The Compensation-Productivity Divide in the Euro Area: a Time-Varying approach*

Elena Bobeica † Eliza Lis ‡ Maria Sole Pagliari §

June 14, 2019
PRELIMINARY DRAFT

Abstract

Over the last decades, despite rising labor productivity in advanced economies, wages have not kept up at the same pace. This has also been the case in the Euro Area, where the decoupling between productivity and compensation growth has become more evident after the entry into force of the Maastricht Treaty, a coincidence that has got attention both in academia and policy circles. Our paper contributes to the ongoing debate by, first, providing anecdotal evidence on the existing gap between compensation and productivity growth, and, then, using static and time-varying econometric techniques to assess how extensively this phenomenon has affected the economies in the euro zone. Our results suggest that both the aggregate Euro Area and its four biggest economies have experienced a significant decrease in the pass-through of productivity on to compensation, such decoupling being a rather long-lasting phenomenon with a certain degree of cross-country heterogeneity in terms of magnitude and timing. Notably, while in France the gap between compensation and productivity growth has been more or less constant over time, in Germany there has been a general decrease in both compensation and productivity growth. Finally, in Italy and Spain, periods of linkage and delinkage have alternated over time.

Keywords: productivity, compensation, Euro Area economy, ARDL model, time-varying parameters VAR, stochastic volatility, Bayesian estimation

JEL Codes: C11, C22, C23, E23, E24, O52

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*The views expressed in this paper are solely of the authors and should not be attributed to the European Central Bank nor its Executive Board.

†European Central Bank, Sonnemannstrasse 20, 60314, Frankfurt am Main.

‡European Central Bank, Sonnemannstrasse 20, 60314, Frankfurt am Main.

§Corresponding author: European Central Bank and Rutgers University, Sonnemannstrasse 20, 60314, Frankfurt am Main. E-mail: maria_sole.pagliari@ecb.europa.eu

1 Introduction

(...) we have acknowledged the progress on the growth front, on the recovery front. We are pretty confident that, as this will proceed, this slack will close, the labour market conditions will improve. We'll start seeing [that] wage growth, which is the lynchpin of a self-sustained increase in inflation. That is the key variable that we should look at (Draghi (2017)).

Productivity is considered to be the most relevant driver of real wage growth over the medium to long run. The alignment between productivity and real wages is important, as it speaks to the extent to which the income produced by firms at the macro level is enjoyed by individuals at the household level (Atkinson (2009)). Besides this, the interaction between the growth in real wages and labour productivity has implications for external competitiveness and overall macroeconomic stability (Mihaljek, Saxena, et al. (2010)). For these reasons, the link between the two has always received attention in academia and policy circles, and even more so in the context of the marked slowdown in wage growth after the Great Recession. The latter, indeed, has been widely considered as the most relevant driver of the marked increase in inequality observed in the last decades (IMF (2017), Szörfi and Tóth (2018)).

According to standard economic theory, productivity gains should translate into real wage gains for workers, thus leading to constant real unit labor costs and, hence, a constant labor share of income (Kaldor (1957)). This seems to have been the case also in the Euro Area from the early 1970s to the 1990s (see Figure 1). Since then, however, the distribution of income has substantially changed, leading to a decline in the labor share (Karabarbounis and Neiman (2014)), as also confirmed by the widening divergence between productivity and compensation growth, with the former being faster than the latter (see Figure 2) [1].

In this regard, the relevant literature provides mixed evidence as to whether an effective decoupling between labor productivity and compensation has taken place[2]. Feldstein (2008) shows

[1]In our analysis, we define productivity as the amount of GDP per hour worked and compensation as the ratio between total compensation and total hours worked. The two measures are then deflated using the GDP deflator and the CPI respectively.

[2]As reported by Stansbury and Summers (2017), "Using compensation rather than wages is important. The share of compensation provided in non-wage benefits such as health insurance significantly rose over the postwar period, particularly during the 1960s and 1970s, meaning that comparing productivity against wages alone would imply a larger divergence between productivity and workers' pay than has actually occurred."

that there is no evidence of decoupling in the US in the first half century, once non-wage benefits are taken into account, something that is also supported by Lawrence (2016), who, however, underlines how the historic divergence in the US is due to the depreciation of labor productivity. Bivens and Mishel (2015), on the other hand, document the presence of a wedge in the US, starting from the 1970s, and they find that rising inequality explains most of it, in line with Schwellnus, Kappeler, and Pionnier (2017) and OECD (2018). The latter, however, also provides evidence that decoupling in advanced economies has been mainly driven by global developments, like technological progress, and the expansion of global value chains.

These contrasting results are partially due to the use of different measures of compensation and productivity. Some papers, indeed, study the divergence between productivity and the typical worker's compensation[3], while others prefer to focus on the discrepancy between productivity and average compensation, which is conceptually equivalent to the decline in labor share [4]. Finally, Stansbury and Summers (2017) use both average, median and production/non supervisory compensation, all deflated by consumer price indexes. Even if they find substantial evidence of linkage between productivity and compensation, nonetheless the estimated elasticity is less than one, meaning that there exist other orthogonal factors that have been dampening the increase in compensation in spite of the acceleration in productivity. The authors however rule out that these factors include technological progress[5]. In addition to the above mentioned, the existing literature finds it also difficult to quantify the precise magnitude of the drop in the labor share of income, as well as to pinpoint the starting date of the decline[6].

As to the rationale behind the phenomenon, however, alternative explanations have been provided. Some researchers agree with the so-called "accumulation view" (Rognlie (2015)), whereby the fall in the labor share is mainly attributable to shocks that have led to higher capital accumulation. Piketty (2014), for instance, argues that aggregate savings have risen globally relative to national incomes, which has led to an increase in the capital-output ratios. Karabarbounis and

[3]See, for instance, Bivens and Mishel (2015), where compensation is quantified by using median compensation and average production/non supervisory worker compensations, both deflated by consumer price deflators.

[4]For example, Feldstein (2008) compares labor productivity in the nonfarm business sector to average nonfarm business sector compensation, deflated by the producer price deflator.

[5]A less than one-to-one relation is also documented by Pasimeni (2018), who analyses the increasing gap between productivity and compensation for a sample of 34 countries over the past half century. In particular, the author lists cyclical conditions and labor market structures among the factors affecting the link.

[6]See Karabarbounis and Neiman (2014), Piketty and Zucman (2014), and Dao, Das, Koczan, and Lian (2017) among others.

Neiman (2014), instead, state that a drop in the price of investment goods relative to consumer goods led to an increase in the capital share, due to a rise in capital accumulation. However, these explanations require an elasticity of substitution between capital and labor superior to one, which seems an unrealistic assumption (see Lawrence (2015) and Grossman, Helpman, Oberfield, and Sampson (2017))[7].

On the other hand, a more recent strand of literature focuses on the role of human capital. Jones (2016), for instance, reports a slowdown in educational attainment in the US, that has led to a decrease in human capital accumulation. Grossman, Helpman, Oberfield, and Sampson (2017), by incorporating optimal schooling choice in a neoclassical growth model, shows that a productivity slowdown can decrease the labor share of income due to a deceleration in human capital accumulation.

As an alternative to these views, Karabarbounis and Neiman (2018) show that the rise in imputed payments to capital in the US is not enough to account for the decline in payments to labor, but there is a significant amount of residual payments, which they call "factorless income", that have been growing as a share of value added.

Finally, part of the literature focuses on labor markets imperfections to justify the divergence between wage and productivity rates. Notably, imperfect competition on labor markets leads to the materialization of rents to the employment relationship for both workers and employers. As both parties might face search costs, they might also want to close employment agreements at wage rates divergent from productivity rates, in order to then divide total rent according to the relative bargaining positions (see Pissarides (1985) and Manning (2011))[8].

Against this backdrop, it is then important to study how the relationship between compensation and productivity has evolved over time, in order to understand whether the observed stylized facts are due to an effective decoupling of compensation vis-à-vis productivity or to a change in the relationship between the two. With this purpose, we use a time-varying VAR with stochastic volatility to analyze the evolution of the productivity-compensation link over time, as this frame-

[7]Other possible explanations include: a shift in the bias of technology in favor of capital (Oberfield and Raval (2014)); the automation of tasks previously performed by labor (Autor and Dorn (2013) and Acemoglu and Restrepo (2016, 2019)).

[8]This strand of research also highlights the structural relationship between goods and labor markets structure, as shown in Blanchard and Giavazzi (2003).

work seems the best-suited to model the relationship of interest[9]. Conceptually, our approach builds on three strands of research: i. empirical studies of the co-movements of productivity and compensation (e.g. Bivens and Mishel (2015), Stansbury and Summers (2017), Pasimeni (2018)); ii. analyses of the decline in the labor share of income (e.g. Karabarbounis and Neiman (2014, 2018), and Lawrence (2015)); iii. models of the inflation-unemployment link (e.g. Galí (2011), Gordon (2013), Galí and Gambetti (2019)).

From a methodological standpoint, on the other hand, our paper relates to the literature studying significant time variations in the joint dynamics of output, labor compensation and employment. In this respect, the works that are closest to ours are Galí and Gambetti (2009), Benati and Lubik (2014) and Guglielminetti and Pouraghdam (2018). That being said, we provide a contribution to the existing literature along the following dimensions: i. we show that a time-varying setup is better-suited to analyze the patterns of interest (e.g., the break in the one-to-one relationship evidenced by data and tests in Section 2 below); ii. we investigate the relationship between productivity and compensation, while also controlling for the dynamics of unemployment (i.e. accounting for the endogenous production function); iii. we provide a deeper understanding of whether and how the relationship between productivity and compensation would react to some particular shocks.

The remainder of the paper is structured as follows: Section 2 presents some preliminary empirical analysis; Section 3 describes the methodological framework and discusses the results; Section 4 concludes.

2 Preliminary empirical evidence

In this Section, we perform some hypothesis testing that help support the stylized facts exposed in Section 1 above. Notably, results of break tests on y-o-y growth rates of compensation and productivity show that there is a significant break in the link between the two variables, both at the aggregate Euro Area level and in the four biggest economies, even if at different dates. Moreover, Levene's tests detect a change in volatility for both productivity and compensation growth in the whole Euro Area, as well as in France, Germany, Italy and Spain, with breaks

[9]This is also supported by the preliminary empirical analysis in Section 2.

ranging from 1977Q3 (France) to 2010Q2 (Spain) (see Table 1).

