Fakultät für Wirtschaftswissenschaften
Facoltà di Economia
Faculty of Economics and Management

BEMPS –
Bozen Economics & Management
Paper Series

NO 86/ 2021

What are the drivers of Labor Productivity?

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August 23, 2022

Abstract: We propose a new structural VAR with four shocks identified via sign restrictions to identify the drivers of labor productivity in Italy for the period spanning 1996Q1-2018Q4. In particular, we disentangle two supply shocks (productivity and labor supply shocks) and two demand shocks: (i) a demand shock that triggers a positive correlation between output and total hours (demand 1 shock) and (ii) a demand shock that allows for a negative correlation between these two variables (demand 2 shock). We find that the latter demand shock is the dominant source of variations in labor productivity across horizons. Furthermore, the productivity shock is an important driver of labor productivity fluctuations in the short run while labor market shocks are important drivers at longer horizons. We show that the productivity, labor supply, and demand 2 shocks trigger procyclical reactions to labor productivity while the demand 1 and wage bargaining shocks generate countercyclical reactions to productivity. The procyclical response of labor productivity to the demand 2 shock indicates the use of labor hoarding, thereby supporting that firms adjust more the intensive margin. The countercyclical response of labor productivity to the demand 1 shock suggests that firms are eager to adjust the extensive margin when the expected duration of the business cycle phase is persistent.

Keywords: Labor productivity, VAR, sign restrictions.
JEL Codes: C11, C32, E32.

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*We thank Massimiliano Pisani for detailed comments on the preliminary version of this paper during the 8th SIdE-IEA Workshop for PhD Students in Econometrics and Empirical Economics. We are indebted to Francesco Furlanetto and Marco Lorusso whose insightful comments have improved this paper. We also benefited from discussions with Luca Gambetti, Emanuele Bacchiocchi, and Marco Lombardi. We are grateful to Nicolò Maffei-Faccioli for nice comments and for sharing his codes with us. Finally, we would like to thank participants at the 9th Italian Congress of Econometrics and Empirical Economics and the 8th SIdE Workshop for PhD students in Econometrics and Empirical Economics for useful comments. Josué Diwambuena gratefully acknowledges financial support from the Free University of Bozen-Bolzano PhD Fellowship during the duration of PhD studies. Francesco Ravazzolo acknowledges financial support from Italian Ministry MIUR under the PRIN project Hi-Di NET - Econometric Analysis of High Dimensional Models with Network Structures in Macroeconomics and Finance (grant 2017TA7TYC).

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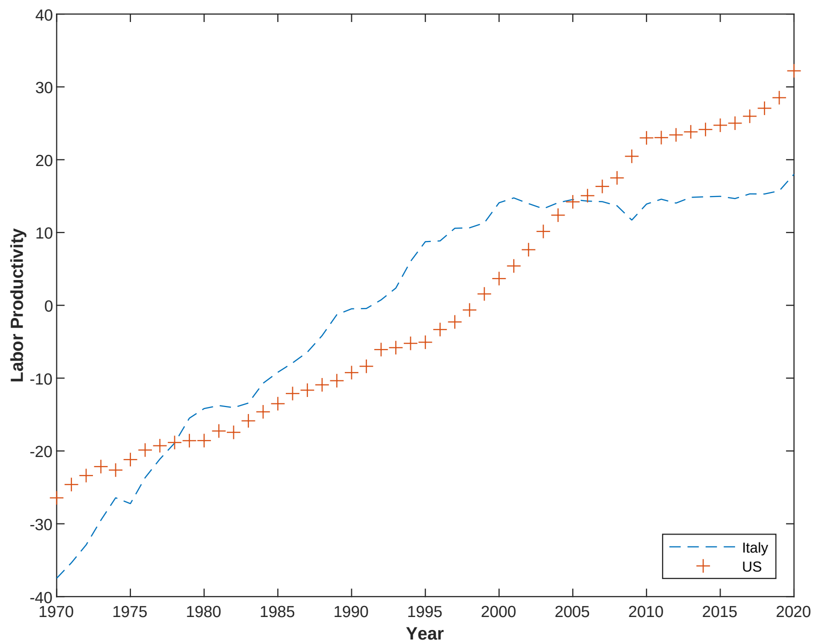
1 INTRODUCTION

This paper identifies the main drivers that explain movements in labor productivity in Italy over the period spanning 1996Q1-2018Q4. Labor productivity in Italy has become stagnant and has been slowing down since the early 2000s. The decline in the Italian labor productivity growth in the last two decades is greatly documented in the literature (see Daveri, Jona-Lasinio & Zollino 2005 and Hall, Lotti & Mairesse 2009). This pattern has also been witnessed in all major advanced economies (Moss, Nunn & Shambaugh 2020). Figure 1 presents the annual evolution of labor productivity in Italy and in the US over the period 1970-2020.

Figure 1: Labor Productivity in Italy and US from OECD (1970-2020).



Source: OECD

These series are taken from the OECD and are defined as the ratio of output per hours worked. This figure shows that labor productivity has been higher in Italy than in the US in the pre-Great Recession era. In the post-Great Recession, labor productivity in Italy has stagnated and has remained below the US productivity level since 2007 and the gap has been widening. Dossche, Gazzani & Lewis (2022) use data spanning the period 1984Q1-2019Q4 for a panel of OECD countries and document a new stylized fact: countries with lower employment volatility are characterized by more procyclical labor productivity.[1] They propose a business cycle model with different labor market adjustment mechanisms and variable effort to explain this pattern.

[1]They propose two candidates explanations: First, productivity shocks are the dominant sources of business cycle fluctuations in countries characterized by highly procyclical productivity while demand shocks are more important in countries where the cyclicality of labor productivity is low. Second, they argue that the Great Recession is widely believed to have been driven by deficient demand (see Christiano,

Their model shows that variation in effort associated with greater labor market frictions triggers procyclical labor productivity which in turn reflects the reluctance of firms to adjust the workforce. Similarly, Lewis, Villa & Wolters (2019) document a highly procyclical labor productivity in the Euro area. Using an estimated New-Keynesian DSGE model with labor search frictions and variable factor utilization in both capital and labor, they find that two interesting results: (i) the effort margin outperforms capital utilization, and (ii) the presence of increasing returns to hours generates a procyclical labor productivity and this is achieved through variations in effort.

In this paper, we document two important changes in the Italian labor market dynamics using the same data used by Dossche, Gazzani & Lewis (2022). To identify important changes, we split the sample into the pre-2000 and the post-2000 period and the cut-off period is chosen to coincide with the period that marks the beginning of the observed stagnation of the Italian labor productivity (see section 2 for further details on the statistics). First, the correlation between labor productivity and output has significantly declined. Second, the relative volatility of employment has substantially decreased while the relative volatility of hours has significantly risen. This is in line with Dossche, Lewis & Poilly (2019) who report that in Italy, Germany and France, around half of the cyclical adjustment of hours worked is in terms of hours per person. Nunziata (2003) finds that stricter employment protection and looser working time regulations are related with a lower volatility of employment over the cycle. This suggests that during a contraction, firms that are reluctant to fire workers may adjust the labor input along the intensive margin. The Euro area labor market is also characterized by small employment flows, reflecting great institutional frictions in labor market adjustment (Gnocchi, Lagerborg & Pappa 2015).

This paper contributes to the debate on the response of total hours in reaction to productivity and non-productivity shocks within SVARs using sign-restrictions (see Dedola & Neri 2007, Peersman & Straub 2009 and Conti, Guglielminetti & Riggi 2019 among others) and on the cyclicality of labor productivity (see Galí & Gambetti 2009, Barnichon 2010, Galí & Van Rens 2021 among others). So far in the literature, factors that explain the slowdown in the Italian labor productivity growth are identified from studies that draw inferences based on cross-sectional variation in microeconomic data (see Pianta & Vaona 2007 and Lucidi & Kleinknecht 2010).[2]

To the best of knowledge, this is the first paper that identifies the factors that explain movements in the Italian labor productivity within a VAR system using a theory-based identification that

Eichenbaum & Trabandt (2015) among others). They show that in a demand-driven recession, a decline in labor productivity is difficult to explain with standard business cycle models in the absence of variable factor utilization. They propose a model with variations in effort to generate procyclical labor productivity.

[2]The main drivers of labor productivity growth include among others (i) the decline in total factor productivity (Daveri, Jona-Lasinio & Zollino 2005); (ii) the exhaustion of capital deepening (Pianta & Vaona 2007); (iii) the reallocation of resources resulting from labour market reforms (Brandolini, Casadio, Cipollone, Magnani, Rosolia & Torrini 2007) and finally (iv) insufficient research and development (R&D) investment by Italian firms (European Commission 2006).

differs fundamentally from previous literature.[3] In this paper, we model four shocks (productivity, labor supply, demand 1 and demand 2 shocks) as candidates sources for the observed cyclicality of the Italian labor productivity. We find two dominant sources that explain variations in labor productivity: (i) the use of labor hoarding and variations in the intensive margin (hours per worker and effort) and (ii) the increase in the importance of demand and labor market shocks relative to the productivity shock as sources of business cycle fluctuations. In particular, we find that: (i) the productivity shock explains a great share of fluctuations in labor productivity only at short horizons; (ii) the demand and labor market shocks are important drivers of labor productivity in the middle run and at longer horizons. The demand 1 and the wage bargaining shocks generate countercyclical responses of labor productivity while the demand 2 shock, the productivity shock and the labor supply shock trigger procyclical reactions of labor productivity. We show that the demand shock that causes a negative correlation between output and total hours (i.e. the demand 2 shock) generates a procyclical reaction of labor productivity, thereby suggesting the use of labor hoarding. In contrast, the demand shock that leads to a positive correlation between output and total hours (i.e. the demand 1 shock) triggers a countercyclical reaction of labor productivity. The demand 1 and demand 2 shocks resemble respectively the persistent and non-persistent demand shocks discussed by Conti, Guglielminetti & Riggi (2019). In line with these authors, we argue that firms use labor hoarding and adjust more the intensive margin (hours and effort) when the business cycle phase is not very persistent (see Lewis, Villa & Wolters 2019 and Dossche, Gazzani & Lewis 2022). In contrast, when the cycle phase is very persistent, the cost of adjusting employment via the extensive margin becomes a valuable option as firms expect shocks to have prolonged consequences on aggregate demand. We check the robustness of the baseline results to various changes in the baseline specification. More importantly, we show that in the pre-Great Recession, all shocks generate procyclical responses of labor productivity. In contrast, in the aftermath of the Great Recession, labor productivity turns countercyclical to demand shocks and labor supply shocks. This evidence suggests that firms adjust more the extensive margin during crises such as the Great Recession. Finally, this paper sheds light on the structural factors that explain the recent increase in the Italian labor force participation. In particular, we emphasize the role of the matching efficiency shock since this participation trend occurs during two major labor market reforms (Fornero and Job Act reforms). Our simulation confirms the dominant role of the matching efficiency shock in explaining this pattern.

Related Literature. This paper is related to the literature on the concept of labor hoarding that dates back to the works of Oi (1962), Okun (1963), Rotemberg & Summers (1990) and Burnside, Eichenbaum & Rebelo (1993) among many other contributions. It is also related to a more recent literature that seeks to explain the vanishing procyclicality of the US labor productivity

[3] We find only few VAR studies with a focus on Italy that identify shocks through long run restrictions. Examples include Gavosto & Pellegrini (1999), Fabiani, Locarno, Oneto & Sestito (2001), Fabiani, Locarno, Oneto & Sestito (2001),Gambetti & Pistoresi (2004) and Di Giorgio & Giannini (2012) among others.

since mid-1980s on one hand and the highly procyclical behavior of labor productivity in the Euro area on the other hand. Several explanations have been put forward. The first explanation is based on labor market deregulation. For instance, Barnichon (2010) attributes the vanishing procyclicality of the US labor productivity to a more flexible labor market with lower hiring costs and a more elastic hours per worker which have reduced the cost of adjusting employment and hours. Galí & Van Rens (2021) and Mitra (2021) argue that reduced hiring and firing frictions in the US since mid-1984 have diminished the use of effort as a labor adjustment margin and have amplified employment fluctuations so that labor productivity becomes less procyclical. Fernald & Wang (2016) show empirically that lower variation in factor utilization (namely the workweek of capital and labor effort) is the main factor explaining the US productivity trend. Using data for a panel of OECD countries, Dossche, Gazzani & Lewis (2022) document a new stylized fact: countries with lower employment fluctuations are characterized by more procyclical labor productivity. They show that a procyclical labor productivity is triggered through variations in labor utilization (effort), which in turn result from the reluctance of firms to adjust the workforce extensively.[4] The second explanation is based on changes in the relative importance of different drivers of business cycle fluctuations. Barnichon (2010) shows that the reduction in the size of non-productivity shocks relative to productivity shocks since mid-1984 explain the US productivity behavior. Garin, Pries & Sims (2018) explain this pattern through the fall in the importance of aggregate shocks relative to reallocative shocks. Vom Lehn & Winberry (2022) argue that shocks to investment hubs have become more important after 1984, resulting in less sectoral comovement and less cyclical labor productivity. Schaal (2017) finds that volatility shocks drive unproductive firms out of the market so that employment declines and aggregate productivity rises. The third explanation is based on structural changes in the US labor market that have induced firms to diminish the practice of labor hoarding (Van Zandweghe 2010).

There is by now many papers that empirically analyze the responses of total hours and labor productivity to productivity shocks and non-productivity shocks within the context of SVARs using long run restrictions. The seminal work of Gali (1999) followed by Francis & Ramey (2005), Basu, Fernald & Kimball (2006) and Canova, Lopez-Salido & Michelacci (2010) among others spawned a large literature on the negative effect of productivity shocks on total hours and on the procyclicality of labor productivity.[5] Christiano, Eichenbaum & Vigfusson (2004) show that the response of total hours to productivity shocks is sensitive to its specification in

[4]Dossche, Gazzani & Lewis (2022) provide two main explanations for this pattern. First, productivity shocks are the dominant source of business cycle fluctuations in countries with strongly procyclical labor productivity while demand shocks are more important in countries where the cyclicality of labor productivity is low. Second, in a demand-driven recession like the Great Recession (see Christiano, Eichenbaum & Trabandt 2015 on deficient demand), a fall in labor productivity is difficult to explain with standard business cycle models in the absence of variable factor utilization. With unchanged productivity, a procyclical labor productivity is triggered by variations in factor utilization. Lewis, Villa & Wolters (2019) show that effort outperforms capital utilization in terms of explaining the Euro Area business cycle.

