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The distributional effects of technology shocks. Evidence from the Czech Labour market.*

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Abstract

This paper uses administrative labour market data from Czechia to investigate the heterogeneous effects of technology shocks. Using a FAVAR, the shock is identified using medium run restrictions à la Uhlig (2004b). Workers on low wages reduce their hours in response to the shock, while the shock has a positive effect on hours for workers with wages at and above the median. Analysis of industrial and demographic groups indicates that the latter group is likely to consist of males, to be educated or to work in services.

JEL Classification: C32, E32, Q54
Keywords: technology shocks, FAVAR.

* *This paper benefited from comments by the participants*

1 Introduction

A large empirical literature has investigated the prediction of real business cycle theory that technology shocks are important for business cycle fluctuations. Earlier papers in this literature report results that are at odds with this assertion. For example, in a seminal contribution Galí (1999) identifies the technology shock as the only disturbance in a VAR that can affect labour productivity in the long-run. He finds that technology shocks are associated with a decline in hours worked. Similar results are reported in Francis and Ramey (2005). More recent papers have highlighted the drawbacks of VARs with long-run restrictions. For example, Uhlig (2004a) proposes a scheme based on medium run restrictions that are more computationally robust and finds a mild positive response of hours. Using sign restrictions Dedola and Neri (2007) also report that technology shocks lead to an increase in hours worked.[1]

One unifying feature of this literature is the focus on the effect on *aggregate* hours. In contrast, evidence on how the distribution of hours changes after the shock is scarce. Our paper fills this gap in the literature and investigates the possible heterogeneity in the effects of this shock across workers. In particular, we use administrative data from Czechia to show that technology shocks are associated with an increase in hours for workers towards the middle and right of the wage distribution. However, hours for low-wage workers decline after the shock. We find evidence that the positive response of hours reflects the effect of the shock on male workers and those in service industries. In contrast, the response of hours at the left tail of the wage distribution is related to the response of workers who only have primary education, those in agriculture and construction or female workers. The paper is related to Saijo (2019) who show using US data that technology shocks lead to an increase in hours for stock holders and a decline in hours for non-stock holders. The focus of the current paper is broader as we explore the heterogeneous response of hours along the wage distribution and for demographic groups defined by gender, industry, age and education. Moreover, the micro-data in our study has substantially more comprehensive coverage than a survey.[2]

While our findings are based on the Czech data, their relevance likely extends to other small, open, and developed economies. This is because Czechia shares characteristics with these economies, including an industrial focus, consistent GDP growth, global market integration, and EU membership. In terms of within-country income distribution, income

[1]For a comprehensive review of the literature see Ramey (2016).

[2]We also use identification schemes for the technology shock that have superseded the long-run restrictions employed by Saijo (2019).

inequality in the Czech Republic has mirrored the broader trend in developed countries. The Czech National Bank's inflation-targeting strategy and institutional framework resemble those of other central banks.

The paper is organised as follows: Section 2 describes the empirical model and the data. The main results are presented in section 3. Section 4 concludes.

2 Empirical model and data

In order to estimate the effects of the technology shock on the distribution of hours we employ a Factor Augmented VAR (FAVAR) (see Bernanke *et al.* (2005)). The model is defined by the VAR:

$$Y_t = BX_t + u_t, \tag{1}$$

$$u_t \sim N(0, \Sigma) \tag{2}$$

where $Y_t = \begin{pmatrix} Z_t \\ F_t \end{pmatrix}$. Z_t is a measure of productivity for the Czech Republic, while F_t denotes a set of common factors extracted from both aggregate and individual-level data. The vector $X_t = [Y'_{t-1}, \ldots, Y'_{t-P}, 1]'$ is $(NP+1) \times 1$ and defines the regressors in each equation and B denotes the $N \times (NP+1)$ matrix of coefficients $B = [B_1, ..., B_P, c]$.

The observation equation of the model is defined as:

$$\begin{pmatrix} Z_t \\ \tilde{X}_t \end{pmatrix} = \begin{pmatrix} 1 & 0 \\ 0 & \Lambda \end{pmatrix} \begin{pmatrix} Z_t \\ F_t \end{pmatrix} + \begin{pmatrix} 0 \\ v_t \end{pmatrix} \tag{3}$$

$\tilde{X}_t$ is a $M \times 1$ vector of variables that include quarterly aggregate measures of macroeconomic and financial conditions. $\tilde{X}_t$ also contains measures of hours constructed using individual-level data. These series include average hours in groups defined by each wage decile, groups defined by level of education, age, gender and industry. These disaggregated series are available at an annual or bi-annual frequency.

Finally, v_t is a $M \times 1$ matrix that holds the idiosyncratic components which are assumed to be autocorrelated and follow an $AR(q)$ process. Note that the idiosyncratic components corresponding to the hours data can be interpreted as shocks that are specific to those groups and also capture possible measurement error in the individual-level data. In contrast, the shocks to equation 1 represent macroeconomic shocks that are of interest in this exercise. This ability to estimate the impact of macroeconomic shocks while accounting for idiosyncratic disturbances is a key advantage of the FAVAR over a VAR where these two sources of fluctuations may be conflated (see Giorgi and Gambetti (2017)). Moreover, by incorporating a large data set, the FAVAR reduces the problem of information deficiency (see e.g. Forni and Gambetti (2014)). In addition, the model allows us to easily incorporate data on hours that are only available annually before 2012 and twice a year, thereafter. As described in the appendix, we assume that these observations are averages of quarterly hours that are treated as additional unobserved states variables.

2.1 Identification of the productivity shock

Uhlig (2004a) shows that an identification scheme based on medium-run restrictions performs better than long-run identification schemes (Galí (1999)) in recovering the productivity shock.This long-run scheme has the drawback that the infinite horizon impulse response has to be estimated and this can be challenging using a short span of data (see Erceg *et al.* (2005)). The method of Uhlig (2004a) is less susceptible to this computational issue as it works with medium horizons. We adopt this strategy as our benchmark approach.

The structural shocks are defined as $\varepsilon_t = A_0^{-1}u_t$ where $A_0A_0' = \Sigma$. A_0 is not unique and the space spanned by these matrices can be written as $\tilde{A}_0Q$ where Q is an orthonormal rotation matrix such that $Q'Q = I$ The productivity shock is identified by imposing the restriction that this shock makes the largest contribution the forecast error variance (FEV) of Z_t at the one year horizon. The appendix provides details of this calculation and also shows that our main results do not depend on the identifying scheme.

2.2 Data and Estimation

The data set $\tilde{X}$ consists of 84 aggregate series. In addition, we include 23 series on hours constructed from the labour market data described below. The aggregate series (listed in the appendix) cover the main sectors of the economy: Real activity, inflation, monetary and financial series. The series are quarterly from 2002Q1 to 2019Q4. The source of the data is the FRED database and Global Financial database. All non-stationary series are transformed by taking log-differences.

Labour market data at the individual level is obtained from the administrative ISPV dataset, which provides rich contract-level information at annual frequency from 2002 to 2011 and bi-annual frequency thereafter to 2020.[3] The data covers a large proportion

[3] Informační systém o průměrném výdělku (Average Earnings Information System),

of all Czech labor market contracts. The key variables include wage per-hour, hours worked and employee characteristics, such as gender, age, and education level. We merge the data with the RES Business Register database, which provides information on the business sector in which the employer operates.[4]

We construct average hours in groups defined by a number of characteristics. First, we consider 10 groups defined by the deciles of wage that are denoted by $P_1, \ldots, P_{10}$. In addition, we construct groups based on the following characteristics.

1. Education: The averages are calculated from individuals with primary, secondary or tertiary level education.

2. Age: We consider three age groups: individuals less than 35 years of age, individuals between the ages of 35 and 50 and individuals older than 50 years.

3. Sector of employment: We include average hours in Agriculture, Manufacturing, Construction and Services.

4. Gender: We construct average hours for males and females.

In the benchmark model we include these series in logs. However, as discussed below, the results are robust to using log differences.

The model is estimated using a Gibbs sampling algorithm that is described in details in the appendix along with the prior distributions and convergence diagnostics. In the benchmark case, we set the number of factors to 6 based on the IC_{p2} criterion of Bai and Ng (2002). The lag lengths in equation 1 is fixed at 4 while the idiosyncratic components follow an AR(1) process.

3 Results

Before moving on to the distributional response of hours, it is instructive to consider the response of aggregate variables shown in Figure 1. The productivity shock has an ambiguous effect on average hours: the median response is negative over the medium horizon and at odds with real business cycle theory, albeit with large error bands. The shock is expansionary and increases real activity, stock prices and long-term interest rates, while pushing down inflation in the medium term. The shock is associated with a real exchange rate appreciation supporting the findings of Enders *et al.* (2011) reported for the US.