Given this and following Stansbury and Summers (2017), we estimate a single-equation model with quarterly data[10]. We then use the bounds testing procedure proposed by Pesaran, Shin, and Smith (2001) to check for the presence of a long-run relationship between compensation and productivity growth, regardless of whether the variables considered are integrated of order zero or one ($I(0)/\ I(1)$ respectively) or cointegrated. More specifically, we set up an autoregressive distributed lag (ARDL) model as follows:

$$comp_t = \alpha + \sum_{i=1}^{p} \phi_i comp_{t-i} + \sum_{i=0}^{q} \beta_i prod_{t-i} + \gamma unemp_{t-1} + \varepsilon_t \tag{1}$$

where $comp_t$ and $prod_t$ are the y-o-y growth rates of hourly compensation and productivity respectively, while $unemp_{t-1}$ is the lagged unemployment rate (treated as exogenous). Equation (1) can then be reparametrized in conditional Error Correction (EC) form:

$$\begin{aligned}\Delta comp_t = \alpha - \delta(comp_{t-1} - \theta prod_{t-1}) + \sum_{i=1}^{p-1} \psi_i \Delta comp_{t-i} + \omega \Delta prod_t \\ + \sum_{i=1}^{q-1} \zeta_i \Delta prod_{t-i} + \gamma \Delta unemp_{t-1} + \varepsilon_t\end{aligned} \tag{2}$$

where $\delta = 1 - \sum_{i=1}^{p} \phi_i$ is the speed of adjustment, while $\theta = \frac{\sum_{i=0}^{q} \beta_i}{\delta}$ is the long-run coefficient. The optimal lag lengths, p and q, are chosen via the Schwartz Information Criterion (SIC)[11] and the model in Equation (2) is estimated via OLS. Then an F-test is conducted for the joint null hypothesis: $H_0^F : (\delta = 0) \cap (\sum_{i=0}^{q} \beta_i = 0)$. If H_0^F is rejected, a t-statistic is computed to test for the null $H_0^t : \delta = 0$. The existence of a (conditional) long-run relationship is confirmed if both H_0^F and H_0^t are rejected, on the basis of the lower and upper bounds for the asymptotic critical values provided by Pesaran, Shin, and Smith (2001). Results, reported in Table 2 below, show that, in most cases, both the null hypotheses can be rejected at the conventional significance levels, thus providing evidence of the presence of a long-run relationship between compensation and productivity growth. Estimates for Italy in the period 1980Q2-2018Q1 are less conclusive, as the p-value for the t-test on I(0) variables is below 10%, which does not allow to accept the null

[10] See Appendix A for a description of data and sources.

[11] We set the maximum number of lags as suggested by Schwert (1989): $p_{max} = [12 \times (\frac{T}{100})^{1/4}]$.

hypothesis completely. On the other hand, the test rejects the presence of a long-run relationship for Spain in the overall 1980Q1-2018Q1 period, but not in the two subsamples.

Table 3 reports the estimates of Equation (2) using Euro Area data[12]. Results indicate that the long-run coefficient of productivity growth has decreased over time, with a drop from 1 (*strong linkage*) to 0 (*strong delinkage*) before and after 1993Q3[13]. In addition, the coefficient for the overall period is 0.878, which however is not statistically significant from 1 (full pass-through from productivity to compensation), according to the result of the F-test. Moreover, compensation growth seems to follow a process which has become more and more persistent and slow-moving over time, as indicated by the estimates of both the adjustment and the short-run coefficients. These results provide interesting insights, in particular given the fact that the detected break date (1993Q3) coincides with the entry into force of the Maastricht Treaty, establishing the convergence criteria for the European Monetary Union and, hence, the adoption of the single currency.

That being said, aggregation across Euro Area countries might anyways conceal important country-specific dynamics, as also partially disclosed by Figure 2. Hence, we estimate Equation (2) separately for the four biggest EA economies: France, Germany, Italy and Spain. Results, displayed in Tables 4 and 5, show a strong and significant decrease in the long-run coefficient for Germany and Italy (slightly less pronounced for France), which, in turn, is in line with a generalized weakening in the productivity-compensation link over time (Karabarbounis and Neiman (2014)). However, the long-run estimates are not significant for Spain. Moreover, the full-sample coefficient for Germany is not statistically different from 1. This heterogeneity in the magnitude, the significance and the timing of the findings might be due to different levels of cyclical adjustment as well as market flexibility (see, for instance, Kügler, Schönberg, and Schreiner (2018)). Moreover, according to OECD (2018), cross-country differences can be determined by both firm-level dynamics and discrepancies in public policies and institutional settings. In this regard, the adoption of the euro seems to have entailed a structural change in the relationship of interest at the Euro Area level, thus seemingly confirming the generalized opinion that the single currency (or rather the process leading to its adoption) might have generated a compression of

[12] Tests and estimation are performed using the Stata `ardl` module of Kripfganz and Schneider (2018).

[13] For estimates that exceed 1, we run an F-test to check whether they are statistically different from 1. In all instances, the F-test fails to reject the null hypothesis ($H_0 : \hat{\theta} = 1$).

compensation due to a loss in external competitiveness[14]. However, country-level results do not support this interpretation. Moreover, existing literature has provided evidence that the interplay between external competitiveness and labor costs in the Euro Area does not always follow a clear-cut direction (see Gabrisch and Staehr (2014)).

The possible presence of time variation in the estimates as well as of a long-run relationship between productivity and compensation call for the adoption of a framework accounting for both issues. The choice of the model, however, depends on whether the time variation is continuous or discrete. With this aim, we test for the presence of continuous time variation in the compensation-productivity link, by using the time-varying paramenter median unbiased estimator (TVP-MUB) approach proposed in Stock and Watson (1998), Benati (2007) and Benati and Lubik (2014)[15]. Results, reported in Table 6, provide strong evidence of random walk time variation in the equation for compensation both for the Euro Area as an aggregate and for France, Germany, Italy and Spain separately.

3 Continuous time framework

As already explained in Section 1 and further supported by the empirical evidence discussed in Section 2, the type of patterns detected in the productivity-compensation link in the Euro Area and its biggest economies require a modelling approach that accounts for some important non-linearities in such relationship. Moreover, the outcome of the TVP-MUB test has shown that these non-linearities can be best captured in a continuous time framework, rather than via discrete changes[16]. For these reasons, and following Galí and Gambetti (2009), Benati and Lubik (2014) and Guglielminetti and Pouraghdam (2018), our analysis will be based on the estimation of a time-varying parameter VAR with stochastic volatility (TVP-VAR SV) à la Primiceri (2005) and Del Negro and Primiceri (2015). Notably, we estimate the following reduced-form model:

$$Y_t = B_{0,t} + B_{1,t}Y_{t-1} + \cdots + B_{k,t}Y_{t-k} + \nu_t \equiv X_t'\theta_t + \nu_t \tag{3a}$$

[14] See Micossi (2015).

[15] See Appendix B for details.

[16] This finding is also supported by the evidence provided by labor studies at the micro level, in particular as far as the "composition effect" over wage distribution is concerned (Fern'andez-Val, van Vuuren, and Vella (2018)).

$$X'_t = I_N \otimes [1, Y'_{t-1}, \ldots, Y'_{t-k}] \tag{3b}$$

$$\theta_t = [B_{0,t}, B_{1,t}, \ldots, B_{k,t}] \tag{3c}$$

where $Y_t = [prod_t, comp_t, u_t]$ is a $T \times 3$ vector of endogenous variables, $B_{0,t}$ is a vector of time-varying intercepts, $B_{i,t}, i = 1, \ldots, k$ are matrices of time-varying coefficients and ν_t is a $T \times 3$ vector of unconditionally heteroskedastic disturbance terms with time-varying covariance matrix Σ_t. Equations (3b) and (3c) provide the state-space representation of the model. As to the variables included, $prod_t$ and $comp_t$ are real productivity growth and real compensation growth per hour respectively, while u_t is the log-unemployment rate. Following Primiceri (2005) and Del Negro and Primiceri (2015), all the time-varying coefficients are modeled as random walks with independent innovations[17]. Moreover, we assume that the reduced-form innovations ν_t are a time-varying linear transformation of the underlying structural shocks, ε_t:

$$\nu_t \equiv Q_t \varepsilon_t$$

which implies that $Q_t Q'_t = \Sigma_t$. In our specification, as in Peneva and Rudd (2017), we estimate a recursive TVP-VAR SV, where the relevant structural shocks are identified via a Choleski factorization of Σ_t, with the endogenous variables ordered as presented above. In addition, we set $k = 4$. We then use a Bayesian MCMC algorithm to estimate the model.

3.1 Results

Figure 3 displays how the impulse response function of compensation to a shock in productivity growth has evolved from the 1970s to today. Generally speaking, the effect has become less and less significant over time, though at different pace in the four economies. This heterogeneity is more evident when considering the 4-quarter-ahead impact of productivity shock over compensation (Figure 4). For France and Italy, indeed, the delinkage looks to have taken place earlier on, between the 1970s and the 1980s, with a decrease in the average cumulative response of around 39 pps and 54 pps respectively. In Germany, on the other hand, the turning point seems to be placed at the beginning of the 1990s, with an average decrease in the 4-ahead impact of 65 pps.

[17]See Appendix C for additional technical details.

Finally, in Spain, the response has dropped on average by 8 pps before and after 2010Q2, which is far lower than the decrease estimated for the other countries. At the same time, however, this downward trend has been reverting more recently in France, where the estimated impact in 2018Q1 is at the same level as in the 1980s.

Given these results, it is worth investigating further what are the underlying drivers of the linkage. With this aim, we compute the historical decomposition of hourly compensation (Figure 5). What emerges from the exercise confirms the above-mentioned evidence, notably that productivity shocks have become less and less relevant over time, especially in countries like Germany and Spain. The picture also reveals another important fact, i.e. that compensation and productivity shocks have become less synchronized, with the former showing a higher persistence than the latter, which is in line with the results of the univariate estimations in Section 2. In other words, compensation has become more and more inelastic over time to macroeconomic factors.

We further explore this finding by tracking the evolution of the productivity-compensation dynamic multiplier, which is computed on the basis of the impulse responses generated by the TVP-VAR SV as follows[18]:

$$\Phi_t^i(k) \equiv \frac{\sum_{k=0}^{K} \frac{\partial prod_{t+k}}{\partial \varepsilon_t^u}}{\sum_{k=0}^{K} \frac{\partial comp_{t+k}}{\partial \varepsilon_t^u}} \tag{4}$$

where $K = 0, 1, \ldots, 8$ and ε_t^u is the structural unemployment shock. Results, shown in Figure 6, unveil some interesting differences across countries. In Germany, for instance, multiplier estimates a quarter ahead of the shock in unemployment are, on average, not statistically different from one, implying that productivity and compensation react to macroeconomic conditions to the same extent. However, the estimate drops below 1 in the decade between 1985 and 1995, where compensation has been actually more reactive to macroeconomic shocks than productivity. Estimates for Spain, on the other hand, are on average above one, thus highlighting a higher responsiveness of productivity compared to compensation, with some notable exceptions like the period between 2009 and 2014, which also broadly corresponds to the euro zone crisis. Results for Italy, instead, depict a somewhat different picture, with estimates consistently below unity, which seems indicating that, on average, compensation reacts more to macroeconomic shocks than productivity. Finally, France stands out as an exception to the previous findings, as the

[18] Galí and Gambetti (2019) use this approach to estimate the wage inflation-unemployment multiplier in a TVP-VAR setting. See also Barnichon and Mesters (2019).

one-quarter-ahead multipliers are constantly negative throughout the estimation sample, with a re-bounce in positive domain as of the second quarter which is more evident over the late 1970s-early 1980s and in the early 2000s.