[5]See also Pesavento & Rossi (2005), Galí & Rabanal (2004) and Fève & Guay (2009) among many other contributions.

the VAR system. On one hand, they show that total hours rise in reaction to the productivity shock when the VAR is estimated using the level of hours. On the other hand, they find that productivity shocks trigger a fall in total hours when the growth of hours is used in the VAR. In similar vein, Chang & Hong (2006) find that the effect of productivity shocks on employment varies greatly across manufacturing industries. Herwartz (2019) uses a statistical identification approach and confirms the stronger role of productivity shocks in shaping temporary profiles of US unemployment during the recessionary period 1973Q3–1975Q1. Using VARs with time-varying coefficients, Galí & Gambetti (2009) find, among other things, a sign switch in the response of total hours over time (i.e. negative at the beginning of the post-war sample and positive or zero towards the end), an increase in the volatility of hours relative to output and a shrinking contribution of non-productivity shocks. The recent work of Cantore, Ferroni & Leon-Ledesma (2017) generalize the findings of Galí & Gambetti (2009) by estimating a VAR on overlapping windows of fixed length. They conjecture a supply-side structural explanation that is based on changes in the skill composition of the labor force and biases in technological change. Another strand of empirical studies has documented the effects of productivity and other structural shocks on total hours and labor productivity with VARs using sign-restrictions that are consistent with the predictions of popular classes of DSGE models (i.e. RBC vs NK-DSGE). Dedola & Neri (2007) and Peersman & Straub (2009) find a significant increase in total hours in response to productivity shocks and their results are robust to different specifications of total hours. They show that productivity shocks remain undeniably important sources of variations in output and total hours but they question their dominance as the main source of business cycle fluctuations as predicted in RBC models.[6]

This paper is mostly related to recent empirical studies that further disentangle productivity shocks from demand shocks and labor market shocks and allow them to be competing sources of variations in US labor market variables. Studies include among others Foroni, Furlanetto & Lepetit (2018) on labor supply, wage bargaining and matching efficiency shocks; Hairault & Zhutova (2018) on reallocation and matching efficiency shocks in US and France; Bergholt, Furlanetto & Faccioli (2019) on automation and wage markup shocks and Kiguchi & Mountford (2019) on immigration shocks.[7] Differently from these studies, we propose a new VAR applied to Italy in which we allow supply, demand and labor market shocks to compete as sources of variations in total hours and labor productivity. Italy is an interesting case study because

[6]The identification of Dedola & Neri (2007) relies on imposing restrictions on labor productivity, output, investment, consumption, and real wages and is not sufficient to disentangle productivity shocks from government spending shocks in the NK-DSGE models with limited asset market participation (e.g. Galí, López-Salido & Vallés 2007). Peersman & Straub (2009) do not impose any restriction on total hours and the resulting response of total hours allows them to discriminate between the NK-DSGE and the RBC models. See also Mumtaz & Zanetti (2012).

[7]We note few applications on other countries such as Maffei-Faccioli & Vella (2021) Maffei-Faccioli & Vella (2021) and Furlanetto & Robstad (2019) on the role of immigration shocks in Germany and Norway respectively; Schiman (2021) on the importance of labor supply shocks for the Austrian Beveridge curve. Other studies include among others Benati & Lubik (2014), Guglielminetti & Pouraghdam (2018), Galí & Gambetti (2019), Foroni & Furlanetto (2022).

it features important labor market rigidities, many labor market reforms and a stagnant labor productivity.

The remainder of this paper is structured as follows. Section 2 briefly discusses the structural changes that occurred in the Italian labor market. Section 3 explains the SVAR and the identification strategy. Section 4 presents the results of the baseline model. Section 5 summarizes the results of robustness and sensitivity checks. Section 6 concludes.

2 STRUCTURAL CHANGES IN THE ITALIAN LABOR MARKET

The Italian labor market is characterized by several rigidities including among others a two-tier wage bargaining mechanism, a low female labor force participation, long duration of unemployment spells, high mismatch and great regional disparities (Garibaldi & Taddei 2013; Adda et al. 2017; Schrader & Ulivelli 2017). Italy had one of the strictest employment protection legislation (EPL) among OECD countries (Boeri & Jimeno 2005) and has introduced in the last two decades several reforms aimed at enhancing the flexibility of its labor market (see Pinelli et al. 2017 and Cirillo, Fana & Guarascio 2017 for a survey on reform packages). Beginning with the Treu Package (Law 196/1997), these reforms have changed EPL at the margin only, mostly offering more flexible types of contracts for new hires (atypical contracts), without amending the rules for workers with permanent contracts (d'Agostino et al. 2018). These authors note that the combination of the reduced protection for new atypical contracts and rigid legislation for standard employment has raised concerns over the risk for workers to be trapped in positions of temporary employment, with lower wages, lower bargaining power and a lower level of rights and social protection. The reform which targeted fixed-term contracts in 2001 and apprenticeship contracts in 2003 (the Biagi law), have contributed to improve labor market flexibility extensively.

The Great Recession has amplified the fragility of Italian labor market institutions and has called for more structural changes in the labor market to enhance flexibility and to redress the daunting unemployment and output trends (see Destefanis & Fonseca 2007; Fana, Guarascio & Cirillo 2016; Marino & Nunziata 2017). The Italian economy has undergone a double dip-recession between 2008 and 2013 causing deep contractions in aggregate demand (GDP and investment), massive destruction of jobs and productive capacity (Marino & Nunziata 2017). From 2006 to 2014, GDP and productive capacity fell by 7.1 percent and 25 percent respectively and unemployment rate rose from 6.7 percent to 12.7 percent (Fana, Guarascio & Cirillo 2016). In the aftermath of the Great Recession, Italy introduced the Fornero reform whose target was to further change EPL for permanent contracts, to reduce labor market duality (i.e. the so called two-tier systems discussed by Boeri & Garibaldi (2007)) and to introduce universal unemployment benefits (Schrader & Ulivelli 2017). Building on the Fornero reform, the Job Act (JA) introduced measures to rationalize employment protection (via the establishment of subsidies for new hirings and the weakening of firing costs for permanent contracts), to strengthen active labor market policies (ALMPs) and to make social protection more effective. The ultimate goal of these measures was to further shrink labor market duality and to increase job matching efficiency.

These structural changes have helped to augment the aggregate and female labor force participation rate in Italy. OECD (2019) observes for instance that the female participation rate in Italy has increased from 40 percent in 2000 to 56 percent in 2017 albeit it remains below the trends in Southern european countries (70 and 60 percent for Spain and Greece in 2017 respectively). In a recent study, De Philippis (2017) documents significant variations in labor supply in Italy which have greatly contributed to increase the unemployment rate and the labor force participation rate over the period 2011-2016. He identifies structural and long-lasting factors driving this pattern: (i) the rise in the population's share of highly-educated individuals, who are more strongly attached to the labor market; (ii) the positive labor supply effects of the recent pension reform; and (iii) a surge in women's participation.

In what follows we document changes in labor market dynamics using Italian quarterly data spanning the period 1984Q1-2019Q4 borrowed from Dossche et al. (2022). We refer the reader to the latter for further details regarding data sources. We compute changes in the correlation between the cyclical behavior of labor productivity and output on one hand and changes in the correlation between labor productivity and labor inputs on the other hand. We complete our statistics with the relative volatilities of employment and hours per worker. To illustrate changes in labor market dynamics, we split the sample into two subperiods, pre-2000 (1984Q1-1999Q4) and post-2000 (2000Q1-2019Q4). The break date is chosen to coincide with the observed stagnation of labor productivity (see Figure 1). Moreover, we also compute statistics to account for the Great Recession period (2008Q1-2019Q4). Labor productivity is measured as quarterly real output per total hours. Cyclical components of labor productivity, employment, hours per worker and output are extracted with the HP filter (Hodrick & Prescott 1997). All data are expressed in natural logs. Relative volatility of labor inputs (employment and hours per worker) is measured as the ratio of the standard deviation of each labor input to output. The cyclicality of labor productivity is measured as the correlation between the cyclical components of output and labor productivity. Table 1 reports changes in the Italian labor market dynamics.

Table 1: Labor Market Dynamics

	1984Q1-2019Q4	1984Q1-1999Q4	2000Q1-2019Q4	2008Q1-2019Q4
Corr(Y,LP)	0.47	0.58	0.36	0.28
Corr(LP,HpW)	-0.21	-0.30	-0.05	-0.14
Corr(LP,N)	-0.32	-0.50	-0.24	-0.26
σ_n/σ_y	0.66	1.05	0.50	0.43
σ_{hpw}/σ_y	0.65	0.46	0.79	0.93

Corr denotes correlation, Y, LP, N, HpW denote respectively output, labor productivity, employment and hours per worker. σ_x/σ_y denotes the volatility of labor input relative to output.

The first column of Table 1 shows the statistics for the whole sample. The second and the third columns show the statistics respectively the pre-2000 and the post-2000 periods. The last column reports the statistics for the Great Recession era. The first row presents the correlation between labor productivity and output across periods. The second row shows the correlation between labor productivity and hours per worker across periods. The third presents the correlation between labor productivity and employment across periods. The fourth and the fifth rows show respectively the relative volatility of employment and the relative volatility of hours per worker. Labor productivity is mildly procyclical for the entire sample and the pre-2000 period. Productivity is acyclical for the post-2000 and the Great Recession periods. We document a negative correlation between labor productivity and labor inputs (hours per worker and employment) across periods. However, the relation looks much stronger for the extensive than the intensive margin. The relative volatility of employment is much higher for the pre-2000 period than the other periods. In fact, the relative volatility of employment drops in the post-2000 and in the Great Recession. In contrast, the relative volatility of hours is much higher in the post-2000 and in the Great Recession periods than before. This evidence suggests that firms rely more strongly on the intensive margin as argued by Dossche, Lewis & Poilly (2019).

3 The SVAR MODEL AND THE IDENTIFICATION STRATEGY

We consider the standard reduced-form VAR model as in Furlanetto, Ravazzolo & Sarferaz (2019):

$$Y_t = C + \sum_{j=1}^{p} A_j Y_{t-j} + u_t \qquad (1)$$

where Y_t is a $n \times 1$ vector containing all the endogenous variables, C is a $n \times 1$ vector of constants, $A_j, \dots A_p$ are the $n \times n$ matrices of coefficients associated with the p lags of the dependent variable, $u_t \sim \mathcal{N}(0, \Sigma)$ is a $n \times 1$ vector of reduced form residuals where Σ is a $n \times n$ variance-covariance matrix. Given great uncertainty around parameters, we estimate the VAR using Bayesian methods and the variables in level as Bayesian methods can be applied regardless of the presence of non-stationary in data (Sims, Stock, Watson et al. 1990). We specify diffuse priors for the reduced form parameters so that the posterior distribution has the usual Normal Inverse-Wishart form and that the information in the likelihood becomes dominant. In order to map the economically meaningful structural shocks from the estimated residuals, we need to impose restrictions on the variance-covariance matrix previously estimated. In particular, let $u_t = S\epsilon_t$ where $\epsilon_t \sim \mathcal{N}\ (0, \mathbb{I})$ is the $n \times n$ vector of structural disturbances with unit variance. S is a non-singular parameter matrix such that $SS' = \Sigma$. To obtain identification via sign-restrictions, we follow the algorithm described in Rubio-Ramirez, Waggoner & Zha (2010).[8]

[8]The algorithm by Rubio-Ramirez, Waggoner & Zha (2010) includes the so-called Haar-prior which, as discussed in Baumeister & Hamilton (2015), is informative about the structural parameters of the model,

Keeping up with Canova & Paustian (2011), we impose restrictions on impact only since they are sufficient to disentangle four shocks under consideration. We include two supply shocks (the productivity shock and the labor supply shock) and two demand shocks (the demand shock and the demand 2 shock). The restrictions are summarized in Table 2 and find theoretical support in business cycle models featuring an explicit role for labor supply shocks (e.g. Galí, Smets & Wouters 2012 and Foroni, Furlanetto & Lepetit 2018). Further details regarding the Bayesian estimation and the identification strategy are provided in the Appendix A.1.

Our dataset is quarterly and spans the period 1996Q1-2018Q4. The beginning of the dataset is constrained by the availability of data for the GDP deflator. The end of the dataset coincides with the year we started this project. Consistent with the restrictions summarized in Table 2, the set of endogenous variables Y_t includes four variables for the Italian economy: real GDP (chained linked GDP at market prices), real wages (defined as compensation of employees adjusted for inflation using harmonized CPI), GDP deflator (GDP implicit price deflator, index 2015=100) and total hours. The first two variables are taken from the Eurostat database. The third variable comes from the OECD and is extracted from the FRED database. The series on total hours is constructed by Ohanian & Raffo (2012) and has been extended until 2019 by Dossche, Gazzani & Lewis (2022). All the variables are expressed in natural logarithms. The baseline model is estimated with two lags, an average of the AIC, HIC and BIC criteria.

Table 2: Sign Restrictions

	Supply	Demand 1	Labor Supply	Demand 2
GDP	+	+	+	+
Prices	–	+	–	+
Wage	+	NA	–	NA
Hours	NA	+	+	–

Table describes the restrictions used for each variable (in rows) to identified shocks (in columns) in our VAR. + and - denote positive and negative restriction respectively. NA denotes unrestricted. Demand 2 is our residual demand shock.

The expansionary aggregate supply shock or the productivity shock drives output and prices in opposite directions and triggers an increase in real wages, as in most real business cycle or new Keynesian models under standard parameterizations. Since the reaction of total hours after the productivity shock is inconclusive in the literature, we leave it unrestricted. The use of data on real wages helps to disentangle the productivity shock from the labor supply shock. We disentangle the two shocks by assuming that the labor supply shock generates an inverse co-movement between output and real wages. An exogenous increase in labor supply leads to a rise in the number of job seekers, makes it easier for firms to fill up vacancies and to reduce

even asymptotically (see Uhlig 2017 and Inoue & Kilian 2020 for further details.). However, Uhlig (2017) finds no evidence that Haar priors may imply informative priors for impulse responses. In the presence of more than three variables, this prior is concentrated around a zero impact response to shocks (Foroni, Furlanetto & Lepetit 2018).

hiring costs, thereby resulting in a drop in real wages and in prices and an increase in output and in employment at the intensive margin.

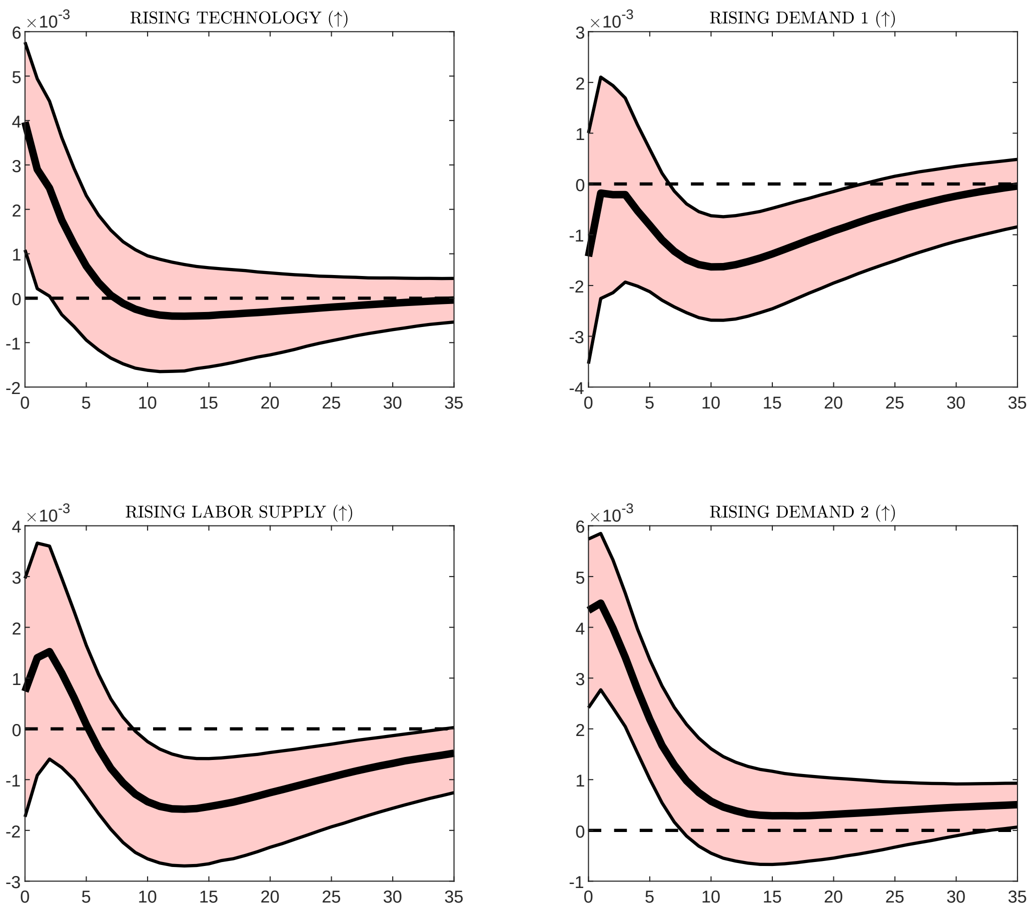
The expansionary demand 1 shock moves output and prices in the same direction and increases employment at the extensive and intensive margins. These dynamics are consistent with the effects induced by monetary policy, government spending, marginal efficiency of investment, discount factor, and most financial shocks.[9] We disentangle the demand 1 shock from the demand 2 shock by imposing that the latter triggers a negative co-movement between output and total hours. The use of data on prices allows us to separate demand shocks from the productivity and labor supply shocks. By identifying two demand shocks with asymmetric effects on total hours, we implicitly allow for the presence of persistent and non-persistent demand shocks discussed by Conti, Guglielminetti & Riggi (2019). These authors show that in the presence of convex employment adjustment costs, firms' incentive to react to shocks by varying the intensive margin relative to the extensive one depends on the persistence of the business cycle phase. So, the more transitory the demand shock, the more firms will hoard labor, meeting changes in demand by varying the intensive margin. On the contrary, when firms expect the duration of the business cycle phase to be persistent, they are more willingness to make gradual changes in the number of employees (the extensive margin) since the presence of hiring and firing costs limit large employment flows. The approach of Conti, Guglielminetti & Riggi (2019) is more restrictive because they disentangle the two demand shocks by imposing that persistent demand shocks trigger a countercyclical co-movement between output and labor productivity while non-persistent demand shocks generate a procyclical co-movement between these two variables.

