to account for the time trend. We find that the results do not differ. The figures based on growth rates can be found in the working paper version of this chapter.

[7] The data obtained from Saks and Wozniak (2011) do not include the District of Columbia, Alaska and Hawaii because they are not part of the contiguous US. Moreover, these data contain only aggregated internal in- and outflows by state. For the period prior to 1990 we thus lack observations at the region level.

[8] Our aim is to account for migrants which move into/out of the domestic labor market. Our migration data is compiled at the household level and thus may also include persons not belonging to the labor force, such as dependents and non-working spouses. In US-IRS data, for instance, these persons are part of the "personal exemptions" category. For large households we would thus likely overestimate

Table 2.1: Migration between US regions and EA member states

Major US regions					EA members				
	Mean	Mean	Median	SD		Mean	Mean	Median	SD
		% of pop					% of pop		
New England	48508	2.49	2.34	0.46	Austria	12569	0.15	0.15	0.04
Mid-Atlantic	201305	1.61	1.62	0.17	Belgium	16060	0.15	0.15	0.06
EN Centr.	140574	1.62	1.57	0.21	Cyprus	2736	0.32	0.29	0.09
WN Centr.	61420	2.60	2.48	0.38	Estonia	1011	0.08	0.07	0.02
South Atlantic	152119	2.94	2.92	0.25	France	39270	0.06	0.06	0.01
ES Centr.	94332	2.28	2.26	0.26	Germany	50701	0.06	0.06	0.02
WS Centr.	156374	2.29	2.19	0.43	Greece	8233	0.08	0.07	0.02
Mountain	74403	3.88	3.72	0.85	Italy	15979	0.03	0.03	0.01
Pacific	176510	2.87	2.86	0.44	Latvia	2150	0.11	0.09	0.04
					Lithuania	1839	0.06	0.07	0.03
					Luxembourg	5138	0.97	0.99	0.48
					Netherlands	10346	0.06	0.06	0.02
					Portugal	9394	0.09	0.09	0.02
					Slovakia	2344	0.04	0.05	0.01
					Slovenia	1204	0.06	0.06	0.04
					Spain	20099	0.04	0.04	0.01
Average	123838	2.51	2.42	0.78	Average	15275	0.16	0.08	0.28

Notes: Migration is average of in- and outmigration (gross migration) for each region/country. Mean is the average number of persons per year. For US regions the sample runs from 1991 to 2017, regions as defined in Table 2.A.2. For EA members data runs from 1999 to 2020. No reliable migration data available for FIN, IRE and MLT. Data sources: see Appendix Table 2.A.1.

we have to omit Ireland from the estimation sample and the descriptive statistics for migration because we lack microdata in this instance.

In Table 2.1 we report descriptive statistics for gross migration (average of in- and outmigration) for major US regions (left panel) and EA member states (right panel). To economize on space, we delegate a detailed breakdown for US states to the appendix; see Table 2.A.4. In principle, a Mundellian perspective would call for a focus on net migration, and in our ASY-analysis below we do use net migration data, but gross migration is more informative here as we want to learn about labor mobility in general. For each region or country, we report the mean of annual gross migration over all years of the sample as well as a number of statistics expressing migration in percent of the population (mean, median, and standard deviation). There is considerable variation among EA members and among US states. Among EA members migration is lowest for Italy, Slovakia and Spain, and highest for Luxembourg and Cyprus. In fact, the migration rate for Luxembourg (0.97%) dwarfs the numbers for all EA member states. In our analysis below, we shall therefore verify that our results for EA19 members presented in Section 2.4.1 are not driven by Luxembourg. The mean migration rate in the EA is

migration in and out of the labor force. We calculate an average size of migrating households equal to 2 persons for the US, and equal to 2.4 persons for the EA. Since it is quite possible that all members of a household participate in the labor market, we are therefore confident that our data do not imply substantial overestimation of migration into and out of the labor force.

0.16 percent compared to 2.51 percent for US regions. It is 2.67 for US states (Table 2.A.4) and thus almost 15 times higher compared to EA members. For the median the difference is even larger, since in this case the high migration rate of Luxembourg matters less. Also, the standard deviation is 2-3 times higher in the US.[9]

The top panels of Figure 2.2 show the median (gross) migration rate over time. The left panel depicts state-to-state migration as well as region-to-region migration for the US (red-dotted line for coarse classification, blue-dashed line for fine classification of regions). Note, first, that migration rates across states are about twice as large as migration rates across regions (black solid line vs red dotted line). Intuitively, there is much more migration over the short distance, say from Massachusetts to Connecticut or New York, than over the long distance, say from the Northeast to the Midwest of the US. Second, migration rates are trending downwards in the US, at the level of state-to-state migration as well as region-to-region migration. This is consistent with earlier findings (Molloy et al. 2011, e.g. Dao et al. 2017; Basso and Peri 2020). Importantly, these trends may be related to changing employment opportunities and may not necessarily reflect a reduced capacity of the US economy to absorb regional shocks. Kaplan and Schulhofer-Wohl (2017), for example, show that interstate migration has fallen substantially due to an increasing job similarity across local labor markets in the US. Also, Şahin et al. (2014) find that geographical mismatch between job vacancies and unemployed workers does not contribute to mismatch unemployment in a meaningful way.

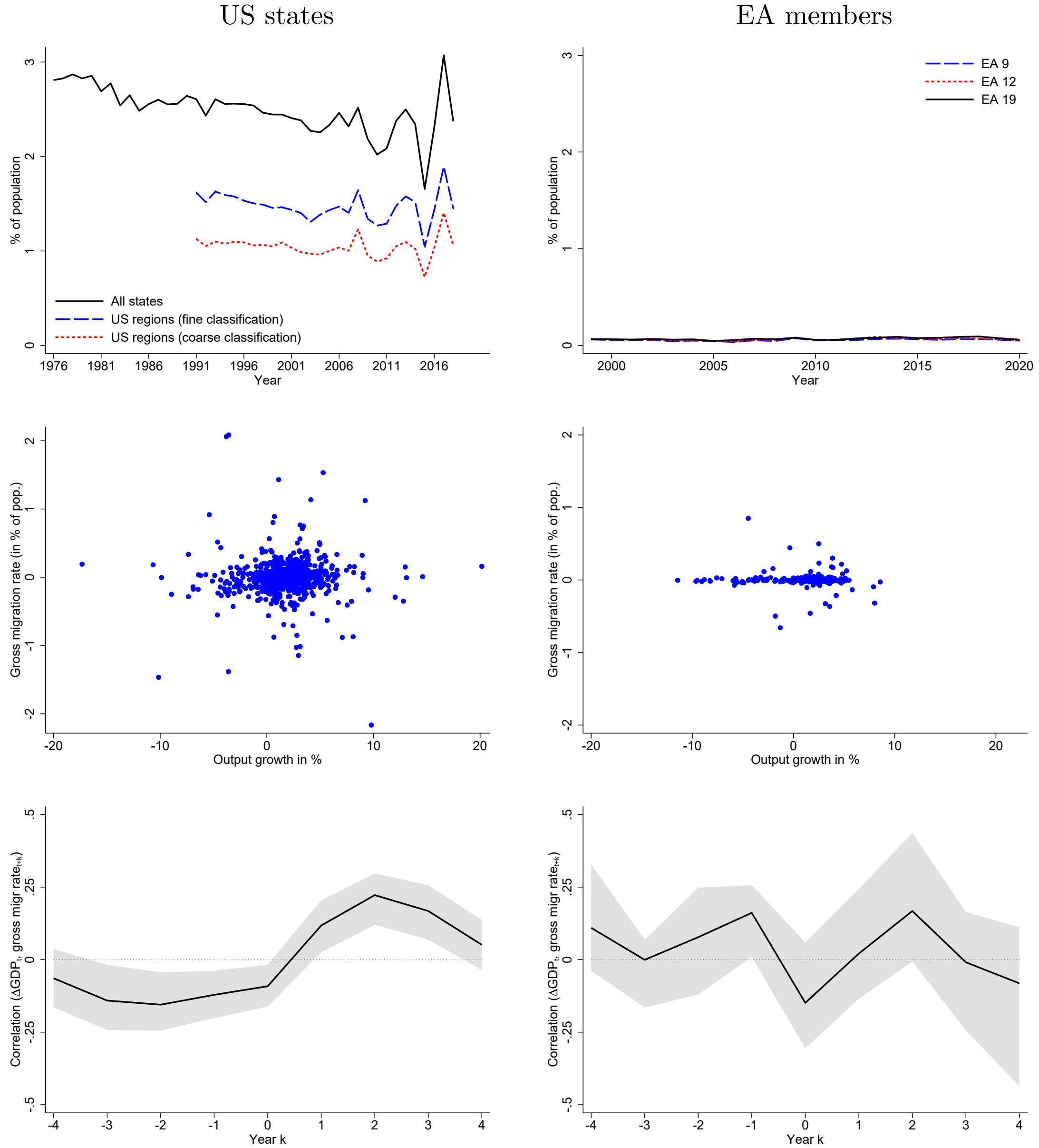
The right panel of Figure 2.2 depicts country-to-country migration for different country groups in the EA. The difference between the US and the EA is again rather stark: if benchmarked against the US, any increase in labor migration observed in the EA appears to be small or even negligible, in line with the results by Head and Mayer (2021) and Dorn and Zweimüller (2021) referred to above. Once we consider EA migration rates at the country level, we find a fair degree of homogeneity. In particular, there is a moderate upward trend in migration rates since 2005; see Figure 2.A.1 in the appendix. Still, we do not observe significant changes in migration patterns in response to the financial crisis and the subsequent sovereign debt crisis in the euro area.

The middle panels of Figure 2.2 correlate output growth and de-trended gross migration rates for all time-state/country observations in the US (left) and the EA (right). Taken at face value, the figure suggests that there is no systematic variation. The correlation coefficient for US states is -0.04 and -0.05 for EA members. At the state- and country-level correlations are also small; see Tables 2.A.5 and 2.A.6 in the Appendix. However, judging from more detailed analyses, migration decisions within the US are influenced to a substantial extent by income and employment prospects (e.g. Lkhagvasuren 2012). Similarly, for the EA Beine et al. (2019) find that both aggregate fluctuations and employment rates in the destination countries affect migration flows.

The contemporaneous correlation may be an insufficient metric to capture the cyclical

[9] These observations are in line with recent evidence put forward in House et al. (2019). Using administrative (national) data for EA countries, they obtain somewhat higher migration rates (0.34 on average), but they consider in- and outmigration with respect to EU27 countries, rather than EA19 member states.

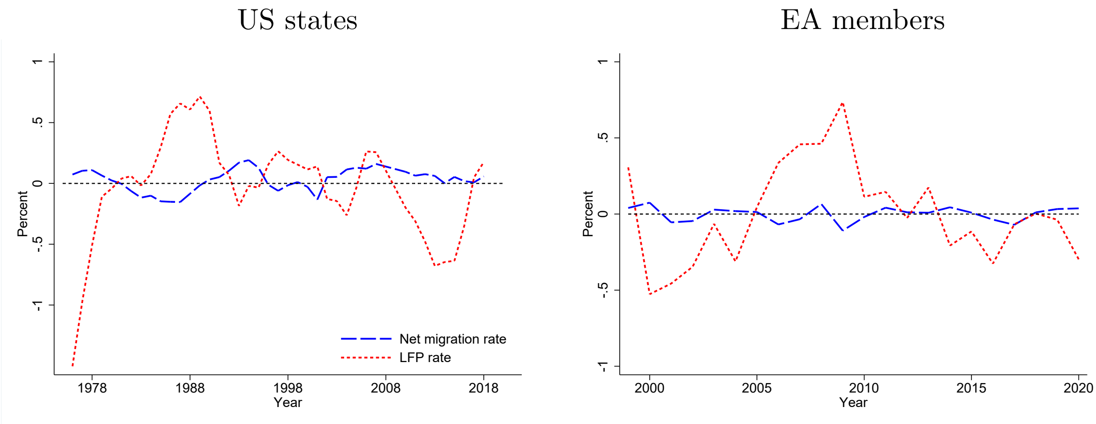
Figure 2.2: Migration rates and output growth



Notes: Top panels show median gross migration rates in % of population for US interstate and inter-region migration (left) and across EA9, EA12 and EA19 member states (right). Middle panels correlate output growth and detrended gross migration rate. Bottom panels show correlation of output growth in year t and detrended gross migration rate in year $t + k$, with $k = 0, ..., \pm 4$. Shaded areas indicate the 25% and 75% interquartile range. Observations for Ireland in 2015 are dropped from the sample. For the US, inter-region migration data starts in 1991, interstate migration data starts in 1976 (until 1991 w/o Alaska, Hawaii and DC). Data sources: see Appendix Table 2.A.1.

nature of migration rates for there may be non-trivial lags because, say, migration takes time to adjust. To account for this complication, we compute the cross-correlation function for output growth in year t and de-trended gross migration rates in year $t \pm k$, where k runs from -4 to +4. We compute the cross correlation function state-by-state/country-by-country and display the mean (black solid line) in the bottom panels of Figure 2.2, for the US in the left panel and for the EA in the right panel. The shaded area indicates the

Figure 2.3: Net migration and labor force participation



Notes: dashed and dotted lines show cyclical component of the net migration rate and the domestic labor force participation rate, respectively, for the US (left panel) and the EA (right panel); time trend removed with HP-Filter. All rates expressed in % of population. Data sources: see Table 2.A.1.

25% and 75% interquartile range. We find a positive correlation of current output growth and future gross migration rates for US states, while there is no significant pattern for EA members for all leads and lags of gross migration rates.

To be sure, these correlations are not necessarily informative of a causal effect of output on migration. To establish a causal relationship between output and migration flows one would have to control for relative local economic conditions both in the country of origin and destination of the migrant. This requires more advanced econometric methodologies (like the use of instrumental and proxy variables to account for the distance between origin and destination locations) compared to simple correlations. Saks and Wozniak (2011) shed light on this issue by examining long-distance migration patterns to infer whether labor market adjustments contribute to business cycle fluctuations. They find that internal migration is strongly procyclical in particular for younger persons in the labor force. Furthermore, they conclude that the net benefit of moving rises during booms. Since we focus on risk sharing in currency unions in this chapter we cannot further inform this debate here. Instead, we offer a complementary perspective on how labor market adjustments contribute to smoothing output fluctuations based on bilateral migration data potentially involving long-distance migration within the US or the EA, respectively.

Finally, in Figure 2.3 we plot the de-trended net migration and labor force participation rate for the US (left panel) and the EA (right panel) in order to shed some light on the potential for risk sharing through migration and labor force participation.[10] Comparing net migration and the participation rate, we observe considerably more variation in the labor force participation rate in both currency areas. This observation underscores the importance to control for labor force participation when it comes to quantifying the migration channel of risk sharing. From a theoretical point of view, as we shall argue

[10]For more details on participation rates, see Tables 2.A.7 and 2.A.8 and Figure 2.A.2 in the Appendix.

below, both migration and changes in labor market participation have similar effects when it comes to smoothing of shocks to aggregate output.

2.3 Empirical strategy

In this section, we explain how we extend the framework of ASY to account for migration as a distinct channel of risk sharing. We first provide an intuitive discussion of international risk sharing in the baseline case, focusing on the factor trade channel, the transfer channel, and the credit channel. Then, we extend the approach by introducing the migration channel. Finally, we describe the sample and the empirical implementation.

2.3.1 Point of departure

The standard ASY-approach focuses on smoothing of real consumption per capita (c) relative to real output per capita (y) that operates through three channels. The first is what we call the factor trade channel: If households derive capital income from internationally diversified asset portfolios, then national real income per capita (ni) may to some extent be insulated from shocks to output per capita. A similar effect arises from cross-border labor income based on commuting. The second is the transfer channel: International transfer payments, whether of the public or the private sort, may insulate aggregate disposable real income (di) relative to variations in national income. And finally, there is the credit channel: Cross-border lending and borrowing allows for households as well as the public sector to smooth aggregate real consumption per capita relative to variations in disposable national income. Formally, the ASY-approach is based on the following identity

$$y \equiv \frac{y}{ni}\frac{ni}{di}\frac{di}{c}c. \tag{2.2}$$

Writing this in log-changes, multiplying out by $\Delta \log y$ and forming expectations, we may write[11]

$$\begin{aligned} \mathrm{Var}\left[\Delta \log y\right] \quad \equiv \quad & \mathrm{Cov}\left[\Delta \log y, \Delta \log y - \Delta \log ni\right] \\ & + \mathrm{Cov}\left[\Delta \log y, \Delta \log ni - \Delta \log di\right] \\ & + \mathrm{Cov}\left[\Delta \log y, \Delta \log di - \Delta \log c\right] \\ & + \mathrm{Cov}\left[\Delta \log y, \Delta \log c\right]. \end{aligned} \tag{2.3}$$

[11]To understand this variance decomposition, consider the simplified identity $y \equiv (y/ni)\, ni$. Let $\mathbb{E}$ denote the expectations operator so that $\mathrm{Cov}[\Delta \log y, \Delta \log y - \Delta \log ni] = \mathbb{E}\left[\Delta \log y(\Delta \log y - \Delta \log ni)\right] - \left[\mathbb{E}(\Delta \log y)\right]^2 + \mathbb{E}(\Delta \log y)\mathbb{E}(\Delta \log ni)$ and $\mathrm{Cov}(\Delta \log y, \Delta \log ni) = \mathbb{E}(\Delta \log y \Delta \log ni) - \mathbb{E}(\Delta \log y)\mathbb{E}(\Delta \log ni)$. Adding, we obtain $\mathrm{Cov}\left[\Delta \log y, \Delta \log y - \Delta \log ni\right] + \mathrm{Cov}(\Delta \log y, \Delta \log ni) = \mathbb{E}\left[(\Delta \log y)^2\right] - \left[\mathbb{E}(\Delta \log y)\right]^2 = \mathrm{Var}(y)$. Equation (2.3) follows by straightforward extension.

If we divide both sides by $\mathrm{Var}[\Delta \log y]$ and look at all changes as empirical realizations for different countries we obtain

$$1 \equiv \hat{\beta}_F + \hat{\beta}_T + \hat{\beta}_C + \hat{\gamma}_U, \tag{2.4}$$

where $\hat{\beta}_F$ is the OLS estimator of β_F in the regression $\Delta \log y - \Delta \log ni = \beta_F \Delta \log y + \varepsilon$, and analogously for $\hat{\beta}_T$ and $\hat{\beta}_C$, while $\hat{\gamma}_U$ is the OLS estimator in the regression $\Delta \log c = \gamma_U \Delta \log y + \varepsilon$ and $\hat{\gamma}_U \equiv 1 - \hat{\beta}_F - \hat{\beta}_T - \hat{\beta}_C$. Thus, $\hat{\gamma}_U$ measures the extent to which shocks to output per capita remain unsmoothed, i.e., get passed though to consumption shocks, and the β-coefficients measure the contribution of the above channels to smoothing of consumption vis à vis variations in output per capita. Note that the factor trade channel (F) works *ex ante*, through diversification of income sources, while the transfer channel (T) and the credit channel (C) work *ex post*, after shocks have materialized. Moreover, it is worth emphasizing that the estimation of the parameters in Equation (2.4) in no way aims at establishing causality since all of the variables involved here are jointly endogenous. Instead, the parameter estimates serve as a convenient empirical description of international risk sharing among the set of countries appearing in the sample used.

2.3.2 Extension: migration

This chapter argues that the ASY approach needs extension to cover labor market adjustments. Arguably, the most likely shocks hitting an economy are demand or supply shocks to its *aggregate output*, and the extent to which such shocks feed into changes in output per person is a matter of labor market adjustment. In this chapter we focus on changes in the labor force as a mechanism of absorbing aggregate demand or supply shocks. In line with our interest in mechanisms of *international* risk sharing, we split it in two parts: changes in the labor force participation (a domestic mechanism), and changes due to international labor mobility as suggested by the Mundellian criterion of optimal currency areas.[12]

To address these adjustment mechanisms, we modify our perspective by looking at how migration affects macroeconomic aggregates per person of the *total* labor force L, rather than per capita. Note that the total labor force includes the current-period inflow of foreign labor while excluding the current-period outflow of labor. Using M to denote the current period net inflow of labor (net immigration), we compute the *domestic* labor force as $L_d = L - M$. We define $\bar{y} := Y/L_d$, where Y denotes aggregate real output. Moreover, we use a tilde to denote variables per person in the labor force L, e.g., $\tilde{y} := Y/L$ and accordingly for all other aggregates appearing in Equation (2.2). We extend this identity to

$$Y \equiv \frac{Y}{\bar{y}} \frac{\bar{y}}{\tilde{y}} \frac{\tilde{y}}{\widetilde{ni}} \frac{\widetilde{ni}}{\widetilde{di}} \frac{\widetilde{di}}{\tilde{c}} \tilde{c}. \tag{2.5}$$

[12]Changes in labor force participation as a mechanism of absorbing labor demand shocks is also considered in the influential study of Blanchard and Katz (1992) referenced in the introduction.

In perfect analogy to Equation (2.4), we now have

$$1 \equiv \hat{\beta}_P + \hat{\beta}_M + \hat{\beta}_F + \hat{\beta}_T + \hat{\beta}_C + \hat{\gamma}_U. \tag{2.6}$$

In this identity, $\hat{\beta}_P$ denotes the OLS estimate of the regression $\Delta \log Y - \Delta \log \bar{y} = \beta_P \Delta \log Y + \varepsilon$ and $\hat{\beta}_M$ denotes the OLS estimate of the regression $\Delta \log \bar{y} - \Delta \log \tilde{y} = \beta_M \Delta \log Y + \varepsilon$. We refer to risk sharing as evidenced by the coefficients $\hat{\beta}_P$ and $\hat{\beta}_M$, respectively, as the *participation* channel and the *migration* channel. The meaning of the other estimates in Equation (2.6) follows by analogy to the explanation of Equation (2.4) above. The final coefficient relates to the regression $\Delta \log \tilde{c} = \gamma_U \Delta \log Y + \varepsilon$. The participation and the migration channel are both *ex-post* in nature, as the pertinent decisions are being made subsequent to the materialization of shocks.

We should like to point out that the coefficient $\hat{\beta}_P$ captures a risk sharing channel that is *domestic* and not *international* in nature. We include it primarily for a precise identification of the Mundellian labor-mobility channel within the ASY-framework, which works through the coefficient $\hat{\beta}_M$. These coefficients should therefore be thought of as a single, unified extension of the framework. A coefficient $\hat{\beta}_P \in (0, 1]$ means that a positive (negative) shock to Y leads to an increase (reduction) in the participation rate among the pre-existing population so that Y/L_d increases (falls) by less, in percentage terms, than output Y. The responsiveness of labor participation to shocks thus contributes to smoothing of consumption relative to the labor force.

2.3.3 Sketchy thoughts on theory

The ASY-framework is generally agnostic regarding structural details of the different risk-sharing channels, and this also applies to the extension in terms of our two labor market channels. We therefore abstain from specifying a particular theoretical mechanism that may lie behind (large or small) values of the elasticities of our coefficients $\hat{\beta}_P$ and $\hat{\beta}_M$. Clearly, these coefficients do not permit any structural interpretation without further assumptions. However, it may be useful to venture some general thoughts on the kind of adjustment which operates through the participation and the migration channel.