The TVP-VAR SV model also allows us to study time variation in the long-run behavior of the variables of interest, by computing their unconditional means. More specifically, Equation (3a) above can be also rewritten in companion form as:

$$\mathbf{Y}_t = \mu_t + \mathbf{C}_t \mathbf{Y}_{t-1} + \epsilon_t \tag{5}$$

where $\mathbf{Y}_t' = [Y_t', \ldots, Y_{t-k+1}']$, $\epsilon_t = [\nu_t', 0, \ldots, 0]$ and:

$$\mathbf{C}_t = \begin{bmatrix} B_{1,t} & B_{2,t} & \ldots & B_{k-1,t} & B_{k,t} \\ I_N & 0 & \ldots & 0 & 0 \\ 0 & I_N & \ldots & 0 & 0 \\ \vdots & & \ddots & & \vdots \\ 0 & \ldots & \ldots & I_N & 0 \end{bmatrix}, \qquad \mu_t = \begin{bmatrix} B_{0,t} \\ 0 \\ \vdots \\ 0 \end{bmatrix}.$$

It follows that $E_t(\mathbf{Y}_t) = (I_N - \mathbf{C}_t)^{-1}\mu_t$ is the unconditional long-run mean of the vector $\mathbf{Y}_t$ at time t. Figure 7 below depicts the median long-run means for productivity and compensation growth. The long-run results mirror country-specific dynamics that are partially in line with the ARDL estimates above[19]. Notably, there are instances of a less-than-one pass-through from productivity to compensation over time. However, while in France the wedge between the two growth rates is more or less constant since the 1970s, in Italy and Spain, on the other hand, the discrepancy between the two means is particularly pronounced in some specific periods, like the end of the 1980s in Italy and the mid 2000s in Spain, where compensation growth in the long-run plunges far below productivity growth. Moreover, in the case of both France and Spain, there is evidence that the productivity-compensation gap, after a widening during the Great Recession, is closing up. As to Germany, surprisingly, the two long-run means are highly correlated, showing an effective strong linkage between compensation and productivity. While

[19] Galí and Gambetti (2019) show that the key qualitative findings from the unconditional reduced form regressions emerge as well in the conditional (structural) evidence.

this could seem contradicting the results provided in Table 4 for the ARDL regression, however it is less so when looking carefully at the long-run mean in the second half of the sample (i.e. from 1990s onward) in Figure 7, as both productivity and compensation growth show a marked downward trend which is unique to this country. So, for Germany, one cannot really speak of a decoupling, but rather of a strong decrease in both productivity and compensation, something that could not be captured in a discrete time model.

4 Concluding remarks

The productivity-compensation delinkage is widepread phenomemon across advanced economies. The extent to which changes in productivity are transmitted to movements in wages is crucial for determining how income produced at the macroeconomic level is then distributed across households, thus giving rise to more or less income inequality. For this reason, the decoupling between wages and productivity has attracted more and more attention on the part of the policymakers. Against this backdrop, the Euro Area case has become particularly relevant, in light of the apparent effects stemming from the adoption of the single currency.

Our paper contributes to the ongoing debate by providing some new evidence on the dynamics of the productivity-compensation decoupling in the Euro Area. Notably, we show not only that there is a wedge between compensation and productivity, but also that the extent of this delinkage has changed over time, with a structural break in the long-run relationship between compensation and productivity growth taking place around the end of 1993. In addition, our analysis highlights the existence of significant cross-country heterogeneity, when considering the four biggest Euro Area economies (Germany, France, Italy and Spain) separately. Specifically, in countries like France the gap between compensation and productivity growth has been more or less constant over time, whereas in Germany, on the other hand, there is not an effective gap, but the apparent delinkage observed in the data is rather due to a general decrease in both compensation and productivity growth from the mid 1990s on. Finally, in countries like Italy and Spain, there is an alternation between periods of linkage and delinkage, with compensation growth dropping far below productivity growth only over very short time spans.

These findings call for a more in-depth analysis of what are the factors driving the productivity-compensation divide in the Euro Area. In this regard, the investigation of the main drivers in the model setting used in Section 3 above provides an interesting avenue for future research.

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Tables

Table 1: Break test and test of equality of variances across subsamples.

Break Test*				
	Date	**Statistic**	**P-value**	
Euro Area	1993q3	121.57	0.00	
France	1977q3	122.67	0.00	
Germany	1991q2	68.25	0.00	
Italy	1980q1	87.40	0.00	
Spain	2010q2	44.37	0.00	
Changes in volatility **				
	Pre	**Post**	**Ratio**	**P-value**
Productivity				
Euro Area	0.01	0.01	1.59	0.00
France	0.02	0.01	1.44	0.00
Germany	0.02	0.01	1.25	0.03
Italy	0.02	0.02	1.35	0.01
Spain	0.06	0.01	6.17	0.00
Compensation				
Euro Area	0.01	0.01	1.59	0.00
France	0.02	0.01	1.44	0.00
Germany	0.02	0.01	1.25	0.03
Italy	0.02	0.02	1.35	0.01
Spain	0.06	0.01	6.17	0.00

* Supremum Wald test on the coefficients of the regression: $comp_t = \alpha_0 + \alpha_1 prod_t + \varepsilon_t$, where $comp_t$ and $prod_t$ are the y-o-y log-differences of hourly compensation and productivity respectively;
** Levene's test based on break dates found by Wald test; H_0: variances are equal across subperiods.

Table 2: Tests for existence of long-run relationship.

	F - test	**t -test**	**F - test**	**t -test**	**F - test**	**t -test**
France	1960q1-2018q1		1960q1-1977q2		1977q4-2018q1	
Statistic	12.76	-4.92	6.41	-3.53	31.04	-7.87
P-values:						
I(0)	[0.000]	[0.000]	[0.019]	[0.010]	[0.000]	[0.000]
I(1)	[0.000]	[0.000]	[0.037]	[0.026]	[0.000]	[0.000]
Germany	1970q1-2018q1		1970q1-1991q1		1991q3-2018q1	
Statistic	17.70	-5.13	8.96	-3.11	24.24	-6.93
P-values:						
I(0)	[0.000]	[0.000]	[0.003]	[0.029]	[0.000]	[0.000]
I(1)	[0.000]	[0.000]	[0.006]	[0.070]	[0.000]	[0.000]
Italy	1970q1-2018q1		1970q1-1979q4		1980q2-2018q1	
Statistic	3.09	-2.45	3.19	-1.99	3.94	-2.76
P-values:						
I(0)	[0.198]	[0.123]	[0.189]	[0.246]	[0.105]	[0.062]
I(1)	[0.303]	[0.220]	[0.289]	[0.365]	[0.177]	[0.128]
Spain	1980q1-2018q1		1980q1-2010q1		2010q3-2018q1*	
Statistic	3.38	-2.52	6.27	-3.37	6.40	-3.55
P-values:						
I(0)	[0.159]	[0.104]	[0.019]	[0.013]	[$<$ 0.025]	[$<$ 0.01]
I(1)	[0.253]	[0.192]	[0.037]	[0.037]	[$<$ 0.05]	[$<$ 0.025]
Euro Area	1970q1-2018q1		1970q1-1993q2		1993q4-2018q1	
Statistic	11.25	-4.67	6.33	-3.42	8.84	-3.97
P-values:						
I(0)	[0.000]	[0.000]	[0.019]	[0.012]	[0.003]	[0.002]
I(1)	[0.001]	[0.001]	[0.036]	[0.034]	[0.006]	[0.007]

Notes:
[1] P-value in brackets, based on the bounds of asymptotic critical values in Pesaran, Shin, and Smith (2001).
[2] (H_0: no long-run relationship) is rejected at $(\alpha \times 100)\%$ significance level if both the p-values for I(1) variables are less than α; (H_0: no long-run relationship) cannot be rejected at $(\alpha \times 100)\%$ significance level if both the p-values for I(0) variables are above α.
[*] The number of lags included in the equation for Spain after 2010Q3 is above the number of observations, thus allowing to compute only thresholds for the p-values.

Table 3: Regression results - **Euro Area**

$\Delta comp_t$	(1) ARDL(5,0) 1970q1-2018q1	(2) ARDL(1,0) 1970q1-1993q2	(3) ARDL(5,0) 1993q4-2018q1
$prod_{t-1}$	**0.878*** **	**1.353*** **	0.190
	(0.232)	(0.403)	(0.275)
$comp_{t-1}$	**-0.197*** **	**-0.225*** **	**-0.288*** **
	(0.042)	(0.066)	(0.073)
$\Delta comp_{t-1}$	0.090		**0.222*** **
	(0.069)		(0.083)
$\Delta comp_{t-2}$	**0.265*** **		**0.263*** **
	(0.069)		(0.088)
$\Delta comp_{t-3}$	**0.281*** **		**0.298*** **
	(0.069)		(0.087)
$\Delta comp_{t-4}$	**-0.223*** **		**-0.196** **
	(0.072)		(0.094)
U_{t-1}	**-0.077** **	-0.033	-0.063
	(0.032)	(0.048)	(0.043)
Constant	**0.710** **	0.119	**0.741* **
	(0.332)	(0.483)	(0.434)
Observations	176	79	98
R^2	0.285	0.152	0.365
F-test - H_0: long-run coefficient equal to 1			
Test statistic	0.28	0.77	8.66
P-value	0.60	0.38	0.00

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. Standard error in parentheses. Break dates are detected via a Supremum Wald test on the coefficients of the regression $comp_t = \alpha_0 + \alpha_1 prod_t + \varepsilon_t$. Lag lengths of the model are selected using the Schwartz information criterion (SIC).

Table 4: Regression results - **France and Germany**.