Following Bergholt, Furlanetto & Faccioli (2019), the impulse responses of labor productivity are backed out from the impulse responses of real GDP and total hours. More specifically, as the variables in the VAR are in natural logarithms, the impulse responses of labor productivity can be simply computed as a linear combination of the impulses of its components:

$$\mathrm{IRF}_{\mathrm{LP},j} = \mathrm{IRF}_{\mathrm{GDP},j} - \mathrm{IRF}_{\mathrm{HOURS},j} \qquad \forall j = 0, \dots J \tag{2}$$

[9] See Furlanetto, Ravazzolo & Sarferaz (2019) for a detailed analysis of demand 1 shocks.

Figure 2: Implied labor productivity responses to shocks



Note: Posterior distributions of impulse responses of labor productivity to an estimated shock of one standard deviation using the baseline identifying restrictions. Median (solid line) and 68% probability density intervals (shaded area) based on 10,000 draws. The median and the percentiles are defined at each point in time.

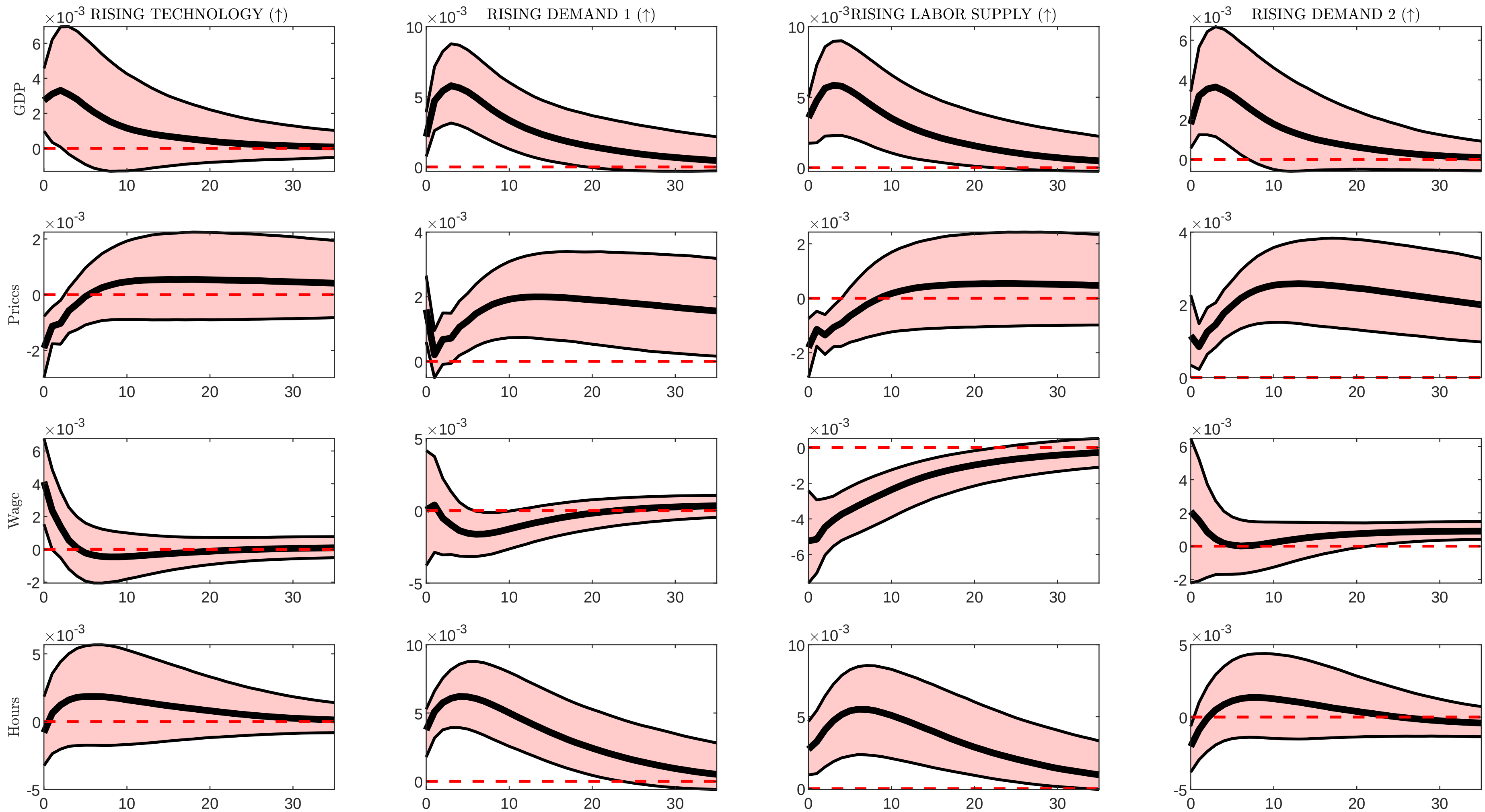
4 RESULTS

This section documents our main empirical results, obtained from the estimated SVAR model.

4.1 LABOR PRODUCTIVITY RESPONSES

We present in Figure 3 the empirical impulse responses for the four variables included in the SVAR in reaction to the four identified shocks. The implied labor productivity responses are documented in Figure 2. In both Figures, the horizontal axis measures time in quarters from

Figure 3: Empirical impulse responses from the baseline VAR model



Note: Posterior distributions of impulse responses to an estimated shock of one standard deviation using the baseline identifying restrictions. Median (solid line) and 68% probability density intervals (shaded area) based on 10,000 draws. The median and the percentiles are defined at each point in time.

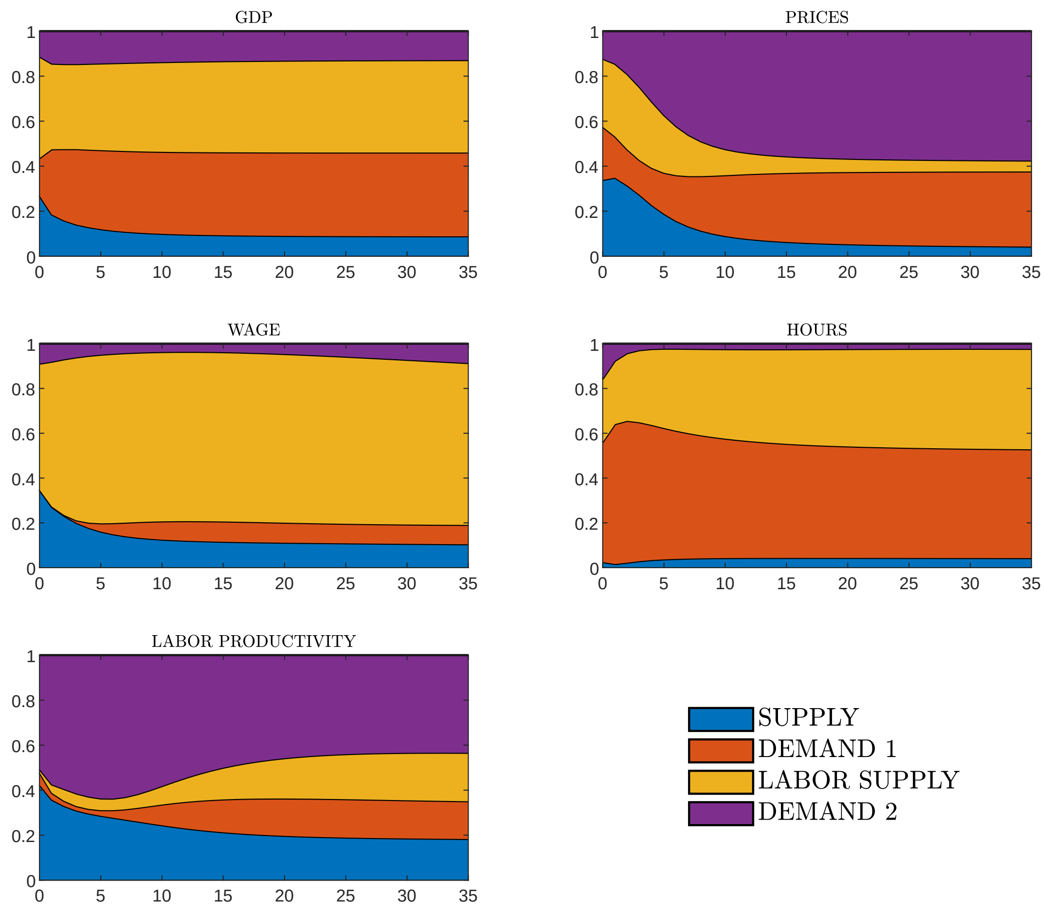
impact to 36 quarters after the disturbances have occurred. The vertical axis represents the responses in percent.

The expansionary productivity shock triggers large and persistent increases in GDP and total hours although the latter is not statistically significant, a temporary rise in real wages and a temporary fall in prices. The positive co-movement between GDP and total hours is well documented in the literature (Dedola & Neri 2007; Peersman & Straub 2009). The expansionary productivity shock affects output and productivity indirectly via its effects on the level of total hours. Since the expansionary productivity shock causes increases in total hours and GDP, the reaction of labor productivity rises in the short-run and dampens in the middle-run (Van Zandweghe 2010). The negative correlation between labor productivity and total hours is documented in the literature (see Gali 1999). The expansionary demand 1 shock generates large and persistent rises in GDP and total hours, a permanent increase in prices and leads to a persistent and statistically insignificant decrease in real wages though we do not restrict its response. The expansionary demand 1 shock incites firms to expand employment in both extensive and intensive margins and this pushes labor productivity to fall permanently. The countercyclical reaction of labor productivity to an expansionary demand 1 shock is documented in the literature (see Conti, Guglielminetti & Riggi 2019 among others). These authors show that the negative correlation between total hours and productivity is conditional on the expected duration of the business cycle. The expansionary labor supply shock leads to protracted increases in GDP and total hours, a temporary drop in prices and a permanent fall in real wages. The reaction of real wages in the short-run is the only source of identification between the productivity shock and the labor supply shock. The procyclical response of labor productivity in the short run is well documented in the literature (see Chang & Schorfheide 2003 and Conti, Guglielminetti & Riggi 2019). The demand 2 shock triggers a large and persistent rise in GDP, a permanent increase in prices and a temporary statistically insignificant rise in real wages. The adverse total hours effects of the demand 2 shock are rather short-lived. The responses of real wages and total hours in the short-run are the two sources of identification between the demand 1 shock and the demand 2 shock. The procyclical response of labor productivity in reaction to the demand 2 shock signals short run increasing returns to labor or the use of labor hoarding. The use of labor hoarding is well documented in the literature and is often described in terms of variations in effort margin which results from the reluctance of firms to adjust employment in the extensive margin (see Van Zandweghe 2010; Dossche, Gazzani & Lewis 2022 and Lewis, Villa & Wolters 2019).

4.2 THE MAIN DRIVERS OF LABOR PRODUCTIVITY

In this section, we ask the SVAR to quantify the relative importance of the four structural shocks under consideration. To this end we compute the share of the variance of a given variable attributable to each shock in the system. This is done at different frequencies from impact to 36 quarters ahead. Figure 4 shows the results of the forecast error variance decomposition.

Figure 4: Variance decomposition at different Frequencies



Note: The colored areas represent the point-wise median contributions of each identified shock to the forecast error variance of each variable (in levels) at horizons $j = 0, 1, \ldots, 36$ using the baseline identifying restrictions.