First, consider the participation channel. Formally, if Z is the log-change of a (multiplicative) exogenous component of aggregate demand meeting a general equilibrium elasticity of the domestic labor force L_d with respect to Z equal to $\lambda \in (0, 1)$, and if the output elasticity with respect to the labor input is equal to $\alpha \in (0, 1)$, then $\Delta \log \bar{y} = \lambda(\alpha - 1)Z < 0$. Note that $\lambda > 0$ implies an aggregate supply curve which is less than infinitely elastic so that equilibrium output is also determined by aggregate demand. Hence, $\bar{y}$ may move in the opposite direction of Z due to an endogenous adjustment of labor market participation. Intuitively, in response to a negative shock, participation declines but the wage of those still active in the labor force increases because of diminishing marginal returns to labor. Likewise, in response to a positive shock $\bar{y}$ falls because wages decline as employment increases (along a downward-sloping labor demand curve). In both instances, those moving out of/into the labor force experience a change from market income to the level of "home-production", or vice versa. This ensures that it is not just consumption relative to the labor force that is shielded from aggregate income fluctuations, but effective consumption as well. Similar adjustment scenarios may be envisioned regarding supply shocks.[13] Finally, note that barring any labor market adjustment, we would have $\Delta \log \bar{y} = \Delta \log \Delta Y = Z$. This outcome corresponds to $\hat{\beta}_P = 0$. At the other extreme, a value of $\hat{\beta}_P$ equal to 1 implies that $\Delta \log \bar{y} = 0$, which in turn requires $\lambda(\alpha - 1) = 0$ and thus $\alpha = 1$. This would obtain with constant returns to scale production using only labor.

Next, turning to the migration channel, it is important to bear in mind that the domestic labor force, L_d, while reflecting all past net immigration, does not include inflows or outflows of labor that occur in the current period in response to an aggregate demand or supply shock. It is the risk-sharing potential of this type of international migration that is captured by the coefficient $\hat{\beta}_M$ in identity (2.6) above. Writing μ for the general equilibrium elasticity of the labor force with respect to aggregate demand shocks due to current net immigration M, we have[14]

$$\Delta \log \tilde{y} = \alpha \Delta \log Y - \Delta \log L = [\lambda + \mu] (\alpha - 1) Z. \tag{2.7}$$

In terms of the above regression coefficients we have

$$\Delta \log \tilde{y} = \left(1 - \hat{\beta}_P - \hat{\beta}_M\right) \Delta \log Y. \tag{2.8}$$

With demand-determined output, and barring any labor force adjustment, we would have $\lambda + \mu = 0$ and $\Delta \log Y = Z$, while the ASY-framework would deliver $\hat{\beta}_P = 0$ as well as $\hat{\beta}_M = 0$. Again, a similar logic applies to aggregate supply shocks.

Different theoretical models would tell different stories behind the elasticities λ and μ, depending—among other things—on the assumption about price rigidity and on the type of shock considered, and would come up with different conclusions about likely magnitudes of these elasticities. On a general level, risk sharing through labor force participation, as captured by $\hat{\beta}_P$, is best thought of as consumption smoothing through a temporary switch from formal employment (market income) to home-production, or vice versa. For instance, facing a negative aggregate demand shock, households may perceive an incentive to "self-insure" against a fluctuation of consumption through temporarily dropping out of the labor force and consume via home-production instead. While this type of home production and consumption is not observed in the data, we still have observable consumption smoothing. The reason is that with a downward-sloping aggregate labor demand curve, any individual leaving the labor force will reduce the effect that the shock has on those remaining, too. A perfectly analogous reasoning holds for positive aggregate demand shocks, or for supply shocks.

The elasticity μ will crucially depend on the degree of international labor mobility.

[13]Note that this reasoning abstracts from any change in unemployment.

[14]Note that the *domestic* labor force of the current period is equal to the *total* labor force of the previous period. Hence, we have $\Delta L/L = \Delta L_d/L + \Delta M/L$ or $\Delta \log L = (\lambda + \mu) \Delta \log \bar{Y}$.

Moreover, following Mundell (1961), we expect the migration channel to be less important for countries with separate currencies and flexible exchange rates than for countries forming a currency union. But even if formal barriers to migration are absent between countries forming a currency union, as in the euro area, we do not expect the elasticity μ (and a high estimated coefficient $\hat{\beta}_M$) to necessarily be high; because, after all, informal barriers to migration may still be high.

Equation (2.8) is suggestive of how one must interpret $\Delta \log Y$ appearing on the right-hand side of all ASY-type regressions, rather than Δy as in the original version of the ASY-approach. Adding the next stage of the approach renders $\Delta \log \widetilde{ni} = \left(1 - \hat{\beta}_P - \hat{\beta}_M - \hat{\beta}_F\right) \Delta \log Y$. Thus, the $\hat{\beta}$-coefficients tell us about how much of aggregate output changes (caused by some exogenous aggregate shock Z) arrives at national income per labor force L. By way of comparison, the conventional approach based on Equation (2.2) renders $\Delta \log ni = \left(1 - \hat{\beta}_F\right) \Delta \log y$. The coefficient $\hat{\beta}_F$ thus tells us about how much of a certain change in output per capita reappears as a change in national income per capita, but this coefficient is uninformative on the relationship between aggregate output and output per labor force. If, in the context of our specification, one is interested in how much of the aggregate output change ultimately ends up in consumption per capita (as opposed to consumption per labor force), one only needs to extend the identity (2.5) by a term relating consumption per labor force to consumption per capita.[15]

It should be noted that we are not arguing a 'correct' specification of the ASY-framework should *always* have aggregate real output as an 'explanatory' variable on the right-hand side of the equations estimated for the different risk sharing channels. The 'correct' specification depends on what is (or is not) at the center of interest. We do argue, however, that if the Mundellian migration channel of risk sharing is of interest, then the above approach is a preferred way of identifying it within the ASY-framework. Importantly, however, the conventional approach based on identity (2.2) will not, as such, deliver incorrect estimates of the other channels, understood as channels for smoothing consumption per capita relative to *output per capita*. But note that the estimates will differ from those obtained by our approach, simply because they answer different questions, as we have seen in the preceding paragraph. The conventional approach simply fails to address the role that migration plays in smoothing income per capita relative to *aggregate* output shocks. But in focusing on output per capita it also leaves out of the picture the shocks that migration may smooth, viz. shocks to aggregate output. Therefore, the coefficient $\hat{\gamma}_U$ as estimated in a conventional ASY-analysis should not be seen as overestimating the non-smoothed part of shocks to output per capita on account of ignoring the smoothing effect of migration.

The main advantage of our approach is that it allows us to disentangle the migration channel from the participation channel of consumption smoothing. To see this, consider

[15] The identity then reads as $Y \equiv \frac{Y}{\bar{y}} \frac{\bar{y}}{\tilde{y}} \frac{\tilde{y}}{\widetilde{ni}} \frac{\widetilde{ni}}{\widetilde{di}} \frac{\widetilde{di}}{\tilde{c}} \frac{\tilde{c}}{c} c$, which also adds a further layer to our regressions corresponding to the term $\frac{\tilde{c}}{c}$. In addition, the γ-coefficient now relates to the regression $\Delta \log c = \gamma_U \Delta \log Y + \varepsilon$.

the somewhat less detailed approaches towards identifying the migration channel proposed by Asdrubali et al. (1996) and Parsley and Popper (2021). Asdrubali et al. (1996) use decadal information on population changes to estimate consumption smoothing through migration, but they do not formally integrate this into their accounting framework. Parsley and Popper (2021) extend the original ASY-approach by extending identity (2.2) to

$$Y_{\text{nom}} \equiv PN \frac{y}{ni} \frac{ni}{di} \frac{di}{c} c, \tag{2.9}$$

Where P denotes the price level and N denotes the population size.[16] The logic of the approach then leads to a new variance decomposition replacing (2.3) above, with two new top-level entries reading as $\text{Cov}[\Delta \log Y_{\text{nom}}, \Delta \log P]$ and $\text{Cov}[\Delta \log Y_{\text{nom}}, \Delta \log N]$ and the rest appearing as in (2.3) but with y replaced by Y_{nom} throughout. Accordingly, there is now a new identity of OLS coefficients analogous to (2.4), with two new entries capturing the price-level channel and the migration channel, the latter based on $\text{Cov}[\Delta \log Y_{\text{nom}}, \Delta \log N]$. It is straightforward to reformulate this approach for an analysis that focuses on shocks to aggregate *real* output, as we do in this chapter. The identity then reads as

$$Y \equiv N \frac{y}{ni} \frac{ni}{di} \frac{di}{c} c, \tag{2.10}$$

and the OLS coefficient capturing the migration channel uses $\text{Cov}[\Delta \log Y, \Delta \log N]$. Since $N = Y/y$ one may calculate the exact same OLS coefficient using $\text{Cov}[\Delta \log Y, \Delta \log Y - \Delta \log y]$.[17]

This way of addressing the migration channel seems intuitive: emigration prompted by an negative shock to aggregate output should dampen the effect on output per capita, compared to a case with zero labor mobility; and accordingly for a positive shock. However, relative to our approach outlined above, this approach suffers from the drawback that output per capita is not only affected by inflows and outflows of labor, but also by any response of labor market participation. More specifically, if we write l for the labor force participation rate, we have $\Delta \log y = \Delta \log Y - \Delta \log N$ and

$$\Delta \log y = \alpha \Delta \log l - (1 - \alpha) \Delta \log N. \tag{2.11}$$

In this equation α denotes the output elasticity with respect to employment, and it assumes a zero change in unemployment. This equation makes clear that, even if we assume that $\Delta \log N$ is entirely driven by inflows and outflows of labor, and not by natural changes, estimating the magnitude of the migration channel based on identity (2.10) risks confounding the role of migration by reactions of the labor force participation. This is a risk we can avoid by our approach outlined above which rests on observations of changes in the labor force due to inflows and outflows of labor.

[16] Parsley and Popper (2021) use L to denote the population size whereas we use L to denote the labor force.

[17] We have implemented this procedure in the working paper version of this chapter. We are grateful to one of our referees for suggesting the refined procedure outlined above and implemented here, which allows for a clean separation of the labor force participation channel and the migration channel.

2.3.4 Sample and empirical implementation

In the estimation we rely on time-series data for US states and EA member countries. Throughout, the explanatory variable is aggregate output in real terms, Y, measured by gross state and domestic product in our US and EA sample, respectively. In turn, $\bar{y} := Y/L_d$ corresponds to the same variable scaled with the *domestic* labor force, while $\tilde{y} = Y/L$ is output per person of the (total) labor force (*including* net migration). Importantly, the labor force data in a given year includes new migrants of that same year. Therefore, in order to correctly identify the participation channel running through the *domestic* labor force, we deduct *net* migration in the first step so as to obtain L_d. The labor force comprises the active (civilian) population (employed and unemployed) aged 16 and older in the US and 15 to 74 in the EA. For the US we use labor force data from the US Bureau of Economic Analysis and for the EA we take the labor force data from Eurostat. Data on migration flows are taken from the US-IRS and the EA-LFS, respectively, as detailed in Section 2.2.2 above.[18]

Next, we consider gross state or gross national income, $\widetilde{ni}$, again all in real terms per person of the labor force L. For the EA members, the difference between gross domestic product and gross national income reflects the balance of primary income (or net factor income), for US states also federal nonpersonal taxes.[19] We obtain gross disposable income $\widetilde{di}$ by subtracting net current transfers from gross national income. For EA members transfers are dominated by remittances, which are also linked to migration but not directly related to the migration channel which is the focus of our study.[20] In addition, net transfers of EA members also represent payments to and from the EU's common budget. In the past, that is, during our sample period, net payments have still been moderate. For US states, the wedge between gross national income and gross disposable income represents the difference between federal transfers going to and federal taxes paid by each state, as explained in ASY.

Lastly, we consider final consumption expenditure, $\tilde{c}$, which includes both private and public consumption expressed in real terms and relative to the labor force.[21] The difference between consumption and gross disposable income represents net savings and depreciation allowances.[22] We provide further details on our data sources in the appendix;

[18]The migration data from the US-IRS as well as from the EU-LFS may potentially overestimate migration into (out of) the labor force for reasons discussed in footnote 8. But since the null hypothesis of our exercise is a zero contribution of the migration channel to risk sharing, overestimating the degree of migration puts us on the "safe side" if we are unable to reject this hypothesis even with overestimated migration figures, as we are for the EA.

[19]Federal nonpersonal taxes are collected at the federal level and then distributed to the states based on the allocation rules of the American Tax Foundation, see ASY.

[20]Balli and Rana (2015) analyse risk sharing by means of remittances in developing economies, also using a modified version of the ASY approach. They find that remittances smooth income fluctuations by 5 percent in their sample.

[21]While we have consistent time series on total consumption available for the EA member states since 1999, for US states data are available since 1997. Before 1997, we rely on state-level commercial retail sales data from ASY to proxy total consumption at the state level. Therefore, we observe a jump in the time series for consumption. This does not affect our estimates because we convert all variables into log differences and include time fixed effects.

[22]Hoffmann et al. (2019) allow for a distinct depreciation channel of risk sharing.

see Table 2.A.1 and Figure 2.A.3.

Formally, we estimate the following (panel) regression equations:

$$\Delta \log Y_{it} - \Delta \log \bar{y}_{it} = \tau_{t,P} + \eta_{i,P} + \beta_P \Delta \log Y_{it} + \varepsilon_{it,P} \tag{2.12}$$

$$\Delta \log \bar{y}_{it} - \Delta \log \tilde{y}_{it} = \tau_{t,M} + \eta_{i,M} + \beta_M \Delta \log Y_{it} + \varepsilon_{it,M} \tag{2.13}$$

$$\Delta \log \tilde{y}_{it} - \Delta \log \widetilde{ni}_{it} = \tau_{t,F} + \eta_{i,F} + \beta_F \Delta \log Y_{it} + \varepsilon_{it,F} \tag{2.14}$$

$$\Delta \log \widetilde{ni}_{it} - \Delta \log \widetilde{di}_{it} = \tau_{t,T} + \eta_{i,T} + \beta_T \Delta \log Y_{it} + \varepsilon_{it,T} \tag{2.15}$$

$$\Delta \log \widetilde{di}_{it} - \Delta \log \tilde{c}_{it} = \tau_{t,C} + \eta_{i,C} + \beta_C \Delta \log Y_{it} + \varepsilon_{it,C} \tag{2.16}$$

$$\Delta \log \tilde{c}_{it} = \tau_{t,U} + \eta_{i,U} + \gamma_U \Delta \log Y_{it} + \varepsilon_{it,U} \tag{2.17}$$

In these equations, i denotes US states (regions) or EA members, and t denotes the time period. denote the error terms. The specification includes time fixed effects ($\tau_{t.}$) in order to control for common shocks affecting all states/member countries equally. This allows us to focus on state- or country-specific variation in aggregate output, which is what matters for risk sharing. For reasons of symmetry we also include state- and country fixed effects ($\eta_{i.}$), but we find it hardly matters for the results.

2.4 Results

We now report our results, again contrasting those for the US with those for the EA. We first present estimates for the baseline specification, estimated over the full sample and considering a one year time horizon for risk sharing. Subsequently, we present results for longer horizons and consider specific subsamples.

2.4.1 Baseline

We estimate Equations (2.12) through (2.17) one by one using OLS with panel-corrected standard errors clustered at the state- or country-level, respectively.[23] We use annual observations both for the US and the EA. The sample runs from 1976 to 2017 for the US including all states and the District of Columbia, and for the EA the sample runs from 1999 to 2020 including all EA19 countries.[24] For the US, we distinguish between three different levels of regional aggregation: 4 regions (coarse classification), 9 regions (fine classification), and 51 states. For the EA, we distinguish between different delineations of the euro area: EA9, EA12 and EA19 (see Tables 2.A.2 and 2.A.3 for details).[25] It should be noted that the country groupings for the EA do not represent different levels of regional disaggregation, but instead follow the historic evolution of European integration and the adoption of the euro. We report the results for the baseline in Table 2.1. Each

[23] We verify that our results are robust to estimating Equations (2.12) through (2.17) by feasible GLS as in ASY.

[24] We use the concept of a changing composition of the EA19 based on membership accession to fully account for the effect of being in a currency union. For details, see Table 2.A.3

[25] As explained in Section 2.2.2, we exclude observations for Ireland because we do not have LFS data on migration available.

panel provides details on one of the six regressions given in Equations (2.12) through (2.17) above. The coefficients reported provide measures for specific channels of risk sharing or, in the case of Equation (2.17), a measure for the residual fraction of output fluctuations that remains uninsured and is passed-through into consumption per person of the labor force. In each panel, we also report the number of observations used in the regressions, N, and the value of R^2. The number of observations varies across levels of aggregation, but also somewhat, for reasons of data availability, across the channels of risk sharing.

The two top panels report results for what is new in our analysis: the participation and the migration channel. Consider first the results for the participation channel in the top panel: It presents the fraction of aggregate fluctuations *not* passed through to income per person of the labor force. We find that fraction to be quite sizeable throughout. For the US (left panel), depending on the specification, the participation channel smooths some 10 percent of output fluctuations. The estimates for the EA are even larger: 17 percent of output fluctuations are smoothed through this channel in the EA19 and a full 27 percent in the EA9. The coefficient estimates are highly significant in most cases.

Note that the participation channel, while quantitatively important, is not operating at the international level. Instead, the migration channel is. Hence, our focus is on the estimated coefficient for migration reported in the second panel, based on estimating equation (2.13). Here, numbers are generally more moderate, both for the US and the EA. The coefficients for the EA are not significantly different from zero, while there is a significant if small contribution of migration to risk sharing across US states (and also across the 9 US regions). They buffer some 4 percent of output fluctuations at the state level and 7 percent at region level (fine classification). However, the migration channel is not significant across the four large regions. The fact that the migration channel is less significant for regions than for states is consistent with the observation that migration in the US is more frequent across states than across regions; see again the upper-left panel of Figure 2.2. Most importantly, the result that migration does not contribute to risk sharing in the EA is rather sharp, although perhaps not surprising given the received wisdom and the descriptive statistics presented in Section 2.2.2 above. Still, the deficiency of the migration channel in providing international risk sharing across the EA becomes particularly apparent when compared to the results for the US and the results for the other channels of risk sharing.

Migration is not subject to legal barriers in the EA because labor mobility is one of the EU's "four freedoms". In light of our results, one may wonder to what extent informal barriers to migration prevent the migration channel to make a meaningful contribution to risk sharing in the EA. A natural candidate are language barriers which are present in the EA but not in the US. In order to assess this hypothesis, we re-estimate our model on two "language clubs" of the EA. Countries of the EA in these subsamples either share the same language or have languages belonging to the same language family. This should facilitate migration and assimilation and thus enhance the role of migration for risk sharing among countries belonging to such a group. Specifically, we form two

Table 2.1: Quantification of risk sharing channels in US states and EA members

	US			EA members		
	4 Regions	9 Regions	All states	EA9	EA12	EA19
Participation						
$\hat{\beta}_P$	0.14*	0.08	0.09***	0.27***	0.16**	0.17***
	(0.05)	(0.08)	(0.02)	(0.06)	(0.06)	(0.04)
R^2	0.84	0.68	0.44	0.53	0.46	0.54
N	104	234	2046	189	230	298
Migration						
$\hat{\beta}_M$	0.03	0.07*	0.04***	0.00	0.05	0.04
	(0.03)	(0.03)	(0.01)	(0.00)	(0.05)	(0.03)
R^2	0.06	0.09	0.09	0.06	0.11	0.09
N	104	234	2046	189	230	298
Factor Trade						
$\hat{\beta}_F$	0.24*	0.33***	0.52***	0.10**	0.10**	0.06*
	(0.08)	(0.08)	(0.07)	(0.04)	(0.03)	(0.05)
R^2	0.93	0.84	0.53	0.17	0.13	0.09
N	104	234	2091	189	230	298
Transfers						
$\hat{\beta}_T$	0.00	0.05**	0.06***	−0.01	−0.05	−0.05
	(0.02)	(0.02)	(0.01)	(0.01)	(0.05)	(0.11)
R^2	0.96	0.95	0.87	0.16	0.14	0.10
N	104	234	2091	187	228	296
Credit						
$\hat{\beta}_C$	0.07*	0.12	0.15***	0.20*	0.22*	0.33***
	(0.03)	(0.10)	(0.04)	(0.10)	(0.11)	(0.09)
R^2	0.98	0.97	0.85	0.26	0.24	0.25
N	104	234	2091	187	228	296
Unsmoothed						
$\hat{\gamma}_U$	0.51***	0.34***	0.17***	0.45***	0.53***	0.45***
	(0.04)	(0.09)	(0.03)	(0.08)	(0.09)	(0.09)
R^2	0.99	0.99	0.9	0.72	0.67	0.65
N	104	234	2091	189	230	298

Notes: Results from estimation of equations (2.12) through (2.17). For US states, the sample extends from 1976 to 2017 and for US regions the sample extends from 1991 to 2017. For EA members the sample extends from 1999 to 2020. State-/country- and time-fixed effects are included but not reported. Standard errors are reported in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

groups: the first includes countries sharing Germanic languages and the second includes countries sharing neo-Latin languages; see Table 2.A.3 for details.[26] We find indeed

[26] Note that we sort Belgium and Luxembourg in both groups because in both countries a Germanic as well as a neo-Latin language are widely spread among the population. Hence, migration may well be directed to France or Germany and the Netherlands in both instances.

that the migration channel contributes to a larger extent to risk sharing within each language club: 9 percent and 7 percent for the Germanic and the neo-Latin language club, respectively. Still, the estimates are not significant; see Table 2.A.9 in the appendix. Hence, the evidence remains somewhat inconclusive but suggests that the "language hypothesis" holds considerable promise and deserves further investigation in future work.

With the exception of Parsley and Popper (2021), the migration channel has been neglected in the analysis of international risk sharing à la ASY. Our results for the US suggest a smaller role than theirs (8%), but the results are not directly comparable as they look at shocks to aggregate nominal output while we look at real shocks. More importantly, as stressed above, we control for the participation channel in order to quantify the migration channel correctly. That said, we want to highlight a caveat. In our extension of the ASY-approach, we define the migration channel as pertaining to labor mobility within the currency unions we look at (the US and the EA). This is crucial, given our principal interest in the Mundellian labor mobility criterion for optimum currency areas, but it implies that the smoothing effect of migration to and from third countries will be picked up by the participation channel. However, such external migration is unlikely to have a strong cyclical and country-specific component that could confound the migration channel of risk sharing among US states or member countries of the EA, particularly since we include time- and country-fixed effects in our preferred specification.