[4] Registr ekonomických subjektů (Business Register). See the on-line appendix for detailed description of the data

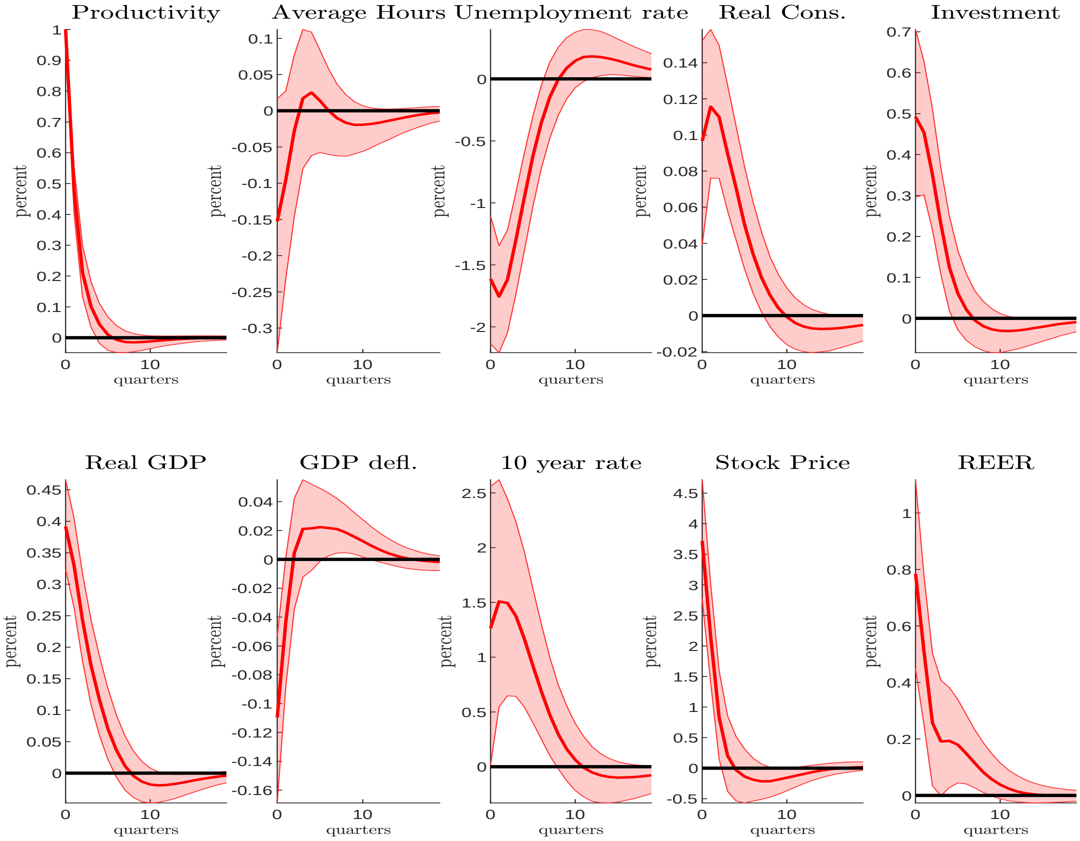

Figure 1: Response of selected aggregate variables to a productivity shock. Real Cons. is real consumption, GDP defl. is GDP deflator inflation and REER denotes the real effective exchange rate. The shaded area displays the 68% error bands.

3.1 Heterogeneous effects of the shock

Figure 2 presents our key result. The figure shows the response of hours in selected wage deciles on the left and right tail of the wage distribution. The response of hours for individuals that earn wages below the median resembles the aggregate hours response shown in Figure 1 with the median showing a decline at short and medium horizons. In contrast, hours increase towards the right tail of the wage distribution and the response

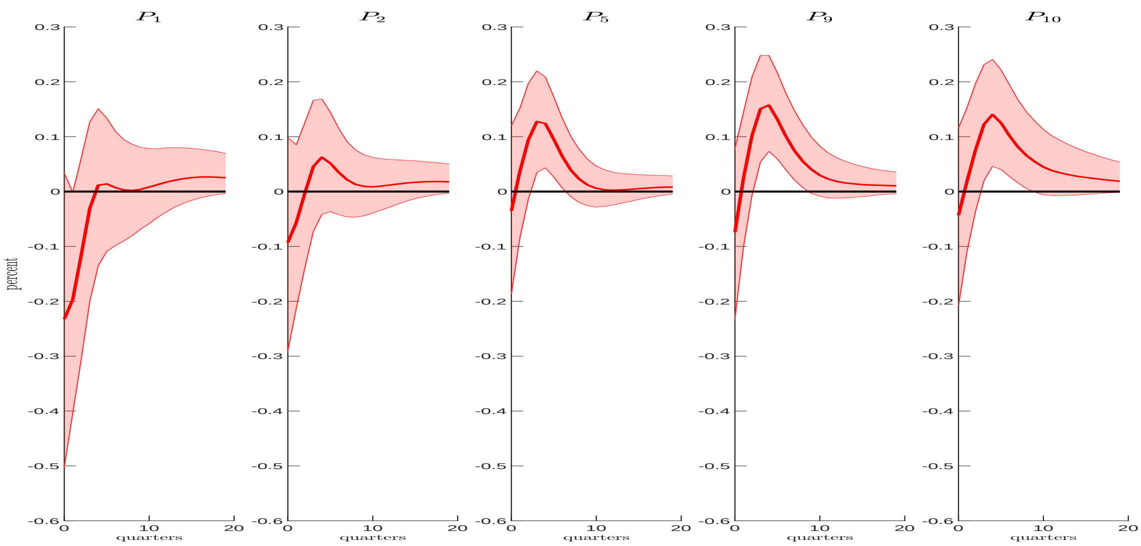

Figure 2: Response of hours in wage decile groups. For e.g. P_1 denotes the first decile, while P_{10} is the last decile. The shaded area displays the 68% error bands

is statistically different from zero about one year after the shock. [5]
Figure 3 investigates this heterogeneity further by exploring the response of hours by demographic groups and sectors. The top panel shows the negative response of hours is more evident for workers with primary education who are concentrated at the left tail of the wage distribution (see Figure 1 in the online appendix). The second row of the Figure shows that there is limited heterogeneity across the age distribution. In contrast, the response clearly varies across sectors. Hours decline for workers in agriculture and construction. The response for manufacturing is imprecisely estimated, but is mildly negative at short and long-horizons, while hours display an increase in the services sector that is statistically different from zero at the one year horizon. As services dominate the right tail of the wage distribution while manufacturing and agriculture is more prevalent towards the middle and left tail (see Figure 4 in the appendix), these impulse responses are consistent with the distributional results in Figure 2. The final row of the figure shows that it is male workers that increase hours after the shock. As Figure 1 in the appendix shows, male workers are substantially more likely to be high wage earners.
Broadly speaking, these results are consistent with skill biased technological change whereby the shock disproportionally increases the productivity and demand for high skilled workers. Hours may increase for these workers if they take advantage of higher returns to skill. The heterogeneity may also be driven by stock holding as in Saijo (2019).

[5]The online appendix presents the results for all 10 decile groups.

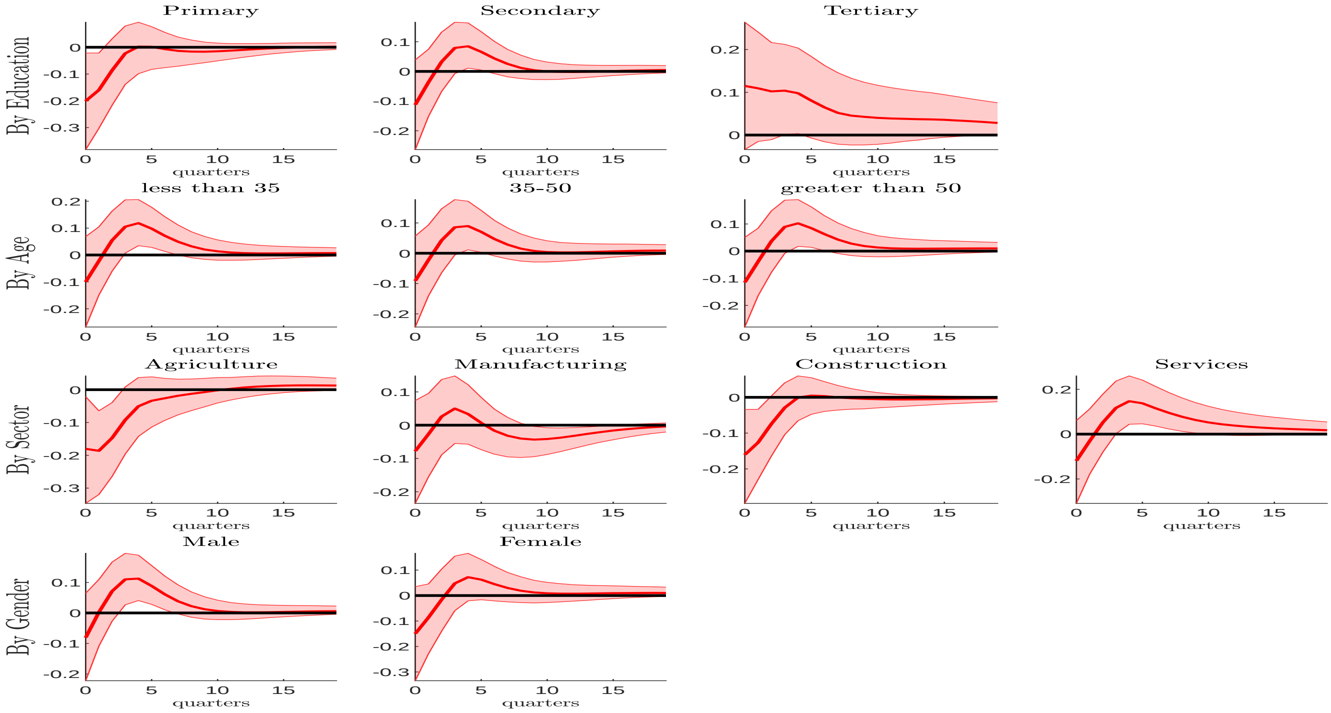

Figure 3: Response of hours for different demographic groups and sectors. The shaded area displays the 68% error bands

If high earners hold stock, then they may increase hours worked to benefit from the wealth effect generated by the technology shock.