	France			Germany		
	ARDL(7,6)	ARDL(2,2)	ARDL(4,1)	ARDL(6,2)	ARDL(1,0)	ARDL(2,7)
$\Delta comp_t$	1970q1-2018q1	1970q1-1977q2	1977q4-2018q1	1970q1-2018q1	1970q1-1991q1	1991q3-2018q1
$prod_{t-1}$	**0.382****	**0.576****	**0.436*****	**0.962*****	**1.595*****	0.331
	(0.164)	(0.279)	(0.088)	(0.293)	(0.582)	(0.366)
$\Delta prod_t$	**0.288*****	0.126	**0.321*****	0.015		-0.163
	(0.065)	(0.105)	(0.076)	(0.079)		(0.117)
$\Delta prod_{t-1}$	**-0.432*****	**-0.561*****		**-0.300*****		**-0.305*****
	(0.0678)	(0.101)		(0.0764)		(0.112)
$\Delta prod_{t-2}$	0.023					-0.075
	(0.060)					(0.108)
$\Delta prod_{t-3}$	**0.143****					-0.016
	(0.063)					(0.083)
$\Delta prod_{t-4}$	**0.175*****					**-0.405*****
	(0.066)					(0.080)
$\Delta prod_{t-5}$	**-0.229*****					0.056
	(0.068)					(0.086)
$\Delta prod_{t-6}$	**0.118****					**-0.335*****
	(0.067)					(0.081)
$comp_{t-1}$	**-0.268*****	**-0.306*****	**-0.383*****	**-0.248*****	**-0.231*****	**-0.321*****
	(0.054)	(0.087)	(0.049)	(0.048)	(0.074)	(0.046)
$\Delta comp_{t-1}$	**0.437*****	**0.533*****	**0.169*****	**0.191****		**0.269*****
	(0.077)	(0.116)	(0.063)	(0.077)		(0.085)
$\Delta comp_{t-2}$	**0.256*****		**0.265*****	0.074		
	(0.075)		(0.063)	(0.073)		
$\Delta comp_{t-3}$	0.066		**0.276*****	**0.130***		
	(0.068)		(0.065)	(0.069)		
$\Delta comp_{t-4}$	**-0.365*****			-0.061		
	(0.069)			(0.070)		
$\Delta comp_{t-5}$	**0.203*****			**0.334*****		
	(0.068)			(0.068)		
$\Delta comp_{t-6}$	**0.118****					
	(0.052)					
U_{t-1}	**-0.133*****	0.150	**-0.108*****	**-0.0878****	0.024	**-0.172*****
	(0.035)	(0.209)	(0.031)	(0.043)	(0.074)	(0.053)
Constant	**1.393*****	0.735	**1.206*****	0.665	-0.492	**1.631*****
	(0.372)	(0.783)	(0.319)	(0.419)	(0.625)	(0.465)
Observations	215	56	162	176	71	107
R^2	0.634	0.694	0.521	0.353	0.219	0.614
F-test - H_0: long-run coefficient equal to 1						
Test statistic	14.22	2.31	40.69	0.02	1.05	3.35
P-value	0.00	0.14	0.00	0.90	0.31	0.07

Standard errors in parentheses, ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. Break dates are detected via a Supremum Wald test on the coefficients of the regression $comp_t = \alpha_0 + \alpha_1 prod_t + \varepsilon_t$. Lag lengths of the model are selected using the Schwartz information criterion (SIC).

Table 5: Regression results - **Italy and Spain**.

	Italy			Spain[†]		
	ARDL(9,1)	ARDL(5,0)	ARDL(9,1)	ARDL(5,5)	ARDL(1,1)	ARDL(8,9)
$\Delta comp_t$	1970q1-2018q1	1970q1-1979q4	1980q2-2018q1	1980q1-2018q1	1970q1-2010q1	2010q3-2018q1
$prod_t$	0.084	**0.753****	-0.0341	0.550	0.348	-0.412
	(0.265)	(0.317)	(0.223)	(0.451)	(0.341)	(0.683)
$\Delta prod_t$	**0.210****		**0.242*****	**0.564*****	**0.517*****	**1.002***
	(0.083)		(0.084)	(0.110)	(0.097)	(0.502)
$\Delta prod_{t-1}$				-0.096		-0.681
				(0.108)		(0.531)
$\Delta prod_{t-2}$				**-0.398*****		-0.492
				(0.108)		(0.440)
$\Delta prod_{t-3}$				-0.165		-0.619
				(0.114)		(0.443)
$\Delta prod_{t-4}$				**0.257****		0.498
				(0.111)		(0.331)
$comp_{t-1}$	**-0.181****	**-0.493***	**-0.238*****	**-0.189*****	**-0.206*****	**-0.352****
	(0.074)	(0.248)	(0.086)	(0.049)	(0.057)	(0.145)
$\Delta comp_{t-1}$	-0.102	**0.348****	-0.051	-0.080		**0.515****
	(0.087)	(0.163)	(0.094)	(0.085)		(0.214)
$\Delta comp_{t-2}$	0.042	**-0.497*****	**0.232****	**0.184****		**0.543****
	(0.087)	(0.163)	(0.095)	(0.085)		(0.216)
$\Delta comp_{t-3}$	**0.170****	**0.295****	**0.207****	**0.155***		**0.720****
	(0.086)	(0.126)	(0.096)	(0.083)		(0.247)
$\Delta comp_{t-4}$	**-0.557*****	**-0.656*****	**-0.543*****	**-0.329*****		-0.064
	(0.083)	(0.142)	(0.091)	(0.082)		(0.171)
$\Delta comp_{t-5}$	**-0.166****		-0.122			**0.417****
	(0.071)		(0.077)			(0.164)
$\Delta comp_{t-6}$	0.040		0.109			0.256
	(0.071)		(0.077)			(0.191)
$\Delta comp_{t-7}$	**0.170****		**0.184****			**0.465****
	(0.070)		(0.077)			(0.179)
$\Delta comp_{t-8}$	**-0.272*****		**-0.211*****			
	(0.070)		(0.074)			
U_{t-1}	-0.008	-0.002	0.014	-0.034	-0.027	-0.300
	(0.054)	(0.605)	(0.051)	(0.026)	(0.039)	(0.165)
Constant	0.214	0.790	0.049	0.612	0.645	**6.655***
	(0.543)	(3.429)	(0.503)	(0.414)	(0.539)	(3.354)
Observations	176	28	152	136	106	30
R^2	0.539	0.805	0.543	0.517	0.388	0.916
F-test - H_0: long-run coefficient equal to 1						
Test statistic	11.92	0.61	21.43	1.00	3.66	4.28
P-value	0.00	0.45	0.00	0.320	0.059	0.066

Standard errors in parentheses, $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. Break dates are detected via a Supremum Wald test on the coefficients of the regression $comp_t = \alpha_0 + \alpha_1 prod_t + \varepsilon_t$. Lag lengths of the model are selected using the Schwartz information criterion (SIC).
[†] For the sake of brevity, coefficient estimates for $\Delta prod_{t-i}, i = 5, \ldots, 7$ in the Spain regression are omitted as they are not significant.

Table 6: Test results based on Stock-Watson TVP-MUB methodology.

	Euro Area		*France*		*Germany*	
	EW	SW	EW	SW	EW	SW
Statistic	16.22	40.07	53.52	116.78	13.65	35.77
P-value	(0.000)	(0.000)	(0.00)	(0.00)	(0.000)	(0.000)
$\hat{\lambda}$	0.047	0.049	0.036	0.036	0.058	0.063
	Italy		*Spain*			
	EW	SW	EW	SW		
Statistic	60.52	129.79	7.29	22.00		
P-value	(0.00)	(0.00)	(0.014)	(0.009)		
$\hat{\lambda}$	0.034	0.034	0.039	0.043		

Statistics - EW: *exp*-Wald test; SW: *sup*-Wald test; H_0: no random walk time variation in the sum of coefficients; p-values in parentheses. Standard errors are computed using the Newey-West HAC covariance estimator.

Charts

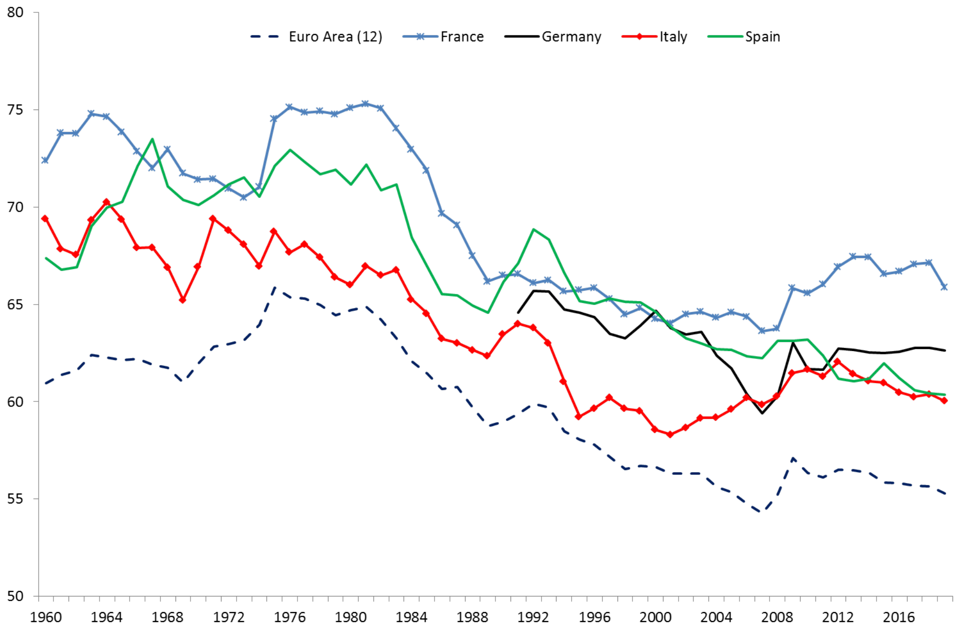


Figure 1: Adjusted wage share for Euro Area and selected European economies. *Source:* AMECO