Finally, we turn to the remaining channels that have also been the subject of analysis in earlier work. Consider factor trade first, for which we show results in the third panel of Table 2.1. The factor trade channel plays the largest role for risk sharing in the US. It smooths up to 52 percent of income fluctuations. The factor trade channel is also operative for the EA19 but much less important than in the US. It is, however, more important for EA9 and EA12 where we find that 10 percent of output fluctuations are smoothed through factor trade. These results confirm findings of earlier studies established for smaller samples and less recent time spans.[27] The lack of risk sharing via the factor trade channel for EA19 is consistent with the notion that the degree of capital market integration is only limited for this group of countries.[28] Next, we turn to the transfer channel. Note that the transfer channel may operate via payments to and from the federal government in the US and to and from the common budget of the EU for the members of the EA. In the latter case, the transfer channel may also operate outside the fiscal sector, say via remittances. Still, we find significant estimates only for the US,

[27]ASY, in particular, report a similar number for the US (for what they call the "capital markets" channel), based on data from 1964 to 1990. The European Commission (2016) reports estimates of 44.8 percent and 5.6 percent for the US and the EA, respectively. They do not, however, consider the full EA19 sample. Traditionally, estimates for the EA are only based on selected member states. The European Commission (2016) does not include new member states as well as Austria and Greece. Their sample covers the period from 2000 to 2015. Sørensen and Yosha (1998) focus on the former members of the European Community until 1990, including Denmark and UK, but leave out southern European countries as well as new member states in their analysis.

[28]The EU commission has initiated various efforts to "complete" the so-called "capital markets union" (European Commission 2020). In fact, in the present context capital market integration plays a dual role: the factor trade channel operates through cross-border ownership of financial assets (the stock view), while the credit channel considered below operates through cross-border lending or borrowing (the flow view).

reported in the fourth panel of the table. We conclude that transfers do not contribute to international risk sharing in the EA, which is consistent with earlier estimates (European Commission 2016). Moreover, our estimates for the US suggest that the role of transfers for risk sharing has declined somewhat, relative to the earlier estimate of 13 percent reported by ASY. However, the larger role of transfers for risk sharing across US states seems noteworthy in light of the efforts in Europe to increase risk sharing via a common budget and/or a union-wide unemployment reinsurance scheme (e.g. Ignaszak et al. 2020; Nettesheim 2020).

The fifth panel of the table shows results for the credit channel. It is the second most important channel for the US, accounting for 15 percent of risk sharing across US states. Remarkably, however, we find that its role for risk sharing in the EA is even larger, shouldering as much as 33 percent. For the EA9 and the EA12 estimates for this channel are smaller, but still sizable. Overall, our estimates for the US are somewhat smaller compared to those of ASY, but in the ballpark of European Commission (2016).

Lastly, we consider the variation of output that remains uninsured and hence passed through into variations of consumption (bottom panel). For US states that fraction amounts to 17 percent, for the EA19 the corresponding number is 45 percent—more than twice as large. Turning to US regions (rather than states) and subsamples of the EA, we find differences in risk sharing to be less dramatic, but still sizeable. Across the 4 large US regions 51 percent of income fluctuations remain unsmoothed and 34 percent between the 9 smaller regions. For EA9 and EA12 the number is 45 and 53 percent, respectively. Again, this result is in line with recent estimates for selected EA countries (Cimadomo et al. 2020; Hoffmann et al. 2019).[29]

We also verify that our results for the EA are not driven by outliers, that is, by countries with specific economic characteristics. For this purpose, we consider samples which exclude, in turn, Luxembourg and Greece from our sample. We find that the results for the participation channel and the migration channel are quite similar to our baseline in all instances; see Table 2.A.9 in the appendix. In sum, we find robustly that there is considerably less risk sharing among members of the EA than among US states. By and large, these results confirm earlier findings, even though our analysis accounts for additional channels of risk sharing, more countries and more recent observations.

2.4.2 Alternative time horizons

The results reported in Table 2.1 are based on annual observations. As such, they provide a breakdown into different channels of risk sharing that takes place at a one-year horizon. But the extent of risk sharing may differ across time horizons. Moreover, the ASY decomposition does not account for the fact that shocks tend to differ in terms of

[29]As regards the unsmoothed fluctuations of output per capita, the European Commission (2016) reports values of 17.6 and 75.7 percent for US states and a sample of 13 EA countries, respectively. A much earlier study by Sørensen and Yosha (1998) reports similarly high values for the unsmoothed part of income fluctuations among the members of the European Community considering the 1960s to the 1990s; and the original estimate for US states obtained by ASY is as low as 25 percent, that is, in the same ballpark as our result for US states.

Table 2.2: Quantification of risk sharing channels in US states and EA members over alternative time horizons

	US all states			EA19		
	$k=1$	$k=2$	$k=3$	$k=1$	$k=2$	$k=3$
Participation						
$\hat{\beta}_P$	0.09^{***}	0.07^{***}	-0.02	0.17^{***}	0.19^{***}	0.18^{**}
	(0.02)	(0.02)	(0.02)	(0.05)	(0.02)	(0.07)
R^2	0.44	0.51	0.54	0.54	0.72	0.79
N	2046	1944	1842	298	262	226
Migration						
$\hat{\beta}_M$	0.04^{***}	0.11^{***}	0.21^{***}	0.04	0.04	0.06
	(0.01)	(0.02)	(0.02)	(0.03)	(0.03)	(0.04)
R^2	0.09	0.1	0.18	0.09	0.10	0.16
N	2046	1944	1842	298	262	226
Factor Trade						
$\hat{\beta}_F$	0.52^{***}	0.43^{***}	0.41^{***}	0.06^{*}	0.11^{***}	0.11^{***}
	(0.07)	(0.05)	(0.04)	(0.05)	(0.04)	(0.03)
R^2	0.53	0.54	0.56	0.09	0.17	0.29
N	2091	2040	1989	298	280	262
Transfers						
$\hat{\beta}_T$	0.06^{***}	0.08^{***}	0.08^{***}	-0.05	-0.03	-0.02
	(0.01)	(0.02)	(0.02)	(0.11)	(0.10)	(0.12)
R^2	0.87	0.9	0.92	0.10	0.09	0.11
N	2091	2040	1989	296	278	260
Credit						
$\hat{\beta}_C$	0.15^{***}	0.07	0.03	0.33^{**}	0.18^{*}	0.14
	(0.04)	(0.04)	(0.04)	(0.09)	(0.11)	(0.14)
R^2	0.85	0.87	0.89	0.25	0.30	0.36
N	2091	2040	1989	296	278	260
Unsmoothed						
$\hat{\gamma}_U$	0.17^{***}	0.26^{***}	0.29^{***}	0.45^{***}	0.52^{***}	0.52^{***}
	(0.03)	(0.03)	(0.03)	(0.09)	(0.11)	(0.14)
R^2	0.9	0.92	0.93	0.65	0.64	0.68
N	2091	2040	1989	298	280	262

Notes: Results from estimation of equations (2.12) through (2.17). The data are differenced using intervals of k years. For US states, the sample extends from 1976 to 2017 and for EA members the sample extends from 1999 to 2020. State-/country- and time-fixed effects are included but not reported. Standard errors are reported in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

persistence which, in turn, is key when it comes to risk sharing. For this reason, Becker and Hoffmann (2006) distinguish between permanent and transitory shocks within a cointegrated VAR model. They find that while risk sharing in response to transitory shocks is virtually complete, both within the US and among OECD countries, there is basically no risk sharing when it comes to permanent shocks. While a full-fledged analysis along these lines is beyond the scope of the present chapter, we may nevertheless approach the issue informally and assess how the contribution of individual risk sharing channels changes for longer time horizons.

Specifically, we difference the data over horizons of up to 3 years, both for US states and EA19 members, and report results in Table 2.2. For US states, we observe that the contribution of the channels indeed changes as the time horizon increases. First, we find that, consistent with Becker and Hoffmann (2006), risk sharing as a whole works best in the short run, when only 17 percent of output fluctuations are left unsmoothed. That fraction increases gradually as we consider longer time horizons. Once we consider a three-year horizon, 29 percent of output fluctuations are left unsmoothed. Zooming in on specific channels, a number of observations are in order. First, and perhaps most strikingly, the relative importance of the participation and the migration channel varies across horizons in the US—but not in the EA. For the EA, the participation channel remains important also at the two-year and three-year horizon and, perhaps more importantly, the migration channel remains negligible. This pattern is consistent with the view that changes in labor force participation in Europe are quite persistent. For US states, the participation channel no longer matters at a longer horizon. Instead, the quantitative importance of the migration channel increases rather dramatically—from 4 percent when the time horizon is one year to 21 percent when the time horizon is 3 years. This pattern, in turn, is consistent with the notion that while labor force participation in the US adjusts rather strongly to shocks in the short run, it sets in motion migration flows which take over as a risk sharing mechanism over time—in sharp contrast to what happens in the EA.

Second, turning to the credit channel, we find that its importance declines strongly for longer time horizons. This finding is also consistent with theoretical work which shows that transitory fluctuations are easier to (self) insure (Baxter and Crucini 1995). It is also in line with earlier estimates by ASY. They, too, find a substantial decline in the importance of the credit channel over longer horizons. Finally, we find that the importance of the factor trade and the transfer channel is relatively stable over time.[30]

2.4.3 Subperiods

While the nature of shocks matters for risk sharing, the relative contribution of transitory and permanent shocks to macroeconomic fluctuations can change over time. As a result, our estimates based on the whole sample period may paint a somewhat distorted picture. For instance, a short and sharp recession may be largely smoothed through credit markets and changes in domestic labor market participation, while a decade-long downturn may

[30]We obtain similar results for US regions and the other EA groupings; see Tables 2.A.10 and 2.A.11. Consistent with our above results, the migration channel is less important across US regions compared to US states, also at longer horizons. Moreover, the extent of risk sharing across regions is reduced over longer horizons, not least because of the much diminished role of the credit channel. Similarly, the results for EA9 and EA12 are similar to those for EA19; in particular, the importance of migration as a risk sharing channel does not increase for longer horizons.

induce an adjustment via migration. In order to account for a possible variation of the relative importance of shocks over time, we estimate equations (2.12) through (2.17) for a number of subperiods.

Table 2.3: Quantification of risk sharing channels in US states for subperiods

	US all states			
	1976–1985	1986–1995	1996–2007	2008–2017
Participation				
$\hat{\beta}_P$	0.04	0.08**	0.05**	−0.01
	(0.04)	(0.04)	(0.02)	(0.05)
R^2	0.83	0.64	0.35	0.23
N	432	444	561	459
Migration				
$\hat{\beta}_M$	0.08***	0.06***	0.00	0.06
	(0.02)	(0.02)	(0.02)	(0.05)
R^2	0.24	0.11	0.02	0.2
N	432	444	561	459
Factor Trade				
$\hat{\beta}_F$	0.49***	0.55***	0.61***	0.39***
	(0.07)	(0.18)	(0.05)	(0.01)
R^2	0.58	0.47	0.64	0.46
N	459	459	561	459
Transfers				
$\hat{\beta}_T$	0.07***	0.06***	0.06***	0.11
	(0.02)	(0.01)	(0.02)	(0.05)
R^2	0.77	0.81	0.89	0.8
N	459	459	561	459
Credit				
$\hat{\beta}_C$	0.24**	−0.01	−0.37	0.37***
	(0.09)	(0.14)	(0.45)	(0.10)
R^2	0.17	0.21	0.79	0.49
N	459	459	561	459
Unsmoothed				
$\hat{\gamma}_U$	0.14***	0.29***	0.66	0.09
	(0.05)	(0.08)	(0.46)	(0.06)
R^2	0.24	0.36	0.8	0.56
N	459	459	561	459

Notes: Results from estimation of equations (2.12) through (2.17).The total sample extends from 1976 to 2017. State- and time-fixed effects are included but not reported. Standard errors are reported in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Table 2.3 reports the results for US states, with each column pertaining to a specific subperiod, starting with the period 1976–1985 in the left column. The latest period runs from the global financial crisis to the end of our sample period. As expected, there is considerable variation across sample periods. While the migration channel is significantly operative in the first two decades that we consider, it disappears in the latter two decades. This result is in line with earlier work which has been concerned with the decline of interstate migration in the US (Molloy et al. 2011; Kaplan and Schulhofer-Wohl 2017). The participation channel is active in the middle part of the sample but disappears after the financial crisis. For the factor trade and the transfer channel we observe a fairly stable pattern of risk sharing over the four decades. Finally, the evidence for the credit channel is again mixed: it contributes most to smoothing income fluctuations during times of economic crises but plays no role during times of moderation.

Our sample for the EA is considerably shorter than for the US, so we focus our subsample analysis on the periods before and after 2010. This date marks the beginning of the sovereign debt crisis in the EA during which the issue of risk sharing, and possibly the lack thereof, took center stage in many policy debates. We show results in Table 2.4 and stress a number of results. First, there is considerably less risk sharing since 2010, consistent with the received wisdom that risk sharing did not work well in the EA during the crisis period. Second, this is mostly the result of the credit channel shutting down in the post-2010 sample period. The importance of the other channels also changes, but less dramatically than in case of the credit channel. Third, and most importantly, the results for the participation and the migration channel do not change fundamentally across sample periods. In particular, the results for the migration channel point to a mixed picture. The estimated coefficients are quite a bit smaller, but no longer insignificant in the post-2010 sample.[31]

In light of this result, we flag yet another caveat. As stressed above, the importance of transitory and permanent shocks to macroeconomic fluctuations can change over time and because of that our subsample analysis may fail to detect changes in the risk-sharing capacity of different channels. For instance, the fluctuations prior to the euro crisis might have been driven largely by transitory shocks such that there was a fair amount of risk sharing from an ex post point of view—even though the risk sharing capacity in the EA was arguably not particularly high at that time. The crisis period, in turn, was potentially characterized by more permanent shocks. And so, even allowing for the possibility that the risk sharing capacity as such did improve over time, we may not be able to detect this—simply because the shocks during that period are harder to insure than the ones occurring during the earlier period. Our mixed results for migration are consistent with this hypothesis, and we leave it for future research to assess it in more detail as more data become available. Yet, at this point we observe, somewhat reassuringly, that while there is a mild increase in migration rates at the country level, these changes have been fairly moderate, see again Figure 2.A.1. Hence, we conclude—tentatively—that we are unlikely

[31] A similar pattern emerges if we split the sample into a period before and after the global financial crisis, that is, if we consider data up to 2007 and from 2008 onward. We show results in the appendix both for the US and the EA; see Tables 2.A.12 and 2.A.13. In this case we also find a decline in the credit channel in the post-crisis period, but the effect is strongest for EA12, possibly because the crisis was particularly severe in Greece. Comparing the sample splits along the global financial crisis and the euro area crisis, we find the latter induces more substantial changes in risk sharing in the EA.

Table 2.4: Quantification of risk sharing channels for EA members before and after the start of the euro crisis

	Before 2010			Since 2010		
	EA9	EA12	EA19	EA9	EA12	EA19
Participation						
$\hat{\beta}_P$	0.26***	0.12	0.12	0.12*	0.08*	0.12***
	(0.05)	(0.13)	(0.10)	(0.06)	(0.04)	(0.03)
R^2	0.69	0.50	0.51	0.53	0.64	0.69
N	90	109	113	90	110	170
Migration						
$\hat{\beta}_M$	0.00	0.10	0.08	0.01**	0.03*	0.03*
	(0.00)	(0.09)	(0.08)	(0.00)	(0.02)	(0.01)
R^2	0.08	0.12	0.11	0.06	0.13	0.08
N	90	109	113	90	110	170
Factor Trade						
$\hat{\beta}_F$	0.07	−0.07	−0.05	0.10	0.28	0.13
	(0.05)	(0.15)	(0.14)	(0.05)	(0.22)	(0.12)
R^2	0.20	0.12	0.16	0.15	0.17	0.09
N	90	109	113	90	110	170
Transfers						
$\hat{\beta}_T$	0.00	−0.07	−0.07	−0.03	−0.09	−0.06
	(0.01)	(0.06)	(0.05)	(0.07)	(0.08)	(0.06)
R^2	0.25	0.16	0.20	0.22	0.20	0.16
N	90	109	113	88	108	168
Credit						
$\hat{\beta}_C$	0.29*	0.64***	0.63**	0.17	0.00	0.28*
	(0.14)	(0.28)	(0.25)	(0.11)	(0.13)	(0.11)
R^2	0.61	0.47	0.53	0.22	0.18	0.19
N	90	109	113	88	108	168
Unsmoothed						
$\hat{\gamma}_U$	0.38**	0.29**	0.28**	0.64***	0.70***	0.51**
	(0.13)	(0.13)	(0.12)	(0.09)	(0.09)	(0.11)
R^2	0.62	0.58	0.62	0.86	0.80	0.73
N	90	109	113	90	110	170

Notes: Results from estimation of equations (2.12) through (2.17). The sample extends from 1999 to 2009 (left panel) and 2010 to 2020 (right panel). Country- and time-fixed effects are included but not reported. Standard errors are reported in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

to miss a major change in the importance of the migration channel of risk sharing in the EA.

2.5 Conclusion

In this chapter we suggest an extension of the framework introduced by ASY that allows us to account for migration as an additional channel of risk sharing, and we apply this extension to quantify the significance of migration as a channel of risk sharing in the two most important currency unions, that is in the US and in the EA. The extension rests on the fact that macroeconomic shocks are, first and foremost, shocks to aggregate output and on the intuition that migration is likely to cushion the effect that such shocks have on income per person. The simplest extension of the ASY-approach therefore seems to require no more than refocusing the analysis on fluctuations of *aggregate* rather than *per capita* output, as argued in recent literature. However, the Mundellian perspective on optimum currency areas requires looking at internal migration within a currency union. We therefore develop a somewhat more refined approach that brings data on internal migration within the US and the EA to bear on the analysis of risk sharing. In particular, we refocus the analysis on aggregate output versus output per person in the labor force adjusted for internal migration. We employ this framework in order to compare the contribution of internal migration to consumption smoothing across US states and regions with that of migration across member countries of the euro area.

We find that there is considerably more risk sharing among US states than among countries of the EA. For US states only 17 percent of output fluctuations are unsmoothed, for the members of the EA the corresponding number is 45 percent. The relative importance of the various risk sharing channels differs, too. In particular, migration among US states smooths as much as 4 percent of output fluctuations at a one year horizon and up to 21 percent at a three year horizon. In stark contrast, migration does not contribute significantly to risk sharing in the EA, no matter what time horizon one looks at. These results are consistent with descriptive evidence on migration across US states and across the member states of the EA: it shows that migration rates are about 15 times higher in the US than in the EA. Moreover, we find that while the migration channel has been operative in the US in the past, its importance seems to have been falling in more recent times, consistent with evidence on declining labor mobility. Yet, in the absence of a structural model underlying these results, one should be cautious in concluding that they reflect a fall in US labor market efficiency.

What are the policy conclusions? Our finding, based on two decades of experience with the euro in turbulent times, dashes the hope for an endogenous fulfilment of the Mundellian criterion of labor mobility. Yet, our results for the US indicate that the idea of migration as a risk sharing device can in fact work. The fact that it did not work for the EA at a time when it apparently did for the US, leaves two possible conclusions. One is to see this as suggestive evidence that the Mundellian criterion will never truly work for the EA, the four freedoms of the single market notwithstanding, because of deep-rooted historical, cultural and social conditions that will always set Europe apart from the US when it comes to labor mobility. The other is to argue that EA members and the EU as a whole simply did not try hard enough so far and that the US case suggests high returns to further efforts of increasing intra-European labor mobility.

A missing migration channel would not matter much if, in their entirety, other channels of risk sharing were to provide a satisfactory amount of consumption smoothing in the face of asymmetric shocks. Alas, this is not the case for the EA. It is only the credit channel where the EA compares favorably to the US. Particularly disappointing, capital markets, a hallmark of the single market, are conspicuously absent as a mechanism of risk sharing among member states of the EA19, although this mechanism is somewhat active for the EA12 and the EA9. Concerns about a lack of success in the EU's efforts towards capital market integration thus appear justified. Less surprising, perhaps, the transfer channel plays an even less important role for risk sharing. The challenge here is how the EA might strengthen this in a way consistent with what the member countries do, or do not, want to aim for as regards the fiscal union. In addition, policy makers should also observe the potential for emigration to have adverse structural effects on troubled economies, say because of "brain drain" or a reduced tax base.

2.A Appendix

Table 2.A.1: Data sources for US states and EA members

Variable	Description	Source
US states		
GSP	Real gross state product (based on aggregate GDP deflator, own calculations)	US Bureau of Economic Analysis (BEA), retrieved from FRED St. Louis
State Income	Real state income (based on aggregate GDP deflator, own calculations)	US Bureau of Economic Analysis (BEA), US Census Bureau Government Finances, The Whitehouse
Disposable State Income	Real disposable state income (based on aggregate GDP deflator, own calculations)	US Bureau of Economic Analysis (BEA), US Census Bureau Government Finances, The Whitehouse
Consumption	Real private and public consumption (based on aggregate GDP deflator, own calculations)	US Bureau of Economic Analysis (BEA), US Census Bureau Government Finances
GDP deflator	GDP (implicit) price deflator (2012=100), seasonally adjusted (federal level only)	US Bureau of Economic Analysis (BEA), retrieved from FRED St. Louis
Gross migration	The average of absolute immigration and emigration based on tax returns filed (number of personal exemptions of US citizens) between US states. For more information, see Section 2.2.2	US Census Bureau, Internal Revenue Service (IRS), Saks and Wozniak (2011)
Gross migration rate	Gross migration in percent of total (state) population, see gross migration	
Net migration rate	The difference between immigration rate and emigration rate, see gross migration.	
Labor force	Civilian labor force aged 16+ (employed and unemployed pers.)	CPS, retrieved from FRED St. Louis
Population	US Census Bureau midyear state population estimates	US Census Bureau, retrieved from FRED St. Louis
EA members		
GDP	Real gross domestic product, seasonally and calendar adjusted (chain linked volumes (2010), own calculations)	Eurostat, Statistical Office of the Slovak Republic (SVK)
GNP	Real gross national product, seasonally and calendar adjusted (chain linked volumes (2010), own calculations)	Eurostat, Italian National Institute of Statistics (ITA), AMECO (LUX)
GNDI	Real gross national disposable income, seasonally and calendar adjusted (chain linked volumes (2010), own calculations)	Eurostat, Italian National Institute of Statistics (ITA), AMECO (LUX, MLT)
Consumption	Real final private and public consumption expenditure, seasonally and calendar adjusted (chain linked volumes (2010), own calculations)	Eurostat, OECD (SVK)
GDP deflator	GDP (implicit) price deflator (2010=100)	Eurostat, Statistical Office of the Slovak Republic (SVK)
Gross migration	The average of absolute immigration and emigration based on bilateral migration flows among EA19 member states. For details, see Section 2.2.2	Eurostat LFS (see Section 2.2.2)
Gross migration rate	Gross migration in percent of total population, see gross migration	
Net migration rate	The difference between immigration and emigration rate, see gross migration	Eurostat LFS
Labor force	Active population (employed and unemployed) aged 15-74	Eurostat
Population	Population as of 1. January of each year	Eurostat

Notes: In constructing the data for US states we essentially followed ASY and European Commission (2016). Further information on calculations available upon request. Observations for Ireland in 2015 are excluded due to changes in the accounting of GDP. Data for US states and EA members is in annual frequency.