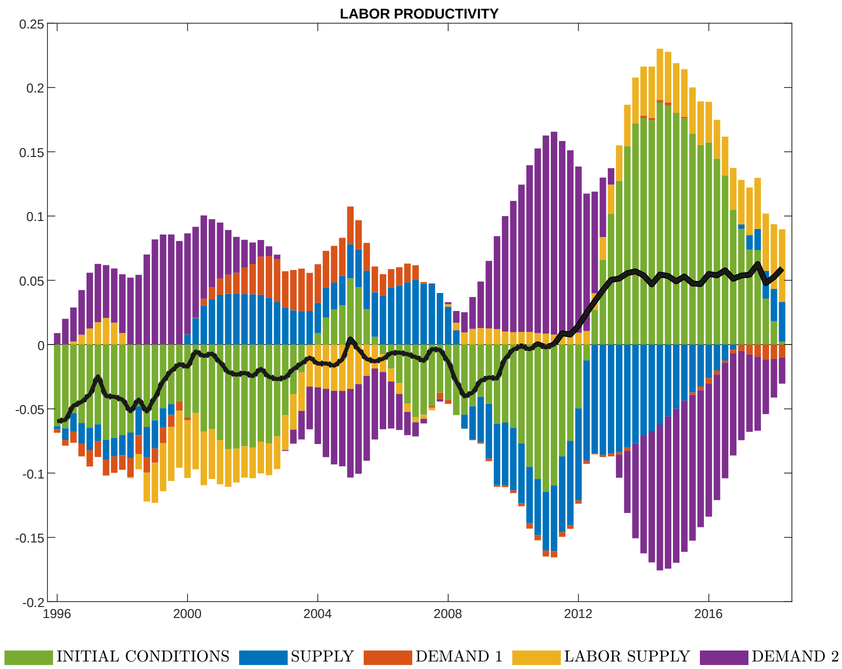
We find that at least half of variations in labor productivity is due to the demand 2 shock. The role of the demand 2 shock is even more prominent in the middle run where it accounts for 60% of fluctuations. Another important driver is the productivity shock which explains at most 40% of labor productivity fluctuations in the short run. At longer horizons, the contribution of the productivity shock is reduced while that of the demand 2 shock remains sizeable. The labor supply shock and the demand 1 shock have weak explanatory power in the short run but their importance is amplified at longer horizons. All in all, the demand 2 shock and the productivity shock are the dominant drivers of labor productivity in the short run and in the middle run while the demand 1 shock and the labor supply shock are important drivers at longer horizons. Our results are in line with previous results in the literature (Dossche, Gazzani & Lewis 2022 and Lewis, Villa & Wolters 2019). First, our results favor the argument by Dossche, Gazzani

& Lewis (2022) who show that the productivity shock is an important source of business cycle fluctuations in countries where employment is stable. Second, the increasing importance of non-productivity shocks (the demand 2 shock and the labor supply shock) as sources of labor productivity fluctuations find support in Van Zandweghe (2010) and Dossche, Gazzani & Lewis (2022). The former argues that structural changes in the labor market have induced firms to diminish the practice of labor hoarding. The latter argues that non-productivity (demand) shocks have become increasingly important since the Great Recession which is widely believed to be mainly driven by deficient demand shocks. They show that the procyclicality of labor productivity is explained through variations in the intensive margin (hours worked and effort).
An important role for the demand 2 shock can be explained intuitively. It is the expansionary demand shock that generates a negative correlation between GDP and total hours on impact. This co-movement find support in Lewis, Villa & Wolters (2019) who show that a demand shock can trigger a negative effect on hours per worker in business cycle models with sticky prices and variable labor effort. With labor productivity defined as GDP per total hours worked, we notice that the response of each variable favors a rise of labor productivity except in the presence of the demand 2 shock. Put simply, a procyclical labor productivity is triggered only when the denominator of labor productivity (total hours) responds less to shocks than the numerator (GDP).
Next, we discuss the role of the four identified shocks for the remaining variables in the system. We find that the demand 1 shock and the labor supply shock explain the bulk of fluctuations in GDP and hours. Fluctuations in real wages, in contrast, are mainly driven by the labor supply shock and to some extent the productivity shock in the short run. At first glance it might seem surprising that the demand 2 shock, while being important for labor productivity, plays a minor role for the rest of macroeconomic variables but prices. *lewis2019labor find that demand shocks that generating procyclical reaction of labor productivity are important sources of fluctuations in labor productivity. Finally, turning to prices, they are well explained by the productivity shock, the labor supply shock and the demand shocks. At longer horizons, prices fluctuations are mainly driven by the demand 2 shock. Our results are broadly in line with common findings in the literature (see Lewis, Villa & Wolters 2019, Foroni, Furlanetto & Lepetit 2018, Klein & Schiman 2022).

4.3 THE RECENT LABOR PRODUCTIVITY STAGNATION

This section computes the relative importance of different shocks in explaining the stagnation of labor productivity observed in data. To achieve this goal, we carry out a historical decomposition of labor productivity. Figure 5 shows the decomposition of labor productivity in deviation from its mean.

Figure 5: A historical decomposition of labor productivity



Note: The colored bars present the evolution of labor productivity, in deviations from its mean, attributable to the deterministic components (initial conditions) of the VAR and to each structural shock based on the median-target model of Fry & Pagan (2011)

.

A brief remark about the deterministic component (initial conditions) is needed. This component can be interpreted as our model-based forecast of labor productivity in the very beginning of the sample, given the estimated VAR coefficients and the initially discarded observations. That forecast shows an evolution of labor productivity broadly in line with its initial observations. The role of the deterministic component through time is trivial and is attributed to the use of flat priors (see Giannone, Lenza & Primiceri 2019 for further discussion on the role of initial conditions in VAR models). Turning to the structural shocks of interest, it is clear that, according to our model, the labor supply shock, the productivity shock and the demand 2 shock are key for understanding the post-2000 labor productivity evolution. After the Great Recession, the role of labor market shocks in explaining movements in labor productivity is concentrated around the period 2012-2016 where two major labor market reforms were introduced (see Pinelli et al. 2017).

5 ROBUSTNESS AND SENSITIVITY

In this section we check the robustness of the baseline results to a battery of sensitivity checks and we perform a number of extensions to the baseline specification.

5.1 ALTERNATIVE LAG SPECIFICATIONS AND PRIORS

The baseline SVAR shown in the previous section is estimated using 2 lags and imposing on impact the sign restrictions in Table 2 using the variables in level with a flat prior on a quarterly data spanning the period 1996Q1-2018Q4. We assess the robustness of our baseline results to changes in lag specifications and in priors. For the sake of exposition, we present only the variance decompositions of labor productivity corresponding to these sensitivity checks, but a complete set of results is available upon request. The first and second rows of Figure 10 present the variance decompositions of labor productivity using, respectively different lags specifications and different priors. Changing lag specifications at which the VAR is estimated does not seem to change the baseline results. The demand 2 shock and the productivity shock remain the dominant drivers of labor productivity fluctuations. The demand 1 shock and the labor supply shock remain non-negligible sources of fluctuations in labor productivity in the middle run. Now, we discuss the results when we estimate the baseline VAR using the dummy observation prior proposed by Sims & Zha (1998) and the priors for the long run (PLR) of Giannone, Lenza & Primiceri (2019). In the latter, we compute the median-target impulse responses proposed by Fry & Pagan (2011). Overall, the results are in line with our baseline when we use the VAR with the sum of coefficients prior though the role of the labor supply shock is significantly reduced. When we estimate the VAR with the PLR dummy prior, we find similar results to the baseline VAR but with marginal role for labor supply and demand 1 shocks.

5.2 LARGE MODEL

In this section, we externally validate our empirical approach and the identification of the different shocks in the VAR by including additional variables in the VAR which are important for understanding labor productivity dynamics (see Fernald 2014 and Furlanetto et al. 2021). In what follows, we analyze the responses of these variables to the different shocks in the system and we add, one by one, the following unrestricted variables to the VAR: investment-GDP ratio (Dieppe, Francis & Kindberg-Hanlon 2021), capital utilization (Fernald & Wang 2016) and long term (LT) real interest rate (Cette, Fernald & Mojon 2016*a*). We then estimate the augmented SVAR with the same baseline restrictions summarized in Table 2. The results are reported in Figure 11. The first row exhibits the impulse responses and the variance decomposition of investment. Results show that investment increases in reaction to all the four identified shocks. The variance decomposition shows that the labor supply shock and the demand shock are the major sources of variations in investment. In line with Furlanetto et al. (2021), the demand shock and the labor supply shocks are important drivers of investment in the short run and in the middle run. Furlanetto et al. (2021) disentangle permanent and temporary productivity shocks and find them to be important sources of variations in labor productivity. The relative importance of these shocks let us conjecture that the labor supply shock should play a big role in explaining variations in investment especially at longer horizons. The second row presents the impulse responses and the variance decomposition of capital utilisation. Fernald & Wang (2016) show that reduced variations in capital utilisation is an important factor of the vanishing cyclicality of the US labor productivity and attributes this pattern to the increased flexibility of labor market. We find a procyclical response of capital utilisation to all the four identified shocks. In line with Fernald & Wang (2016), the productivity shock is the dominant source of movements in capital utilisation in the short run while the two demand shocks and the labor supply shocks play a big role in the middle run. Keeping with Fernald & Wang (2016), this procyclicality of capital utilisation triggers an increase in labor productivity (not shown here but available upon request). The third row shows the impulse responses and the variance decomposition of long term (LT) real interest rate using data from Cette, Fernald & Mojon (2016*b*) for the period 1996Q1-2015Q4. We find a procyclical reaction of LT real interest rate to the supply shocks (productivity and labor supply shocks) as in Cette, Fernald & Mojon (2016*b*) and a countercyclical response of this variable to the two demand shocks. In line with Caballero et al. (2017) and Neri & Gerali (2019), most of changes in LT real interest rate are explained by the demand 2 shock and the productivity shock.

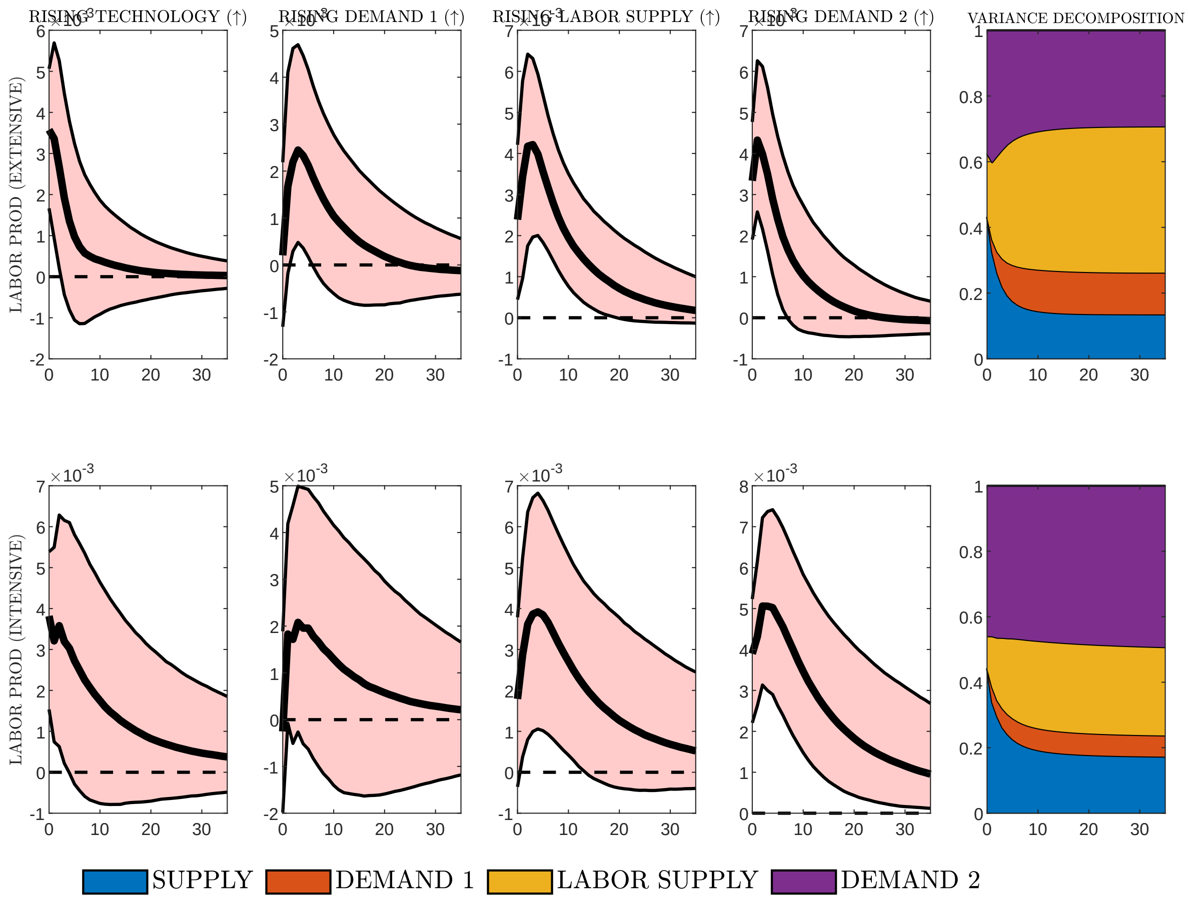
5.3 EXTENSIVE AND INTENSIVE MARGINS

In this section, we test the robustness of the baseline results to changes in the labor input keeping constant all the other features of the baseline model discussed in sub-section 5.1. Conti, Guglielminetti & Riggi (2019) also analyze the behavior of the extensive and the intensive margins. For the sake of exposition, we only present the results for the labor productivity but other results are available upon request.

The first row of Figure 6 presents the impulse responses and the variance decomposition of labor productivity when total hours is replaced by employment per head (the extensive margin). We find a large procyclical response of labor productivity to all the four identified shocks. The procyclical reaction of labor productivity in response to both demand shocks suggests even strong support for the use of labor hoarding. We remark that labor productivity does not turn negative in this case. Using the extensive margin does not seem to change the sources of fluctuations in labor productivity. The demand 2 shock and the productivity shock are still the dominant drivers of labor productivity in the short run. The labor supply shock and the demand 2 shock remain the two major drivers of labor productivity at long horizons while the fraction of variation explained by the demand 1 shock remains constant. The explanatory power of the labor supply shock is amplified in this specification. The second row of Figure 6 shows the impulse responses and the variance decomposition of labor productivity when total hours is replaced by hours per worker (the intensive margin). Similarly, all the shocks generate large procyclical reactions of labor productivity. The demand 2 shock and the productivity shock are still the majors drivers of labor productivity. The large explanatory power of the demand 2 shock throughout horizons suggests an even greater use of labor hoarding in this case as firms prefer to adjust the labor input intensively to avoid costly employment adjustment costs. The role of the labor supply shock is larger than in the baseline case and it is substantial at longer horizons. The demand 1 shock still plays a minor role in accounting for labor productivity fluctuations.

In conclusion, we observe that the reaction of labor productivity is sensitive to the measurement of the labor input used in the system. We show that both the extensive and intensive margins of the labor input provide more or less the same results in terms of the responses of labor productivity and the variance decompositions. However, we remark that total hours (a combination of both margins) is the only labor input that generates the countercyclical reaction of labor productivity in response to the demand shock and the productivity shock (in the middle run). The explanation is simple: the countercyclical reaction of labor productivity to the demand shock is triggered because the response of the denominator (total hours) is larger than the numerator (GDP). Instead, the strong procyclical response of labor productivity to all shocks when using both margins is triggered by an inverse mechanism (i.e. GDP grows more than employment and hours per worker).

Figure 6: Empirical impulse responses from the baseline VAR model using employment and hours per worker.



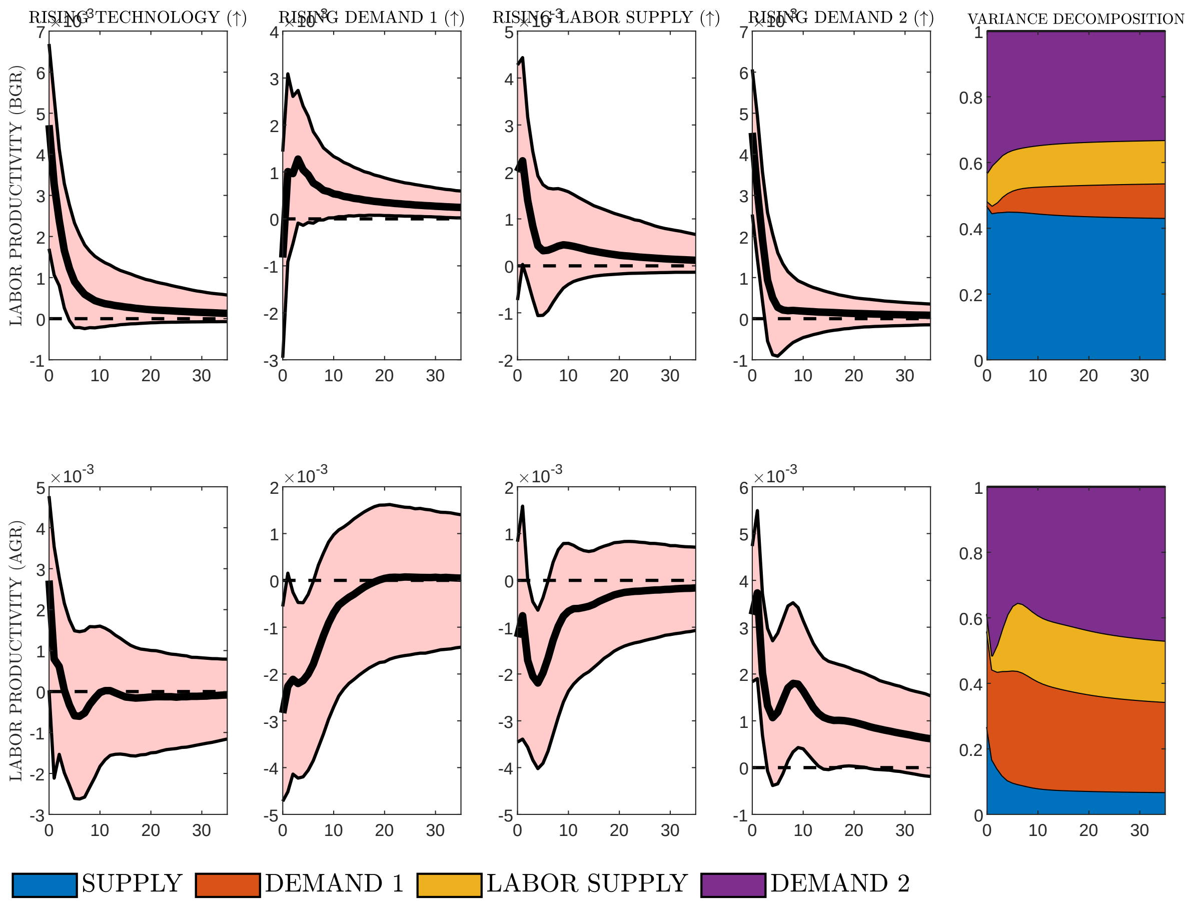
Note: Posterior distributions of impulse responses of labor productivity to an estimated shock of one standard deviation using the baseline identifying restrictions. Median (solid line) and 68% probability density intervals (shaded area) based on 10,000 draws. The median and the percentiles are defined at each point in time.