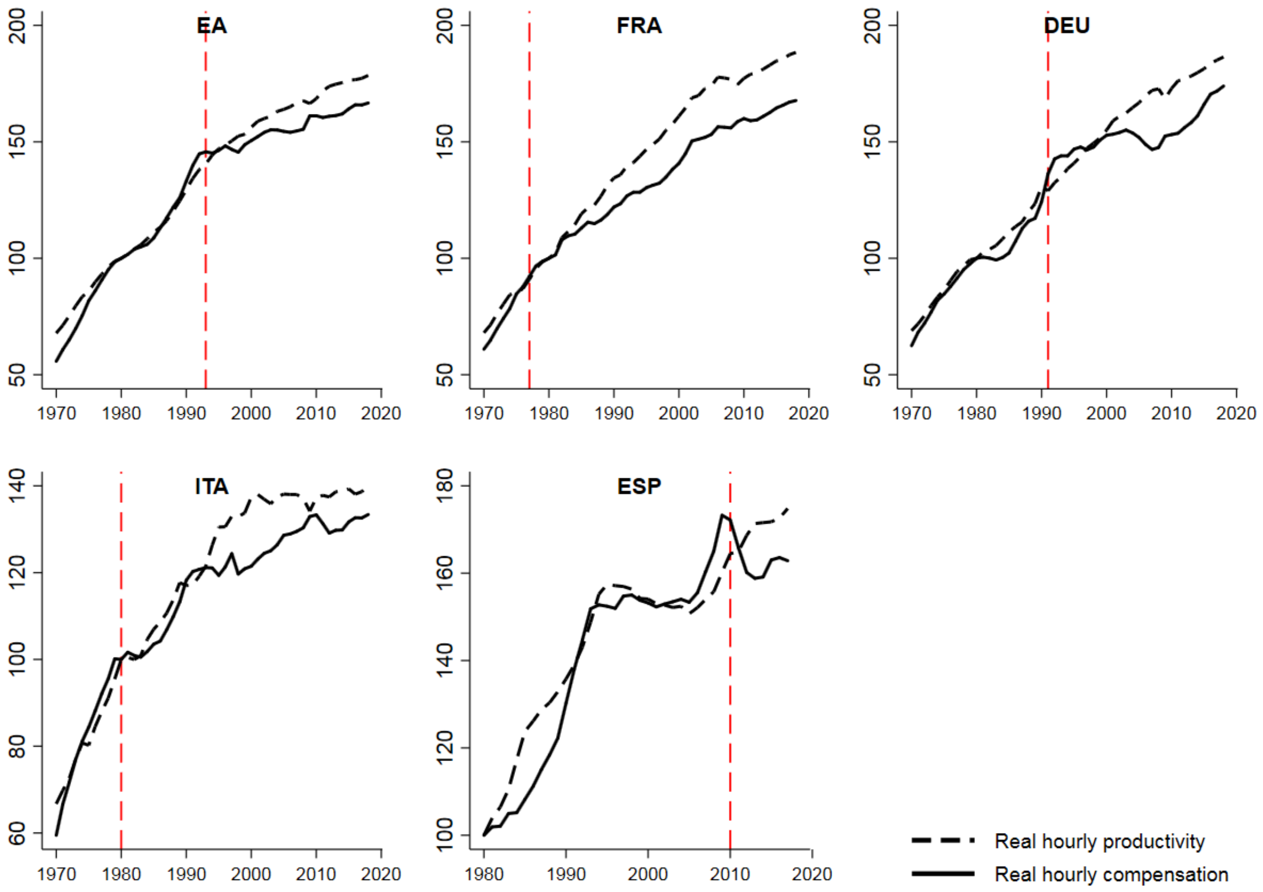
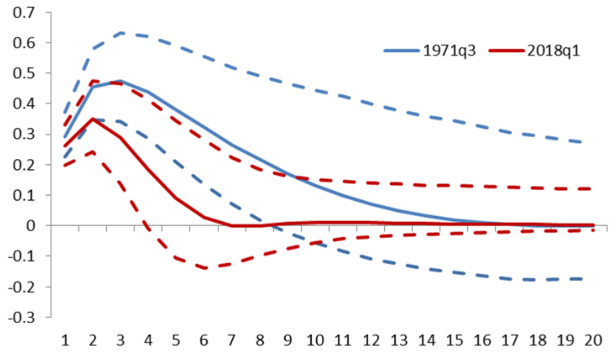
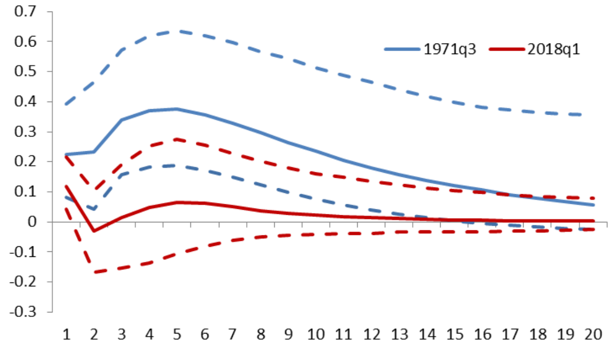


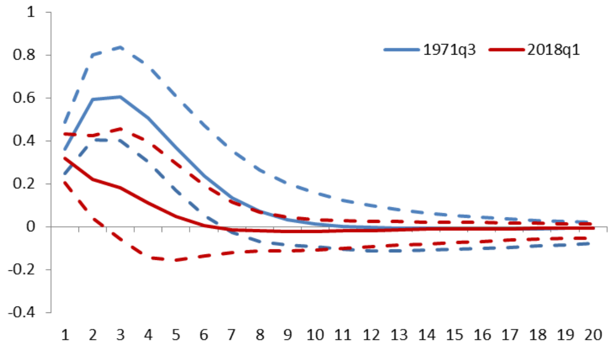
Figure 2: Real hourly compensation and productivity. *Sources:* National authorities and Eurostat.
Notes: 1980 = 100. Red dashed lines indicate the break dates as reported in Table 1. Compensation is deflated using the consumer price index, while productivity is deflated using the GDP deflator.



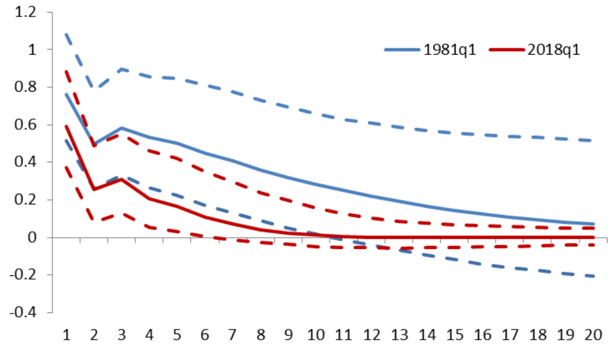
(a) France



(b) Germany

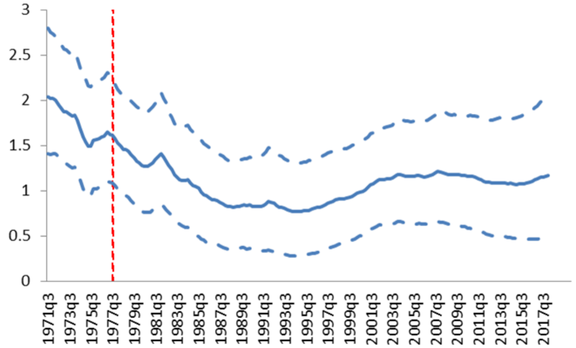


(c) Italy

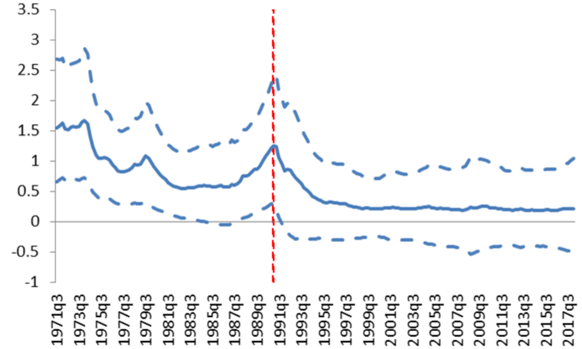


(d) Spain

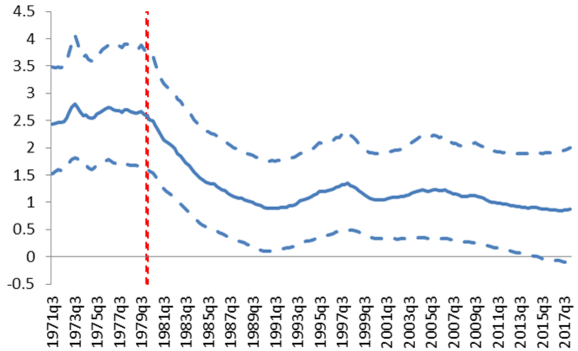
Figure 3: IRFs of hourly compensation growth to a 1 s.d. shock in productivity growth at beginning (blue) and end of sample (red). *Notes*: Dashed lines are 68% confidence bands. The sample for Spain starts in 1981q1.



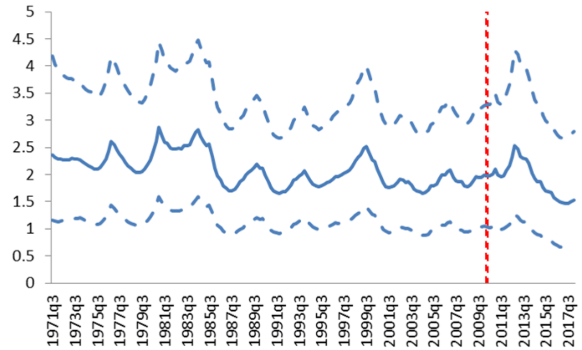
(a) France



(b) Germany

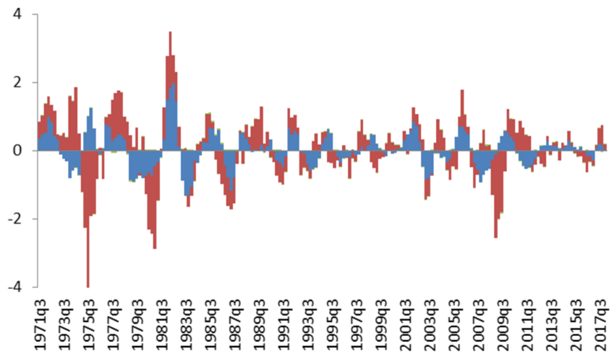


(c) Italy

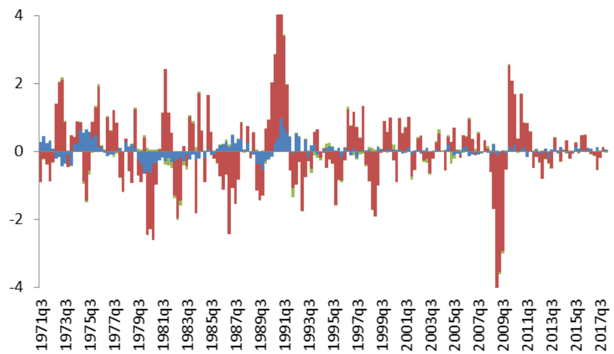


(d) Spain

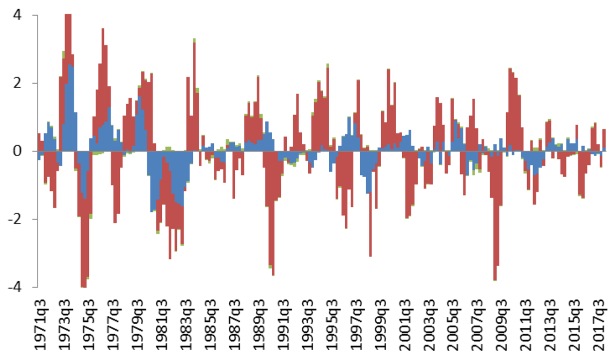
Figure 4: 4-quarters-ahead cumulative impact of a 1 s.d. shock in productivity growth on compensation growth. *Notes*: Dashed lines are 68% confidence bands. Red dotted lines indicate the break in the data.