Table 2.A.2: Region classifications for the US

A) Fine region classification (9 regions)	
New England	Connecticut, Maine, Massachusetts, New Hampshire, Rhode Island, Vermont
Mid-Atlantic	New Jersey, New York, Pennsylvania
East North Central	Illinois, Indiana, Michigan, Ohio, Wisconsin
West North Central	Iowa, Kansas, Minnesota, Missouri, Nebraska, North Dakota, South Dakota
South Atlantic	Delaware, Florida, Georgia, Maryland, North Carolina, South Carolina, Virginia, West Virginia, DC
East South Central	Alabama, Kentucky, Mississippi, Tennessee
West South Central	Arkansas, Louisiana, Oklahoma, Texas
Mountain	Arizona, Colorado, Idaho, Montana, Nevada, New Mexico, Utah, Wyoming
Pacific	Alaska, California, Hawaii, Oregon, Washington
B) Coarse region classification (4 regions)	
Northeast	New England, Mid-Atlantic
Midwest	East North Central, West North Central
South	South Atlantic, East South Central, West South Central
West	Mountain, Pacific

Notes: Region classification follows official classification of US Census Bureau.

Table 2.A.3: Country groupings of EA member states

EA9 (founding members except LUX & IRL)	BEL, DEU, FIN, FRA, ITA, NLD, AUT, PRT, ESP
EA12 (found. members except IRL + GRC (2001))	BEL, DEU, FIN, FRA, ITA, LUX, NLD, AUT, PRT, ESP, GRC
EA 19 (changing composition (excl. IRL), last accession 2015)	BEL, DEU, FIN, FRA, ITA, LUX, NLD, AUT, PRT, ESP, GRC (2001), EST (2011), LVA (2014), LTU (2015), MLT (2008), SVK (2009), SVN (2007), CYP (2008)
EA language clubs	
Germanic	AUT, DEU, NLD, LUX, BEL
Neo-Latin	ITA, PRT, ESP, FRA, LUX, BEL

Table 2.A.4: Migration in US states and the District of Columbia

State	Mean	Mean	Median	SD	State	Mean	Mean	Median	SD
		% of pop					% of pop		
Alabama	95683	2.22	2.16	0.39	Montana	28947	3.30	3.24	0.55
Alaska	32279	4.90	4.65	0.86	Nebraska	45525	2.71	2.58	0.90
Arizona	154514	3.59	3.34	0.97	Nevada	78036	4.94	4.82	1.38
Arkansas	63993	2.51	2.49	0.50	New Hampshire	38599	3.42	3.14	0.75
California	441723	1.44	1.38	0.35	New Jersey	157810	1.95	1.91	0.26
Colorado	144096	3.73	3.75	0.83	New Mexico	61054	3.71	3.50	0.88
Connecticut	75123	2.24	2.08	0.50	New York	267830	1.44	1.41	0.14
Delaware	24314	3.24	3.17	0.46	North Carolina	191312	2.49	2.52	0.23
DC	36502	6.07	6.02	0.55	North Dakota	22914	3.43	3.12	1.08
Florida	405257	2.86	2.67	0.67	Ohio	171770	1.54	1.47	0.23
Georgia	200970	2.66	2.72	0.25	Oklahoma	88681	2.65	2.53	0.58
Hawaii	50483	3.92	3.72	1.22	Oregon	85509	2.69	2.59	0.47
Idaho	44986	3.73	3.65	0.78	Pennsylvania	178277	1.46	1.46	0.14
Illinois	205989	1.71	1.65	0.23	Rhode Island	23733	2.33	2.30	0.30
Indiana	114058	1.93	1.92	0.25	South Carolina	101907	2.64	2.67	0.28
Iowa	61062	2.09	2.04	0.28	South Dakota	22252	2.98	2.93	0.39
Kansas	80064	3.08	2.98	0.46	Tennessee	134739	2.49	2.50	0.27
Kentucky	84125	2.13	2.12	0.26	Texas	384730	1.99	1.89	0.41
Louisiana	88095	2.01	1.98	0.35	Utah	57688	2.81	2.66	0.47
Maine	27673	2.24	2.11	0.40	Vermont	17090	2.96	2.69	1.29
Maryland	125512	2.46	2.46	0.23	Virginia	205284	3.06	3.06	0.38
Massachusetts	108832	1.76	1.76	0.23	Washington	144328	2.66	2.61	0.42
Michigan	131885	1.38	1.31	0.19	West Virginia	39374	2.13	2.00	0.40
Minnesota	79291	1.69	1.65	0.22	Wisconsin	79168	1.53	1.53	0.24
Mississippi	62782	2.30	2.23	0.30	Wyoming	25906	5.21	4.70	1.27
Missouri	118834	2.20	2.14	0.30					
Average	113522	2.67	2.48	1.12					

Notes: Migration is average of in- and outmigration (gross migration) for each state. Mean is the average number of persons per year. The data runs from 1976 to 2017. Data sources: see Appendix Table 2.A.1.

Table 2.A.5: Correlation between output growth and gross migration rate for all US states

State	$\rho(\Delta$ log gsp, gross migr)	State	$\rho(\Delta$ log gsp, gross migr)
Alabama	-0.27	Montana	0.15
Alaska	0.14	Nebraska	0.23
Arizona	0.36	Nevada	0.22
Arkansas	-0.01	New Hampshire	0.05
California	0.42	New Jersey	0.57
Colorado	0.47	New Mexico	0.46
Connecticut	0.43	New York	-0.08
Delaware	-0.16	North Carolina	0.37
DC	0.25	North Dakota	-0.18
Florida	0.30	Ohio	0.03
Georgia	-0.30	Oklahoma	0.16
Hawaii	-0.30	Oregon	0.37
Idaho	0.37	Pennsylvania	0.40
Illinois	0.06	Rhode Island	0.01
Indiana	-0.19	South Carolina	0.53
Iowa	0.01	South Dakota	-0.17
Kansas	-0.08	Tennessee	0.23
Kentucky	-0.14	Texas	0.37
Louisiana	0.13	Utah	0.34
Maine	-0.01	Vermont	-0.41
Maryland	0.15	Virginia	0.14
Massachusetts	0.12	Washington	0.49
Michigan	-0.47	West Virginia	-0.21
Minnesota	-0.18	Wisconsin	0.01
Mississippi	0.47	Wyoming	-0.02
Missouri	0.28		
Average	0.12		

Notes: Data sources: see Appendix Table 2.A.1.

Table 2.A.6: Correlation between output growth and gross migration rate for EA19 member countries

Country	$\rho(\Delta$log gdp, gross migr)	Country	$\rho(\Delta$log gdp, gross migr)
Austria	-0.29	Latvia	0.45
Belgium	-0.14	Lithuania	0.86
Cyprus	-0.14	Luxembourg	-0.20
Estonia	0.23	Netherlands	-0.25
France	0.38	Portugal	-0.04
Germany	-0.14	Slovakia	-0.14
Greece	0.22	Slovenia	0.39
Italy	0.10	Spain	0.12
Average	0.07		

Notes: No microdata for IRE available, time series for FIN and MLT excluded due to short sample size. Data sources: see Appendix Table 2.A.1.

Table 2.A.7: Labour force participation in US regions and EA member countries

	Major US regions				EA members			
	Mean	Mean	Median	SD		Mean	Mean	Median	SD
	Ths pers.	% of pop.				Ths. pers.	% of pop.		
New England	1 185.21	67.68	68.33	1.58	Austria	4 135.20	73.93	74.35	2.18
Mid-Atlantic	6 322.34	63.18	63.55	1.52	Belgium	4 724.95	66.82	67.10	1.36
EN Centr	4 419.71	66.41	66.43	1.85	Cyprus	416.95	74.09	73.80	1.05
WN Centr	1 410.51	69.65	70.00	2.29	Estonia	655.84	77.09	75.20	1.06
S Atlantic	2 690.25	64.54	65.25	1.55	Finland	2 619.65	75.43	75.20	1.06
ES Centr	1 922.38	61.34	61.65	1.85	France	27 819.74	70.43	70.10	1.20
WS Centr	3 637.63	63.03	63.70	1.50	Germany	40 669.47	75.47	76.45	2.61
Mountain	1 052.07	67.18	67.99	1.83	Greece	4 762.59	66.66	67.20	1.59
Pacific	4 165.24	66.98	67.16	1.86	Ireland	2 113.84	72.44	72.00	1.45
					Italy	24 339.35	62.84	62.70	1.70
					Latvia	948.68	76.64	76.85	1.21
					Lithuania	1 421.33	76.55	76.45	1.60
					Luxemburg	234.53	67.88	67.85	2.89
					Malta	205.57	67.50	67.85	6.14
					Netherlands	8 529.27	78.48	78.80	2.36
					Portugal	5 050.83	73.32	73.40	1.02
					Slovakia	2 701.47	71.08	70.55	2.15
					Slovenia	1 004.69	72.10	71.65	1.62
					Spain	21 560.65	71.29	73.05	3.42
Average	2 978.37	65.55	65.41	3.08	Average	9 751.07	71.63	72.20	4.75

Notes: Labor force participation for each region/country. Mean is the average number of persons per year. For US regions the data runs from 1976 to 2017, regions as defined in Table 2.A.2. For EA members the data runs from 1999 to 2020. Data sources: see Appendix Table 2.A.1.

Table 2.A.8: The labor force in US states and the District of Columbia

State	Mean	Mean	Median	SD	State	Mean	Mean	Median	SD
	Ths pers.	% of pop				Ths pers.	% of pop		
Alabama	1 995.99	60.63	61.28	2.27	Montana	447.10	66.10	66.68	1.81
Alaska	294.91	71.18	72.23	2.36	Nebraska	897.15	70.61	71.43	2.61
Arizona	2 255.26	63.24	63.45	2.00	Nevada	925.79	68.99	69.68	3.19
Arkansas	1 198.91	61.14	61.48	1.93	New Hampshire	635.35	70.44	70.93	1.83
California	15 607.52	65.29	65.68	1.60	New Jersey	4 137.25	65.43	65.89	1.46
Colorado	2 174.01	70.65	70.95	2.04	New Mexico	781.65	61.73	62.57	1.93
Connecticut	1 761.70	67.74	67.64	1.67	New York	8 905.23	61.48	61.69	1.40
Delaware	382.86	66.13	66.68	2.95	North Carolina	3 856.15	65.93	66.63	2.28
District of Colu	329.55	67.34	67.42	2.08	North Dakota	346.65	69.64	70.68	3.05
Florida	7 207.08	60.84	61.97	2.35	Ohio	5 537.66	64.91	65.30	1.76
Georgia	3 809.53	66.14	66.95	2.21	Oklahoma	1 606.91	63.07	63.74	1.55
Hawaii	571.27	65.81	66.45	2.34	Oregon	1 663.29	65.90	66.25	2.18
Idaho	613.52	66.97	66.81	2.29	Pennsylvania	5 970.71	62.55	63.07	1.93
Illinois	6 131.00	66.56	66.39	1.60	Rhode Island	527.02	66.22	66.48	1.34
Indiana	2 982.92	66.20	66.17	1.92	South Carolina	1 860.13	63.54	64.03	2.55
Iowa	1 560.75	69.77	69.93	2.56	South Dakota	391.17	70.00	70.09	2.36
Kansas	1 352.59	69.07	69.28	1.60	Tennessee	2 652.70	62.98	62.89	2.01
Kentucky	1 858.78	61.65	62.15	1.45	Texas	9 882.66	67.06	67.36	1.85
Louisiana	1 965.08	60.63	60.78	1.29	Utah	1 042.42	69.26	69.69	2.83
Maine	630.61	64.99	65.41	2.28	Vermont	315.32	69.55	70.55	2.17
Maryland	2 687.56	68.84	69.12	1.63	Virginia	3 474.21	67.68	67.88	1.48
Massachusetts	3 265.19	66.97	67.07	1.21	Washington	2 814.90	66.27	66.95	2.24
Michigan	4 700.99	64.22	64.24	2.32	West Virginia	780.28	54.05	54.39	1.56
Minnesota	2 596.26	71.98	71.59	2.38	Wisconsin	2 786.45	69.92	69.87	2.39
Mississippi	1 208.47	59.83	59.96	2.25	Wyoming	262.37	69.89	70.43	1.82
Missouri	2 760.76	66.30	66.42	2.66					
Average	2 635.36	65.95	66.30	4.15					

Notes: Labor force for each state. Mean is the average number of persons per year. The data runs from 1976 to 2017. Data sources: see Appendix Table 2.A.1.

Table 2.A.9: Quantification of risk sharing channels in EA language clubs an EA19 members excluding Luxembourg and Greece in turn

	EA language clubs		EA19 members	
	Germanic	Neo-Latin	w/o Luxembourg	w/o Greece
Participation				
$\hat{\beta}_P$	0.03	0.18	0.21***	0.18***
	(0.14)	(0.15)	(0.03)	(0.07)
R^2	0.56	0.55	0.62	0.53
N	105	126	277	278
Migration				
$\hat{\beta}_M$	0.09	0.07	0.01*	0.05
	(0.07)	(0.06)	(0.01)	(0.04)
R^2	0.23	0.18	0.08	0.1
N	105	126	277	278
Factor Trade				
$\hat{\beta}_F$	0.24**	0.05	0.04	0.07
	(0.07)	(0.06)	(0.03)	(0.06)
R^2	0.22	0.21	0.12	0.09
N	105	126	277	278
Transfers				
$\hat{\beta}_T$	−0.18	−0.13	−0.01	−0.07
	(0.12)	(0.09)	(0.03)	(0.06)
R^2	0.3	0.22	0.1	0.09
N	105	124	275	276
Credit				
$\hat{\beta}_C$	0.30	0.41	0.28**	0.43**
	(0.19)	(0.29)	(0.11)	(0.09)
R^2	0.37	0.28	0.16	0.26
N	105	124	275	276
Unsmoothed				
$\hat{\gamma}_U$	0.52***	0.44**	0.47***	0.36***
	(0.10)	(0.12)	(0.09)	(0.06)
R^2	0.63	0.67	0.52	0.64
N	105	126	277	278

Notes: Results from estimation of equations (2.12) through (2.17). The sample extends from 1999 to 2020. Country- and time-fixed effects are included but not reported. For details regarding the language clubs, see Table 2.A.3 in the appendix. Standard errors are reported in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Table 2.A.10: Quantification of risk sharing channels between US regions for changing difference intervals

	US states — 4 regions			US states — 9 regions		
	$k = 1$	$k = 2$	$k = 3$	$k = 1$	$k = 2$	$k = 3$
Participation						
$\hat{\beta}_P$	0.14*	0.16*	0.16**	0.08	0.14	0.14**
	(0.05)	(0.05)	(0.05)	(0.08)	(0.08)	(0.06)
R^2	0.84	0.88	0.92	0.68	0.75	0.78
N	104	96	88	234	216	198
Migration						
$\hat{\beta}_M$	0.03	0.05	0.06	0.07**	0.09**	0.08**
	(0.03)	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)
R^2	0.06	0.07	0.12	0.09	0.08	0.09
N	104	96	88	234	216	198
Factor Trade						
$\hat{\beta}_F$	0.24*	0.18*	0.19**	0.33***	0.27**	0.24***
	(0.08)	(0.06)	(0.04)	(0.08)	(0.08)	(0.06)
R^2	0.93	0.92	0.88	0.84	0.83	0.77
N	104	100	96	234	225	216
Transfers						
$\hat{\beta}_T$	0.00	0.04	0.06*	0.05**	0.07***	0.08***
	(0.02)	(0.03)	(0.02)	(0.02)	(0.02)	(0.01)
R$\hat{2}$	0.96	0.98	0.99	0.95	0.97	0.98
N	104	100	96	234	225	216
Credit						
$\hat{\beta}_C$	0.07*	−0.11	−0.20*	0.12	0.03	−0.05
	(0.03)	(0.09)	(0.06)	(0.10)	(0.11)	(0.09)
R^2	0.98	0.98	0.99	0.97	0.97	0.98
N	104	100	96	234	225	216
Unsmoothed						
$\hat{\gamma}_U$	0.51***	0.66***	0.71***	0.34***	0.40***	0.46***
	(0.04)	(0.09)	(0.04)	(0.09)	(0.09)	(0.09)
R^2	0.99	0.99	0.99	0.99	0.99	0.99
N	104	100	96	234	225	216

Notes: Results from estimation of equations (2.12) through (2.17). The data are differenced using intervals of k years. The sample extends from 1976 to 2017. State- and time-fixed effects are included but not reported. Standard errors are reported in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Table 2.A.11: Quantification of risk sharing channels for EA9 and EA12 members for changing difference intervals

	EA9			EA12		
	$k = 1$	$k = 2$	$k = 3$	$k = 1$	$k = 2$	$k = 3$
Participation						
$\hat{\beta}_P$	0.27***	0.33***	0.36**	0.16**	0.17***	0.16*
	(0.06)	(0.09)	(0.12)	(0.06)	(0.06)	(0.09)
R^2	0.53	0.6	0.62	0.46	0.63	0.69
N	189	171	153	230	208	186
Migration						
$\hat{\beta}_M$	0.00	0.02	0.03	0.05	0.04	0.07
	(0.00)	(0.01)	(0.02)	(0.05)	(0.04)	(0.06)
R^2	0.06	0.06	0.12	0.11	0.13	0.19
N	189	171	153	230	208	186
Factor Trade						
$\hat{\beta}_F$	0.10**	0.11**	0.10**	0.10**	0.14**	0.12***
	(0.04)	(0.04)	(0.03)	(0.03)	(0.04)	(0.03)
R^2	0.17	0.29	0.31	0.13	0.20	0.33
N	189	180	171	230	219	208
Transfers						
$\hat{\beta}_T$	−0.01	0.00	0.00	−0.05	−0.03	−0.01
	(0.03)	(0.02)	(0.02)	(0.05)	(0.04)	(0.03)
R^2	0.16	0.15	0.15	0.14	0.15	0.16
N	187	178	169	228	217	206
Credit						
$\hat{\beta}_C$	0.20*	0.12	0.07	0.22*	0.05	−0.01
	(0.01)	(0.09)	(0.07)	(0.11)	(0.06)	(0.06)
R^2	0.26	0.31	0.34	0.24	0.29	0.32
N	187	178	169	228	217	206
Unsmoothed						
$\hat{\gamma}_U$	0.45***	0.46***	0.43***	0.53***	0.63***	0.65**
	(0.08)	(0.07)	(0.10)	(0.09)	(0.08)	(0.11)
R^2	0.72	0.67	0.66	0.67	0.66	0.67
N	189	180	171	230	219	208

Notes: Results from estimation of equations (2.12) through (2.17). The data are differenced using intervals of k years. The sample extends from 1999 to 2020. Country- and time-fixed effects are included but not reported. Standard errors are reported in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Table 2.A.12: Quantification of risk sharing channels in US states and EA members before 2008

	US states			EA members		
	4 Regions	9 Regions	All states	EA9	EA12	EA19
Participation						
$\hat{\beta}_P$	0.19***	0.08	0.08***	0.30***	0.16	0.16
	(0.04)	(0.06)	(0.02)	(0.07)	(0.13)	(0.13)
R^2	0.9	0.8	0.59	0.7	0.62	0.62
N	64	144	1536	72	87	87
Migration						
$\hat{\beta}_M$	0.00	0.07*	0.05***	0.00	0.13	0.13
	(0.02)	(0.03)	(0.01)	(0.01)	(0.13)	(0.13)
R^2	0.02	0.08	0.03	0.09	0.16	0.16
N	64	144	1536	72	87	87
Factor Trade						
$\hat{\beta}_F$	0.08	0.35***	0.56***	0.00	−0.13	−0.13
	(0.05)	(0.01)	(0.08)	(0.05)	(0.15)	(0.15)
R^2	0.85	0.75	0.59	0.22	0.11	0.11
N	64	144	1581	72	87	87
Transfers						
$\hat{\beta}_T$	0.03	0.05	0.06***	−0.00	−0.07	−0.07
	(0.05)	(0.03)	(0.01)	(0.01)	(0.05)	(0.05)
R^2	0.93	0.92	0.82	0.3	0.25	0.25
N	64	144	1581	72	87	87
Credit						
$\hat{\beta}_C$	−0.01	−0.05	0.10***	0.28***	0.66*	0.66**
	(0.05)	(0.11)	(0.05)	(0.11)	(0.30)	(0.30)
R^2	0.99	0.98	0.89	0.47	0.36	0.36
N	64	144	1581	72	87	87
Unsmoothed						
$\hat{\gamma}_U$	0.70**	0.50***	0.18***	0.42***	0.25	0.25
	(0.12)	(0.13)	(0.03)	(0.14)	(0.19)	(0.19)
R^2	0.99	0.99	0.91	0.63	0.59	0.59
N	64	144	1581	72	87	87

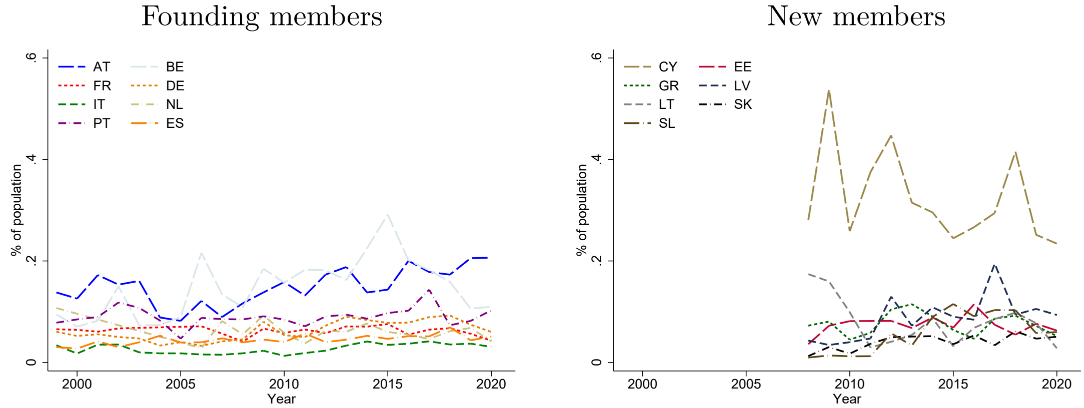
Notes: Results from estimation of equations (2.12) through (2.17). For US states, the sample extends from 1976 to 2007 and for US regions the sample extends from 1991 to 2007. For EA members the sample extends from 1999 to 2007. Note that the sample is the same for EA12 and EA19 because new member states joined the EA starting in 2008. State-/country- and time-fixed effects are included but not reported. Standard errors are reported in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Table 2.A.13: Quantification of risk sharing channels in US states and EA members after 2008