3.2 Robustness

We carry out a number of robustness checks that are presented in detail in the on-line appendix:

1. Identification: We identify the productivity using the sign restrictions methodology in Dedola and Neri (2007) and Francis *et al.* (2003). Figure 8 in the appendix shows that the distributional pattern of the hours response is similar to benchmark. The results are less precise when long-run restrictions are used to identify the productivity shock (Figure 9 in the appendix). This unsurprising given the short span of our data. However, the median responses accord well with our benchmark results.

2. Specification: Figure 10 in the appendix shows that the results are very similar to benchmark when the number of factors is increased to 8. We also estimate the model using hours in log-differences. The results in this case are supportive of

the benchmark and show an increase in hours towards the right tail of the wage distribution, in services, for males and those with higher than primary eduction.

4 Conclusions

Using administrative labour market data for Czechia, this paper shows that technology shocks have a heterogeneous effect on hours worked. Hours increase for high earners and decline for workers on low wages. The former group appears to consist of more educated individuals, male workers and those employed in services.

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The distributional effect of productivity shocks. Online Appendix

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Abstract

Online Appendix

JEL Classification: C32, E32, Q54
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1 Labour market Data

To analyze the response of the wage distribution to monetary policy shocks, we explore the universe of granular, contract-level data from the Czech labor market. This data is accessed via the administrative ISPV[1] dataset, which provides rich contract-level information at annual frequency from 2002 to 2011 and bi-annual thereafter to 2020. The data is collected by the Czech Ministry of Labor and Social Affairs as the main source of information on average earnings and is used for budgetary planning of social security expenditure.

In each data vintage, the variables include the average wage per-hour and its structure over the relevant period (including bonuses and other types of compensation), hours worked (with details on paid and unpaid leave, sick leave, etc.), employee characteristics, such as gender, age, and education level, and also characteristics of the employer, such as location and number of employees (full-time-equivalent). To gather more information on employers, we merge the data with the RES[2] Business Register database, which provides information on the prevailing business sector in which the employer operates.

The data covers a large proportion of Czech labor market contracts, with around 1.5 million cross-sectional units (contracts) in the most recent vintages. While many contracts appear and disappear during the observed time sample, we can still follow the duration of each contract, which is a separate data entry. The inclusion of a contract in the sample depends on the size of the firm. Firms with 250+ employees are included in each vintage, while smaller firms are covered on a rotational basis to reduce the administrative burden on small businesses. To correct for any bias this may cause, the under-sampled smaller firms are assigned a higher weight to represent those which were omitted from the vintage.

The data on hours worked reflects two main sources of variation. The first comes from the coverage of part-time agreements in the data. Out of 1.2 million contracts covered in the 2022 vintage of the data, close to 77% are full-time. The rest comprises of contracts recorded as part-time contracts (close to 23%). However, a significant portion of these contracts is close to full-time.[3] Hours are adjusted for absence (paid and unpaid), overtime and sickness. The dataset also includes contracts, which start or terminate during the respective year. The variation coming from this source, however, does not provide much information about the supply of labor. Therefore, we extrapolate the hours worked under such contracts as if the contract lasted for the whole year. For example, if there were x

[1] Informační systém o průměrném výdělku (Average Earnings Information System), https://www.ispv.cz/en/homepage.aspx

[2] Registr ekonomických subjektů (Business Register), https://www.czso.cz/csu/res/business_register

[3] About 11% of these contracts have hours above 0.95 of full-time hours.

hours worked under a contract terminated after a half of a year, we multiply these by 2.

The administrative character of the dataset, together with its wide coverage, overcomes the usual pitfalls of survey data, such as imperfect coverage of the upper and lower tails of the wage distribution. However, the data has several limitations. The contract-level and anonymous nature of the granular data do not allow us to follow an individual through different employments. For the same reason, we also do not have access to information about the total income of individuals, who may have a substantial non-wage income or be employed under several simultaneous contracts. We therefore focus on wage inequality as a distinct channel of total income inequality. While we do not have information about employees' contract history, we can measure their turnover rate by observing the average length of the present contract.

Figure 1 shows the characteristics of employees and respective contracts along the wage distribution (i.e. percentiles of the average hourly wage), averaged over the period 2002–2020. Higher wage percentiles are associated with a higher education level, and the relationship is strictly increasing. Gender inequality is illustrated by lower shares of females in higher wage percentiles and by decreasing shares of females toward the higher end of the wage distribution. Both tails of the wage distribution are associated with a higher average age, marking the line between workers who were able to climb the seniority ladder and increase their wages over lifetime and those who struggled to do so, leaving them with a lower wage toward the end of their working lives. As a result, wage inequality increases with age. Contract lengths are longer at the right tail of the wage distribution. The data offers many important insights into the structure of the Czech labor market. Figure 2 shows the histogram of the log average hourly wage distribution in the last data vintage used in this paper – 2020. The data on hours worked shows two main sources of variation. First, part-time agreements: of the 1.2 million contracts in the 2022 data, about 77% are full-time, while nearly 23% are part-time. A notable portion of part-time contracts (11%) has hours close to full-time (above 0.95 of full-time hours). Second, actual hours worked account for absences (paid or unpaid), overtime, and sickness. The dataset also includes contracts starting or ending within the year, but we extrapolate these as if the contract lasted the full year to better assess labor supply. Following figures illustrates several notable trends in the Czech labor market mentioned in the text. Figure 3 shows that the service sector has the highest female representation, with women making up more than half of its workforce. Thus, men dominate all other sectors, comprising 65% of the workforce in the industrial sector. The highest average wage is generally reported in the construction sector, closely followed by services and manufacturing. However, it is