5.4 LABOR PRODUCTIVITY DURING THE GREAT RECESSION

This section examines to what extent the pre and post Great Recession periods have shaped the responses of labor productivity to the four identified shocks. Conti, Guglielminetti & Riggi (2019) argue that the Great Recession has inflicted deep scars on the euro area economy and has triggered substantial changes in macroeconomic dynamics. In the aftermath of this crisis, the euro area has been experiencing a prolonged recovery. Since 2008, many studies attribute observed macroeconomic dynamics to more persistent demand shocks, which are found to be dominant sources of euro area business cycle fluctuations (see among others Conti, Neri &

Nobili 2015 and Ciccarelli et al. 2017). These authors argue that the persistence of the shocks hitting the economy affects the composition of total labour input as long as firms can vary both the extensive and the intensive margin of labor utilization.

Figure 7: Empirical impulse responses before and after the Great Recession.



Note: Posterior distributions of impulse responses of labor productivity to an estimated shock of one standard deviation using the baseline identifying restrictions. Median (solid line) and 68% probability density intervals (shaded area) based on 10,000 draws. The median and the percentiles are defined at each point in time.

The fist row of Figure 7 presents the impulse responses and the variance decomposition of labor productivity when the baseline VAR is estimated by considering the sample spanning the period 1996Q1-2008Q2. The cut-off period is chosen as in Conti, Guglielminetti & Riggi (2019), that is before the Great Recession period (BGR). We find a procyclical response of labor productivity in reaction to the productivity shock, the labor supply shock and the demand 2 shock. Labor productivity responds negatively to the demand 1 shock on impact but then turns positive for the rest of horizons. The productivity shock and the demand 2 shock are the largest drivers of fluctuations in labor productivity in the BGR era. The role of the labor supply shock is quite significant while that of the demand shock is very limited. The second row of Figure 7 shows the impulse responses and the variance decomposition of labor productivity when the baseline VAR is estimated by considering the sample spanning the period 2008Q3-2018Q4, that is the after Great recession (AGR). Labor productivity reacts procyclical to the productivity shock and the demand 2 shock and countercyclical to the labor supply shock and to the demand 1 shock as in Conti, Guglielminetti & Riggi (2019). These authors show that the cost of adjusting employment by the extensive margin become a valuable option if firms expect the shock to have prolonged consequences on aggregate demand. Hence, keeping with them, our interpretation is that since 2008 firms responded more to persistent demand shocks by adjusting employment more extensively than what they had been doing in the pre-crisis period.

5.5 THE ROLE OF WAGE BARGAINING SHOCKS

This section examines the role of wage bargaining shocks in explaining cyclical movements in the Italian labor productivity. Wage bargaining shocks can be interpreted as policy changes in the Italian wage setting mechanism. Real wages in Italy have grown more than labor productivity since Italy joined the euro and this has eroded corporate profits and capital returns (Garcia-Macia 2020). Terzi (2016) shows that labor costs in Italy have grown by 60 percent over an 18-year period starting in 1990s and he attributes this trend to inflation developments. Blanchard & Wolfers (2000) argue that better coordination in wage bargaining schemes may lead to a faster adjustment of real wages to productivity changes. This growth of labor cost is tied to the features of the Italian wage bargaining system. Wage bargaining institutions in Italy have been historically designed to achieve strong nominal wage compression (see Boeri, Ichino, Moretti & Posch 2021 for futher discussion).

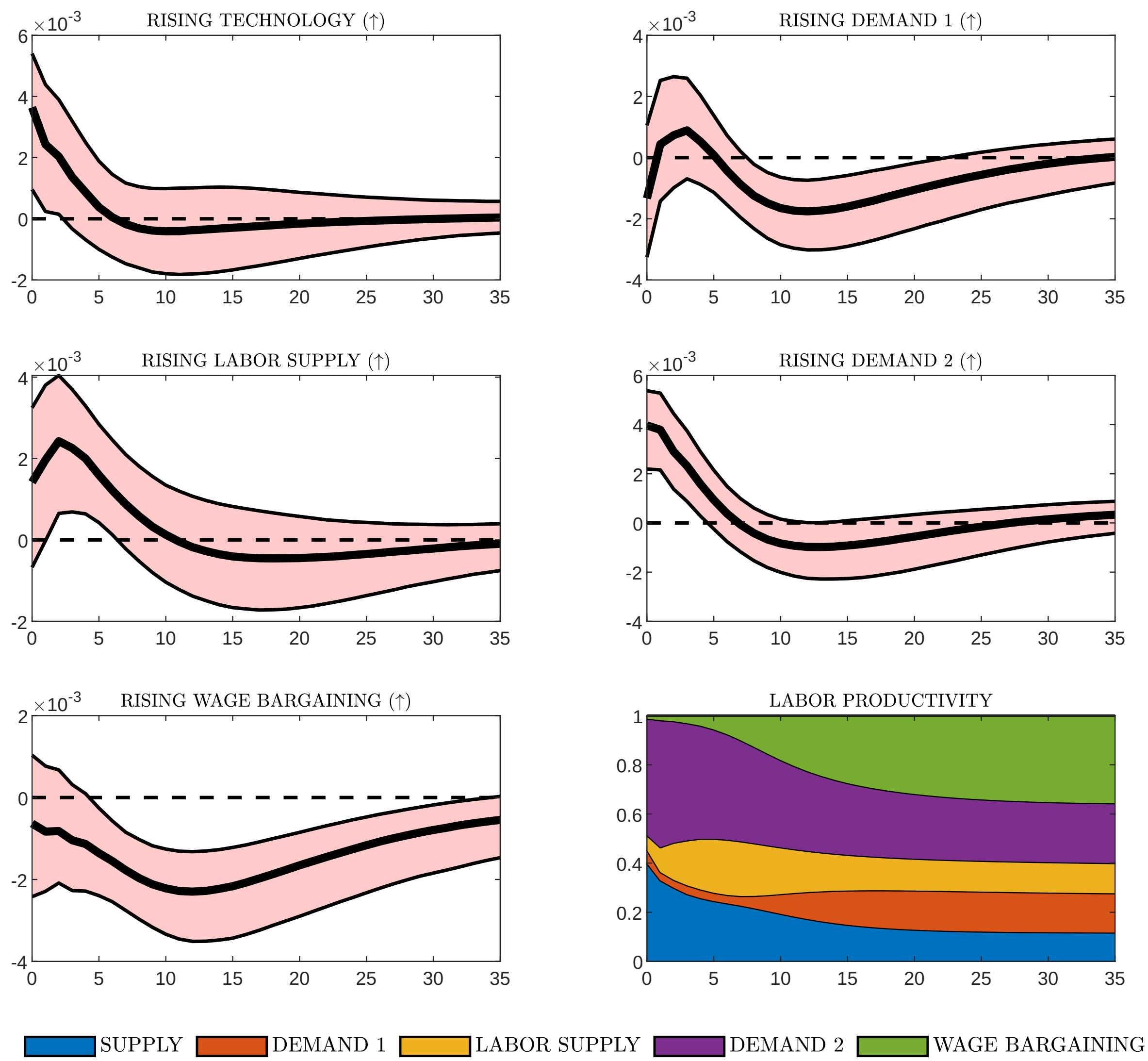
Italy is characterized by a centralised wage-setting mechanism that was established in 1993 and which to some extent is still in place today (Schindler 2009; Terzi 2016). This system is described as a two-tier wage bargaining system as bargaining takes place at industry and company-level. In Italy, more than 97 percent of dependent employment in the social security system is covered by national contracts (Boeri, Ichino, Moretti & Posch 2021). Industry level collective negotiations between employers and trade unions determine the main clauses of the employment contract, mostly take place at national level and set minimum (base) salaries that need to be renewed every three years for each job category and level of seniority. In addition, they also establish, among other things, hours and holidays, health and safety, training, and the use of temporary workers. Company-level negotiations take place between the employer and the company representatives elected to work councils and can only change selected clauses of the nationally negotiated contracts, where explicitly allowed by the latter. This represents only wage components related to profitability or productivity and are supplements to national wages. This decentralized bargaining is limited because it is only allowed to increase wages above the levels set by the national agreements. In general, Italian firms cannot pay a salary below the level established at the national level, regardless of their profitability and product demand conditions (Boeri, Ichino, Moretti & Posch 2021). These authors argue that despite large geographic differences in productivity across regions, firms in a given industry face the same wage floors. In recent years, the use of fixed term contracts has increased wage flexibility as it allowed to pay wages below national contracts to a limited number of employees per firm (Daruich, Di Addario, Saggio et al. 2020). It is evident that a reform of collective wage bargaining which shifts the determination of base salaries from the national to the regional level for all contracts, in the public and private sectors is desirable since it would allow wages and productivity in Italy to be aligned (Terzi 2016). We examine to what extent changes in wage setting mechanism in Italy could affect labor productivity. Previous studies who assess the role of wage bargaining shocks include among others Foroni, Furlanetto & Lepetit (2018) for the US and Klein & Schiman (2022) for Germany. Table 3 presents the sign restrictions when we separetely identify the labor supply shock from the wage bargaining shock (see Foroni, Furlanetto & Lepetit 2018).

Table 3: Sign restrictions

	Supply	Demand 1	Labor Supply	Demand 2	Wage Bargaining
GDP	+	+	+	+	+
Prices	–	+	–	+	–
Wage	+	NA	–	NA	–
Hours	NA	+	+	–	+
Unemployment	NA	–	+	–	–

We use unemployment data to disentangle the two labor market shocks. The reason is simple. An exogenous increase in labor supply generates an increase in the number of participants in the labor market. Therefore, some new workers will find a job within the period. However, it is plausible to assume that a fraction of the new workers will join the unemployment pool for the first quarter, as discussed by Blanchard & Quah (1989). In contrast, a reduction in the bargaining power of workers leads to a drop in wages. This is now the time for firms to hire, and as a result vacancy posting increases and unemployment falls. The restrictions on other variables remain applicable for the wage bargaining shock. The responses of unemployment to the productivity shock is unrestricted and this follows from the ambiguity on the sign of total hours. Demand shocks are expected to trigger a decrease in unemployment. For the sake of exposition, Figure 8 only presents the impulse responses and the variance decomposition of labor productivity. Figure 12 shows the impulse responses to all shocks. The procyclical reactions of labor productivity to the productivity shock, the labor supply shock and the demand 2 shock are still preserved but the latter turns countercyclical in the middle run, thereby indicating the reduction in the practice of labor hoarding. The countercyclical response of labor productivity to the demand 1 shock is temporary as it turns procyclical for four quarters before returning countercyclical for a long period.

Figure 8: Implied labor productivity responses to shocks



Note: Posterior distributions of impulse responses of labor productivity to an estimated shock of one standard deviation using the baseline identifying restrictions. Median (solid line) and 68% probability density intervals (shaded area) based on 10,000 draws. The median and the percentiles are defined at each point in time.

The wage bargaining shock generates a persistent countercyclical response of labor productivity, thereby confirming its role in increasing the flexibility of the labor market. The variance decomposition confirms the role of the demand 2 shock, the wage bargaining shock and the productivity shock as dominant sources of fluctuations in labor productivity. The labor supply shock plays quite a significant role in the middle run. The wage bargaining shock and the demand 2 shock are the dominant drivers of labor productivity variations at longer horizons. The contribution of the demand 1 shock remains the same at longer horizons.

5.6 THE RECENT RISE IN PARTICIPATION RATE

Our goal in this section is to identify the drivers that contribute to explain the recent increase in the aggregate labor force participation rate in Italy. In a recent study, De Philippis (2017) documents a sharp rise in Italy's participation rate by 2.6 percentage points between 2011 and 2016. He identifies: (i) the upsurge in the population's share of highly educated individuals (more strongly attached to the labor market); (ii) the positive labor supply effects of the recent pension reforms; and (iii) a surge in women's participation to the labor market as the main structural factors explaining this trend. To analyze the behavior of the participation rate to structural shocks and to identify the sources of variations in this variable, we proceed in two steps.

In the first step, we estimate the baseline VAR summarized in Table 2 over the period 1996Q1-2018Q4 and we introduce unrestricted one by one the following variables: (i) aggregate participation rate, (ii) participation rate by gender (men and women), and (iii) participation rate by educational level. Eurostat provides data on quarterly participation rate by educational level for the period 1996Q1-2018Q4. Eurostat classifies participation according to three education levels: (a) less than primary, primary, and lower secondary education, (b) upper secondary and post-secondary non-tertiary education and (c) tertiary education. We proxy these groups respectively as low-skill, middle-skill, and high-skill workers. In the second step, we check the robustness of the baseline results by estimating the VAR specification outlined in Table 4 over the period 2004Q1-2018Q4. The beginning of these data is constrained by data availability for vacancies. The latter framework as well as the sign restrictions are taken from Foroni, Furlanetto & Lepetit (2018). Klein & Schiman (2022) recently use this specification to analyze the factors that explain the German labor market miracle. Since we only focus on the responses of participation and not on labor productivity, we think that the new VAR specification is better suited to identify the drivers of participation. Thus, we remove total hours. We introduce aggregate participation as an unrestricted variable although this can be used to further disentangle the labor supply shock from the wage bargaining shock as in Foroni, Furlanetto & Lepetit (2018). We choose not to impose additional restrictions as all the five shocks are fully identified. The recent increase in the Italian participation rate coincides with the adoption of two important labor market reforms (i.e., the Fornero reform and the Job Act) during this period.