	US states			EA members		
	4 Regions	9 Regions	All states	EA9	EA12	EA19
Participation						
$\hat{\beta}_P$	0.01	−0.01	−0.01	0.01	−0.08	0.03
	(0.04)	(0.05)	(0.05)	(0.06	(0.12)	(0.08)
R^2	0.75	0.49	0.23	0.42	0.50	0.58
N	36	81	459	108	132	199
Migration						
$\hat{\beta}_M$	0.05	0.04	0.06	0.01*	0.06	0.04
	(0.07)	(0.05)	(0.05)	(0.00)	(0.06)	(0.03)
R^2	0.12	0.05	0.2	0.07	0.12	0.08
N	36	81	459	108	132	199
Factor Trade						
$\hat{\beta}_F$	−0.79**	−0.17	0.39***	0.11*	0.15*	0.07
	(0.21)	(0.41)	(0.10)	(0.06)	(0.08)	(0.07)
R^2	0.76	0.74	0.46	0.19	0.16	0.09
N	36	81	459	108	132	199
Transfers						
$\hat{\beta}_T$	0.67**	0.39**	0.11**	0.03	−0.07	−0.05
	(0.14)	(0.15)	(0.05)	(0.05)	(0.07)	(0.05)
R^2	0.59	0.67	0.8	0.2	0.18	0.14
N	36	81	459	106	130	197
Credit						
$\hat{\beta}_C$	0.77**	0.58**	0.37***	0.41***	0.35*	0.46***
	(0.16)	(0.23)	(0.10)	(0.14)	(0.12)	(0.10)
R^2	0.89	0.84	0.49	0.26	0.23	0.25
N	36	81	459	106	130	197
Unsmoothed						
$\hat{\gamma}_U$	0.28	0.17*	0.09	0.45***	0.59***	0.45***
	(0.17)	(0.09)	(0.06)	(0.12)	(0.11)	(0.10
R^2	0.86	0.8	0.56	0.81	0.77	0.69
N	36	81	459	108	132	199

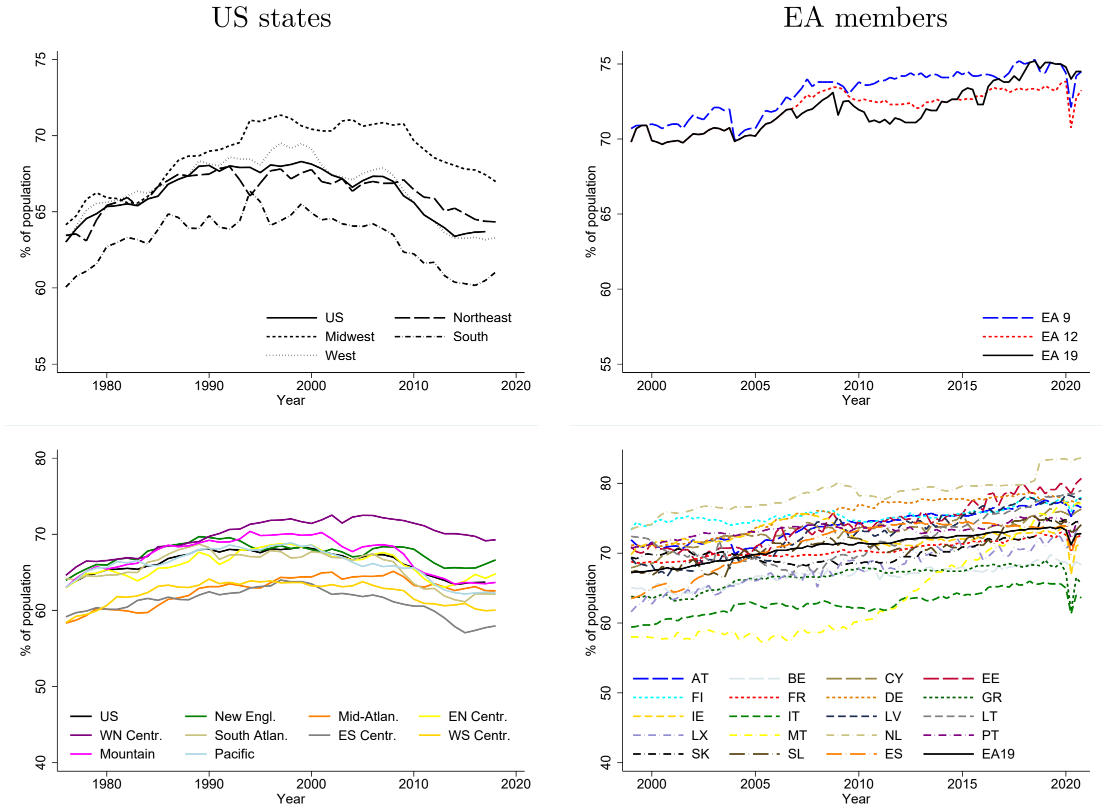
Notes: Results from estimation of equations (2.12) through (2.17). For US states, the sample extends from 2008 to 2017 and for EA members the sample extends from 2008 to 2020. State-/country- and time-fixed effects are included but not reported. Standard errors are reported in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Figure 2.A.1: Gross migration rates in EA members



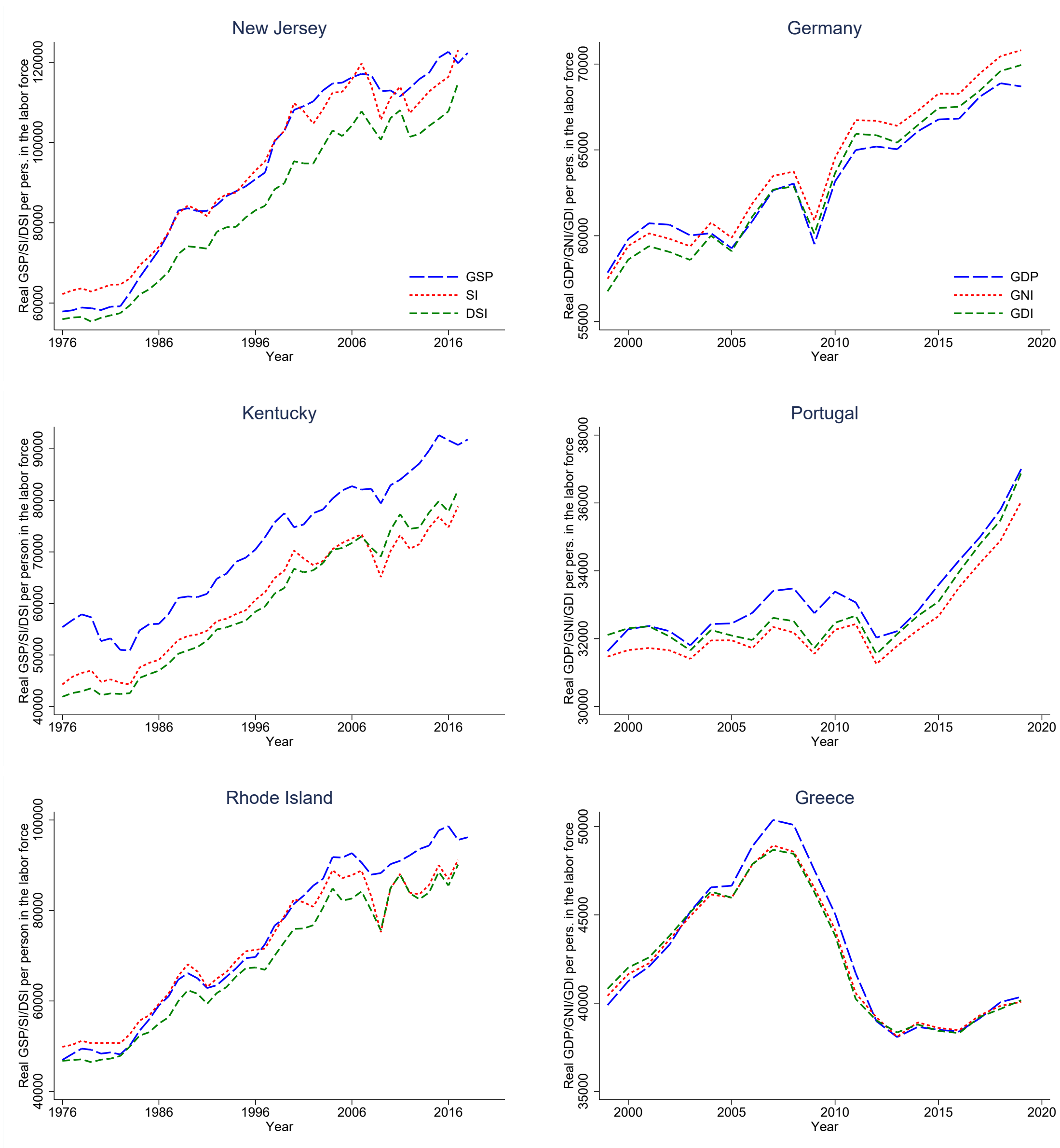
Notes: Figure shows gross migration rates country-by-country for EA members. LUX, IRE, FIN and MLT are excluded due to few observations/major outliers. Data sources: see Appendix Table 2.A.1.

Figure 2.A.2: Labor force participation rates in the US and the EA



Notes: Left column shows labor force participation rates for the 4 (top) or respectively 9 (bottom) major US regions. Right column shows labor force participation rates for the EA (top) and individual EA members (bottom). Data sources: see Table 2.A.1 in the Appendix

Figure 2.A.3: GDP, income and consumption per person in the labor force in US states and EA members



Notes: Figure shows real output, income and domestic income per person in the labor force over time for selected US states (left panel) and EA members (right panel). The sample for the US extends from 1976 to 2017 and the sample for EA members extends from 1999 to 2019 (2020 excluded due to beginning of the pandemic). Data sources: see Appendix Table 2.A.1.

Chapter 3

The Phillips curve in the euro area: New evidence using country-level data

3.1 Introduction

The Phillips curve is the most important and widely-used workhorse model for inflation in economics illustrating the trade-off between inflation and unemployment. It was originally proposed by Phillips (1958) and further discussed by Samuelson and Solow (1960). Over the past decades, the Phillips curve has constantly been subject to criticism and refinements. Nowadays, the New Keynesian Phillips curve featuring inflation expectations has become its state-of-the-art specification. However, in 2022, when we observed rapidly increasing inflation across the globe in response to the Covid-19 pandemic and the war in Ukraine while unemployment remained stable on low levels, the Phillips curve is on trial again. Especially in case of the euro area (EA), where the rise of inflation has not yet come to a halt with a view to the energy crisis, there is an urgent need for further research on the Phillips curve. Against this backdrop, we ask in this chapter whether the Phillips curve trade-off between inflation and unemployment still exists in the EA. Moreover, we examine whether country-level data can provide new insights into the Phillips curve and how these new results relate to findings of the recent literature estimating the Phillips curve using aggregate data for the EA.

In order to answer these questions, we build on a new model of a *regional* Phillips curve developed by Hazell et al. (2022) exploiting the variation in inflation and unemployment that we observed in the EA over the last decades. In their spirit, we set up a non-tradable goods' price index to measure inflation and estimate the regional Phillips curve on country-level data for the EA member states covering the period from 2001 to 2021. In addition, we compare our findings based on the regional Phillips curve with results obtained from estimating the aggregate Phillips curve using different measures of inflation expectations. Lastly, we discuss these findings with respect to the recent related literature.

In the aftermath of the financial crisis, when unemployment rose strongly but disinflation did not materialize as expected in most advanced countries, criticism around (the stability of) the Phillips curve increased (Hall 2011, cp.). Since then, a large body of literature has emerged assessing the trade-off in light of the Great Recession, mostly in case of the US (Ball and Mazumder 2011; Blanchard 2016; Coibion and Gorodnichenko 2015b, e.g.) but also for the EA (Mazumder 2012, e.g. Riggi and Venditti 2015; Hindrayanto et al. 2019; Ball and Mazumder 2020) and advanced and emerging economies across the globe (Blanchard et al. 2015; Forbes et al. 2021, e.g.). As mentioned above, the Covid-19 pandemic and the subsequent severe supply chain shock leading to rapidly increasing inflation at low levels of unemployment put the Phillips curve yet again to the test. Overall, the literature finds very different results for the Phillips curve slope, that is the parameter that measures how sensitive inflation is to unemployment or any other measure of economic slack, such as the output gap. Most papers estimate the Phillips curve using aggregate data (both in case of the US and the EA) and direct measures of inflation expectations. Early on after the financial crisis, Mavroeidis et al. (2014) have pointed out that there are several caveats to this: first, there is considerable heterogeneity and variation in inflation and unemployment especially in the EA which might not be captured appropriately by aggregate data. Moreover, aggregate (survey) data suffers from a problem of weak instruments. Therefore, they argue, new methodologies and data are necessary to pin down the slope of the Phillips curve more clearly. Additionally, Hazell et al. (2022) argue that simultaneity problems may arise because of the difficulty to disentangle demand and supply shocks in aggregate data. We tackle these issues and estimate a new formulation of the Phillips curve for the EA exploiting country-level panel data. In this way, we exploit variation in inflation and unemployment across the EA and direct measures of inflation expectations become obsolete.

Specifically, we estimate an empirical specification of the *regional* Phillips curve proposed by Hazell et al. (2022) to infer about the sensitivity of inflation to unemployment in the EA. They derive this modified version of the Phillips curve within a standard multi-region New Keynesian model of a monetary union and relate it to the “traditional” aggregate Phillips curve. Importantly, they set out how the problem of accounting for shifts in long-term inflation expectations when estimating the Phillips curve, for example induced through changes in the long-run monetary policy regime, can be overcome by the use of a panel data specification including time-fixed effects. Intuitively, long-run inflation expectations are common across member states of a monetary union and therefore “cancel out” in the estimation using cross-sectional data (Hazell et al. 2022, p. 5). Therefore, it is not necessary to proxy for inflation expectations using for example survey data. Thus, measurement errors and identification problems are substantially reduced. Another essential theoretical feature of the regional Phillips curve is that it only relies on inflation in non-tradable goods. Prices of tradable goods are set at the level of the monetary union and are therefore equal (up to transportation and logistical costs). Hence, they do not contribute to inflation differentials across the member states of the union and are therefore not informative of the slope of the regional Phillips curve. To account for this feature, we construct a non-tradable goods price index using HICP-subcomponents on a 4-digit-level from Eurostat taking advantage of the harmonization of price index construction across EA member states. We also use several different approaches for identification and follow Hazell et al. (2022) in constructing a tradable-demand instrument. This instrument takes advantage of the regional setting and exploits the idea that supply shocks in the tradable goods sector differently affect demand in the non-tradable goods sector depending on the degree of exposition of a country to the supply shock. We also estimate an empirical version of the regional Phillips curve as presented in the recent related literature and compare our results with those reported in Hazell et al. (2022) for the US. Finally, we contrast our results for the slope of the regional Phillips curve with estimates of the aggregate Phillips curve using different measures of inflation expectations, and place our results into the context of existing literature.

We evaluate the regional Phillips curve on quarterly data for EA member states over the period 2001-2021.[1] We find that indeed the slope of the Phillips curve in the EA is small and thus the Phillips curve itself comes across as flat but robust. In our preferred specification, the slope coefficient κ is only 0.0043, though statistically significant, which is substantially smaller compared to estimates we obtain from aggregate data ranging between 0.0971 and 0.3812. However, our finding coincides with the estimated slope parameter for the US reported by Hazell et al. (2022) who obtain a value of 0.0062 in the preferred specification. Similar to Hazell et al. (2022), we conclude that the Phillips curve is substantially flatter though stable judging from country-level data compared to aggregate data. This finding is also robust across a number of different specifications regarding methodological aspects of the regional Phillips curve. Our findings clarify why there has been no disinflation in the years after the financial and sovereign debt crises and why inflation has remained below target in the late 2010s when unemployment decreased to record-low levels: the Phillips curve is alive but robustly flat in the EA and inflation has been stabilized by firmly anchored inflation expectations.

The chapter proceeds as follows. In the remainder of the introduction, we place the chapter in a broader literature context. Section 3.2 introduces the model of the regional Phillips curve based on Hazell et al. (2022). Afterwards, in Section 1.2, we describe the data and show some stylized facts on the Phillips curve in the EA. Section 3.4 introduces the empirical specification of the model illustrated in Section 3.2 and presents the empirical results of estimating the regional Phillips curve on EA panel data. It also compares findings with estimates of an aggregate Phillips curve and the recent literature. Section 1.5 concludes.

Related literature. This chapter touches upon several strands of the literature on the Phillips curve. After all, the Phillips curve is still an important tool for policymakers at central banks to analyze inflation (Belz et al. 2020; Eser et al. 2020; Hasenzagl et al. 2022).

The literature on using regional or cross-sectional panel data to estimate the Phillips

[1] Essentially, the data starts in 1998 but due to the construction of non-tradable goods price inflation we lose 3 years of observations

curve is still scarce. To date, there has been no attempt to use EA country-level data to estimate a regional Phillips curve specification, however, there are some papers that use US state- or city-level data (Kiley 2015; Babb and Detmeister 2017).[2] The paper most closely related to ours is Hazell et al. (2022) since we use their newly developed regional Phillips curve model based on regional data to infer about the slope of the Phillips curve in the euro area as described above. In their paper, they develop a regional Phillips curve within a New Keynesian model and estimate this new version of the Phillips curve using a newly-constructed dataset on state-level price indices for non-tradable goods for the US. In their analysis they put special emphasis on the (seeming) difference between the period of the Volcker disinflation and the period since 1990. Based on the new data and the new specification of the Phillips curve, they find that its slope was and is still small which makes the Phillips curve flat. Importantly, they do not use explicit measures of inflation expectations to arrive at this conclusion. In a similar fashion, though with a focus on the optimal inflation target when identifying the Phillips curve, McLeay and Tenreyro (2020) use cross-sectional regional variation in US metropolitan unemployment and price data to infer about the slope of the Phillips curve. They obtain larger estimates of the slope of the Phillips curve compared to estimates based on aggregate data. Similarly, Fitzgerald et al. (2020) estimate the Phillips curve using US state-level data to identify the structural relationship between unemployment and inflation. They find a relatively stable relation between unemployment and inflation since the 1970s. Hooper et al. (2020) estimate a conventional expectations-augmented Phillips curve using panel data for US states and cities and find a negative slope of the Phillips curve.

Several papers have recently investigated the aggregate Phillips curve for the euro area. They focus on estimating the Phillips curve using aggregate data to explain the puzzling behavior of inflation after the financial crisis (Moretti et al. 2019; Passamani et al. 2021).[3] Ball and Mazumder (2020), for example, estimate the Phillips curve for the EA focusing on core inflation and using professional forecasters' inflation expectations. They find that there was no missing disinflation after the financial crisis. Oinonen and Vilmi (2021) use the New Keynesian Phillips Curve (NKPC) to analyze the inflation outlook in the EA. Including both survey and professional inflation expectations, they find that the Phillips curve explains recent inflation dynamics well. Other literature has studied inflation on the level of EA member states individually, agreeing on a negative but stable slope of the Phillips curve since the financial crisis (see Amberger and Fendel 2016, 2017; Hindrayanto et al. 2019). Still, there is considerable heterogeneity across EA member states (Ribba 2020, e.g.).

[2] To our best knowledge, the only paper using country-level data of EA member states to identify the slope of a structural (aggregate) New Keynesian Phillips curve is Eser et al. (2020). However, they do not estimate a regional Phillips curve in the spirit of Hazell et al. (2022).

[3] Equivalently, Coibion and Gorodnichenko (2015b), Ball and Mazumder (2011, 2018), Del Negro et al. (2020) do so for explaining US inflation behavior in the aftermath of the financial crisis.

3.2 The regional Phillips curve

In this Section, we shortly summarize the set up of the New Keynesian model in Hazell et al. (2022) in order to set the stage for presenting the regional and aggregate Phillips curve. We will state the assumptions necessary to arrive at the regional Phillips curve and elaborate on the role of cross-sectional data in estimating it. Finally, we present the regional Phillips curve and contrast it to the related strand of the literature.

3.2.1 Model setup

Hazell et al. (2022) develop the regional Phillips curve in a two-region New Keynesian, open economy model with a tradable and non-tradable goods' sector. Both regions of the model form a monetary and fiscal union. The population of Home (H) and Foreign (F) sum up to one and labor is perfectly mobile within regions but not across regions. Each region features a single labor market. Financial markets are complete across regions. Agents form full-information rational expectations.

Households have preferences according to Greenwood et al. (1988) (abbr. as GHH hereafter) and consume a composite consumption good with consists both of tradable and non-tradable goods. Assuming GHH preferences simplifies the derivation of a regional and aggregate Phillips curve, see Section 3.2.2. These type of preferences imply that there are no wealth effects on labor supply, which means that marginal costs are independent from consumption.[4] Importantly, non-tradable goods are consumed only within the region they are produced whereas the market for tradable goods is fully integrated across regions. Therefore, the price index for non-tradable goods may differ across regions but the price index for tradable goods does not. Households maximize utility subject to a sequence of period budget constraints. Ponzi-schemes are ruled out such that household debt cannot exceed the present value of future income.

There is a continuum of firms both in the tradable and non-tradable goods sector which are specialized in the production of differentiated goods. Firms only use labor as input in the production of these goods (hence the production is linear in labor with constant returns to labor). Firms' price setting in both sectors follows Calvo (1983). Thus, in each period a fraction of firms $1 - \alpha$ can reset their prices while the remaining fraction α cannot adjust their prices. Firms in the non-tradable sector only produce for the region where they are located (i.e. either Home or Foreign), firms in the tradable goods sector face demand from both regions forming the monetary union.

The government conducts a common monetary policy for both regions. Economy-wide inflation and unemployment are both a population weighted average of inflation and unemployment, respectively, of each region. Monetary policy is subject to a time-varying inflation target. Variation in long-run inflation yields variation in long-run unemployment since the long-run Phillips curve is not vertical. Moreover, the monetary authority targets

[4]Conversely, assuming separable preferences would imply that the slope of the regional Phillips curve for non-tradable inflation is different from the slope of the aggregate Phillips curve, see appendix of Hazell et al. (2022).

an unemployment rate which is consistent with its long-run inflation target. The interest rate rule follows the Taylor principle ensuring that there exists a unique locally bounded equilibrium. There are no taxes, government spending nor issuance of debt, hence there is no fiscal policy. The government issues a digital currency which is in zero net supply meaning that monetary policy has no fiscal impact. The equilibrium in the two-region economy satisfies household and firm optimization, the government interest rate rule and market clearing.