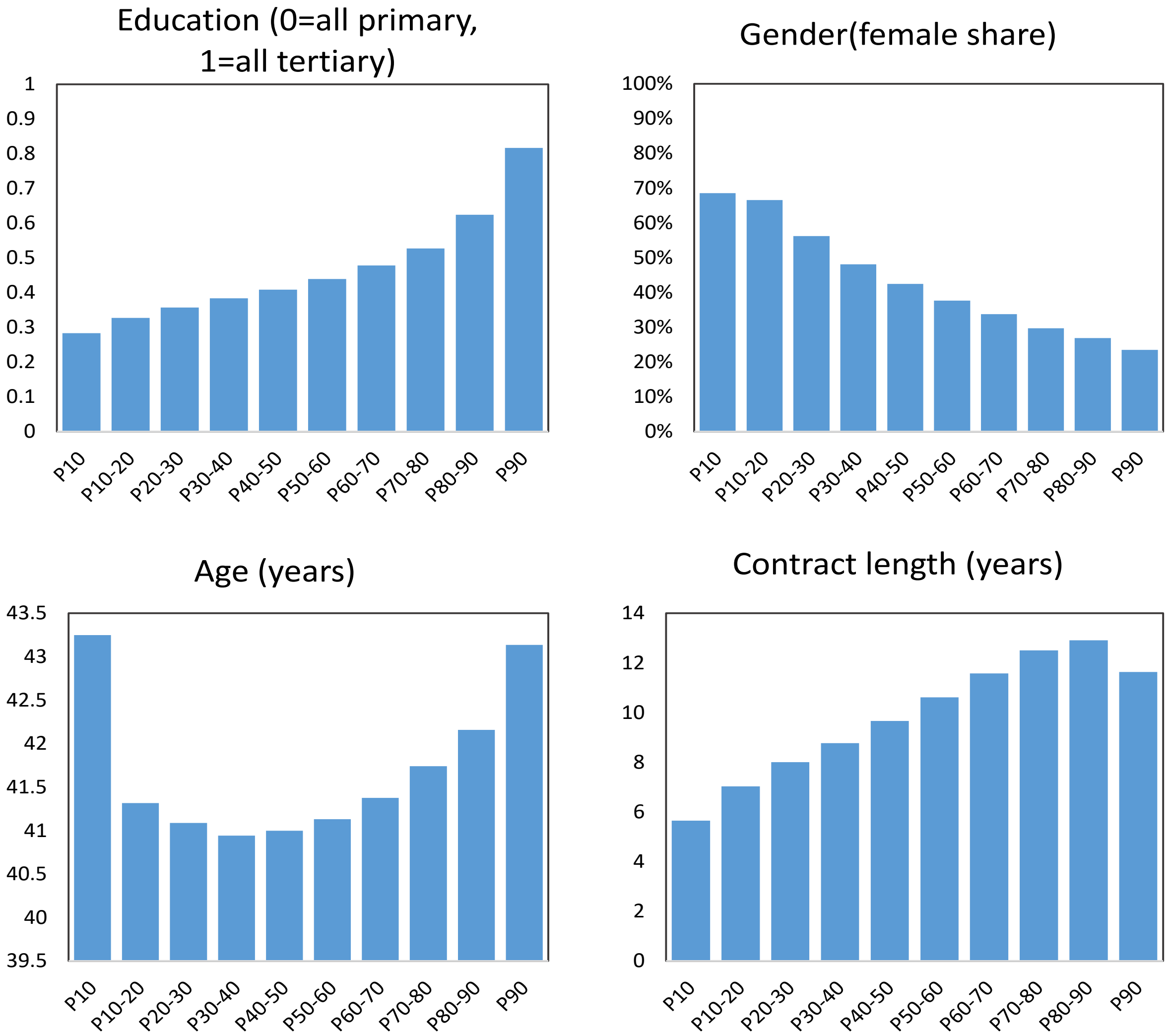

Figure 1: Characteristics of employees and contracts along the wage distribution. P10 to P90 on the X-axis denotes the percentiles of the wage distribution

worth noting that reporting in the construction sector may be influenced by a potentially significant share of the shadow economy, especially for the less qualified labor force. The service sector, followed by construction, requires a relatively higher level of education.

Figure 4 illustrates the wage distribution in different sectors. The average hourly wage is slightly higher in the industrial sector than in the service sector. However, the wage distribution in industry is more uniform, with most workers earning around the wage median or slightly above. In contrast, the service sector has a higher share in the lowest and the highest wage percentiles. Considering the statistics in Figure 3 , this is related on the one hand to the high share of female workers in the lower wage percentiles, and on the other hand to the high average level of education in services compared to other

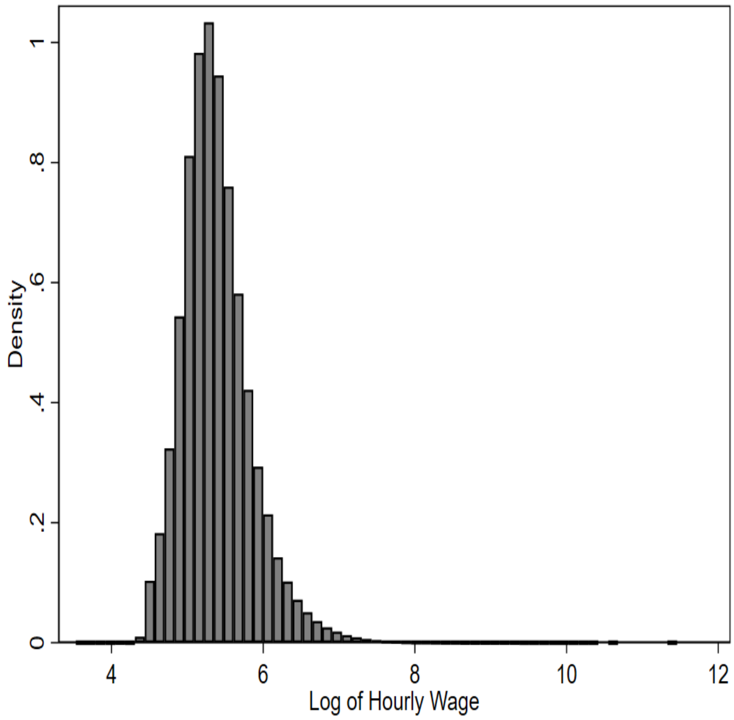

Figure 2: Log average hourly wage distribution in 2020

sectors.

In Figure 5 we show that the older the workers are, the longer their working contracts tend to be. This demonstrates a significant characteristic of the Czech labor market: workers are opting for stable, long-lasting working relationships. This trend is even more pronounced in the agriculture sector, particularly in the countryside where there are fewer job opportunities, and less pronounced in the service sector, which is typically found in larger urban agglomerations.

2 Empirical model

In order to estimate the effects of the productivity shock we employ a Factor Augmented VAR (FAVAR) (see Bernanke *et al.* (2005)). The model is defined by the VAR:

$$Y_t = BX_t + u_t, \tag{1}$$

$$u_t \sim N(0, \Sigma) \tag{2}$$

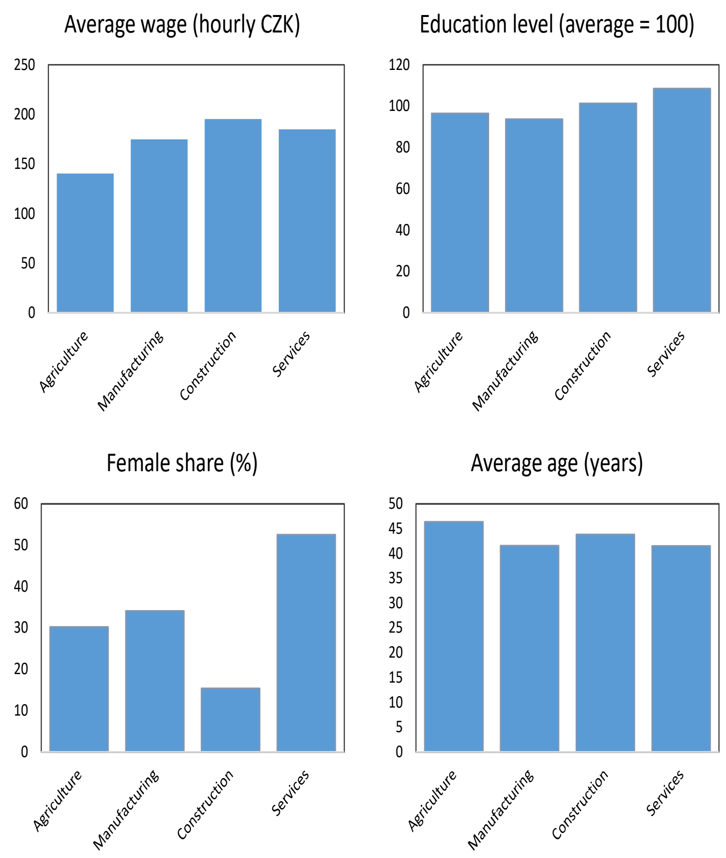

Figure 3: Characteristics of employees across different business sectors

where $Y_t = \begin{pmatrix} Z_t \\ F_t \end{pmatrix}$. Z_t is a measure of productivity for the Czech Republic, while F_t denotes a set of common factors extracted from both aggregate and individual-level data. The vector $X_t = [Y'_{t-1}, \ldots, Y'_{t-P}, 1]'$ is $(NP + 1) \times 1$ defines the regressors in each equation and B denotes the $N \times (NP + 1)$ matrix of coefficients $B = [B_1, ..., B_P, c]$.
The observation equation of the model is defined as:

$$\begin{pmatrix} Z_t \\ \tilde{X}_t \end{pmatrix} = \begin{pmatrix} 1 & 0 \\ 0 & \Lambda \end{pmatrix} \begin{pmatrix} Z_t \\ F_t \end{pmatrix} + \begin{pmatrix} 0 \\ v_t \end{pmatrix} \tag{3}$$

As we describe in detail below $\tilde{X}_t$ is a $M \times 1$ vector of variables that include quarterly aggregate measures of macroeconomic and financial conditions. $\tilde{X}_t$ also contains measures of hours and earnings constructed using individual-level data. These series include average hours and earnings in groups defined by each earnings decile, groups defined by level of