Table 4: Sign restrictions

	Supply	Demand	Labor Supply	Wage Bargaining	Matching Efficiency
GDP	+	+	+	+	+
Prices	–	+	–	–	–
Wage	+	NA	–	–	–
Unemployment	NA	–	+	–	–
Vacancies	NA	NA	NA	+	–

While the Fornero reform focused on pension policies, the Job Act reform aimed to improve the efficiency of matching workers with vacant positions in the Italian labor market(see Pinelli et al. 2017 and Cirillo et al. 2017 for a survey on these reforms). This motivates us to measure the role of the matching efficiency shock in explaining the rise in participation. In the previous section, the wage bargaining shock may also capture shocks to the wage negotiation process and other changes originating from the labor market.[10] Matching efficiency shocks capture technology in the matching function, that is, variations in the ability of the labor market to match workers searching for a job and available vacancies. Like the wage bargaining shock, the improvement in the matching technology reduces hiring costs and wages. Since firms fill up vacancies more easily, employment and output increase. Now, to further disentangle the wage bargaining shock from the matching efficiency shock, we use data on vacancies as in Foroni, Furlanetto & Lepetit (2018). Matching efficiency shocks first appear in Andolfatto (1996) where they represent reallocation shocks so long as they capture potential shifts of the Beveridge curve occasioning unemployment and vacancies to move in the same direction. Furlanetto & Groshenny (2016*b*) show that the positive co-movement between unemployment and vacancies in reaction to matching efficiency shocks mainly depends on the degree of price stickiness. They show that the response of vacancies is unambiguously negative when prices are sticky. Since price rigidity is very high in Italy (see Fabiani et al. 2005), we impose a positive correlation between unemployment and vacancies. The responses of vacancies to the productivity, demand shock and labor supply shocks are left unrestricted (see Foroni, Furlanetto & Lepetit 2018).

The first row of Figure 13 shows the impulse response and variance decomposition of aggregate participation. The productivity shock generates a temporary countercyclical response of participation. The labor supply shock and the demand shock trigger procyclical reaction of participation on impact. The demand shock and the labor supply shock are the major sources of variations in participation. At longer horizons, the demand 2 shock plays a substantial role while the productivity shock plays a minor role. The second row and the third row of Figure 13 present the impulse response and variance decompositions of participation by men and women respectively.

[10] Foroni, Furlanetto & Lepetit (2018) show that the effects of a fall in the unemployment benefits are equivalent to a decline in the bargaining power of workers in a standard business cycle models with labor market frictions.

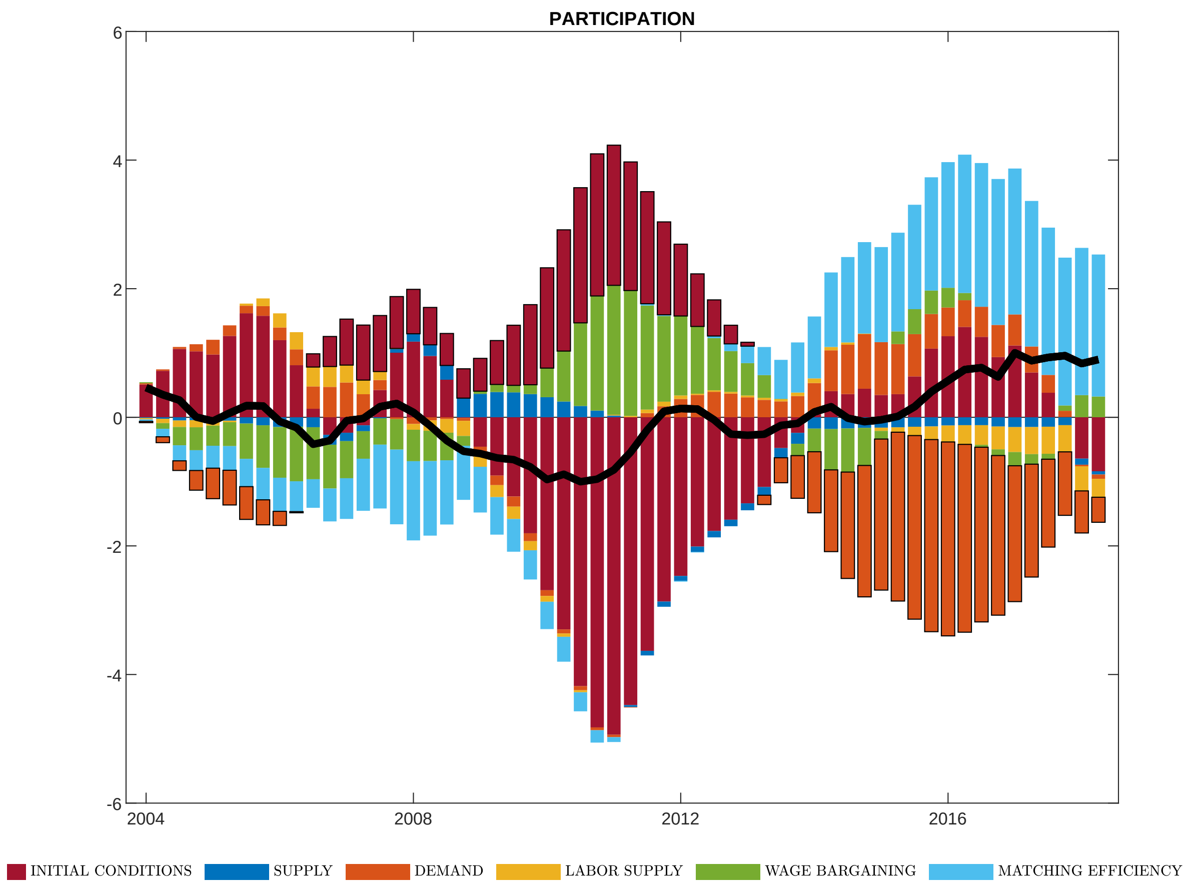
The same reactions of participation is observed when we consider the gender dimension of participation. Both variance decompositions show that the labor supply shock and the demand 1 shock are the dominant sources of movements in men and women participation to the labor market across horizons. The role of the demand 2 shock is reduced in this specification while that of the productivity shock remains very limited. We remark strong differences between the sources of aggregate participation and participation by gender.

The first row of Figure 14 shows the impulse response and variance decomposition of participation by low-skill workers. The second row and the third row of Figure 14 present the impulse responses and variance decompositions of participation by middle-skill and highly-skill workers respectively. We find heterogeneous responses of participation by educational level. The demand 1 shock, the labor supply shock and the demand 2 shock generate procyclical responses of low-skill participation while the productivity shock triggers a fall in labor productivity on impact. The demand 1 shock and the labor supply shock trigger an increase in middle-skill and high-skill participation while the demand 2 shock leads to a fall in these variables. The reaction of middle-skill and high-skill participation to the productivity shock is almost acyclical. The heterogeneous effects of shocks on participation by educational level is reinforced by our variance decomposition results. The demand 1 shock, the labor supply shock and the demand 2 shock are the main factors explaining movements in low-skill participation. The labor supply shock and the demand 1 shock are the dominant sources of variations in middle-skill and high-skill participation. The labor supply shock emerges as the only dominant source of middle-skill participation across horizons. The increasing contribution of the labor supply shock in this specification confirms the role that structural changes in the labor market have played in driving the recent participation trend and this is in line with the results of De Philippis (2017) and Grigoli, Koczan & Topalova (2018).

Now, we discuss the results obtained when using the sign restrictions summarized in Table 4. Figure 15 presents the impulse responses of variables to the five identified shocks. Figure 16 shows the variance decomposition of variables including participation. Despite not imposing restrictions on participation, we notice that the productivity shock and the labor supply shock generate an increase in participation while the demand shock and the wage bargaining shock trigger a fall in participation on impact before turning positive. The matching efficiency shock is the only shock that leads to a significant decrease in participation. In this specification, the matching efficiency shock and the labor supply shock are the dominant drivers of participation while the remaining shocks play a very marginal role. In line with Furlanetto & Groshenny (2016*a*), we find a limited importance of the matching efficiency shock for business cycle fluctuations. However, as stressed by these authors, this evidence does not rule that they may play a relevant role in specific episodes, especially when unemployment and vacancies move in the same direction as in the aftermath of the Great Recession. Our results do not change when we impose additional restrictions on the response of participation to labor supply and wage bargaining shocks and we estimate our VAR using the recent computationally efficient algorithm proposed by Korobilis (2022) (results are available upon request).

Figure 9 presents the historical decomposition of participation. This exercise allows us to identify the drivers that explain the evolution of aggregate participation observed between 2011 and 2016. Our analysis shows that the matching efficiency shock has contributed significantly to the increase in participation during this period. The demand shock and the wage bargaining shock have also played quite a non-negligible role in the recent rise in participation.

Figure 9: Historical decomposition of Participation



Note: The colored bars present the evolution of labor productivity, in deviations from its mean, attributable to the deterministic components (initial conditions) of the VAR and to each structural shock based on the median-target model of Fry & Pagan (2011).

6 CONCLUSIONS

This paper identifies the drivers of labor productivity in Italy using a new VAR with sign restrictions and quantifies the role of these drivers in explaining variations in labor productivity. We estimate the VAR with Bayesian methods using quarterly data over the period 1996-2018.

The Baseline VAR includes four variables and four identified shocks. Our results show that the demand 2 shock, the productivity shock and the labor supply shock are the main sources of fluctuations in labor productivity. The demand 1 shock plays a limited role in the middle run. The demand 1 shock generates a countercyclical response of labor productivity while the demand 2 shock, the productivity shock and the labor supply shock trigger procyclical reactions of labor productivity. The procyclical reaction of labor productivity to the demand 2 shock shows the presence of increasing returns to hours or the use of labor hoarding. In contrast, the countercyclical response of labor productivity to the demand 1 shock aligns with the argument that firms are willing to adjust the extensive margin when the business cycle phase is expected to be persistent as discussed by Conti, Guglielminetti & Riggi (2019). The demand 2 shock and the demand 1 shock resemble respectively the non-persistent demand shock and the persistent demand shock discussed by these authors. In line with them, our results show that when the business cycle phase is not very persistent, firms use labor hoarding to avoid costly employment adjustment costs, thereby relying on the intensive margin. In contrast, when the cyclical phase is very persistent, the cost of adjusting employment by the extensive margin becomes a valuable option as firms expect shocks to have prolonged consequences on aggregate demand. We checked the robustness of the baseline results to changes in lag specifications, in priors, in labor inputs (extensive and intensive margins) and in specific periods with a focus on the Great Recession. We test the external validity of our empirical approach by adding more variables and by analyzing the responses of these variables to shocks. Furthermore, we pay a particular attention on the role of labor market shocks (i.e. labor supply and wage bargaining shocks) in explaining movements in labor productivity because several policy changes have occured in the Italian labor market. Our sensitivity analysis confirms the dominant role of the demand 2 shock, the productivity shock and the labor supply shock as sources of fluctuations in labor productivity. In general, the demand 1 shock is a minor source of variations in labor productivity but its role is significantly amplified in the post-Great Recession period. We also show that estimating the baseline VAR by changing the sample period hides the sign switch of the responses of labor productivity to the demand 1 shock and the labor supply shock. In the pre-Great Recession, all the identified shocks generate procyclical responses of labor productivity. In the post-Great Recession, labor productivity turns countercyclical to demand 1 and labor supply shocks. When we disentangle the labor supply shock from the wage bargaining shock, we remark that the latter triggers a persistent countercyclical reaction of labor productivity and explains a great share of variations in this variable at longer horizons. The countercyclical responses of labor productivity to labor market shocks confirms the important role of structural changes in the labor market in explaining cyclical movements in labor productivity as stressed by Van Zandweghe (2010). Without imposing any restrictions on the responses of unemployment, we show that the productivity shock and the demand shocks decrease unemployment on impact while the labor supply shock leads to a temporary rise in it. This paper also studies the behavior of the Italian participation to shocks and in particular to the matching efficiency shock. The matching efficiency shock coincides with the observed increase in participation. More specifically, we identify the drivers that explain the historical evolution of participation observed between 2011 and 2016. We show that the matching efficiency shock is the dominant source of the increase in the recent participation rate. Given the burgeoning role of labor market shocks, we urge policymakers to keep track of the functioning of Italian labor market institutions very closely.

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A Appendices

A.1 The Model and the Identification Strategy

In this appendix, we explain thoroughly the econometric procedure we apply for the estimation of our model. We consider the following reduced-form VAR representation:

$$Y_t = C_A + \sum_{j=1}^{p} A_i Y_{t-j} + u_t \tag{3}$$

where Y_t is a $(n \times 1)$ vector containing all N endogenous variables, C_A is a $(n \times 1)$ vector of constants, A_i for $i = 1, ..., P$ are $(n \times n)$ parameter matrices. p denotes the number of lags and u_t is a $(n \times 1)$ vector of one step-ahead prediction errors with $u_t \sim \mathcal{N}(0, \Sigma)$ where Σ is the $(n \times n)$ variance-covariance matrix. Given great parameter uncertainty, we estimate our model in level using Bayesian methods because the latter can be applied regardless of non-stationarity in data (Sims, Stock, Watson et al. 1990).

Bayesian Estimation

We write our model in (3) in seemingly unrelated regression (SUR) representation as follows:

$$Y = XA + U \tag{4}$$

where $Y = [y_{p+1} \dots y_T]'$, $A = [C_A \;\; A_1 \dots A_p]'$, $U = [u_1 ... u_T]'$ and

$$X = \begin{bmatrix} 1 & y_0' & \dots & y_{-p}' \\ \vdots & \vdots & \vdots & \vdots \\ 1 & y_{T-1}' & \dots & y_{T-p}' \end{bmatrix}$$

By vectorising (4), we obtain the following:

$$y = (\mathbb{I}_n \otimes X)\alpha + u \tag{5}$$

where $y = vec(Y)$, $\alpha = vec(A)$, $u = vec(U)$ and $vec()$ denotes columwise vectorisation. Given the normality assumption of the error term ε with a mean zero and variance-covariance $\Sigma \otimes \mathbb{I}_{T-p}$, the likelihood function conditional on the parameters of the model α and Σ and the regressors X can be written as follows:

$$L(y|X, \alpha, \Sigma) \propto |\Sigma \otimes \mathbb{I}_{T-p}|^{-\frac{T-p}{2}} \exp\left\{\frac{1}{2}(y - \mathbb{I}_n \otimes X\alpha)'(\Sigma \otimes \mathbb{I}_{T-p})^{-1}(y - \mathbb{I}_n \otimes X\alpha)\right\} \tag{6}$$

where y denotes the available data. Denoting $\hat{\alpha} = \vec{\hat{A}}$ where $\hat{A} = (X'X)^{-1}X'Y$ denotes the OLS estimate and letting $\Lambda = (Y - X\hat{A})'(Y - X\hat{A})$ be the sum of squared errors, then the likelihood function in (6) can be rewritten as follows:

$$L(y|X, \alpha, \Sigma) \propto |\Sigma \otimes \mathbb{I}_{T-p}|^{-\frac{T-p}{2}} \exp\left\{\frac{1}{2}(\alpha - \hat{\alpha})'(\Sigma^{-1} \otimes X'X)(\alpha - \hat{\alpha})\right\} \exp\left\{-\frac{1}{2}\mathrm{tr}(\Sigma^{-1}\Lambda)\right\} \tag{7}$$

We then specify diffuse priors for α and Σ that are proportional to $|\Sigma|^{-\frac{n+1}{2}}$ namely:

$$p(A|\Sigma) \propto 1$$
$$p(\Sigma) \propto |\Sigma|^{-\frac{n+1}{2}}$$

By combining our diffuse priors with the likelihood function using Bayes rule, we then obtain Normal-Inverse Wishart posterior:

$$\begin{aligned} L(\alpha, \Sigma|y, X) &\propto L(y|X, \alpha, \Sigma)p(A|\Sigma)p(\Sigma) \\ &= |\Sigma|^{-\frac{T-p+n+1}{2}} \exp\left\{\frac{1}{2}(\alpha - \hat{\alpha})'(\Sigma^{-1} \otimes X'X)(\alpha - \hat{\alpha})\right\} \exp\left\{-\frac{1}{2}\mathrm{tr}(\Sigma^{-1}\Lambda)\right\} \end{aligned} \tag{8}$$

The likelihood function in (8) is a product of a normal distribution for α given Σ and an inverse Wishart distribution for Σ. Thus, we draw α conditional on Σ from

$$\alpha|\Sigma, y, X \sim \mathcal{N}(\hat{\alpha}, \Sigma \otimes (X'X)^{-1}$$

and Σ from

$$\Sigma|y, X \sim \mathcal{IW}(\Lambda, \nu)$$

where $\nu = T - p - (np + 1) - n - 1$; $\mathcal{IW}$ denotes an inverse-Wishart distribution.