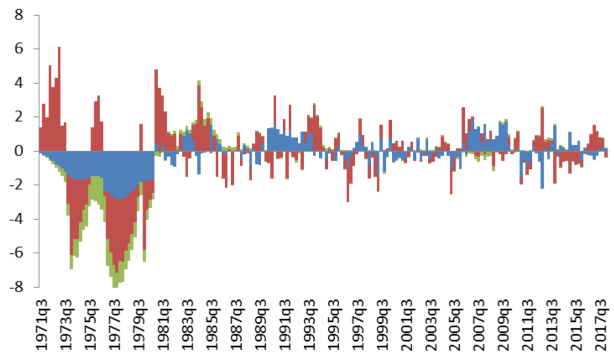
(a) France



(b) Germany

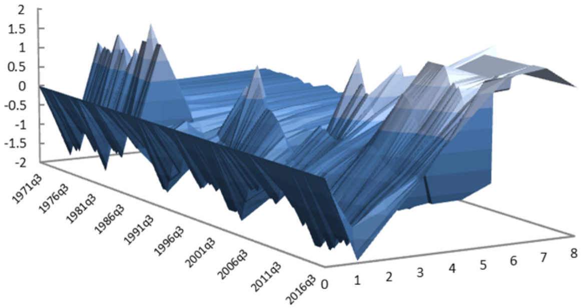


(c) Italy

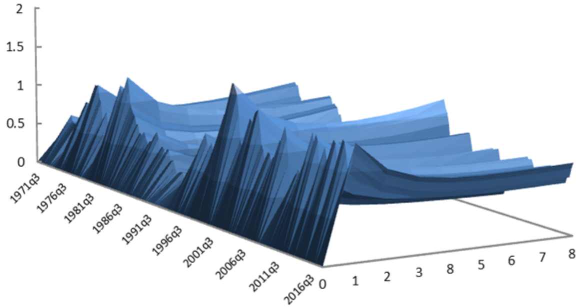


(d) Spain

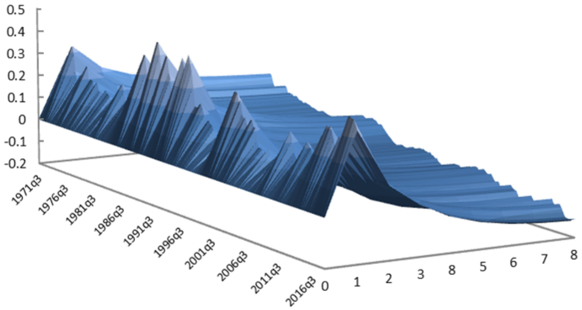
Figure 5: Historical decomposition of hourly compensation growth.
Notes: Productivity shock: blue; Compensation shock: red; Unemployment shock: green.



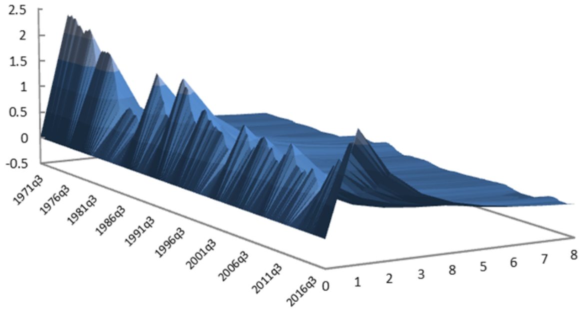
(a) France



(b) Germany

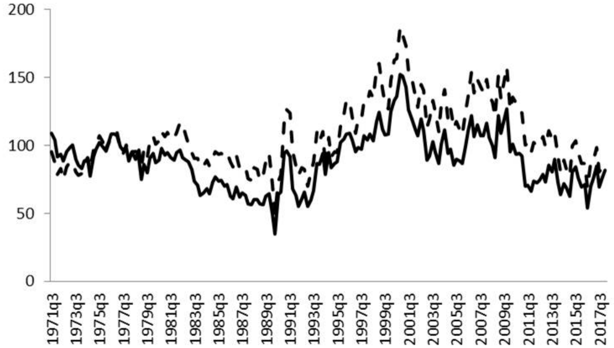


(c) Italy

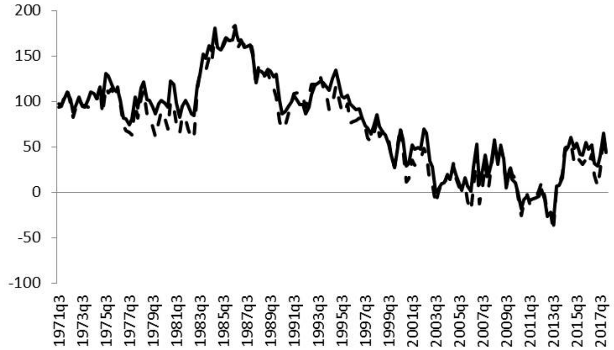


(d) Spain

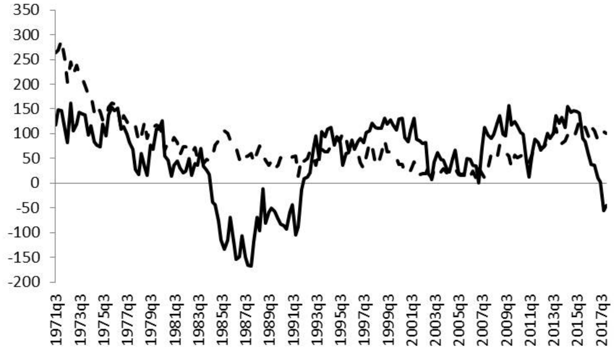
Figure 6: Dynamic multipliers.
Notes: Multipliers are normalized to the cumulative 8-quarter response of unemployment rate to its own shock.



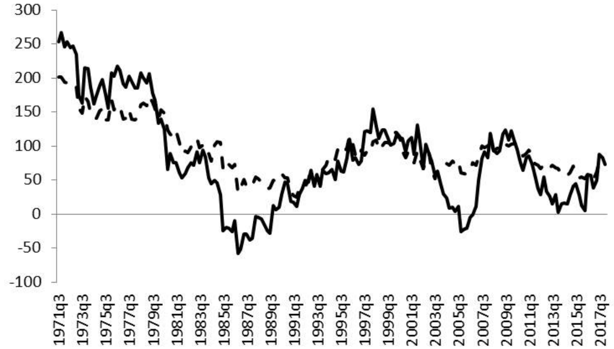
(a) France



(b) Germany



(c) Italy



(d) Spain

Figure 7: Long-run means of productivity (dashed) and compensation (solid) growth.
Notes: The series are indexed on the basis of the breaks found in Section 2. Hence for France: 1977 = 100; for Germany: 1991 = 100; for Italy: 1980 = 100; for Spain: 2010 = 100.

Appendices

A Data

Euro Area

Quarterly data for Euro Area are taken from Eurostat, as of 1995Q1. For the period 1970Q1-1994Q4, series are backcast using the data from the Area-Wide Model database (see Fagan, Henry, and Mestre (2005) and Warne, Coenen, and Christoffel (2008)), which provides coverage from 1970Q1 to 2016Q3 for compensation, GDP, CPI, GDP deflator and unemployment rate. As to hours worked, we backcast the Eurostat aggregate series by using the q-o-q growth rates of the sum of hours across France, Germany, Italy and Spain over the period 1970Q1-1994Q4. In the case of Germany, in order to correct for the jump in the series corresponding to the reunification (1991Q1), we harmonize the series by backcasting data before 1991Q1 using q-o-q growth rates of hours worked in West Germany.

National data

The sources of national data are reported in Table A.1.

Table A.1: National data sources

Variables	**France**	**Germany**	**Italy**	**Spain**
Compensation	INSEE[1]	FSO[2]	ISTAT[3]	INE[4]
CPI	INSEE	Bbk[5]	ISTAT	INE
GDP	INSEE	FSO	ISTAT	INE OECD
GDP deflator	INSEE	FSO	OECD	OECD
Hours	INSEE	FSO Eurostat	ISTAT AMECO	OECD
Unemployment rate	OECD	Bbk	OECD	OECD

[1] Institut national de la statistique et des études économiques;
[2] Federal Statistical Office (Destatis); [3] Istituto Nazionale di Statistica;
[4] Instituto Nacional de Estadística; [5] Bundesbank.

Notes

- **Germany**: data before 1991Q1 are backcast using q-o-q (hours) and y-o-y (GDP) growth rates of West Germany series; GDP is backcast using Gross Value Added;

- **Italy**: quarterly data for hours before 1980Q1 are estimated by backcasting the series using y-o-y growth rates obtained by interpolating annual growth rates from AMECO via Chow-Lin with real GDP y-o-y growth rate as index;
- **Spain**: GDP data before 1980Q1 are obtained by backcast, using y-o-y real GDP growth rates from OECD; hours worked are computed by multiplying hours per employee times the number of employees in the economy (both from OECD).

B The Time-Varying Parameter Median Unbiased estimator (TVP-MUB)

The approach checks for random-walk time variation in the regression model:

$$comp_t = \mu + \alpha(L)comp_{t-1} + \beta(L)prod_{t-1} + \varepsilon_t \equiv \theta' Z_t + \varepsilon_t, \tag{B.1}$$

where $\alpha(L), \beta(L)$ are lag polinomials, $\theta = [\mu, \alpha(L), \beta(L)]$ and $Z_t = [1, comp_{t-1}, \ldots, prod_{t-p}]$, and p is set as indicated by the Schwartz Information Criterion (SIC)[20]. The time-varying version of (B.1) is given by:

$$x_t = \theta_t' Z_t + \varepsilon_t, \tag{B.2a}$$

$$\theta_t = \theta_{t-1} + \eta_t \tag{B.2b}$$

where $x_t = comp_t$. Moreover, $\eta_t \overset{iid}{\sim} \mathcal{N}(0_{4p+1}, \lambda^2\sigma^2 Q)$, $\sigma^2 \equiv Var(\varepsilon_t)$, $Q = E[Z_t Z_t']^{-1}$ and $E[\eta_t \varepsilon_t] = 0$. The coefficients of the transformed regression, $E[Z_t Z_t']^{-1/2} Z_t$, evolve according to a standard $(4p+1)$-dimensional random walk, where λ^2 is the ratio between the variance of each transformed innovation and the variance of ε_t. Following Benati and Lubik (2014), we estimate the matrix Q as $\hat{Q} = [T^{-1} \sum_{t=1}^{T} z_t z_t']^{-1}$.