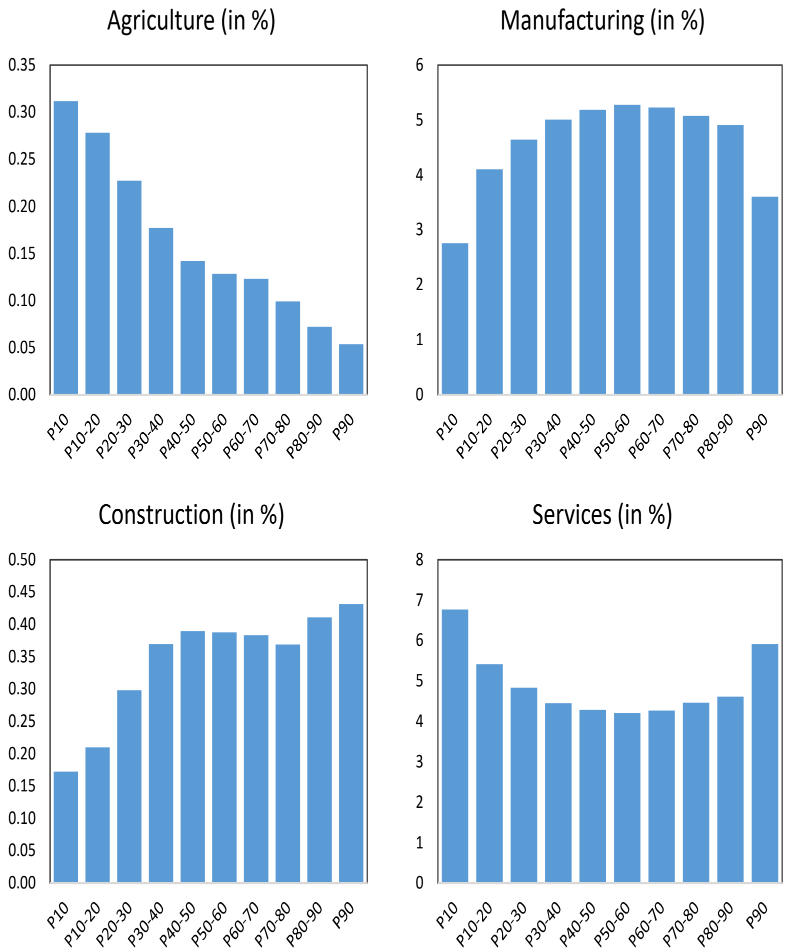

Figure 4: Characteristics of employees across sectors along the wage distribution. Note that the bars add up to 10 % across sectors

education, age, gender and industry. These series are available at an annual or bi-annual frequency.

Finally, v_t is a $M \times 1$ matrix that holds the idiosyncratic components which are assumed to be autocorrelated and follow an $AR(q)$ process. Note that the idiosyncratic components corresponding to the hours and earnings data can be interpreted as shocks that are specific to those groups and also capture possible measurement error in the individual-level data. In contrast, the shocks to equation 1 represent macroeconomic shocks that are of interest in this exercise. This ability to estimate the impact of macroeconomic shocks while accounting for idiosyncratic disturbances is a key advantage of the FAVAR over a VAR where these two sources of fluctuations may be conflated (see Giorgi and Gambetti (2017)).

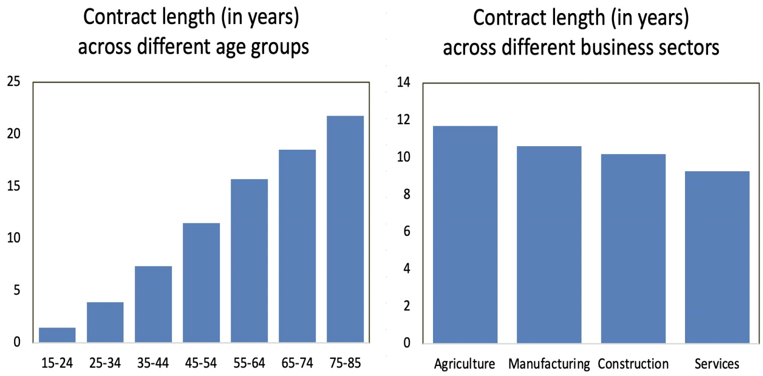

Figure 5: Contract length in years across different age groups and across sectors along the wage distribution

2.1 Temporal aggregation and missing data

The data on hours and earnings is only available annually before 2012 and are then available twice a year. For these series (x_t) the observation equation is defined as:

$$\hat{x}_{jt} = \delta_j F_t + \hat{v}_{jt} \tag{4}$$

where $\hat{x}_{jt}$ denotes unobserved quarterly growth rates of the jth series in x_t and δ_j are the associated factor loadings. We assume the following relationship between low frequency and high frequency growth rates:

$$x_{jt}^{Q} = \sum_{j=0}^{\tilde{q}} \hat{x}_{jt} \tag{5}$$

where $\tilde{q}$ 3 when data is available once a year and 1 when bi-annual observations are available. In other words, the growth rates at the lower frequency are assumed to be the sum of the unobserved quarterly growth rates. As explained below, we treat $\hat{x}_{jt}$ as additional unobserved states and add a step in our MCMC algorithm to draw from their conditional posterior distribution.

2.2 Identification of the productivity shock

Uhlig (2004a) shows that an identification scheme based on medium-run restrictions performs better than long-run identification schemes (Galí (1999)) in recovering the productivity shock. We adopt this strategy as our benchmark approach.

The structural shocks are defined as $\varepsilon_t = A_0^{-1} u_t$ where $A_0 A_0' = \Sigma$.It is well known that A_0 is not unique but the space spanned by these matrices can be written as $\tilde{A}_0 Q$ where

Q is an orthonormal rotation matrix such that $Q'Q = I$

The productivity shock identified by imposing the restriction that this shock makes the largest contribution the forecast error variance (FEV) of Z_t at the one year horizon. Consider the transition equation of the model in structural moving average form:

$$Y_t = B(L) A_0 \varepsilon_t$$

The k period ahead forecast error of the ith variable is given by:

$$Y_{it+k} - \hat{Y}_{it+k} = e_1 \left[\sum_{j=0}^{k-1} B_j \tilde{A}_0 Q \varepsilon_{t+k-j} \right]$$

where e_1 is a selection vector that picks out Z_t in the set of variables. Following Uhlig (2004b), the proposed identification scheme thus amounts to finding the column of Q that solves the following maximisation problem:

$$\arg\max_{Q_1} e_1' \left[\sum_{k=0}^{K} \sum_{j=0}^{k-1} B_j \tilde{A}_0 Q_1 Q_1' \tilde{A}_0' B_j' \right] e_1$$

such that $Q_1' Q_1 = 1$. Here Q_1 is the column of Q that corresponds to the shock that explains the largest proportion of the FEV of the first variable in the transition equation, i.e. productivity growth Z_t. As shown by Uhlig (2004b), the maximisation can be re-written as eigenvalue eigenvector problem and a solution can be readily obtained.[4]

3 Macro Data

The data set $\tilde{X}$ consists of 84 aggregate series. The aggregate series cover the main sectors of the economy. Real activity series include data on GDP, production, employment, unemployment,new orders, exports and imports. The inflation data include CPI, PPI and their components. Monetary series include measures of money supply and credit growth. We also include financial series covering short and long-term interest rates, stock

[4]Denoting $B_j \tilde{A}_0$ by R_j, the objective function is $\arg\max_{Q_1} e_1' \left[\sum_{k=0}^{K} \sum_{j=0}^{k-1} R_j Q_1 Q_1' R_j' \right] e_1$ st $Q_1' Q_1 = 1$. The objective function can be re-written as $\arg\max_{Q_1} e_1' \left[\sum_{k=0}^{K} \sum_{j=0}^{k-1} R_j Q_1 Q_1' R_j' \right] e_1 = \sum_{k=0}^{K} \sum_{j=0}^{k} trace \left[Q_1' R_j' (e_1 e_1') R_j Q_1 \right]$
$= Q_1' \left[\sum_{k=0}^{K} \sum_{j=0}^{k} R_j' (e_1 e_1') R_j \right] Q_1 = Q_1' S Q_1$ where $S = \left[\sum_{k=0}^{K} \sum_{j=0}^{k} R_j' (e_1 e_1') R_j \right]$. The Lagrangian for this maximisation problem is $L = Q_1' S Q_1 - \lambda (Q_1' Q_1 - 1)$ with first order condition $SQ_1 = \lambda Q_1$. Note that the first order condition is the definition an eigenvalue decomposition.

prices and exchange rates. The series are quarterly from 2002Q1 to 2019Q4. The source of the data is the FRED database and Global Financial database (GFD). The series are transformed via log differences (LD) to induce stationarity. See Table 1 for a list of variables and sources.

4 Model Estimation

4.1 Empirical model

The observation equation of the FAVAR model is defined as:

$$\begin{pmatrix} Z_t \\ \tilde{X}_t \end{pmatrix} = \begin{pmatrix} 1 & 0 \\ 0 & \Lambda \end{pmatrix} \begin{pmatrix} Z_t \\ F_t \end{pmatrix} + \begin{pmatrix} 0 \\ v_t \end{pmatrix} \tag{6}$$

where Z_t is a measure of productivity growth. $\tilde{X}_t$ is a $M \times 1$ vector of variables that include aggregate measures of macroeconomic and financial conditions. $\tilde{X}_t$ also contains hours and earnings averaged in groups defined by each earnings decile, groups defined by education, age, gender and industry . Details of the data used are given below. F_t denotes a $K \times 1$ matrix of unobserved factors while Λ is a $M \times K$ matrix of factor loadings. Finally, v_t is a $M \times 1$ matrix that holds the idiosyncratic components. We assume that each row of v_t follows an $AR(q)$ process:

$$v_{it} = \sum_{p=1}^{P} \rho_{ip} v_{it-p} + e_{it}, \tag{7}$$

$$e_{it} \sim N(0, r_i), R = diag\left([r_1, r_2, .., r_M]\right) \tag{8}$$

where $i = 1, 2, .., M$. Collecting the factors in the $N \times 1$ vector $Y_t = \begin{pmatrix} Z_t \\ F_t \end{pmatrix}$, the transition equation can be described as:

$$Y_t = BX_t + u_t, \tag{9}$$

$$u_t \sim N(0, \Sigma) \tag{10}$$

where $X_t = [Y'_{t-1}, \ldots, Y'_{t-P}, 1]'$ is $(NP + 1) \times 1$ vector of regressors in each equation and B denotes the $N \times (NP + 1)$ matrix of coefficients $B = [B_1, ..., B_P, c]$. The covariance matrix of the reduced form residuals u_t is given by Σ. Note that the structural shocks are defined as $\varepsilon_t = A_0^{-1} u_t$ where $A_0 A_0' = \Sigma$.