Sign Identification

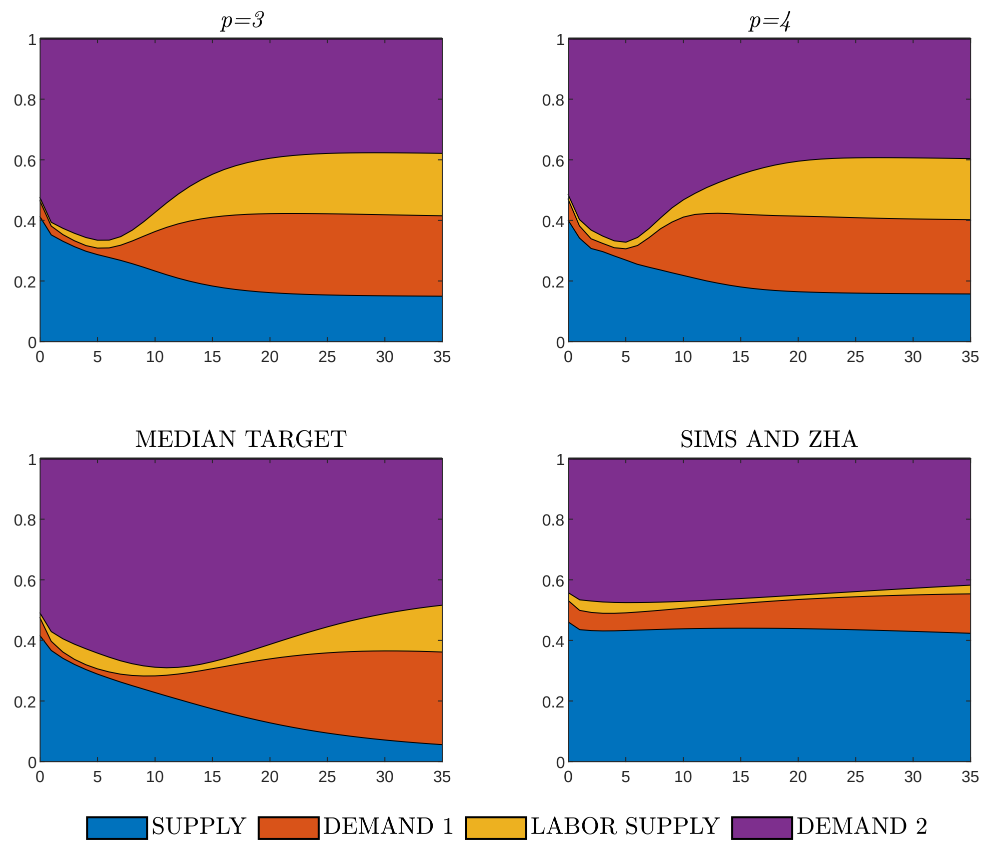
In order to recover the impact of structural shocks from our reduced-form forecast errors, we assume that the forecast error u_t is a linear combination of structural disturbances ϵ_t such that:

$$u_t = S\epsilon_t \tag{9}$$

where $\epsilon_t \sim \mathcal{N}(0, \mathbb{I})$ denotes the $(n \times n)$ variance-covariance matrix of structural disturbances and where S is a non-singular parameter matrix. The variance-covariance matrix in (9) is given by $\Sigma = SS'$. Σ has $\frac{n(n+1)}{2}$ distinct parameters while S has n^2 independent parameters. Thus, in order to identify structural shocks, we need to impose $\frac{n(n-1)}{2}$ restrictions on S. In the Cholesky decomposition, S is restricted to be lower triangular, thereby implying a recursive identification procedure. However, in the Cholesky decomposition, the covariance matrix is assumed as $\Sigma = S\mathbb{I}_N S'$ where $\mathbb{I}_n = QQ'$ and Q denotes an orthonormal matrix. To impose sign restrictions, we need to specify a set of admissible Q matrices (Caldara et al. 2016). To accomplish this task, we follow the procedure proposed by Rubio-Ramirez, Waggoner & Zha (2010). This procedure works as follows. Firstly, we draw from a $\mathcal{MN}(0_N, \mathbb{I}_n)$ and perform a QR decomposition of S with the diagonal of R normalised to be positive, where $QQ' = \mathbb{I}_n$. Secondly, we impose the Cholesky decomposition on S such that $\Sigma = SS'$ where S denotes a Cholesky factor. We then compute candidate impulse responses from SQ' and A_i for $i = 1, \ldots, p$ and check if the generated impulse responses satisfy the sign restrictions or not. If they do satisfy the sign restrictions, store them, otherwise, discard them and return to the initial step. We repeat the same procedure until we obtain 10,000 impulse responses which satisfy our sign restrictions.

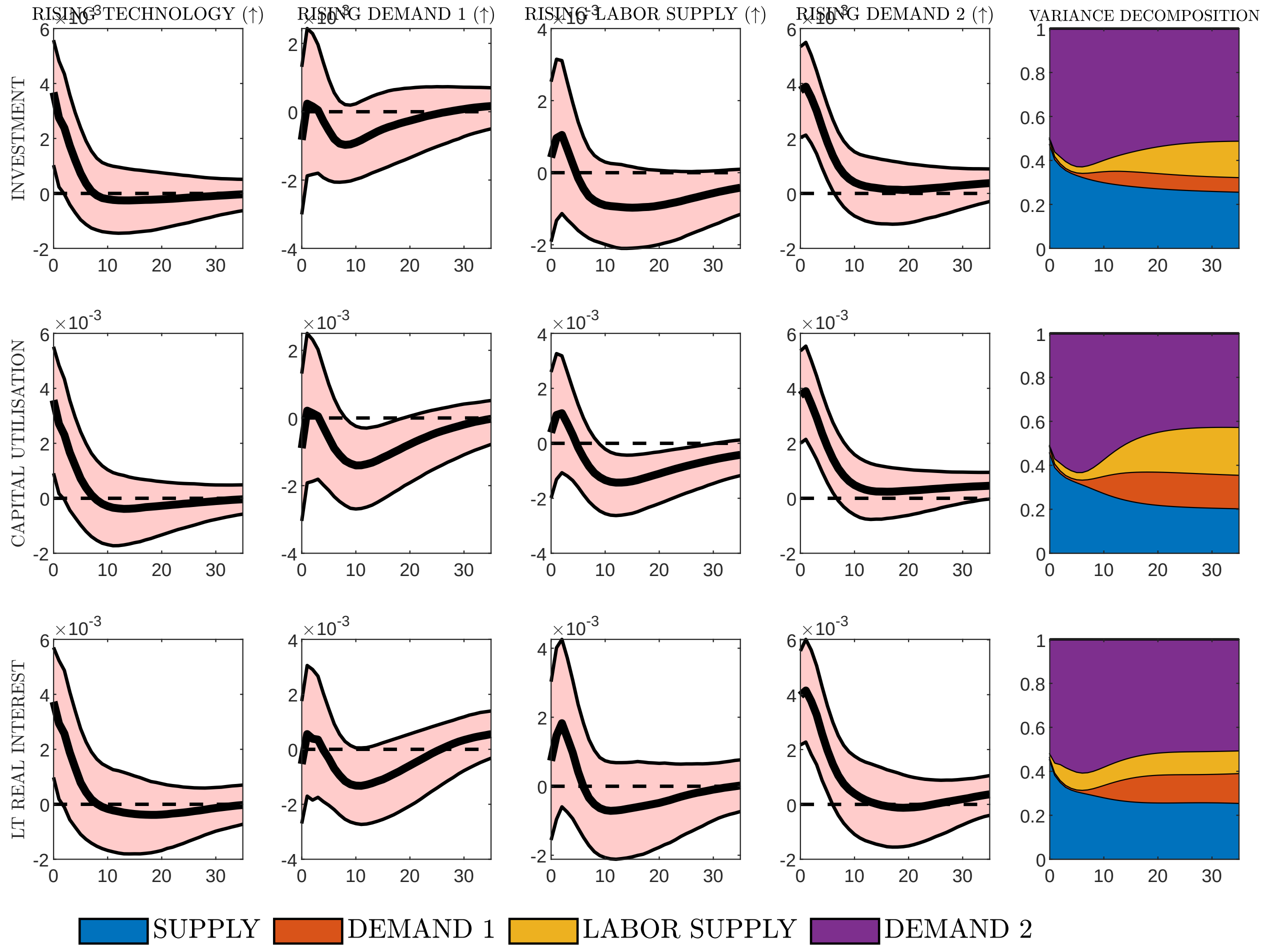
A.2 ADDITIONAL RESULTS

Figure 10: Variance decomposition: sensitivity checks



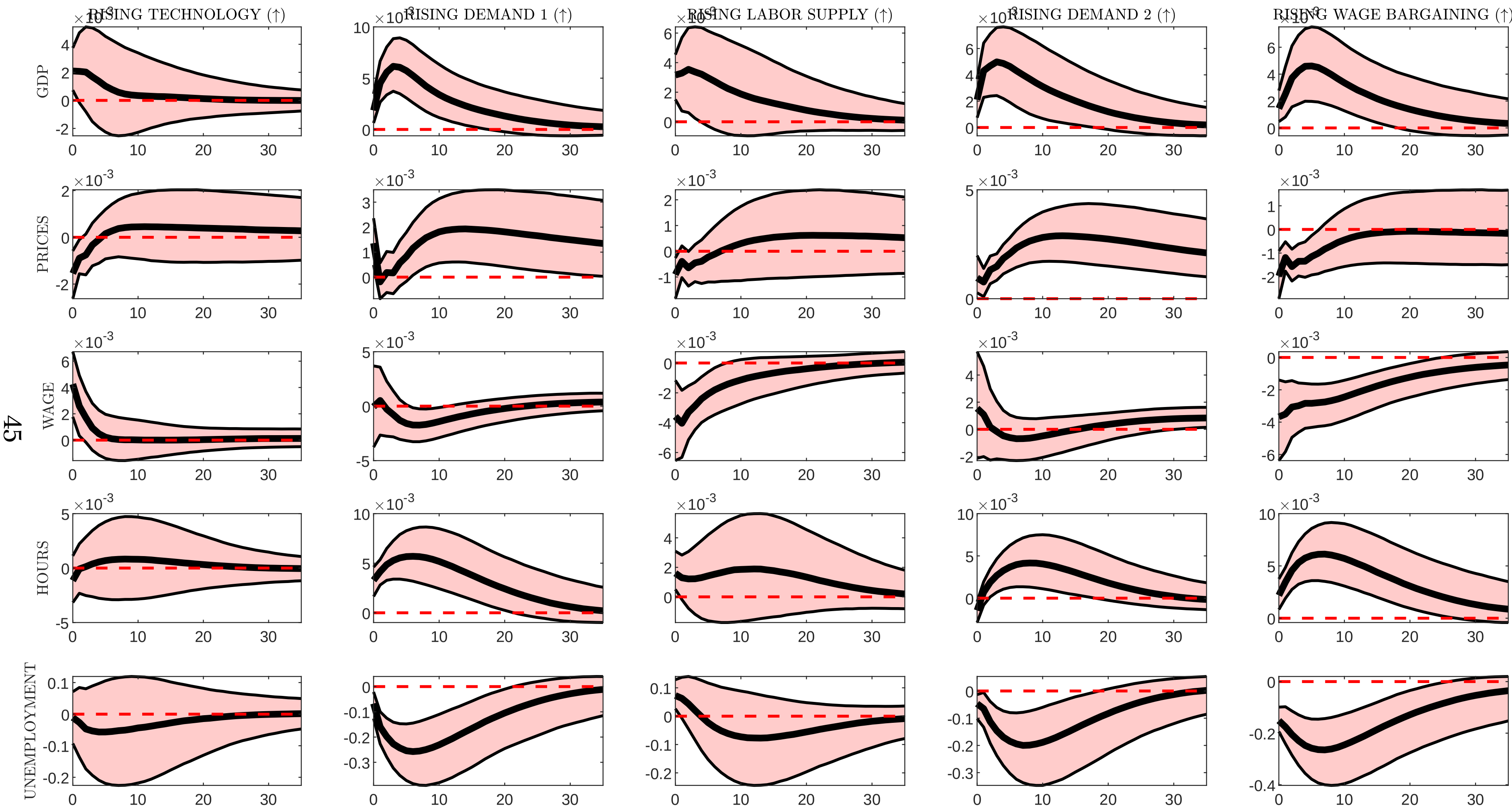
Note: The colored areas represent the point-wise median contributions of each identified shock to the forecast error variance of the labor share (in levels) at horizons $j = 0, 1, \ldots, 36$.