3.2.2 The regional and aggregate Phillips curve derived from theory

Hazell et al. (2022) take a log-linear approximation of the model presented verbally in Section 3.2.1 around a zero-inflation steady state with balanced trade. This yields the following regional Phillips curve for *non-tradable goods* inflation

$$\pi_{Ht}^{N} = \beta E_t \pi_{H,t+1}^{N} - \kappa \hat{u}_{Ht} - \lambda \hat{p}_{Ht}^{N} + \nu_{Ht}^{N}. \tag{3.1}$$

and the aggregate Phillips curve for *overall* inflation

$$\pi_t = \beta E_t \pi_{t+1} - \kappa \hat{u}_t + \nu_t \tag{3.2}$$

where $\kappa = \lambda\varphi^{-1}$ and $\lambda = \frac{(1-\alpha)(1-\alpha\beta)}{\alpha}$. $\pi_{Ht}^{N} = p_{Ht}^{N} - p_{H,t-1}^{N}$ is non-tradable Home inflation, $\hat{p}_{Ht}^{N}$ is the percentage deviation of the Home relative price of non-tradables from its steady state value of one, ν_{Ht}^{N} is a non-tradable Home supply shock and ν_t is an aggregate supply shock. $\hat{u}_{Ht}$ is the percentage deviation of Home unemployment u_{Ht} from its steady state value u_H. Unemployment in Home is defined as $u_{Ht} = 1 - N_{Ht}$ where N_{Ht} is total labor supply in Home. In turn, total labor supply in Home is the sum of labor demanded by firms in the tradable (N_{Ht}^{T}) and non-tradable (N_{Ht}^{N}) goods sector. Hence, in the model of the regional Phillips curve, unemployment comprises both sectors while inflation only refers to the non-tradable goods sector.[5]

The slope of the Phillips curve κ in (3.1) and (3.2) depends on two parameters: the degree of nominal rigidity λ and the Frisch elasticity of labor supply φ. λ, in turn, depends negatively on the fraction α of firms that keep their prices fixed in a given period. Hence, the larger the degree of price stickiness, the smaller λ. For the slope this means that a larger value of α, which reduces λ, ultimately leads to a smaller slope parameter.

From equation (3.1) and (3.2) follows that the slope both of the aggregate Phillips curve for overall inflation and the regional Phillips curve for non-tradable inflation are equal to κ. However, this result does not carry over to the regional Phillips curve including *tradable* inflation.[6] The intuition behind this result is that both regions consume tradable goods produced in Home and Foreign and therefore these goods are priced on the level of the whole economy. Thus, prices of tradable goods do not contribute to differences

[5] These model specifications hold analogously for Foreign (F).

[6] In their appendix, Hazell et al. (2022) show that the slope of the regional Phillips curve for *overall* inflation is smaller than the aggregate Phillips curve by the factor of the expenditure share on non-tradable goods.

in inflation between regions. Conversely, the overall regional price index is partly made up of goods which prices are insensitive to changes in regional unemployment. Building on these theoretical results, we follow Hazell et al. (2022) and use non-tradable goods price inflation when estimating the regional Phillips curve in the cross-section of euro area member states.

The essential difference between (3.1) and (3.2) is the relative price of non-tradables, that is $\lambda \hat{p}^N_{Ht}$, in the regional Phillips curve. It implies that inflation in the non-tradables sector will be lower the higher is the relative price of non-tradables. Thus, the term pushes relative prices for tradables and non-tradables to parity in the long run. Also, local booms will not result in unbounded inflation of home non-tradables because the demand for these goods is also affected by the relative price of non-tradables to tradable goods in the whole economy. From a model point of view, the reason why this term is appearing in the equation is twofold: On one hand, non-tradable inflation is driven by variation in the real wage deflated by prices of non-tradable goods. On the other hand, labor supply is a function of the real wage deflated by the home consumer price index. Therefore, the real marginal cost variable in the non-tradable Phillips curve gives rise both to an unemployment and a relative price term (Hazell et al. 2022). Ultimately, the parameter λ measures the degree of nominal price rigidity in the economy.

To see the benefit from using cross-sectional data in estimating the regional Phillips curve, Hazell et al. (2022) solve equation (3.1) forward assuming that the law of iterated expectations holds.[7]. They obtain

$$\pi^N_{Ht} = -E_t \sum_{j=0}^{\infty} \beta^j (\kappa \tilde{u}_{H,t+j} + \lambda \hat{p}^N_{H,t+j}) + \beta E_t \pi^N_{H,t+\infty} + \tilde{\omega}^N_{Ht} \tag{3.3}$$

where $\tilde{u}_{H,t} = u_{Ht} - E_t u_{H,t+\infty}$ and $\tilde{\omega}^N_{Ht} = E_t \sum_{j=0}^{\infty} \beta^j \nu^N_{H,t+j}$.[8] Importantly, the term $\beta E_t \pi^N_{H,t+\infty}$, that is long run inflation expectations, is constant across regions. This implies that variations in these long run inflation expectations will be absorbed by region- and time-fixed effects. The intuition is that long run inflation expectations are independent of the current business cycle and are solely determined by beliefs about the long run monetary policy regime (essentially the inflation target). These beliefs, in turn, are common across all regions (or countries, respectively) forming a monetary union, because monetary policy is set by the common central bank, which is the ECB in case of the euro area. Thus, beliefs formed by the private sector vary uniformly across regions, or countries, respectively in the monetary union. Mechanically, when estimating the regional Phillips curve, these expectations are then "differenced out" in a panel regression including time-fixed effects (Hazell et al. 2022, cp). From the perspective of the theoretical model, Hazell et al. (2022) obtain this result because productivity growth and other drivers of real costs, have a common trend across regions in the long run. There may still be differences across regions (regarding for example TFP) but if these

[7]Hazell et al. (2022) elaborate on this assumption in their appendix A.10 relying on Adam and Padula (2011) and Coibion et al. (2018).

[8]Again, these equations hold analogously for Foreign.

differences are constant over time, they will be absorbed by region- or country-fixed effects, respectively. Any other remaining variation in long run inflation expectations across regions will be absorbed by the error term $\tilde{\omega}_{Ht}^{N}$. The main conclusion from this result is that long-run inflation expectations can be substituted by time- and region-fixed effects in the estimation. This yields the following regional Phillips curve specification

$$\pi_{it}^{N} = -E_t \sum_{j=0}^{\infty} \beta^j (\kappa u_{i,t+j} + \lambda \hat{p}_{i,t+j}^{N}) + \alpha_i + \gamma_t + \tilde{\omega}_{it}^{N} \tag{3.4}$$

where the subscript i denotes a region, or country, respectively, in the panel. α_i denotes region-fixed effects which absorb constant differences in expected non-tradable goods inflation across regions. γ_t denotes time-fixed effects which absorb time-variation in $E_t\pi_{t+\infty}^{N}$ that is common across all regions in the monetary union. Note also that time-fixed effects do not only absorb common long-run trends in inflation expectations but also time variation in long-run expected unemployment $E_t u_{t+\infty}$. Therefore, Hazell et al. (2022) suggest to replace $\tilde{u}_{i,t+j}$ by $u_{i,t+j}$.

The recent regional Phillips curve literature (Hooper et al. 2020; McLeay and Tenreyro 2020, cp) has established an empirical specification of equation (3.3) which is empirically more tractable, however, it also relies on the assumption that both u_{Ht} and $\hat{p}_{H,t+j}^{N}$ follow AR(1) processes, where $\psi = \kappa/(1-\beta\rho_u)$ and $\delta = \lambda/(1-\beta\rho_{pN})$:

$$\pi_{it}^{N} = -\psi u_{it} - \delta \hat{p}_{it}^{N} + \alpha_i + \gamma_t + \tilde{\omega}_{it}^{N} \tag{3.5}$$

Obviously, the slope coefficients in equation (3.4) and (3.5) are not the same. While κ represents the structural slope coefficient in the regional Phillips curve for non-tradable goods inflation, ψ is a reduced form slope coefficient as estimated in other recent literature. Hazell et al. (2022) argue that since unemployment is quite persistent, ψ will be substantially larger than κ in empirical estimations. Therefore, the literature estimating regional Phillips curves by means of equation (3.5) obtain significantly larger slope estimates compared to traditional estimates based on aggregate data , since they estimate the slope coefficient in equation (3.5) instead of (3.4). The persistence of unemployment then ultimately results in larger slope estimates in this Phillips curve framework using regional data, since ψ does not only reflect the impact of current unemployment on current inflation but also expected infinite future unemployment.

The regional and aggregate Phillips curves derived above are arguably based on strong assumptions which may not necessarily hold. Hazell et al. (2022) acknowledge this and include a discussion on this in their paper.

3.3 Data and descriptive statistics

In this section, we present the country-level panel data we use to estimate the slope of the Phillips curve in the EA. First, we discuss how we construct the non-tradable goods' price index and inflation, respectively, and compare it to other measures of inflation.

Next, we summarize the data on employment and unemployment that we use to measure labor market slack and to construct the tradable demand instrument. We discuss data on inflation expectations that we use in the final part of the chapter to estimate the aggregate Phillips curve in order to compare it with the estimates for the slope of the regional Phillips curve. Lastly, we present some descriptive evidence on the Phillips curve in the EA to set the stage for the formal estimation.[9]

3.3.1 Construction of a non-tradable goods price index

In order to estimate the regional Phillips curve using non-tradable inflation as suggested by Hazell et al. (2022), we set up a non-tradable price index on country-level for all members of the EA. In selecting the HICP sub-components to construct the non-tradable goods price index, we follow the classification of Hazell et al. (2022), see appendix 3.A for details. We rely on Eurostat data for individual HICP sub-components on the 4-digit-level of the so-called *European classification of individual consumption according to purpose* (ECOICOP).[10] This classification on the 4-digit-level comprises 48 industries.[11] The advantage of using Eurostat's HICP and its sub-components is that its definition is harmonized across European countries and thus comparability across countries is ensured. This also makes aggregation of non-tradable sub-components easily possible. For the US, an analogous publicly available constructed index featuring sub-components on non-tradable goods on state-level does not exist. Hence, Hazell et al. (2022) build an index on their own based on microdata on the state-level from the BLS which potentially involves measurement errors and reduces reproducibility. Finally, to compute the index, we also draw on the weights of sub-components available from Eurostat (used to set up the overall HICP).

The construction of the non-tradable price index makes use of the aggregation methodology of Eurostat deployed to set up the overall HICP on the level of individual countries. We use this aggregation method for consistency to establish the price index for non-tradables. This aggregation method comprises several steps. First, the price indexes of the sub-components on 4-digit-level have to be unchained dividing the value of each month by the value of the previous December multiplying by 100. In the next step, we aggregate the components by computing the weighted arithmetical average. Thereby, we multiply the unchained value of component i with its weight and take the sum over all categories. Then, we divide this sum by the sum of weights of all components labelled non-tradables. Finally, we again chain-link this newly computed price index to its value

[9] An overview of all variables and data sources can be found in the appendix in Table A.1.

[10] Unfortunately, these data on sub-components are not seasonally adjusted. However, for estimation we compute year-on-year inflation rates which eliminates seasonality (Hazell et al. 2022). Moreover, we compared headline and core inflation for the euro area both using adjusted and unadjusted data and find that differences are negligible.

[11] Hazell et al. (2022) include 71 industries. However, in the Eurostat ECOICOP classification some individual industries listed in Hazell et al. (2022) are summarized together in one category. For example, "painting entire automobile", "vehicle inspection" and "automotive brake work" are summarized as "Maintenance and repair of personal transport equipment" in Eurostat's ECOICOP classification. An entire list of categories is listed in Section 3.A of the appendix.

of the past December times 100. Data for individual HICP non-tradable components on 4-digit-level is available from 1998 onwards. However, due to the construction of the non-tradable goods price index by means of aggregation and chain-linking, the time series for non-tradable inflation starts only in 2001. For comparison and exposition in the descriptive statistics below, we also compute analogously a tradable goods price index based on HICP sub-components of Eurostat. This price index also draws on the 4-digit-level ECOICOP categories and includes the remaining components which were not classified as non-tradable goods before. The computation of the tradable goods price index is analougous to the non-tradable goods price index.

Figure 3.1 shows 12-month headline, core, non-tradeable and tradeable inflation rates. Several observations are in order. First, we observe that there is considerable heterogeneity among euro area members regarding all four measures of inflation. Second, we observe that there is even more heterogeneity in both non-tradable and tradable goods inflation across EA members compared to overall headline and core inflation. While tradable inflation is more volatile across time also on euro-area average (black solid line lower right panel), non-tradable inflation varies more strongly across countries. This observation is in line with the notion that prices of tradable goods have converged in the monetary union. In some instances, these goods are even priced on the level of the currency union and hence there is less price divergence which implies smaller inflation differentials across the EA (Estrada et al. 2013). Non-tradable goods, on the other hand, respond much more to country-specific marginal costs.[12] The evidence confirming the heterogeneity in non-tradable inflation across the EA strengthens our intention to estimate a regional Phillips curve using country-level data because regional variation is essential for identifying the slope parameter in this model. Moreover, this type of variation helps to overcome caveats of estimating an aggregate Phillips curve for a currency union.

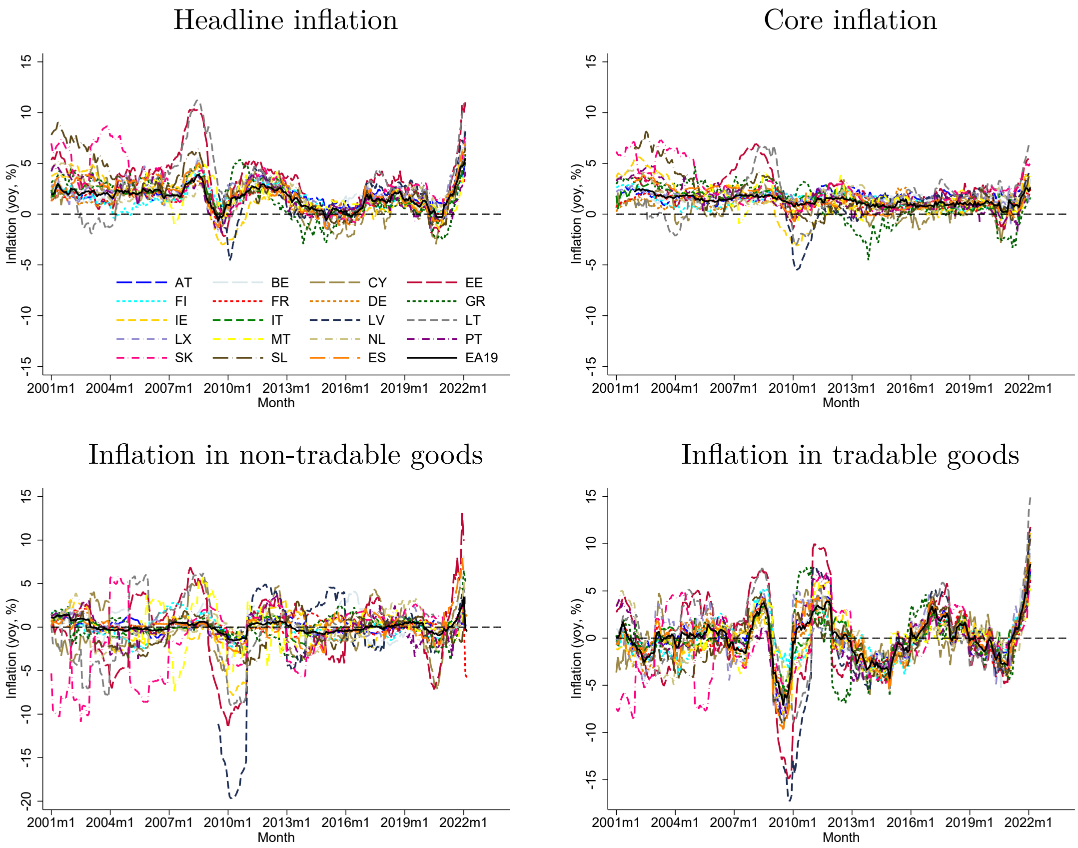
3.3.2 Employment data

For estimating the regional Phillips curve for the euro area following the approach of Hazell et al. (2022), we make use both of country-level unemployment and employment data. Specifically, we use the unemployment rate as as measure of economic slack. Time-series data on unemployment rates for EA members (seasonally but not working-day adjusted) on monthly frequency are available from the ECB. For estimation, we collapse monthly unemployment rates to quarterly frequency by computing the quarterly average. In the final part of the chapter when estimating the Phillips curve using aggregate data we use the aggregate unemployment rate for the EA obtained from the ECB.

Cross-country variation in unemployment among EA member states is essential for identifying the slope of the regional Phillips curve in a panel data set up (Hazell et al. 2022). Figure 3.2 plots unemployment rates for all member states (colored lines) and the aggregate of the EA19 (black solid line) between 2001M1 and 2022M1. Quite strikingly, unemployment rates in the EA vary a great deal over the sample period, both across

[12]Consistently, Hazell et al. (2022) show that there is much more variation across US states in non-tradable inflation compared to tradable inflation by means of a principal component analysis.

Figure 3.1: Different measures of inflation for EA member states

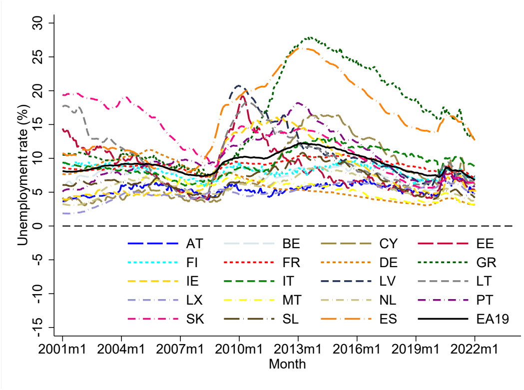


Notes: Different measures of inflation (year-on-year) measured in percent. Top row: headline (left panel) and core inflation (right panel) based on the HICP. Bottom row: non-tradable (left panel) and tradable (right panel) goods inflation. Data sources: Eurostat and own calculations

the members of the currency union and on the level of individual countries. Still, we observe some co-movement over time, especially regarding the hike in response to the financial crisis and the subsequent decline over the past few years. These observations are in line with what Hazell et al. (2022) show for the US, indicating that their approach of estimating the slope of the regional Phillips curve is suitable for the EA, too. In fact, it seems to be even more applicable, as unemployment across the EA varies between roughly 5 percent in core countries (cp. Luxembourg, Austria and Germany) and up to 30 percent for countries of the periphery (cp. Greece and Spain). On the contrary, according to Hazell et al. (2022), unemployment rates in the US vary only between 5 and roughly 12 percent. Hence, exploitable variation is much larger in the EA compared to the US.

For estimating the regional Phillips curve, Hazell et al. (2022) construct a tradable demand instrument based on tradable employment shares in the spirit of Bartik (1991), see Section 3.4.1 below. We follow this practice and use country-specific sectoral employment data for all EA member states extracted from Eurostat to construct the instrument. In the choice of sectors included, we rely again on Hazell et al. (2022), following Mian and

Figure 3.2: Unemployment rates in the EA



Notes: Country-level unemployment rates at monthly frequency are measured in percent and seasonally adjusted. Data source: ECB.

Sufi (2014). Specifically, Hazell et al. (2022) include the following sectors to compute the tradable employment shares: "Agriculture, forestry, fishing and hunting", "Mining, quarrying and oil and gas extraction", and manufacturing.[13] For the EA, sectoral employment data (not seasonally adjusted) is available on quarterly frequency on the level of A10 sectors according to the European Classification of Economic Activities (NACE rev.2). Based on this sectoral classification and aggregation level, we include the sectors "Agriculture, forestry, fishing" and "Industry (w/o construction)" when computing the tradable employment shares.[14] Since the sectoral employment data is not seasonally adjusted, the tradable demand instrument based on employment shares needs to be seasonally adjusted. Again, we follow Hazell et al. (2022) and exponentially smooth the time series based on a moving-average process. For details on the construction of the instrument, see Section 3.4.1 below.

3.3.3 Inflation expectations data

In the last part of the chapter, we compare estimates of the slope of the regional Phillips curve for the EA with slope estimates based on aggregate data and different measures of inflation expectations. Aggregate data on year-on-year headline and core inflation based on the HICP for the EA come from the ECB. These time series are seasonally adjusted and on quarterly frequency.

[13] According to the Standard Industrial Classification (SIC) and the North America Industry Classification System (NAICS) for the US, these are SIC sectors A, B, and D, and NAICS sectors 11, 21, and 31 to 33.

[14] Based on the definition of NACE rev.2, these are sectors A and B-E. B-E, that are the sectors summarized as "Industry w/o (construction)", also include "Electricity etc. supply" (D) and "Water supply and sewage" (E) next to "Mining" (B) and "Manufacturing" (C). These sectors are not included by Hazell et al. (2022) in their employment data. However, the sectors B and C are not separately available from Eurostat, hence we use the composite. We checked employment shares for D and E based on NACE rev.2 A64 classification and find that for sector D it was 0.45 percent and for sector E it was 0.72 percent in 2020 of total employment in the EA. We conclude that these sectors are only of minor importance and will not bias results substantially.

Data on professional inflation expectations come from the Survey of Professional Forecasters (SPF) conducted by the ECB on quarterly frequency.[15] In this survey, professional economists are asked, among other things, about their forecasts of inflation over various horizons. For example, they are asked to provide a point estimate of the year-on-year change in inflation in the future based on the HICP published by Eurostat. The survey question itself covers six different time horizons: current calendar year, next calendar year, calendar year after next, 12-months ahead, 24-months ahead and 60-months ahead. The survey is conducted quarterly in January, April, June and October. Questionnaires are distributed just after the Eurostat press release of the final estimate of last month's inflation rate. Hence, experts know the inflation rate with a lag of one month but have no information on the estimated current inflation rate. Questionnaires completed have to be returned to the ECB within one week. On average, sixty professionals participate each quarter in the survey. However, the panel is unbalanced as forecasters drop out and are replaced by others each round the survey is conducted (López-Pérez 2017). In the estimation below, we draw on two distinct measures of professional inflation expectations: short-term and longer-term forecasts. For the short term we use the 12-month ahead forecasts and for the longer-term expectations we use the 60-month ahead forecasts of the SPF.

Data on quantitative household (or consumer) inflation expectations come from the Business and Consumer Survey (BCS) conducted by the Directorate-General for Economic and Financial Affairs (DGECFIN) of the European Commission (EC). For an overview and evaluation of the data on the country level, see Arioli et al. (2017). Since 1985, the survey is conducted nationally by partner institutions such as ministries or research institutes in each member country of the European Union or respectively the EA. Each partner institution is responsible for the sampling frame and sampling methods. The questionnaires, however, are harmonized across countries. For the EA as a whole, the sample includes around 21,000 households. For each country, the individual sample size differs according to its population size. The survey is conducted on a monthly base and interviews take place in the second or third week of each month. By then, people surveyed know at most the last month's inflation rate. The survey question asks for a quantitative estimate of how consumer prices will develop over the next twelve months. Eventually, the EA aggregate is computed as a weighted average of country-aggregate responses. The time series of monthly quantitative consumer inflation expectations is collapsed to quarterly frequency for estimation purposes.