The innovation variance, σ^2, is computed via the OLS estimation of Equation (B.1). We then

[20] Notably, $p = 2$ for Euro Area aggregates, $p = 1$ for Germany, $p = 5$ for France, $p = 5$ for Italy and $p = 1$ for Spain.

perform *exp*- and *sup*-Wald joint tests for a single unknown break in μ and the sum of α's and β's, using the Newey and West HAC covariance matrix estimator. As in Stock and Watson (1998), the empirical distribution of the test statistic is computed over a 100-point grid of values for λ, over the interval $[0, 0.1]$. For each $\lambda_j, j = 1 \ldots 100$, the corresponding estimate of Q is given by $\hat{Q}_j = \lambda_j^2 \hat{\sigma}^2 \hat{Q}$. Conditional on $\hat{Q}_j$, we simulate the model (B.2a)-(B.2b) 10,000 times, drawing the innovations from a pseudo-random iid $N(0, \hat{\sigma}^2)$. The median-unbiased estimate of λ is then obtained as the particular value for which the median of the empirical simulated distribution of the test is closest to the test statistic computed with actual data. The p-value is computed based on the empirical distribution of the test conditional on $\lambda_j = 0$, which is in turn estimated as in Benati (2007) [21].

C Estimation of the TVP-VAR SV

In the framework described by(3a), (3b) and (3c), we assume that:

$$\nu_t \sim \mathcal{N}(0, \Sigma_t) \tag{C.3a}$$

$$\theta_t = \theta_{t-1} + \eta_t, \qquad \eta_t \sim (0, \Omega), \tag{C.3b}$$

where the variance-covariance matrix, Ω, is assumed to be diagonal and is endogenously determined by the model. Without loss of generality, Σ_t can be decomposed as:

$$\Sigma_t = F_t \Lambda_t F_t', \tag{C.4}$$

[21] We thank Luca Benati for providing us with the MATLAB routine to perform the tests.

with

$$
F_t = \begin{bmatrix} 1 & 0 & \dots & \dots & 0 \\ f_{21,t} & 1 & \dots & \dots & 0 \\ f_{31,t} & f_{32,t} & \ddots & & 0 \\ \vdots & \vdots & & \ddots & \vdots \\ f_{N1,t} & f_{N2,t} & \dots & f_{N(N-1),t} & 1 \end{bmatrix},
$$

$$
\Lambda_t = \begin{bmatrix} \bar{s}_1 \exp(\lambda_{1,t}) & 0 & \dots & \dots & 0 \\ 0 & \bar{s}_2 \exp(\lambda_{2,t}) & \dots & \dots & 0 \\ \vdots & & \ddots & & 0 \\ \vdots & & & \ddots & \vdots \\ 0 & \dots & \dots & 0 & \bar{s}_N \exp(\lambda_{N,t}) \end{bmatrix}. \tag{C.5}
$$

where $\bar{s}_i, i = 1, \dots, N$ are known scaling parameters and $\lambda_{i,t}, i = 1, \dots, N$ are dynamic processes that introduce heteroskedasticity in the model. Notably:

$$
\lambda_{i,t} = \gamma \lambda_{i,t-1} + v_{i,t}, \qquad v_{i,t} \sim \mathcal{N}(0, \phi_i). \tag{C.6}
$$

The set of parameters that need to be estimated consists of $\theta = \{\theta_t, t = 1, \dots, T\}$, $f^{-1} = \{f_i^{-1}, i = 1, \dots, N\}$, $\lambda = \{\lambda_{i,t}, i = 1, \dots, N, t = 1, \dots, T\}$ and $\phi = \{\phi_i, i = 1, \dots, N\}$.
Assuming indipendence across θ, f^{-1} and λ, the posterior density can be written as:

$$
f(\theta, \Omega, f^{-1}, \lambda, \phi | y) \propto f(y|\theta, f^{-1}, \lambda) \pi(\theta|\Omega) \pi(\Omega) \left(\prod_{i=2}^{N} \pi(f_i^{-1}) \right) \left(\prod_{i=2}^{N} \pi(\lambda_{i,t}|\phi_i) \right) \left(\prod_{i=2}^{N} \pi(\phi_i) \right). \tag{C.7}
$$

By the independence of the residuals, ν_t, the likelihood function can be written as:

$$
f(y|\theta, f^{-1}, \lambda) \propto \prod_{t=1}^{T} |F_t \Lambda_t F_t'|^{-1/2} \exp\left(-\frac{1}{2}(y_t - \bar{X}_t\theta_t)'(F_t\Lambda_t F_t')^{-1}(y_t - \bar{X}_t\theta_t) \right). \tag{C.8}
$$

The likelihood function in Equation (C.8) can also be reformulated in compact form, by setting:

$$\underbrace{\begin{bmatrix} y_1 \\ y_2 \\ \vdots \\ y_T \end{bmatrix}}_{NT\times 1} = \underbrace{\begin{bmatrix} \bar{X}_1 & 0 & \dots & 0 \\ 0 & \bar{X}_2 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & \bar{X}_T \end{bmatrix}}_{NT\times pT} \underbrace{\begin{bmatrix} \theta_1 \\ \theta_2 \\ \vdots \\ \theta_T \end{bmatrix}}_{pT\times 1} + \underbrace{\begin{bmatrix} \nu_1 \\ \nu_2 \\ \vdots \\ \nu_T \end{bmatrix}}_{NT\times 1} \tag{C.9}$$

or

$$y = \bar{X}\Theta, \quad \nu \sim N(0, \bar{\Sigma}), \quad \bar{\Sigma} = \underbrace{\begin{bmatrix} \Sigma_1 & 0 & \dots & 0 \\ 0 & \Sigma_2 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & \Sigma_T \end{bmatrix}}_{NT\times NT}.$$

Therefore:

$$f(y|\theta,\Sigma) \propto |\bar{\Sigma}|^{-1/2}\text{exp}\bigg(-\frac{1}{2}(y-\bar{X}\Theta)'\bar{\Sigma}^{-1}(y-\bar{X}\Theta)\bigg) \tag{C.10}$$

We set the priors as follows:

$$\begin{aligned} &\theta|\Omega \sim \mathcal{N}(0,\Omega_0) \\ &\omega_i \sim IG\Big(\frac{\chi_0}{2},\frac{\psi_0}{2}\Big) \\ &f_i^{-1} \sim \mathcal{N}(f_{i,0}^{-1},\Upsilon_{i,0}) \\ &\lambda_i|\phi_i \sim N(0,\Phi_0) \\ &\phi_i \sim IG\Big(\frac{\beta_0}{2},\frac{\delta_0}{2}\Big). \end{aligned} \tag{C.11}$$

The prior for λ_i deserves some additional remarks. Equation (C.6) implies that each $\lambda_{i,t}$ depends on $\lambda_{i,t-1}$, which makes the formulation of $\pi(\lambda_i|\phi_i)$ complicated. There are two alternative approaches that can be considered in this case. The first one is based on the formulation of a joint prior for $\lambda_{i,1},\dots,\lambda_{i,T}$ accounting for the dependence across different sample periods. The second one consists of separating $\pi(\lambda_i|\phi_i)$ into T different priors, where the prior for each individual period t will be conditional on period $t-1$, thus accounting for the dependence with the previous sample period. The joint formulation would result in a joint posterior which takes a non-standard form, so that a Metropolis-Hastings step is required (see below). For the purpose of this paper, we adopt the first approach, which is in turn based on the sparse matrix methodology of Chan and Jeliazkov (2009)[22]. Notably, from Equation (C.6), any value $\lambda_{i,t}$ eventually depends on the initial value $\lambda_{i,0}$ and the shocks $v_{i,t}, t = 1, \ldots, T$. Therefore, Equation (C.6) can be reformulated as:

$$GL_i = v_i, \quad i = 1, \ldots, N \tag{C.12}$$

with

$$G = \begin{bmatrix} 1 & 0 & 0 & \ldots & 0 \\ -\gamma & 1 & 0 & \ldots & 0 \\ 0 & -\gamma & 1 & \ldots & 0 \\ \vdots & & \ddots & & \vdots \\ 0 & \ldots & 0 & -\gamma & 1 \end{bmatrix}, \quad L_i = \begin{bmatrix} \lambda_{i,1} \\ \lambda_{i,2} \\ \vdots \\ \lambda_{i,T} \end{bmatrix}, \quad v_i = \begin{bmatrix} \gamma\lambda_{i,0} + v_{i,1} \\ v_{i,2} \\ \vdots \\ v_{i,T} \end{bmatrix}. \tag{C.13}$$

In this case, $\lambda_{i,0}$ is the initial value of the process, which is assumed to follow a normal distribution of the form $\mathcal{N}(0, \frac{\phi_i(\omega-1)}{\gamma^2})$, where ω is a known variance parameter. This implies that:

$$\begin{aligned} var(\gamma\lambda_{i,0} + v_{i,1}) &= var(\gamma\lambda_{i,0}) + var(v_{i,1}) \\ &= \gamma^2 var(\lambda_{i,0}) + var(v_{i,1}) \\ &= \gamma^2 \frac{\phi_i(\omega-1)}{\gamma^2} + \phi_i \\ &= \phi_i\omega. \end{aligned} \tag{C.14}$$

Following Cogley and Sargent (2005), ω is set equal to 1000 in order to get a diffuse prior for

[22]The same reasoning holds also for the prior of θ. Even in this case, two alternative formulations can be considered: 1. compact formulation: $\theta|\Omega \sim \mathcal{N}(0, \Omega_0)$; 2. conditional formulation: $\pi(\theta|\Omega) = \pi(\theta_1|\Omega) \prod_{t=2}^{T} \pi(\theta_t|\Omega, \theta_{t-1})$. As in the case of λ_i, we opt for the first one.

$\lambda_{i,1}$. Equations (C.6), (C.13) and (C.14) imply that:

$$v_i \sim \mathcal{N}(0, \phi_i I_\omega), \qquad I_\omega = \begin{bmatrix} \omega & 0 & \dots & \dots & 0 \\ 0 & 1 & \dots & \dots & 0 \\ \vdots & & \ddots & & \vdots \\ 0 & & \dots & 0 & 1 \end{bmatrix}. \tag{C.15}$$

Furthermore, Equation (C.12) implies that $L_i = G^{-1} v_i$, which, in turn, leads to:

$$L_i \sim \mathcal{N}(0, G^{-1} \phi_i I_\omega G^{-1\prime}), \tag{C.16}$$

or:

$$L_i \sim \mathcal{N}(0, \Phi_0), \quad \text{with } \Phi_0 = \phi_i (G' I_\omega^{-1} G)^{-1}. \tag{C.17}$$

Hence, the joint prior distribution of λ_i conditional on ϕ_i is a normal with mean 0 and covariance Φ_0.