4.2 Temporal aggregation and missing data

The data on hours and wages at the individual level is available at a lower frequency. These data are observed in the fourth quarter of every year before 2012 and are then available twice a year. For these series (x_t) the observation equation is defined as:

$$\hat{x}_{jt} = \delta_j F_t + \hat{v}_{jt} \tag{11}$$

where $\hat{x}_{jt}$ denotes unobserved quarterly growth rates of the jth series in x_t and δ_j are the associated factor loadings. Over years where annual observations are available, we assume the following relationship between quarterly and monthly data:

$$x_{jt}^{Q} = \frac{1}{4} \sum_{j=0}^{3} \hat{x}_{jt} \tag{12}$$

In other words, the observed hours are an average of the unobserved quarterly hours in that year.
Over years where bi-annual observations are available, we assume the following relationship :

$$x_{jt}^{Q} = \frac{1}{2} \sum_{j=0}^{1} \hat{x}_{jt} \tag{13}$$

In other words, the bi-annual hours are assumed to be the average of unobserved quarterly hours in that half-year. we treat $\hat{x}_{jt}$ as additional unobserved states and add a step in our MCMC algorithm to draw from their conditional posterior distribution.

4.3 Priors

1. Factor loadings Λ. We obtain an initial estimate of the factors F_t using an EM algorithm $\left(F_t^{PC}\right)$. Using this estimate we obtain an OLS estimate of the factor loadings Λ_{ols}. Denote the factor loading for the *ith* series in $\tilde{X}_t$ as Λ_i. The prior for Λ_i is assumed to be $N\left(\Lambda_{i,0}, V_\Lambda\right)$ where V_Λ is set as a diagonal matrix with diagonal elements equal to 0.1 and $\Lambda_{i,0}$ equals Λ_{ols} for the ith series.

2. Factors F_t. The initial values for the factors are assumed to be normal with mean $F_{0\backslash 0}$ and variance $P_{0\backslash 0}$. $F_{0\backslash 0}$ is assumed to be the initial value of F_t^{PC} and $P_{0\backslash 0}$ is set equal to an identity matrix.

3. Equation for Idiosyncratic errors. We use a normal prior for $\rho_i : N(\rho_{i0}, V_{\rho i})$. The prior for r_i is inverse Gamma: $IG(r_{i0}, T_0)$. We set $\rho_{i0} = 0$ and $V_{\rho i} = 1$. The scale parameter and degrees of freedom for the inverse Gamma prior are 0.00001 and 1, respectively.

4. VAR parameters. We use a natural conjugate prior implemented via dummy observations (see Banbura *et al.* (2010)):

$$Y_{D,1} = \begin{pmatrix} \frac{diag(\gamma_1\sigma_1...\gamma_N\sigma_N)}{\tau} \\ 0_{N\times(P-1)\times N} \\ .... \\ diag(\sigma_1...\sigma_N) \\ .... \\ 0_{1\times N} \end{pmatrix}, and\ X_{D,1} = \begin{pmatrix} \frac{J_P \otimes diag(\sigma_1...\sigma_N)}{\tau} & 0_{NP\times 1} \\ 0_{N\times NP+1} & \\ .... & \\ 0_{1\times NP} & I_1 \times c \end{pmatrix} \tag{14}$$

where γ_1 to γ_N denotes the prior mean for the coefficients on the first lag, τ is the tightness of the prior on the VAR coefficients, c is the tightness of the prior on the constant terms and N is the number of endogenous variables, i.e. the columns of Y_t. In our application, the prior means are chosen as the OLS estimates of the coefficients of an AR(1) regression estimated for each endogenous variable. We use principal component estimates of the factors F_t^{PC} for this purpose. We set $\tau = 0.1$. The scaling factors σ_i are set using the standard deviation of the error terms from these preliminary AR(1) regressions. Finally we set $c = 1/10000$ in our implementation indicating a flat prior on the constant. We also introduce a prior on the sum of the lagged dependent variables by adding the following dummy observations:

$$Y_{D,2} = \frac{diag(\gamma_1\mu_1...\gamma_N\mu_N)}{\lambda}, \quad X_{D,2} = \begin{pmatrix} \frac{(1_{1\times P})\otimes diag(\gamma_1\mu_1...\gamma_N\mu_N)}{\lambda} & 0_{N\times 1} \end{pmatrix} \tag{15}$$

where μ_i denotes the sample means of the endogenous variables calculated using F_t^{PC}. The prior tightness is set as $\lambda = 10\tau$.

4.4 Gibbs sampling algorithm

The symbol Θ denotes all other parameters and states. The Gibbs sampling algorithm samples from the following conditional posterior distributions:

1. $G\left(\tilde{B}\backslash\Theta\right)$. $\tilde{B}$ denoted the VAR coefficients in vectorised form: $\tilde{B} = vec(B)$. The

conditional posterior distribution is normal with mean M and variance V where

$$\begin{aligned} M &= \left(S_0^{-1} + \Sigma^{-1} \otimes X_t' X_t\right)^{-1} \left(S_0^{-1} \tilde{B}_0 + \Sigma^{-1} \otimes X_t' X_t \hat{b}\right) \\ V &= \left(S_0^{-1} + \Sigma^{-1} \otimes X_t' X_t\right)^{-1} \end{aligned}$$

The prior for the VAR coefficients based on dummy observations is $N\left(\tilde{B}_0, S_0\right)$.

2. $G(\Sigma \backslash \Theta)$. The conditional posterior is inverse Wishart:

$$IW\left(u_t' u_t + \Sigma_0, T + T_D\right)$$

where Σ_0 and T_D represent the prior scale matrix and degrees of freedom based on the dummy observations specified above.

3. $H(\Lambda|\Theta)$. Given the factors F_t and a draw of the quarterly observations $\hat{x}_t$, the observation equation is set of M independent linear regressions with serial correlation

$$\tilde{X}_{it} = F_t \Lambda_i' + v_{it}$$

where Λ_i denotes the ith row of the factor loading matrix. The serial correlaton can be dealt with via a GLS transformation of the variables:

$$\bar{X}_{it} = \bar{F}_t \Lambda_i' + e_{it}$$

where $\bar{X}_{it} = \tilde{X}_{it} - \rho_i \tilde{X}_{it-1}$ and $\bar{F}_{kt} = F_{kt} - \rho_i F_{kt-1}$. The conditional posterior is normal $\mathcal{N}(M, V)$:

$$\begin{aligned} V &= \left(V_\Lambda^{-1} + \frac{1}{r_i} \bar{F}_t' \bar{F}_t\right)^{-1} \\ M &= V\left(V_\Lambda^{-1} \Lambda_{i,0} + \frac{1}{r_i} \bar{F}_t' \bar{X}_{it}\right) \end{aligned}$$

To account for rotational indeterminancy the top $K \times K$ block of Λ is set to an identity matrix.

4. $H(r_i|\Theta)$. The conditional posterior for r_i is $IG\left(T_0 + T, e_{it}' e_{it} + r_{i0}\right)$ where T is the sample size.

5. $H(\rho|\Theta)$. Given a draw of the factors, the AR coefficients are drawn for each i

independently. The conditional posterior is normal $\mathcal{N}(m, v)$

$$v = \left(V_{\rho i}^{-1} + \frac{1}{r_i} x'_{it} x_{it}\right)^{-1}$$
$$m = V\left(V_{\rho i}^{-1} \rho_{i0} + \frac{1}{r_i} x'_{it} y_{it}\right)$$

where $y_{it} = v_{it}$ and $x_{it} = v_{it-1}$.