Lastly, we also incorporate a measure of market-based inflation expectations in the analysis below. Therefore, we use data on inflation-linked swaps from Refinitiv accessed through Datastream. Daily data is aggregated to quarterly frequency by taking the end-of-quarter value to take all relevant information of market participants in a given quarter into account. Inflation-linked swaps are financial derivatives by which one contracting party (inflation receiver) is entitled to receive a payment equal to the realized inflation rate times a nominal value in exchange for paying a fixed rate (times a nominal

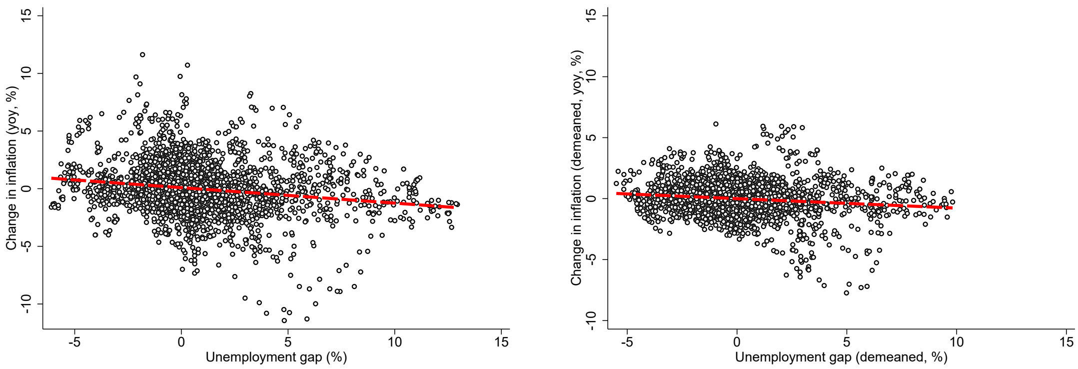
[15] Information on the survey and the questionnaire can be retrieved from the website of the ECB SPF

value) to the other contracting party (inflation payer) over an agreed period of time settled in the contract (Grothe and Meyler 2017). This fixed rate, also called fixed leg, indicates the expected inflation rate over the duration of the contract. At maturity of the swap, the difference in the fixed leg and the realized inflation rate are exchanged. Therefore, inflation-linked swaps with different maturities reflect different horizons of inflation expectations. In the analysis below, we use one-year (five-year) spot rates to measure one-year (five-year) ahead market-based inflation expectations and one-year forward rates to measure inflation expectations two-years ahead. Inflation-linked swaps are indexed to Eurostat's HICP excluding tobacco (HICPxT). However, both time series of inflation based on the HICP and HICPxT move very closely, see Grothe and Meyler (2017), so we do not expect major distortions because of this indexation. Another caveat is the timing of the inflation-linked swap contract, called the indexation lag. Swaps are written on HICPxT inflation realized three months before the contract starts. This means that the fixed rate agreed upon actually only reflects 9-months of *expected* inflation in addition to past 3-month *realized* inflation. Thus, the forecast horizon differs slightly with respect to the other surveys described above. For larger horizons, when drawing on forward inflation swap rates, this distortion diminishes (Miccoli and Neri 2018). Another type of distortion in the fixed rate may also arise due to inflation risk which drives risk premia up. Nevertheless, because of their nature as traded instruments, inflation-linked swaps include expectations of a variety of market participants on a high-frequency level and thus include much more information on an aggregated level compared to alternative measures.

3.3.4 Stylized facts on the Phillips curve in the EA

Before diving into the formal analysis of the Phillips curve in the EA, we want to present some stylized facts about the trade-off. Figure 3.3 plots the accelerationist Phillips curve which results when assuming backward-looking or adaptive inflation expectations. Stock and Watson (2020) refer to this as the "Phillips correlation". We plot the year-on-year change in the 12-month inflation rate against the unemployment gap defined as the difference between the unemployment rate and the NAIRU published by the OECD. Both variables are measured at monthly frequency on country-level. Additionally, observations in the right panel have been demeaned by country and over time to illustrate the impact of controlling for country- and time-fixed effects similarly to the estimation of the regional Phillips curve below. The red dashed lines indicate the linear fit of a regression of the change in inflation on the unemployment gap. A first glance at the scatter plots suggests that inflation across the euro area is relatively insensitive to changes in unemployment. The systematic relationship between inflation and unemployment seems to be only small in the EA similar to the US as Hazell et al. (2022) point out. By means of pure eyeballing, we observe that the fitted line is almost flat in both panels, even more so in the right one. The estimated slope coefficients which are -0.1341 (p-value: 0.0000) in the left panel and even only -0.0775 (p-value: 0.0000) in the right panel support this observation. Hence, this descriptive evidence suggests that the slope substantially reduces when one accounts

Figure 3.3: Phillips correlation - inflation gap vs unemployment gap



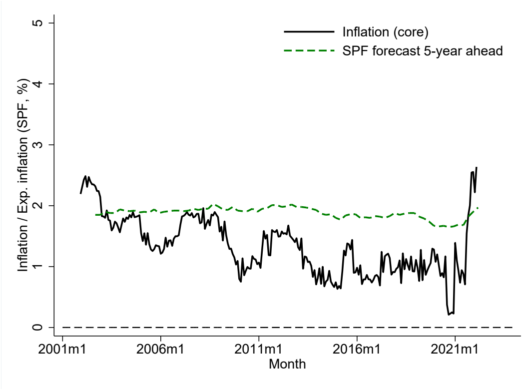
Note: Inflation gap is the year-on-year change in the 12-month inflation rate in percent and the unemployment gap is the difference between the unemployment rate and the NAIRU in percent. Right panel: observations have been demeaned by country and over time. The sample ranges from 2001M1 to 2022M2. The red dashed lines indicate the linear fit of the change in inflation on the unemployment gap. Data sources: ECB, Eurostat, OECD

for common trends across countries and over time, which are nothing more than long-run inflation expectations in the model of the regional Phillips curve according to Hazell et al. (2022).

Figure 3.4 illustrates the 12-month core inflation rate based on the core HICP excluding food and energy and the 5-year ahead expected inflation rate measured by the SPF. We clearly observe that, since the introduction of the euro, longer-term inflation expectations of professional forecasters have been stable at close to but below 2 percent, the inflation target of the ECB until mid-2021. Combining the evidence of very stable long run inflation expectations and the forward-solved formulation of the Phillips curve (as in Hazell et al. (2022)) suggests that there is only little room for a steeper Phillips curve in the EA since long run inflation expectations feed strongly into current inflation. Again, this is a similar observation compared to the US.

Figure 3.5 plots various measures of inflation and inflation expectations. The top left panel of Figure 3.5 plots headline inflation and professional inflation expectations and the top right panel plots headline inflation and consumer inflation expectations. The bottom left panel plots core inflation and professional inflation expectations while the bottom right panel plots headline inflation (excl. tobacco) and market-based inflation expectations based on the inflation-linked swap rate one-year ahead. A number of observations stand out. Evidently, the size of the inflation gap, that is the difference between inflation and expected inflation, depends on the measure of inflation expectations. While the gap is relatively small for professional and market-based inflation expectations, it is quite large when using household inflation expectations. This is in line with recent findings by D'Acunto et al. (2022) who show that household inflation expectations are generally upward biased. The gap only became larger also for professional inflation expectations in late 2021 when the supply chain shock induced by the Covid-19 pandemic finally resulted

Figure 3.4: Core inflation and long run inflation expectations



Note: Inflation is the year-on-year change in the core HICP (excluding food, energy, tobacco and alcohol) at monthly frequency for the euro area aggregate expressed in percent. Expected inflation is the 5-year ahead mean forecast of the SPF conducted by the ECB measured in percent.

in price increases. Still, professional forecasters' expectations were sluggish to adjust. This observation suggests that estimates of the slope of the aggregate Phillips curve may strongly depend on the measure of expectations used, ultimately leading to wrong conclusions also pointed out by Hazell et al. (2022) for the US. We also observe that professional forecasters track core inflation more closely than headline inflation while consumers rather focus on headline inflation including food and energy prices, that is consumption goods of daily life. Moreover, households overstate inflation strongly. This may again blur conclusions derived from the estimation of the aggregate Phillips curve. Finally, a key take away from Figure 3.5 is that the inflation gap between realized and expected inflation is rather small throughout the sample (except for consumer inflation expectations) although unemployment rates in the euro area were high at times across some member states (cp. Figure 3.2). Again, this suggests that the Phillips curve is rather flat.

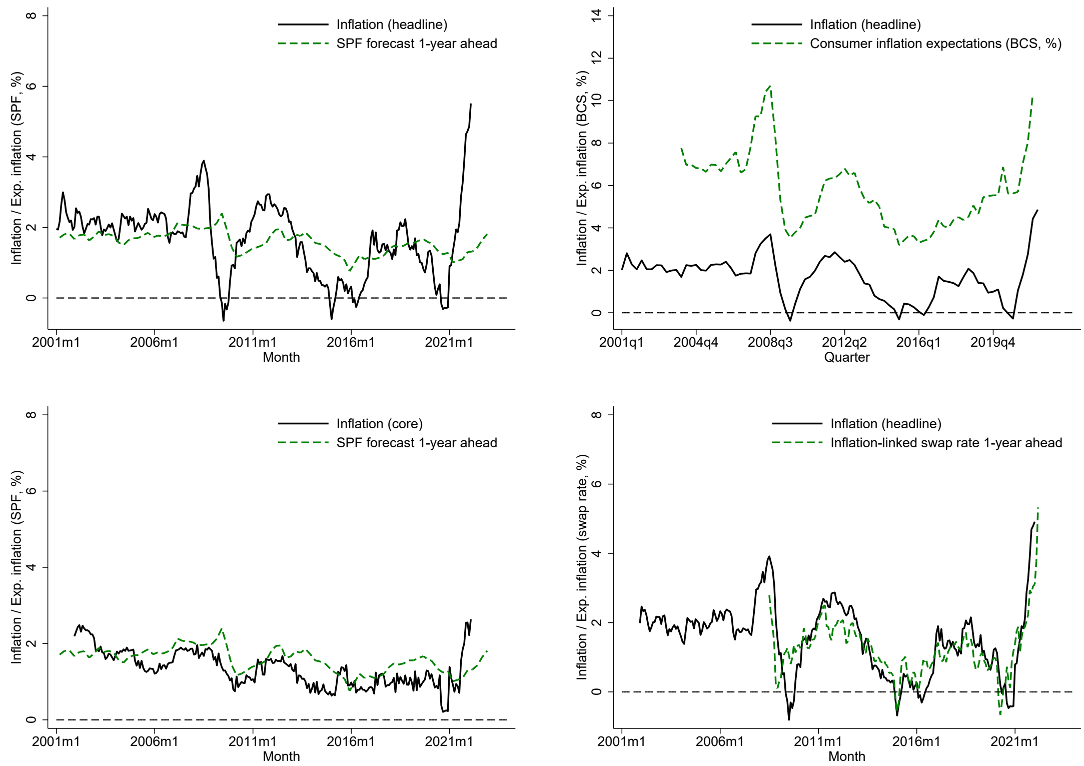
3.4 The slope of the regional Phillips curve in the EA

We start out this section by presenting the empirical specifications that we estimate to determine the slope of the regional Phillips curve. Next, we present our results and discuss robustness checks with respect to the methodology on the fly. Finally, we estimate a specification of the aggregate Phillips curve using several direct measures of inflation expectations and compare our results.

3.4.1 The empirical specification of the regional Phillips curve

In Section 3.2 we have summarized the derivation of the regional and aggregate Phillips curve within a basic New Keynesian model. Of course, equation (3.4) is not suitable for direct estimation using country-level data. Hence, Hazell et al. (2022) propose to replace

Figure 3.5: Inflation and different measures of expected inflation



Note: Headline (core) inflation is the year-on-year change in overall HICP (excluding food and energy) at monthly frequency expressed in percent. Top: Left panel shows expected inflation measured by one-year ahead mean forecast of the SPF in percent. Right panel shows expected consumer inflation over the next year in percent. Bottom: Left panel shows core inflation and one-year ahead professional inflation expectations. Right panel shows 12-month headline inflation (excl. tobacco) and inflation-linked swap rate one-year ahead. All time series refer to the EA aggregate. Data source: ECB, Eurostat, EC, Refinitiv via Datastream.

the expected infinite sums of future employment and the relative price of non-tradeable goods with realized values truncated at $j = T$. This results in the following equation:

$$\pi_{it}^N = -\sum_{j=0}^{T} \beta^j \kappa u_{i,t+j} - \lambda \sum_{j=0}^{T} \beta^j \hat{p}_{i,t+j}^N + \alpha_i + \gamma_t + \tilde{\omega}_{i,t}^N + \eta_{i,t}^N \tag{3.6}$$

Again, α_i and γ_t denote country- and time-fixed effects, $\tilde{\omega}_{i,t}^N$ denotes a sequence of discounted supply shocks and $\eta_{i,t}^N$ denotes an expectation and truncation error term. This empirical specification of the model-derived regional Phillips curve can be estimated in principal using GMM methods by instrumenting for the expected future sums. Hazell et al. (2022) assume β to be 0.99 in the baseline specification. Furthermore, regarding the identification of supply shocks $\tilde{\omega}_{i,t}^N$, Hazell et al. (2022) argue that supply shocks in the tradable goods sector in one region are not systematically correlated with supply shocks to the non-tradable sector in another region.[16] Also, as indicated above, supply shocks common to the monetary union are absorbed by time-fixed effects. Only region-specific supply shocks to the non-tradeable sector are potential confounders.

Hazell et al. (2022) propose two identification strategies to estimate equation (3.6). First, they suggest to instrument for each of the forward sums in equation (3.6) with the four-quarter lagged values of unemployment $u_{i,t}$ and the relative price $\hat{p}^N_{i,t+j}$, itself. They argue that because of the assumption of rational expectations, lagged variables are uncorrelated with the expectations error. Regarding the practical implementation, this means that in the first stage we will truncate the infinite sums at a value of $T = 20$ quarters (following Hazell et al. (2022)) and then regress each one of them on the four-quarter lagged value of unemployment and the relative price including time- and country-fixed effects.[17]. Importantly, due to the truncation of the forward sums at $T = 20$ months, one looses 5 years of observations at the end of the sample.[18] This means the first stage is only estimated on a reduced sample.[19] Standard errors are clustered at the country level and corrected using the correction method of Chodorow-Reich and Wieland (2020) (because of the two-sample 2SLS estimation). In the second stage, we regress four-quarter country-level non-tradable inflation over the previous year on the predicted values for the two forward sums from the first stage regression and country- and time-fixed effects. In this way, measurement errors and seasonality are eliminated. Hazell et al. (2022) argue that using year-on-year inflation compared to quarterly inflation, as defined in the theoretical derivation, implies that estimates of κ have to be divided by four in order to account for time aggregation.[20] We follow this practice here.

The second approach of Hazell et al. (2022) to identify the slope of the regional Phillips curve is to construct an instrumental variable that captures differentiated labor demand in the tradable and non-tradable goods sector across the monetary union.[21] This "tradable-demand spillovers" instrument $Z_{i,t}$ is defined as

$$Z_{i,t} = \sum_x [\bar{S}_{x,i} \times \Delta_{3Y} \log S_{-i,x,t}] \tag{3.7}$$

where $\bar{S}_x, i$ is the average employment share of industry x in country i over time and $\Delta_{3Y} \log S_{-i,x,t}$ is the three-year growth rate in union-wide employment of industry x at time t excluding country i. The identifying assumption is that there are no supply factors that are both correlated with the shifts in $\Delta_{3Y} \log S_{-i,x,t}$ and the average employment

[16]Consider, for example, an energy supply shock in Germany relative to Spain, which is not systematically correlated with changes in hairdresser technology in Spain relative to Germany.

[17]For the matter of illustrating the impact and robustness of their theoretical results regarding the inclusion of fixed effects, they include time- and region-fixed effects consecutively. We will follow this practice here.

[18]Hazell et al. (2022) verify their choice of the truncation length by estimating equation (3.6) on simulated data. In addition to that, they do robustness tests using different values for T. We follow this practice, see below.

[19]Conversely, for the second stage we follow Hazell et al. (2022) and use the whole sample to obtain estimates of κ and λ.

[20]Compare their appendix A.11.

[21]In setting up the instrument, Hazell et al. (2022) follow Bartik (1991).

share $\bar{S}_{x,i}$ in the cross-section.[22] Practically, we will proceed similar to the first approach outlined above: In the first stage regression, we instrument the truncated forward sums with the four-quarter lagged tradable-demand instrument and the four-quarter lagged relative price of non-tradables. Again, this can only be estimated on a reduced sample because of the truncation of the forward sums at $T = 20$ quarters. Then, in the second stage, we regress year-on-year country-level non-tradable inflation on the predicted values from the first stage including country- and time-fixed effects based on the whole sample.[23]. Standard errors are again clustered at the country-level and corrected for sample-size adjustments as in Chodorow-Reich and Wieland (2020).

In addition, Hazell et al. (2022) also provide an empirical specification of the recently developed and more tractable definition of the regional Phillips curve, that is equation (3.5):

$$\pi_{it}^N = \alpha_i + \gamma_t - \psi u_{i,t-4} - \delta p_{i,t-4}^N + \varepsilon_i t \tag{3.8}$$

In estimating equation (3.8) we follow Hazell et al. (2022) and use OLS to regress year-on-year non-tradable inflation on four-quarter lagged unemployment and the four-quarter lagged relative price of non-tradable goods. Secondly, again, we use the tradeable demand instrument described in equation (3.7) and instrument for lagged unemployment.

3.4.2 Baseline results

We estimate the empirical specifications (3.6) and (3.8) of the regional Phillips curve by two-sample 2SLS and apply the correction method of Chodorow-Reich and Wieland (2020) to the standard errors clustered at the country-level to adjust for varying sample size. We include country- and time-fixed effects consecutively in the estimation. The data is in quarterly frequency and the sample runs from 2001Q to 2021Q4. We include all EA19 countries and follow the classification of Ilzetzki et al. (2019) and Corsetti et al. (2021) when including observations for countries having joined the EA after its initial formation.[24]

Table 3.1 summarizes the baseline results from estimating the regional Phillips curve specifications (3.6) and (3.8). We start by summarizing the results obtained for the structural slope coefficient κ shown in the top panel. First, consistently across specifications, we observe that the slope coefficient has the correct sign: when unemployment

[22]To give an example, when costs increase as a result of an increase in energy prices (which is the case across the whole Euro area as a result of the war in the Ukraine) but these increases are on average the same in Spain compared to Germany, then these cost increases will be uncorrelated with the instrument.

[23]This procedure follows again the two-sample 2SLS estimation put forward by Chodorow-Reich and Wieland (2020) and implemented by Hazell et al. (2022).

[24]Corsetti et al. (2021) provide an exchange rate classification based on the coding of Ilzetzki et al. (2019) for all EA19 members. When setting up this classification, they argue that in fact new members already had a peg to the euro before joining the currency union officially, see Table 1 in their paper and the online appendix. Consequently, these countries' monetary policy was not independent but rather guided by the ECB. We build on this argument and include new members before their actual accession given the national currency was pegged to the euro.

Table 3.1: The slope of the regional Phillips curve in the EA

	Lagged Unemployment			Tradable Demand IV
	(1)	(2)	(3)	(4)
Estimates of κ from equation (3.6)				
κ	0.0024**	0.0072**	0.0031	0.0043**
	(0.0009)	(0.0031)	(0.0019)	(0.0018)
N	1346	1346	1346	842
Estimates of ψ from equation (3.8)				
ψ	0.0782**	0.1208*	0.0927**	−0.9939
	(0.0334)	(0.0450)	(0.0397)	(1.3264)
N	1526	1526	1526	1022
Country FE	no	yes	yes	yes
Time FE	no	no	yes	yes

Note: Table shows estimates of equation (3.6) and (3.8). The dependent variable is year-on-year non-tradable inflation measured in percentage points. In column (1) to (3) of the top panel the regressors are the discounted future sum of unemployment in percentage points and the relative price of nontradables in 100 × log points. In column (4) we instrument the discounted sum of future unemployment by the tradable demand instrument according to equation (3.7). In column (1) to (3) of the bottom panel the regressors are the fourth lag of unemployment and the relative price of non-tradables. Country- and time-fixed effects are included according to the bottom two rows. Standard errors are reported in parentheses and clustered at the country level. * p<0.10, ** p<0.05, *** p<0.01.

increases, inflation goes down.[25] Moreover, we consistently observe that the slope of the regional Phillips curve is indeed very small but mostly significant. However, we also notice that the size of the coefficient varies strongly across specifications regarding the inclusion of fixed effects and the choice of the instrument. We start by considering the first three columns. While the coefficient is significant when not including fixed effects and including only country-fixed effects it is not significant when including both types of fixed effects. Moreover, it halves in size and is closer to the estimated coefficient excluding fixed effects completely. This result casts some doubts whether one of the main features of this new approach to estimate the Phillips curve, namely the elimination of long-run inflation expectations by means of time-fixed effects applies to the EA. Comparing only columns (2) and (3), it does not seem to be the case. However, it might also be that using the truncated discounted future sum of unemployment as instrument is not a good choice, as column (4) illustrates. When including the tradable demand instrument, the estimated coefficient is significant and lies in the middle of the estimated coefficients excluding time-fixed effects. Hence, while excluding fixed effects understates the slope of the Phillips curve, only including country-fixed effects overstates it. Only when including both types of fixed effects and relying on the tradable demand instrument we obtain

[25] Recall that the sign of the structural parameter κ in equation (3.4) is negative. For ease of interpretation of the empirical result, we multiplied inflation by (-1) when estimating equation (3.6). In this way, we followed the practice of Hazell et al. (2022).

a more accurate estimate of the size of the slope. Overall, the small values for the estimated slope coefficients are consistent with the notion that the response of inflation to movements was rather insensitive over the last two decades although unemployment varied a lot for some member states, see Figure 3.2. Still, our results show that the Phillips curve itself is flat but stable contrary to what many critics have argued.

To illustrate that our estimates do not suffer from weak instruments, we present results of the first stage regressions for the discounted future sum of unemyployment and the relative price of non-tradables in Table A.1. As we observe in the top panel, lagged unemployment and tradable demand strongly predict the present value of unemployment while the lagged relative price does not. For the present value of the relative price of non-tradables roughly the opposite holds true, as expected. The lagged relative price has a strong predictive power while lagged unemployment only weakly predicts the discounted future sum of the relative price of non-tradables. Moreover, the tradable demand instrument does not significantly predict the relative price. From these observations we conclude that all three variables are appropriate choices of instruments.

Table A.2 shows the estimates for λ, that is the coefficient on the relative price of non-tradable goods in equation (3.6). Here, we consistently observe that the coefficients are close to zero or even zero depending on the choice of fixed effects. These result indicate that prices in the euro area are very rigid, which has been documented before (Dhyne et al. 2006, e.g.) and is comparable to the findings for the US, see Hazell et al. (2022). It also squares with the empirical finding that the slope of the regional Phillips curve is very flat in the EA. Consistent with the theoretical model, a small value of λ indicates a high degree of price stickiness and thus leads to a small slope parameter κ.