Figure 11: Empirical impulse responses from the baseline VAR model- More variables



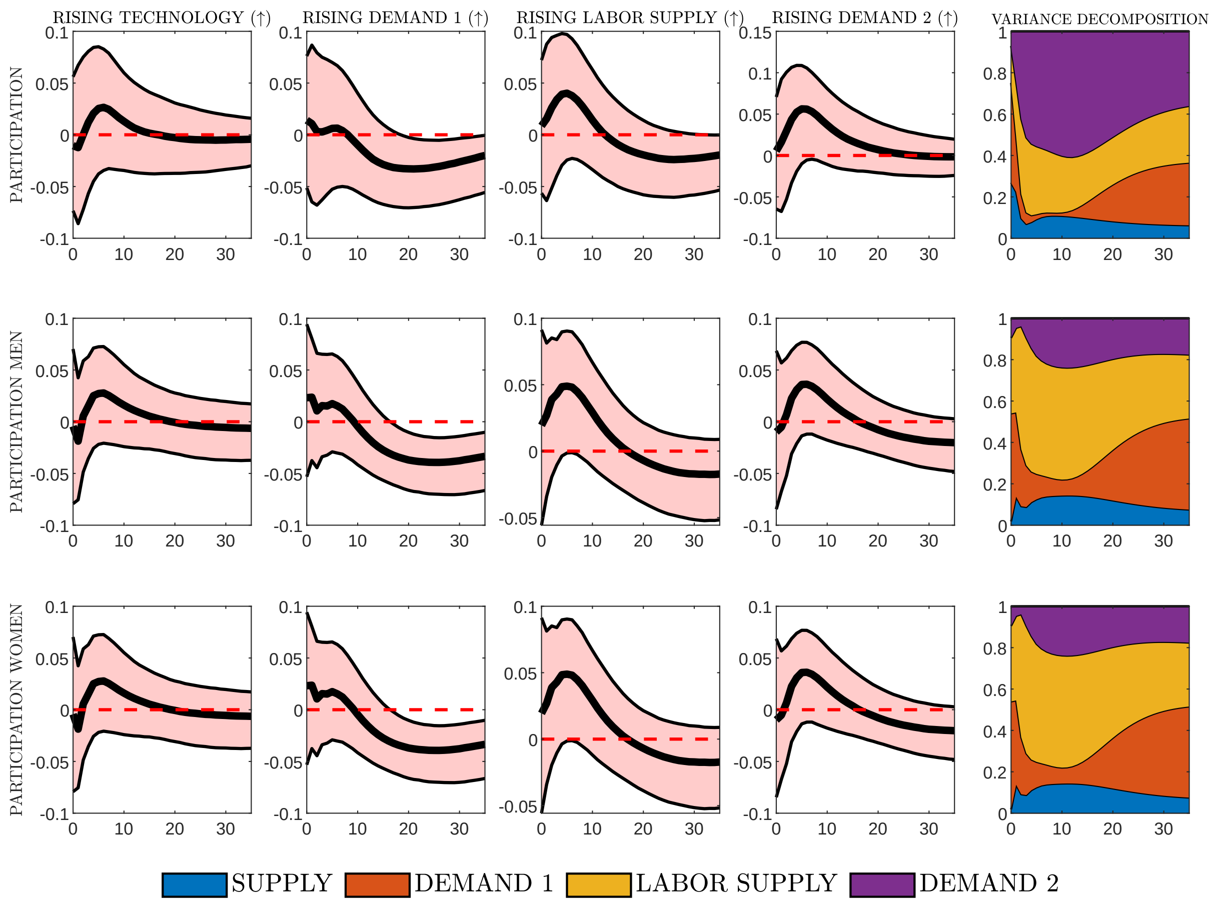
Note: Posterior distributions of impulse responses to an estimated shock of one standard deviation using the baseline identifying restrictions. Median (solid line) and 68% probability density intervals (shaded area) based on 10,000 draws. The median and the percentiles are defined at each point in time.

Figure 12: Empirical impulse responses: the role of wage bargaining shocks



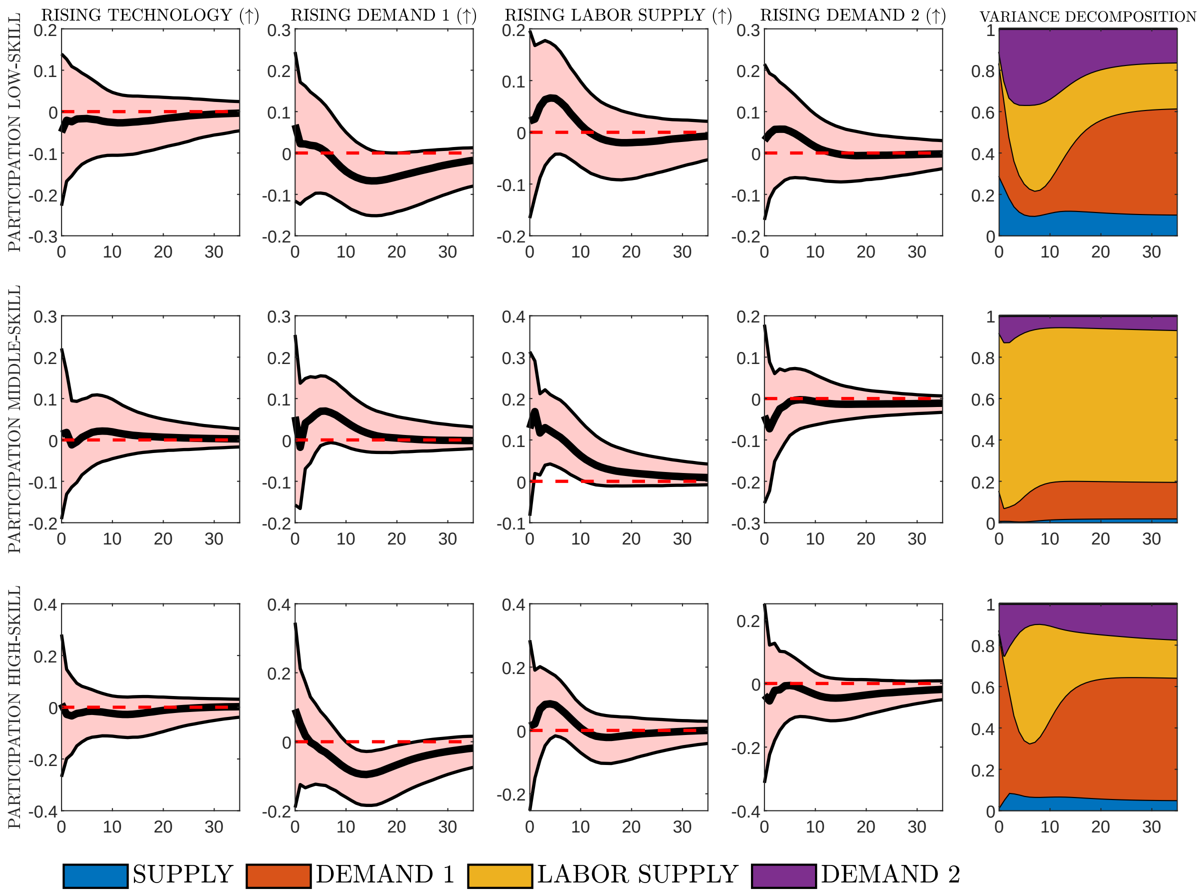
Note: Posterior distributions of impulse responses to an estimated shock of one standard deviation using the baseline identifying restrictions. Median (solid line) and 68% probability density intervals (shaded area) based on 10,000 draws. The median and the percentiles are defined at each point in time.

Figure 13: Empirical impulse responses from the baseline model: Participation by gender



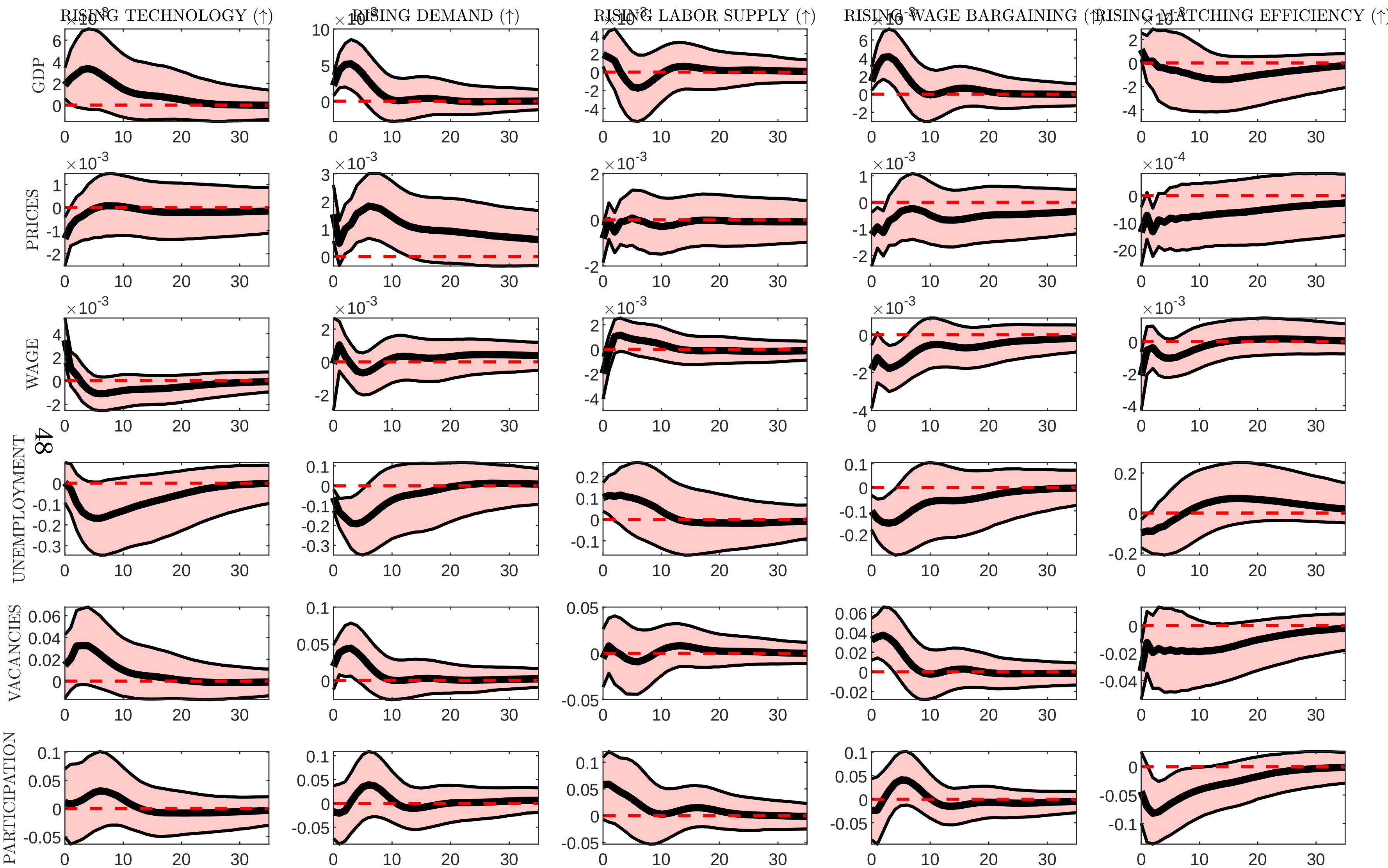
Notes: Posterior distributions of impulse responses of labor productivity to an estimated shock of one standard deviation using the baseline identifying restrictions. Median (solid line) and 68% probability density intervals (shaded area) based on 10,000 draws. The median and the percentiles are defined at each point in time.

Figure 14: Empirical impulse responses from the baseline model: Participation by education



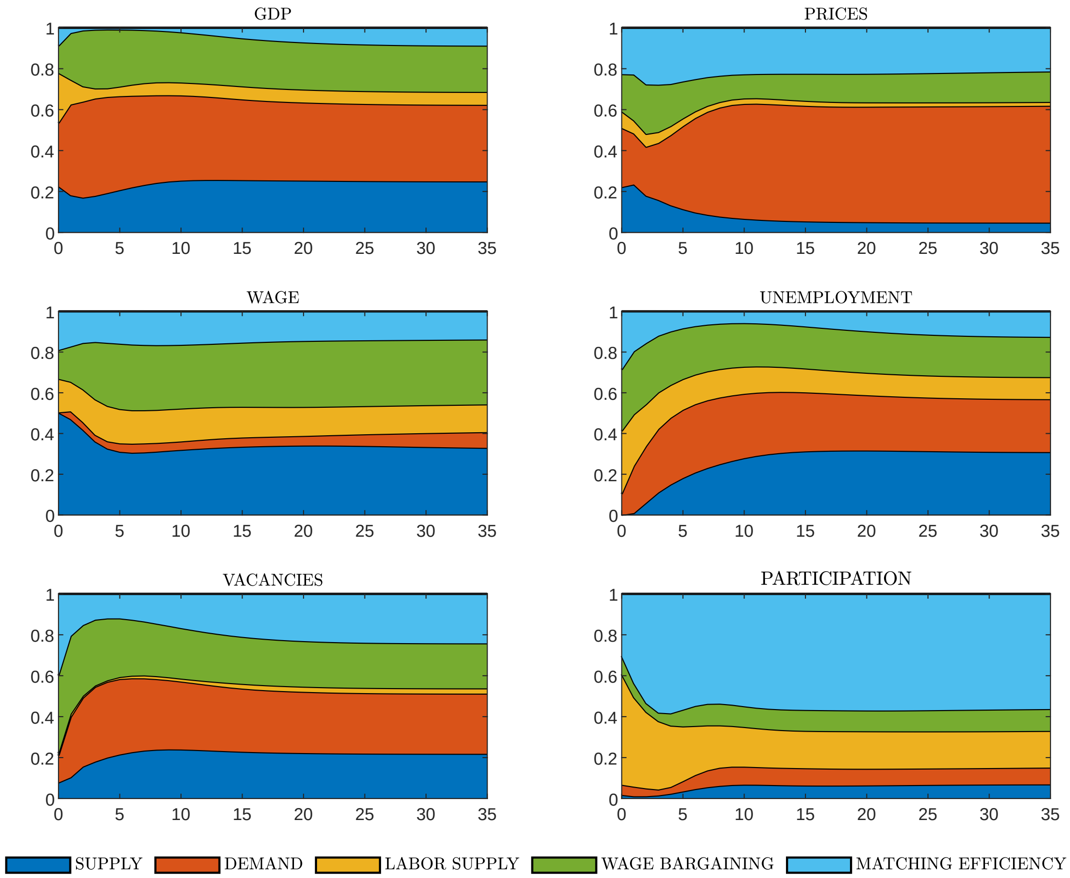
Notes: Posterior distributions of impulse responses of labor productivity to an estimated shock of one standard deviation using the baseline identifying restrictions. Median (solid line) and 68% probability density intervals (shaded area) based on 10,000 draws. The median and the percentiles are defined at each point in time.

Figure 15: Empirical impulse responses: Drivers of Participation



Note: Posterior distributions of impulse responses of labor productivity to an estimated shock of one standard deviation using the baseline identifying restrictions. Median (solid line) and 68% probability density intervals (shaded area) based on 10,000 draws. The median and the percentiles are defined at each point in time.

Figure 16: Variance decomposition at different Frequencies



Note: The colored areas represent the point-wise median contributions of each identified shock to the forecast error variance of the labor share (in levels) at horizons $j = 0, 1, \ldots, 36$.

A.3 DATA SOURCES

This section summarizes the data sources. When the original series is in monthly frequency, we take quarterly averages of monthly data. All data are seasonally adjusted and expressed in logs except unemployment, vacancies and participation. Total hours and hours per worker are taken from Dossche, Gazzani & Lewis (2022).

- Output: seasonally adjusted quarterly gross domestic product(GDP) at market prices taken national accounts, Code namq_10_gdp. Source: Eurostat.
- Prices: seasonally adjusted quarterly GDP deflator computed by taking the change in GDP

at market prices in the current period and GDP in market prices in the previous period multiply by 100. Source: Istat.

- Real wages: seasonally adjusted quarterly nominal compensation of employees adjusted for harmonised consumer price index (HCPI), base year 2015=100, code prc_hicp_midx. Sources: Istat and Eurostat.
- Unemployment rate: seasonally adjusted quarterly unemployment rate aged 15 and over out of labor force from labor force survey. Source: Istat.
- Unemployment by gender: seasonally adjusted quarterly unemployment rate (15 and over) out of labor force from labor force survey. Source: Istat.
- Unemployment rate by education level: quarterly unemployment rate (15 years and over) out of labor force from labor force survey, code $lfsq_{u}rgaed$. Source: eurostat. It is seasonally adjusted using a default implementation of X-12 triggered from Demetra 2.2.3.
- Participation rate: seasonally adjusted quarterly activity rate (15 years and over) from labor force survey. Source: Istat.
- Participation rate by education level: quarterly activity rate (15 years and over) from labor force survey, code $lfsq_{a}rgaed$. Source: eurostat. It is seasonally adjusted using a default implementation of X-12 obtained from Demetra 2.2.3.
- Vacancies: seasonally adjusted quarterly job vacancy rate taken from Istat.
- Investment: seasonally adjusted quarterly gross fixed capital formation, current prices, million euro taken national accounts, Code namq_10_gdp. Source: Eurostat.