Given the likelihood in Equation (C.8) and the priors in Equation (C.11), the joint posterior density is:

$$\begin{aligned}
& f(\theta, \Omega, f^{-1}, \lambda, \phi | y) \\
& \propto \prod_{t=1}^{T} |F_t \Lambda_t F_t'|^{-1/2} \exp\left(-\frac{1}{2} (y_t - \bar{X}_t \theta_t)' (F_t \Lambda_t F_t')^{-1} (y_t - \bar{X}_t \theta_t) \right) \\
& \times |\Omega_0| \exp\left(-\frac{1}{2} \Theta' \Omega_0^{-1} \Theta \right) \\
& \times \prod_{i=1}^{N} \omega_i^{-\frac{\chi_0}{2} - 1} \exp\left(-\frac{\psi_0}{2\omega_i} \right) \\
& \times \prod_{i=1}^{N} \exp\left[-\frac{1}{2} (f_i^{-1} - f_{i,0}^{-1})' \Upsilon_{i,0}^{-1} (f_i^{-1} - f_{i,0}^{-1}) \right] \\
& \times |\Phi_0|^{-1/2} \exp\left(-\frac{1}{2} L_i' \Phi_0^{-1} L_i \right) \\
& \times \prod_{i=1}^{N} \phi_i^{-\frac{\beta_0}{2} - 1} \exp\left(-\frac{\delta_0}{2\phi_i} \right).
\end{aligned} \tag{C.18}$$

Therefore, it is possible to derive the conditional posterior densities for each set of parameters of interest. Notably, for θ:

$$\begin{aligned}
&\theta|(y, \Omega, f^{-1}, \lambda, \phi) \sim N(\bar{\Theta}, \bar{\Omega}), \\
&\text{with} \quad \bar{\Omega}^{-1} = (\Omega_0^{-1} + \bar{X}'\bar{\Sigma}^{-1}\bar{X}) \\
&\text{and} \quad \bar{\Theta} = \bar{\Omega}(\bar{X}'\bar{\Sigma}^{-1}y).
\end{aligned} \tag{C.19}$$

As to the diagonal elements of Ω:

$$\begin{aligned}
&\omega_i|(y, \theta, \omega_{-i}, \Sigma) \sim IG(\bar{\chi}, \bar{\psi}), \\
&\text{with} \quad \bar{\chi} = \frac{\chi_0 + T}{2} \\
&\text{and} \quad \bar{\psi} = \frac{\theta_{i,1}^2/\tau + \sum_{t=2}^T (\theta_{i,t} - \theta_{i,t-1})^2 + \psi_0}{2}.
\end{aligned} \tag{C.20}$$

The non-zero elements of matrix F_t have the following conditional posterior densities:

$$\begin{aligned}
&f_i^{-1}|(y, \theta, f_{-i}^{-1}, \lambda, \phi) \sim N(\bar{f}_i^{-1}), \bar{\Upsilon}_i) \\
&\text{with} \quad \bar{\Upsilon}_i = \Big(\bar{s}_i^{-1} \sum_{t=1}^T \nu_{-i,t} \exp(-\lambda_{i,t}) \nu_{i,t}' + \bar{\Upsilon}_{i0}^{-1}\Big)^{-1} \\
&\text{and} \quad \bar{f}_i^{-1} = \bar{\Upsilon}_i \Big(- \bar{s}_i^{-1} \sum_{t=1}^T \nu_{-i,t} \exp(-\lambda_{i,t}) \nu_{i,t}' + \bar{\Upsilon}_{i0}^{-1} f_{i0}^{-1}\Big).
\end{aligned} \tag{C.21}$$

On the other hand, the conditional posterior for λ is non-standard:

$$\begin{aligned}
&\pi(\lambda_{i,t}|y, \theta, f^{-1}, \lambda_{-i,-t}, \phi) \\
&\propto \exp\Big(- \frac{1}{2} \Big\{ \bar{s}_i^{-1} \exp(-\lambda_{i,t}) (\nu_{i,t} + (f_i^{-1})'\nu_{-i,t})^2 + \lambda_{i,t} \Big\} \Big) \\
&\times \exp\Big(- \frac{1}{2} \frac{(\lambda_{i,t} - \bar{\lambda}_i)^2}{\bar{\phi}} \Big) \\
&\text{with} \quad \bar{\phi} = \frac{\phi_i}{1 + \gamma^2} \\
&\text{and} \quad \bar{\lambda} = \frac{\gamma}{1 + \gamma^2} (\lambda_{i,t-1} + \lambda_{i,t+1}).
\end{aligned} \tag{C.22}$$

Equation (C.22) requires a Metropolis-Hastings step, with the following acceptance function:

$$
\begin{aligned}
&\kappa(\lambda_{i,t}^{(m-1)}, \lambda_{i,t}^{(m)}) \\
&= \exp\Big(-\frac{1}{2}\Big\{\exp(-\lambda_{i,t}^{(m)}) - \exp(-\lambda_{i,t}^{(m-1)})\Big\}\bar{s}_i^{-1}(\nu_{i,t} + (f_i^{-1})'\nu_{-i,t})^2\Big) \\
&\times \exp\Big(\{\lambda_{i,t}^{(m)} - \lambda_{i,t}^{(m-1)}\}\Big).
\end{aligned} \tag{C.23}
$$

For $t = 1$ and $t = T$, Equation (C.23) needs to be slightly adapted as follows. For the first period, a candidate is drawn from $\mathcal{N}(\bar{\lambda}, \bar{\phi})$, with:

$$
\bar{\lambda} = \frac{\gamma \lambda_{i,2}}{\omega^{-1} + \gamma^2} \quad \text{and} \quad \bar{\phi} = \frac{\phi_i}{\omega^{-1} + \gamma^2}. \tag{C.24}
$$

The acceptance function is then given by:

$$
\begin{aligned}
&\kappa(\lambda_{i,1}^{(m-1)}, \lambda_{i,1}^{(m)}) \\
&= \exp\Big(-\frac{1}{2}\Big\{\exp(-\lambda_{i,1}^{(m)}) - \exp(-\lambda_{i,1}^{(m-1)})\Big\}\bar{s}_i^{-1}(\nu_{i,1} + (f_i^{-1})'\nu_{-i,1})^2\Big) \\
&\times \exp\Big(\{\lambda_{i,1}^{(m)} - \lambda_{i,1}^{(m-1)}\}\Big).
\end{aligned} \tag{C.25}
$$

For the last period, the candidate is drawn from $\mathcal{N}(\bar{\lambda}, \bar{\phi})$, with:

$$
\bar{\lambda} = \gamma \lambda_{i,T-1} \quad \text{and} \quad \bar{\phi} = \phi_i. \tag{C.26}
$$

The acceptance function is then given by:

$$
\begin{aligned}
&\kappa(\lambda_{i,T}^{(m-1)}, \lambda_{i,T}^{(m)}) \\
&= \exp\Big(-\frac{1}{2}\Big\{\exp(-\lambda_{i,T}^{(m)}) - \exp(-\lambda_{i,T}^{(m-1)})\Big\}\bar{s}_i^{-1}(\nu_{i,T} + (f_i^{-1})'\nu_{-i,T})^2\Big) \\
&\times \exp\Big(\{\lambda_{i,T}^{(m)} - \lambda_{i,T}^{(m-1)}\}\Big).
\end{aligned} \tag{C.27}
$$

Finally, the conditional posterior distribution for ϕ is:

$$
\begin{aligned}
&\phi_i|(y, \theta, f^{-1}, \lambda, \phi_{-i}) \sim IG\Big(\frac{\bar{\beta}}{2}, \frac{\bar{\delta}}{2}\Big) \\
&\text{with} \quad \bar{\beta} = \beta_0 + T \\
&\text{and} \quad \bar{\delta} = \delta_0 L_i' G' L_i,
\end{aligned} \tag{C.28}
$$

Gibbs sampler

The Gibbs sampling algorithm for the model consists of the following steps:

1. Determination of the initial values ($\theta^{(0)}, \Omega^{(0)}, f^{-1(0)}, \lambda^{(0)}$ and $\phi^{(0)}$):

    - $\theta^{(0)}$ is given by the OLS estimate, $\hat{\theta}$ and $\Omega^{(0)} = diag(\hat{\theta}\hat{\theta}')$.
    - The time-invariant OLS estimate of Σ_t, $\hat{\Sigma}$, is decomposed using a triangular factorization: $\hat{\Sigma} = \hat{F}\hat{\Lambda}\hat{F}'$. $\hat{F}^{-1}$ is then computed and $f_i^{-1(0)}, i = 2, \ldots N$ are set as the non-zero and non-one elements of $\hat{F}^{-1}$.
    - $\lambda_{i,t}^{(0)} = 0, \forall t = 1, \ldots, T$ and $\forall i = 1, \ldots, N$.
    - $\phi_i^{(0)} = 1, \forall i = 1, \ldots, N$.

2. Determination of $\bar{s}_1, \ldots, \bar{s}_N$ using the estimated $\hat{\Lambda}$.

3. Computation of $\Lambda_t^{(0)}, \forall t = 1, \ldots, T$ using $\lambda_{i,t}^{(0)}$ and $\bar{s}_1, \ldots, \bar{s}_N$. Then: $\Sigma_t^{(0)} = F_t^{(0)}\Lambda_t^{(0)}F_t^{(0)\prime}, \forall t = 1, \ldots, T$.

4. At iteration m, the relevant parameters are drawn in the following order:

    - $\theta_t^{(m)}$ is drawn from Equation (C.19).
    - $\omega_i^{(m)}$ is drawn from Equation (C.20).
    - $f_i^{-1(m)}$ is drawn from Equation (C.21), where $\nu_{-i,t}^{(m)}$ and $\nu_{i,t}^{(m)}$ are computed from $\nu_t^{(m)} = y_t - X_t'\theta_t^{(m)}$. Then, $F_t^{-1(m)}$ is computed.
    - $\phi_i^{(m)}$ is drawn from Equation (C.28).
    - a candidate $\lambda_{i,t}^{(m)}, i = 1, \ldots, N, t = 1, \ldots, T$ is drawn from $\mathcal{N}(\bar{\lambda}, \bar{\phi})$ with $\bar{\lambda}$ and $\bar{\phi}$ set according to Equations (C.22), (C.24) and (C.26). The acceptance function in Equation (C.23) is then used and for $i = 1, \ldots, N$, $\lambda_{i,1}^{(m)}, \ldots, \lambda_{i,T}^{(m)}$ are stacked to obtain $L_i^{(m)}$.

5. Computation of $\Lambda_t^{(m)}$ using $\lambda^{(m)}$ and $\bar{s}_1, \ldots, \bar{s}_N$.

6. Computation of $\Sigma_t^{(m)}$ using $\Sigma_t^{(m)} = F_t^{(m)}\Lambda_t^{(m)}F_t^{(m)\prime}$.

Steps 4 to 6 are then repeated for each $m = 1, \ldots, M$. In our estimation, we set $M = 10000$, with a burn-in of 5000 iterations.