6. $H(F_t|\Theta)$. To draw the factors, we write the model in state-space form taking into account the covariance between m_t and u_t and the serial correlation in the idiosyncratic components. The observation equation is defined as:

$$\underbrace{\begin{pmatrix} Z_t \\ \bar{X}_t \end{pmatrix}}_{x_t} = \underbrace{\begin{pmatrix} 1 & 0 \\ 0 & \Lambda \end{pmatrix}, \begin{pmatrix} 0 & 0 \\ 0 & \tilde{\Lambda}_1 \end{pmatrix}, \ldots, \begin{pmatrix} 0 & 0 \\ 0 & 0 \end{pmatrix}}_{H} \underbrace{\begin{pmatrix} Z_t \\ F_t \\ . \\ . \\ . \\ Z_{t-P} \\ F_{t-P} \end{pmatrix}}_{f_t} + \underbrace{\begin{pmatrix} 0 \\ e_t \end{pmatrix}}_{V_t}$$

where $\bar{X}_t = \begin{pmatrix} \tilde{X}_{1t} - \rho_1 \tilde{X}_{1t-1} \\ . \\ . \\ \tilde{X}_{Mt} - \rho_M \tilde{X}_{Mt-1} \end{pmatrix}$ and recall that $\tilde{X}_t$ contains data at the monthly frequency $\tilde{X}_t = \begin{pmatrix} \tilde{X}_t^M \\ \hat{x}_t \end{pmatrix}$. The blocks of the H matrix contain the factor loadings multiplied by the negative of the corresponding serial correlation coefficient. For example $\tilde{\Lambda}_1 = \begin{pmatrix} -\Lambda_1 \rho_1 \\ . \\ . \\ -\Lambda_M \rho_M \end{pmatrix}$ where Λ_i denotes the factor loadings for the ith variable X_{it}. Finally, the variance of V_t is $R = diag([0, r_1, .., r_M])$. The transition equation is defined as:

$$f_t = \mu + \tilde{B} f_{t-1} + U_t$$

where $\tilde{B} = \begin{pmatrix} B_1 & \cdot & \cdot & B_P \\ I_{N(P-1)\times NP} & & & \end{pmatrix}$, $\mu = \begin{pmatrix} c \\ 0_{N(P-1)} \end{pmatrix}$, $U_t = \begin{pmatrix} u_t \\ 0_{N(P-1)} \end{pmatrix}$. The non-zero block of $cov(U_t)$ is given by Σ. Given this Gaussian linear state-space, the state vector can be drawn from the normal distribution using the Carter and Kohn (1994) algorithm.

7. $H(\hat{x}_t|\Theta)$. Conditional on the remaining parameters, an independent state-space model applies for each quarterly series with missing observations. The observation equation is the following when 1 observation is available per-year:

$$x_{jt}^Q = \begin{pmatrix} 1/4 & 1/4 & 1/4 & 1/4 & 0 \end{pmatrix} \begin{pmatrix} \hat{x}_{jt} \\ \hat{x}_{jt-1} \\ \hat{x}_{jt-2} \\ \hat{x}_{jt-3} \\ v_{jt} \end{pmatrix} \text{ if } x_{jt}^Q \neq nan$$

$$x_{jt}^Q = \tilde{u}_{jt} \text{ if } x_{jt}^Q = nan$$

where $var(\tilde{u}_{jt}) = 1e10$. The observation equation is the following when 2 observations is available per-year:

$$x_{jt}^Q = \begin{pmatrix} 1/2 & 1/2 & 0 & 0 & 0 \end{pmatrix} \begin{pmatrix} \hat{x}_{jt} \\ \hat{x}_{jt-1} \\ \hat{x}_{jt-2} \\ \hat{x}_{jt-3} \\ v_{jt} \end{pmatrix} \text{ if } x_{jt}^Q \neq nan$$

$$x_{jt}^Q = \tilde{u}_{jt} \text{ if } x_{jt}^Q = nan$$

where $var(\tilde{u}_{jt}) = 1e10$.

With the assumption of one lag in equation 7, the transition equation is:

$$\begin{pmatrix} \hat{x}_{jt} \\ \hat{x}_{jt-1} \\ \hat{x}_{jt-2} \\ \hat{x}_{jt-3} \\ v_{jt} \end{pmatrix} = \begin{pmatrix} F_t\Lambda_i' \\ 0 \\ 0 \\ 0 \\ 0 \end{pmatrix} + \begin{pmatrix} 0 & 0 & 0 & 0 & \rho_i \\ 1 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & \rho_i \end{pmatrix} \begin{pmatrix} \hat{x}_{jt-1} \\ \hat{x}_{jt-2} \\ \hat{x}_{jt-3} \\ \hat{x}_{jt-4} \\ v_{jt-1} \end{pmatrix} + \begin{pmatrix} e_{jt} \\ 0 \\ 0 \\ 0 \\ e_{jt} \end{pmatrix}$$

$$\text{where } var\begin{pmatrix} e_{jt} \\ 0 \\ 0 \\ 0 \\ e_{jt} \end{pmatrix} = \begin{pmatrix} r_j & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & r_j \end{pmatrix}.$$

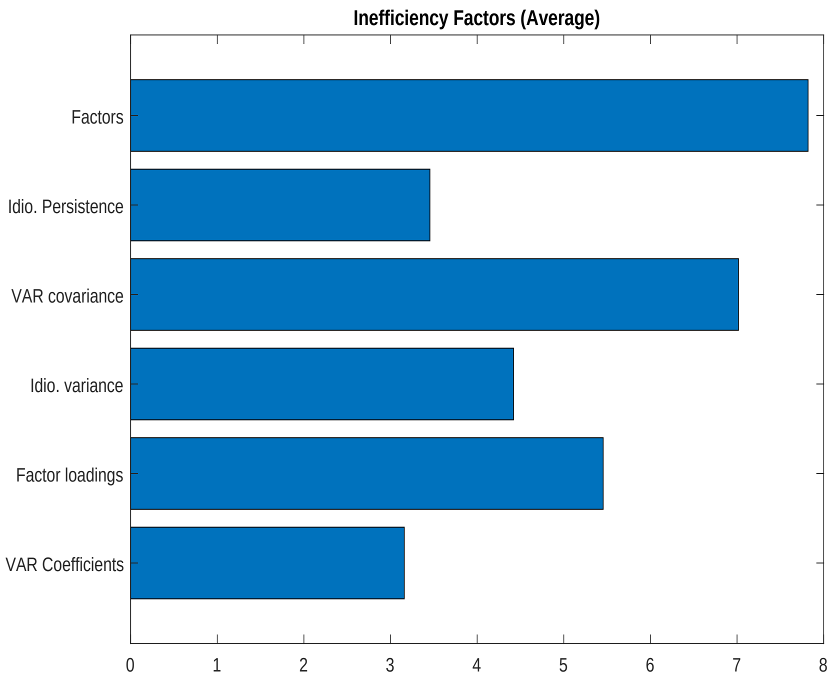

Figure 6: Inefficiency Factors. Average across parameters

5 Further results and Robustness

Figure 6 shows that the inefficiency factors for the benchmark model are less than 20. This suggests evidence in favour of convergence of the Gibbs algorithm. Figure 7 presents

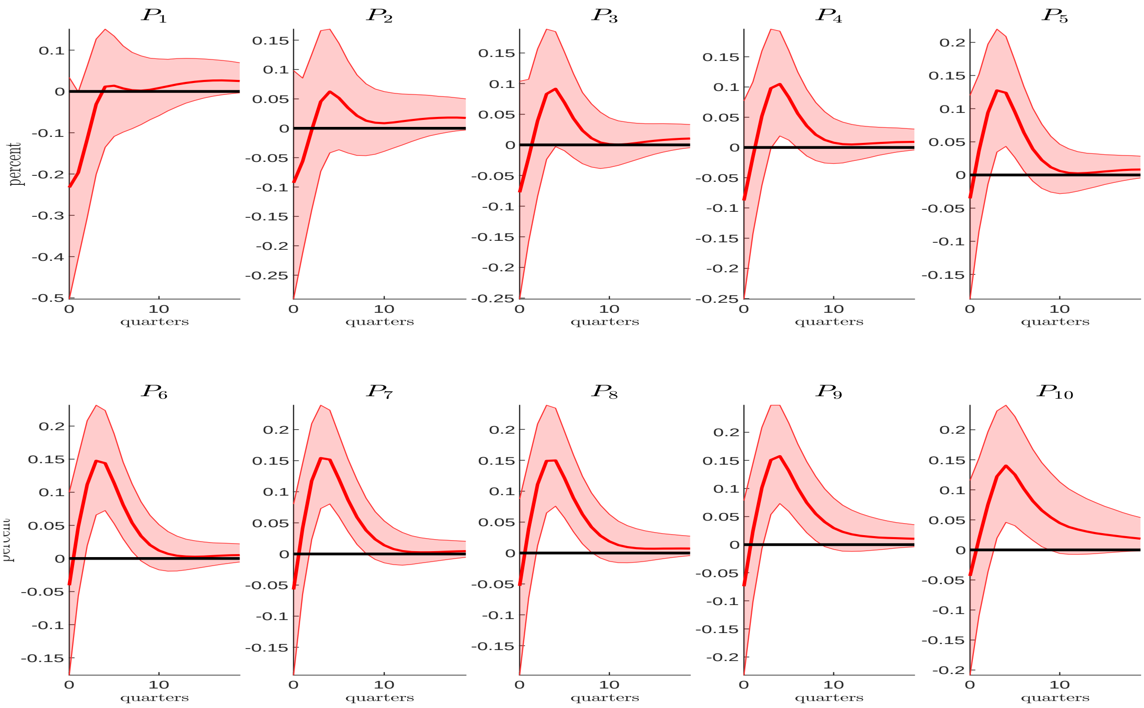

Figure 7: Response of hours in wage decile groups. For e.g. P_1 denotes the first decile, while P_{10} is the last decile. The shaded area displays the 68% error bands

the response of hours in each wage decile group. The response of hours for individuals at the left tail resembles the aggregate response. In contrast, hours increase towards the right tail of the wage distribution and the response is statistically different from zero about one year after the shock.