Regarding the methodology proposed in Section 3.2, there are two robustness checks in order. First, we want to point to the choice of the value of the discount factor β which impacts the slope of the Phillips curve through the instrumented forward sums of unemployment and the relative price of non-tradables. Intuitively, the smaller the value for β the more emphasis firms put on the present compared to the future when setting their price. We show results both for using the truncated sum of future unemployment as well as tradable demand as instrument in Table A.3 in the appendix. We find that the value of κ increases as the value of β decreases. It even triples in size when we move from $\beta = 0.99$ to $\beta = 0.90$. This effect is even larger compared to findings for the US were the slope coefficient only doubles. This indicates that prices adjust even more sluggish in the EA compared to the US (Dhyne et al. 2006, cp.). Still, in absolute terms the estimated slope coefficients are still small and thus the Phillips curve appears flat.

In addition, we vary the choice of the truncation length T from 20 to 30 when computing the discounted forward sums of unemployment and the relative price of non-tradables.[26] Again, we show results for both choices of instruments in Table A.4 in the appendix. We find that in case of using the tradable demand instrument the results are stable across the choice of the truncation length. This is in line with results for the

[26]In contrast to Hazell et al. (2022) we did not extend T to 40 because the sample for the EA is considerably shorter compared to the US sample.

US. For lagged unemployment, the results are a bit mixed but still not significant.

Let us now turn to estimates of ψ based on equation (3.8), see bottom panel of Table 3.1. A robust finding across the specifications in column (1) to (3) is that the slope parameter of the Phillips curve is significantly negative and substantially larger in absolute terms compared to the estimates for κ. This result is reasonable, as Hazell et al. (2022) argue, because unemployment is quite persistent over time and since the variation in the future sum of unemployment is greater than in unemployment itself, also the estimate of ψ should be larger than the estimate of κ. Another consistent finding is that the specification without fixed effects again underestimates the slope while the specification including only country-fixed effects again overestimates the slope. The estimate including both types of fixed effects reconciles the results. Overall, based on these estimates of ψ one would conclude that the Phillips curve is steeper than it actually is, as predicted by Hazell et al. (2022). In contrast to the top panel, we observe that using the tradable demand instrument for identifying the slope in this specification does not show consistent results. The coefficient has the opposite sign contrary to what we expect and is not statistically significant. Hence, when estimating the reduced-form specification of the Phillips curve, the tradable demand instrument seems not to be a good choice for identification.

As we are heavily drawing on the methodology proposed originally by Hazell et al. (2022), we want to compare their results to ours for the EA. Regarding the estimates of κ, we find that overall the results are in a very similar ballpark. Both in the US and the EA the slope coefficients of the Phillips curve are significantly negative and rather small. Comparing their preferred specification using the tradable demand instrument, they find a value for κ of 0.0062 based on the whole sample while we find a value of 0.0043. When they estimate the model on the post-1990 period only, which makes the sample more comparable to ours, they find an even lower value, namely 0.0055. Hence, in both currency unions the Phillips curve is flat but robustly stable over the last two to three decades. Still, we want to mention that their results are invariant to the choice of the instrument (truncated forward sum of unemployment versus tradable demand) while our results are more convincing based on the tradable demand instrument. Regarding the estimates of the reduced-form coefficient ψ, they also obtain consistently larger estimates compared to κ, even much larger compared to ours. However, they do not find discrepancies across the choice of the instrument. Overall, it seems fair to say that the results we obtain are in line with those of Hazell et al. (2022) for the US and the relation between inflation and unemployment does not differ greatly across the monetary unions.

3.4.3 Comparison with aggregate Phillips curve estimates

As we mentioned in the introduction, the current literature on estimating the Phillips curve for the EA relies on aggregate data and uses direct measures of inflation expectations to identify the slope of the Phillips curve. Frequently applied measures of expected inflation are based on household or professional forecaster surveys or even market-based

Table 3.2: The slope of the aggregate Phillips curve using different measures of inflation expectations

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
κ	0.1925***	−0.0668	0.2096***	0.3812***	0.0971	0.1822***	0.2213***
	(0.0575)	(0.0571)	(0.0650)	(0.0550)	(0.0650)	(0.0681)	(0.0586)
N	88	72	89	78	54	54	33

Note: Table presents estimates of equation (3.9). Model (1) uses a moving average of past 4-quarter inflation to proxy adaptive expectations. Model (2) uses one-year ahead consumer inflation expectations from the BCS. Models (3) and (4) use 12-months and 60-months ahead professional inflation expectations from the SPF. Model (5) - (7) use 12-months ahead, 60-months ahead and 1-year-1-year-forward market-based inflation expectations derived from inflation-linked swaps. Standard errors are reported in parentheses and clustered at the country level. * p<0.10, ** p<0.05, *** p<0.01.

using inflation-linked swaps. In the final part of the chapter we now want to compare our results for estimating the regional Phillips curve with "traditional" estimates based on aggregate time series. Therefore, we present our own estimates for a specification of the aggregate Phillips curve or rather the NKPC and compare them to our results summarized in Section 3.4 as well as recent findings in the literature. Following Coibion and Gorodnichenko (2015b), we estimate the following equation:

$$\pi_t = \beta E_t^i(\pi_{t+h}) + \kappa u_t + \varepsilon_t. \tag{3.9}$$

Here, π_t measures year-on-year *headline* inflation at time t, u_t is the unemployment rate at time t and ε_t is the error term. $E_t^i(\pi_{t+h})$ is expected inflation over the horizon h and i denotes the type of direct measure of inflation expectations applied. Specifically, we rely on 4 different types of measures. First, we use adaptive expectations which implies that the best proxy for next quarter's inflation rate is a measure of past inflation. Formally, we use a moving average of past 4-quarter inflation. Next, we use consumer inflation expectations of the BCS and professional forecasters' inflation expectations as described in Section 3.3.3. More precisely, household expectations only extend over the next 12 months, that is $h = 1$ year, while we have a short-term ($h = 1$) and a longer-term ($h = 5$) measure available from the SPF. Lastly, we consider three different measures of inflation expectations based on inflation-linked swaps. We include inflation expectations 1- and 5-years ahead based on spot swap rates and 2-years ahead based on a forward inflation-linked swap. For details on the derivation, we refer to Section 3.3.3.

We present results for κ in Table 3.2.[27] Consistently across specifications, except for (2) where we use consumer inflation expectations, the estimated slope coefficient has the expected sign and is statistically significant. However, we observe that the absolute values of the estimated coefficients are substantially larger compared to the results for κ in Table 3.1. The estimated slope coefficients vary between 0.0971 and 0.3812 depending

[27]To make results comparable with Table 3.1, again we multiplied the inflation rate by (-1) when we estimated equation (3.9).

on the choice of inflation expectations. These values square with the descriptive evidence presented in the left panel of Figure 3.3 where the slope coefficient of the fitted line is 0.1341 in absolute terms. Hence, when using aggregate data, one can get the impression that the slope of the Phillips curve is much steeper compared to estimates using cross-sectional data. We also note that the further ahead inflation expectations reach into the future the larger the estimated coefficient. It roughly doubles in size between one- and five-years ahead into the future. Moreover, the slope is consistently larger across horizons for professional forecasters' expectations compared to market-based expectations. This fits evidence shown in Figure 3.5: market-based expectations follow actual headline inflation most closely, even closer than professional forecaster' expectations, which leads to smaller inflation gaps. Finally, we observe that estimates of κ presented in Table 3.2 exceed estimates of ψ shown in Table 3.1 at least by a factor of two or even three. Altogether, these findings building on aggregate euro area data coincide with several concerns raised in the literature. First, taking an isolated look at Table 3.2, aggregate estimates are quite sensible to the choice of specification, especially with respect to the measure of inflation expectations, a fact already pointed out by Mavroeidis et al. (2014). Depending on the choice of inflation expectations, estimates may be up to three times larger. Hence, direct (survey) measures of inflation expectations may not be as informative as one might assume when estimating the Phillips curve. Hazell et al. (2022) raise a second concern referring to the use of longer-term aggregate expectation measures. They argue that using longer-term expectations instead of one-year ahead expectations (as is the case in our specifications (4), (6) and (7)) one may end up estimating ψ instead of κ and therefore obtain larger estimates. This concern squares with our empirical findings presented in Table 3.2. When we proxy for longer-term expectations, say two- or five-years ahead, estimates become substantially larger. They even exceed estimated values of ψ. Only when one translates estimates from ψ to κ, for example using $\psi = \frac{\kappa}{1-\beta\rho_u}$ aggregate and regional estimates of κ are comparable (Hazell et al. 2022).

Lastly, we compare our results shown in Table 3.1 and 3.2 with the most recent literature estimating Phillips curves using mostly aggregate data for the euro area.[28] Table 3.3 shows the estimated coefficients in recently published studies. At first glance, we observe that the variation in the reported coefficients is quite sizable, ranging from 0.07 to 0.63 which exceeds by far the results we obtain when we estimate an aggregate Phillips curve using different measures of inflation expectations. This finding is not surprising: after all, the slope of the estimated slope parameter depends strongly on the model specification and thus large differences in estimates are likely (Mavroeidis et al. 2014, c.p).

The slope coefficient estimated by Eser et al. (2020) is most close to our estimate of the regional Phillips curve. Interestingly, they estimate an aggregate Phillips curve using a measure of adaptive expectations and pooled country-level data for 18 euro area

[28]We focus our comparison here on the literature that also uses the unemployment rate or gap respectively as measure of economic slack. However, there exists yet another related strand of the literature that use (estimates of) the output gap in the empirical analysis of the Phillips curve (Ball and Mazumder 2020; Oinonen and Vilmi 2021; Passamani et al. 2021, c.p.).

Table 3.3: Estimates of the aggregate Phillips curve - a comparison w/ the literature

Source	Estimated Coefficient
Amberger and Fendel (2017)	0.1010 (0.0445)
Bobeica and Sokol (2019)	0.075 (-)
Eser et al. (2020)	0.0100 (0.0000)
Hindrayanto et al. (2019)	0.6300 (0.2986)
Kulikov and Reigl (2020)	0.1359 (0.0591)
Moretti et al. (2019)	0.07 (-)

Note: absolute values of estimated coefficients are reported to ensure comparability with results reported in Table 3.2. Standard errors reported in parenthesis (not for Bobeica and Sokol (2019) and Moretti et al. (2019) because they provide the median of estimates of thick modelling approaches).)

member states for identification. This coherence shows that building on cross-sectional data to estimate a Phillips curve in a monetary union can significantly change results and contributes to a better understanding of the relationship between inflation and unemployment during a decade of low inflation. Seemingly, the Phillips curve is not dead as people have argued (Hall 2013) but has rather become quite flat but stable over the last years.

Bobeica and Sokol (2019) and Moretti et al. (2019) both find somewhat smaller estimates for the aggregate Phillips curve. However, they both employ a thick-modelling estimation strategy by which they estimate a large number of different specifications and then report the median value for the slope coefficient. Thereby, they alleviate concerns of misspecification for example regarding the choice of inflation expectations. In this way, estimates become closer to the regional Phillips curve which does not rely on explicit measures of expected inflation.[29] Kulikov and Reigl (2020) estimate amongst other things also an aggregate Phillips curve including SPF inflation expectations one-year ahead. Their coefficient of 0.1359 is comparable to our coefficient shown in column (3) of Table 3.2. Lastly, Amberger and Fendel (2017) estimate a hybrid NKPC using professional inflation expectations from Consensus Economics and find a slope coefficient of 0.1010. This value is again smaller than ours, however, they only include the core EA members which leads to different conclusions. Overall, the recent literature finds much larger estimates of the slope of the aggregate Phillips curve, like us, and exceeds by far results based on the regional Phillips curve that we find for the EA using country-level data.

3.5 Conclusion

In this chapter we ask whether the Phillips curve trade-off between inflation and unemployment still exists in the euro area. In this context, we analyze whether country-level data of EA member states can provide new insights into the Phillips curve and how our new findings based on a refined methodological approach relate to the recent literature

[29]Kulikov and Reigl (2020) come up with similar estimation results for their thick modelling approach which are not reported here.

estimating the Phillips curve using aggregate data. To answer these questions, we rely on a new model of a *regional* Phillips curve developed by Hazell et al. (2022). In their spirit, we set up a non-tradable goods price index to measure inflation and estimate the regional Phillips curve on country-level data for the EA member states covering the period from 2001 to 2021. In addition, we compare our findings for the regional Phillips curve with results that we obtain from estimating the aggregate Phillips curve deploying different measures of inflation expectations. Lastly, we discuss these findings with respect to the recent related literature.

We find that the Phillips curve is indeed flat but stable in the EA since the introduction of the common currency. Estimates of the slope of the regional Phillips curve are much smaller compared to estimates we obtain using aggregate data and several measures of inflation expectations. Our results coincide with findings for the US reported by Hazell et al. (2022). Overall, these findings explain the observed insensitivity of inflation to the increase in unemployment after the financial and sovereign debt crisis in the EA and the subsequent missing inflation in the late 2010s when unemployment came down to low levels across the monetary union. Hence, by drawing on country-level data and a new methodological approach to estimate the Phillips curve we can confirm that it still exists but is rather flat in the EA contrary to what aggregate estimates would suggest.

What are the policy implications of a stable but flat Phillips curve? In the face of rapidly increasing inflation in the EA, an urgent question is how the ECB should act to bring down inflation again. If one trusts our findings in this chapter, and what Hazell et al. (2022) have found for the US, the Phillips curve in the EA is by no means as steep as people have been thinking based on estimates from aggregate data. Instead, it is flat. Hence, massively and rapidly increasing interest rates will not do the job. On the contrary, its flatness implies that sharp changes in inflation can only arise from changes in expectations or cost-push shocks inducing shifts in the Phillips curve. Hence, the management of long-term inflation expectations by the ECB, which rests strongly on its credibility, is crucial. Only when the ECB signals decisiveness to bring down inflation, long-term inflation expectations stay anchored. In this way, the Phillips curve stabilizes (or shifts back down) with disinflation at no or only small costs of unemployment.[30] However, the ECB has initially been reluctant to undertake actions, not least because there are a number of obstacles the ECB is facing in doing so.[31] It remains to be seen whether it has acted decisive enough just in time to ensure stable inflation expectations bringing inflation back to target.

[30]For a thorough discussion of this intuition in case of the US, see Steinsson (2022).

[31]For a discussion of these obstacles, see a recent commentary by Reis (2022).

3.A Data appendix

Here, we list the 4-digit-level ECOICOP subcomponents of the HICP from Eurostat that we include in constructing the non-tradable price index. Thereby, we closely follow Hazell et al. (2022) to make results presented in Section 3.4.2 comparable to results for the US.[32]. Additionally, Table A.1 lists all variables and data sources used in the empirical analysis.

- Education services
  - Pre-primary and primary education
  - Secondary education
  - Post-secondary non tertiary education
  - Tertiary education
  - Education not definable by level
- Telephone services
  - Postal services
  - Telephone and telefax services
- Food away from home
  - Restaurants, cafés and the like
  - Canteens
- Other personal services
  - Hair dressing salons and personal grooming establishments
  - Cleaning repairing and hire of clothing
  - Repair and hire of footware
  - Repair of jewellery, clocks and watches
  - Other financial services
  - Other services n.e.c.
- Housing services
  - Accommodation services
  - Insurance connected with dwelling
  - Electricity
  - Water supply
  - Refuse collection

[32]A detailed mapping of the classification of Hazell et al. (2022) into the classification for the EA and the 4-digit ECOICOP codes are available upon request.

- Sewage collection
- Other services relating to the dwelling
- Repair of household appliances
- Repair of furnitures, furnishing and floor coverings
- Services for the maintenance and repair of the dwelling

• Medical services

- Medical services
- Dental services
- Paramedical services
- Hospital services
- Social protection

• Recreational services

- Cultural services
- Recording media
- Repair of audiovisual, photographic and information processing equipment
- Veterinary and other services for pets
- Recreational and sporting services
- Maintenance and repair of other major durables for recreation and culture

• Transportation services

- Passenger transport by road
- Passenger transport by railway
- Passenger transport by sea and inland waterway
- Other purchased transport service
- Insurance connected with transport
- Maintenance and repair of personal transport service
- Other services in respect of personal transport equipment

Table A.1: Variables and data sources

Variable	Description	Source
p_t^N	Non-tradable goods price index, own calculations. For details, see Section 3.3.1	Eurostat
p_t^T	Tradable goods price index, own calculations. For details, see Section 3.3.1	Eurostat
p_t	Headline harmonized index of consumer prices (HICP)	Eurostat
π_t^N	Inflation in non-tradable goods, own calculations	
π_t	Headline inflation, own calculations	
u_t	Unemployment rate, for details see Section 3.3.2	ECB
S_t	Employment shares in NACE rev.2 sectors A and B-E, own calculations see Section 3.3.2	Eurostat
NAIRU	Non-accelerating inflation rate of unemployment	OECD
$E\pi_t^{SPF}$	Professional inflation expectations from SPF one-, two-, and five years ahead, for details see Section 3.3.3	ECB SPF
$E\pi_t^{BCS}$	Consumer inflation expectations from BCS one year ahead, for details see Section 3.3.3	European Commission BCS
$E\pi_t^{M}$	Market-based inflation expectations based on inflation-linked swap rates, for details see Section 3.3.3	Refinitiv Eikon Datastream

3.B Additional tables

Table A.1: First stage regression results for estimates of κ in equation (3.6)

	(1)	(2)	(3)	(4)
Future sum of unemployment				
Lagged unemployment	11.9588***	5.1568**	5.9934***	
	(1.8388)	(1.3361)	(1.9190)	
Lagged relative price	0.0531	−0.0278	−0.0947	0.0048
	(0.0455)	(0.0644)	(0.1695)	(0.1059)
Lagged tradeable demand				0.0237**
				(0.0087)
N	1123	1123	1123	619
Future sum of relative price of non-tradeables				
Lagged unemployment	25.2500	110.5610**	40.5619**	
	(25.3892)	(39.0243)	(18.8976)	
Lagged relative price	18.1915***	20.5452***	3.2838**	−1.7811***
	(1.5160)	(1.9777)	(1.4140)	(0.5814)
Lagged tradeable demand				−0.0323
				(0.1207)
N	822	822	822	335
Country FE	no	yes	yes	yes
Time FE	no	no	yes	yes

Note: Table presents estimates of the first stage regression in equation (3.6). For details, see notes of Table 3.1. Country- and time-fixed effects are included according to the bottom two rows. Standard errors are reported in parentheses and clustered at the country level. * p<0.10, ** p<0.05, *** p<0.01.

Table A.2: Estimates of λ from equation (3.6)

	Lagged Unemployment			Tradable Demand IV
	(1)	(2)	(3)	(4)
λ	0.0000*	0.0000**	0.0006***	−0.0004**
	(0.0000)	(0.0000)	(0.0002)	(0.0002)
N	1346	1346	1346	842
Country FE	no	yes	yes	yes
Time FE	no	no	yes	yes

Note: Table presents estimates of λ from regression (3.6). For details, see notes of Table 3.1. Country- and time-fixed effects are included according to the bottom two rows. Standard errors are reported in parentheses and clustered at the country level. * p<0.10, ** p<0.05, *** p<0.01.

Table A.3: Estimates of κ as β varies

	Lagged Unemployment			Tradable Demand IV		
	$\beta = 0.99$	$\beta = 0.95$	$\beta = 0.90$	$\beta = 0.99$	$\beta = 0.95$	$\beta = 0.90$
κ	0.0031	0.0061**	0.0097**	0.0043**	0.0025	0.0148**
	(0.0019)	(0.0027)	(0.0036)	(0.0018)	(0.0034)	(0.0066)
N	1346	1346	1346	842	842	842

Note: Table presents estimates of regression specifications (3.6) for varying values of β. For details, see notes of Table 3.1. Country- and time-fixed effects are included in all regressions. Standard errors are reported in parentheses and clustered at the country level. * p<0.10, ** p<0.05, *** p<0.01.

Table A.4: Estimates of κ as the truncation length T varies

	Lagged Unemployment			Tradable Demand IV		
	$T = 20$	$T = 25$	$T = 30$	$T = 20$	$T = 25$	$T = 30$
κ	0.0031	0.0014	−0.0017	0.0043**	0.0061**	0.0053***
	(0.0019)	(0.0015)	(0.0013)	(0.0018)	(0.0022)	(0.0016)
N	1346	1346	1346	842	842	842

Note: Table presents estimates of regression specifications (3.6) for varying truncation lengths T. For details, see notes of Table 3.1. Country- and time-fixed effects are included in all regressions. Standard errors are reported in parentheses and clustered at the country level. * p<0.10, ** p<0.05, *** p<0.01.

Conclusion

This dissertation analyzes three distinct new macroeconomic realities that have come to the fore in particular in the aftermath of the financial crisis of 2007/2008: the development of sovereign bond spreads in advanced and emerging economies, migration as a channel of risk sharing in currency unions to insure consumption fluctuations over the business cycle, and the trade-off between inflation and unemployment during times of particularly low inflation. By analyzing these issues, this dissertation hopefully equips policy makers with the necessary understanding to make appropriate monetary and fiscal policy decisions.

In Chapter 1 we have examined whether country spreads behave differently in emerging and advanced economies in particular before and after the financial crisis. Our results show that we can confirm this hypothesis for the time period before 2008 as expected. However, after 2008 this is no longer the case: Spreads of advanced and emerging economies have converged, largely because spreads in advanced economies have caught up to the same level. Moreover, we analyzed the transmission of spread shocks and find it is quite comparable in advanced and emerging economies, also before and after the financial crisis.

In Chapter 2 we extent a well-known methodological framework to analyze the role of migration as a channel of risk sharing in the two most important currency unions: the US and the EA. Our results show that there is in general more risk sharing among US states than among member countries of the EA. Moreover, we find that migration smooths almost one quarter of output fluctuations in the US. On the contrary, the migration channel is not operative in the EA. These results square with the descriptive evidence showing that migration rates are about 15 times higher in the US than in the EA.

Chapter 3 deals with the Phillips curve and asks whether the trade-off between inflation and unemployment still exists in the EA. Based on a refined methodological approach, we examine whether country-level data can provide new insights into this relationship. Our results indicate that the Phillips curve is indeed flat but stable in the EA based on a sample starting with the introduction of the common currency. Estimates are actually smaller compared to estimates based on aggregate data. These findings square with evidence for the US reported in the recent literature.

What are the policy implications that we can draw from the analyses that have been conducted within this dissertation? First, based on Chapter 1, we claim that advanced economies are now more vulnerable to market evaluation regarding economic fundamentals. Policy makers should take this into account for their own sake. Second, inferring from Chapter 2, we argue that labor migration as a channel of risk sharing can in fact work, as evidence for the US shows. Thus, policy makers should put more emphasis on promoting labor migration in the EA, not least because other channels working through capital markets are not operative in the EA despite strong efforts to encourage these mechanisms. Third, drawing on the results of Chapter 3, it appears that the conventional approach to lower inflation by means of raising interest rates and thus induce an increase in unemployment is not an option for policy making given a flat Phillips curve. Hence, we follow the recent literature analysing US inflation and propose to focus policy actions on the management of expectations and the safeguarding of the credibility of the central bank to bring down inflation without an extensive recession.

Hopefully the conclusions presented in this dissertation can contribute to future research and put some more clarity on highly relevant economic developments that have an impact on people across the globe.

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