We carry out the following robustness checks:

Sign restrictions We identify the productivity using the robust sign restrictions proposed in Dedola and Neri (2007). As discussed in Francis *et al.* (2003) the precision of the impulse responses from the sign restrictions scheme can be improved via additional restrictions–we impose the additional restriction that the identified productivity shock should explain at least 50% of the forecast error variance of productivity growth at the 10 year horizon. Figure 8 shows that the pattern of the responses for hours is similar to

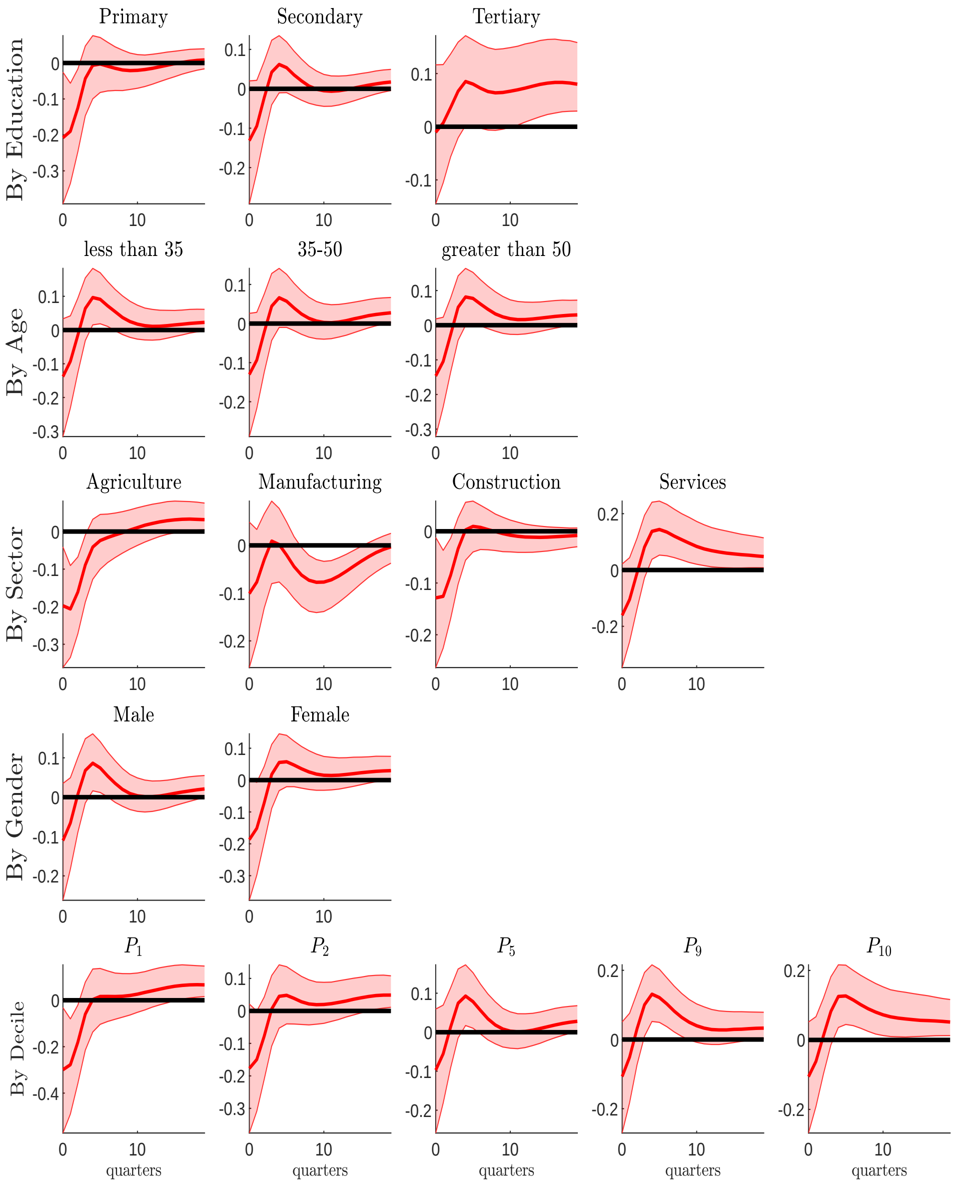

Figure 8: Response of hours for different demographic groups and sectors using sign restrictions. The shaded area displays the 68% error bands

benchmark. Hours increase on the right tail of the wage distribution. They rise for male workers, those in services and those with tertiary education.

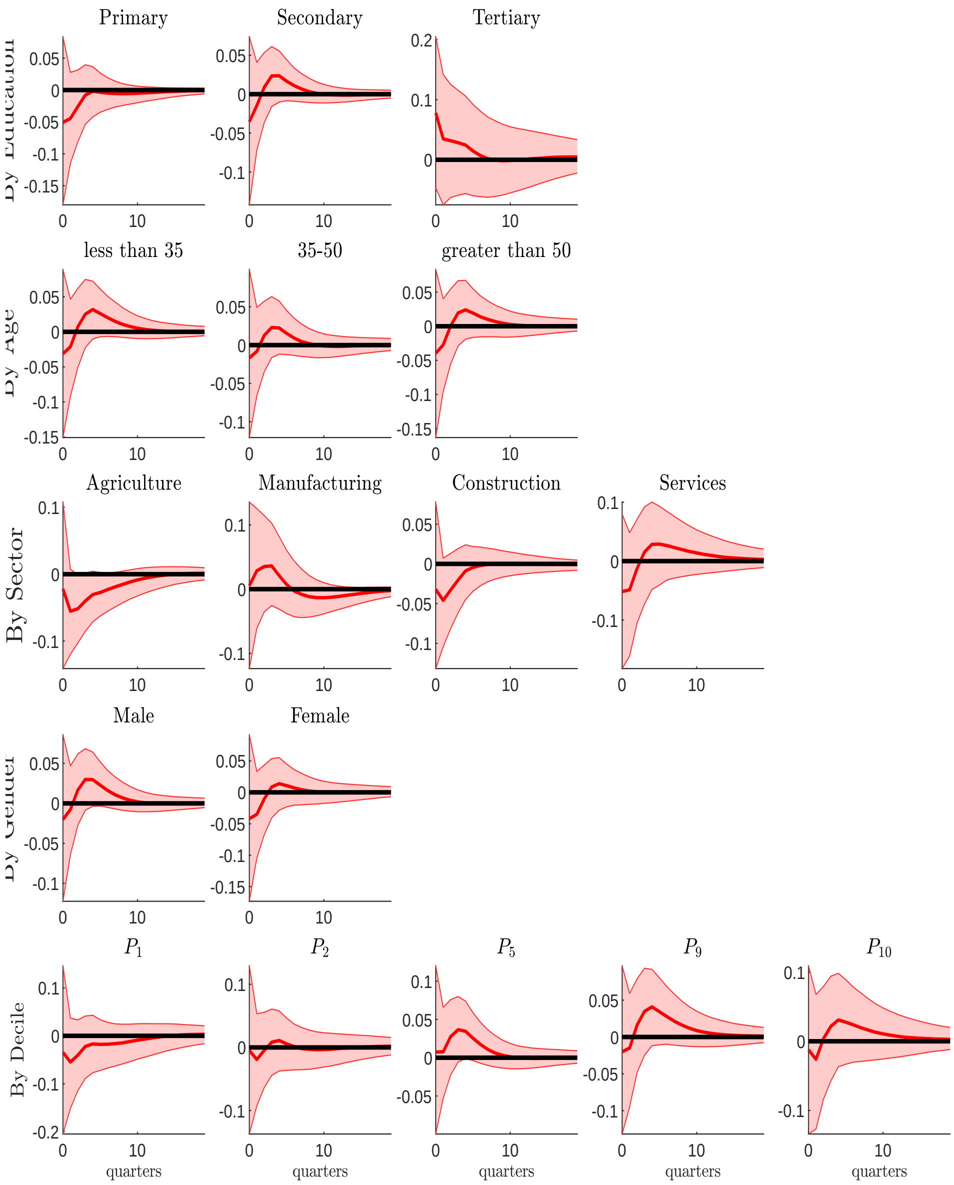

Figure 9: Response of hours for different demographic groups and sectors using long-run restrictions. The shaded area displays the 68% error bands

Long-Run restrictions We identify the productivity shock using the long-run identification scheme of Galí (1999) under which the productivity shock is identified as the only innovation that can affect the level of productivity in the long-run. Given the short-time series, estimation of infinite horizon impulse responses is unreliable and this is reflected in large error bands. However, the median responses in figure 9 follow the same broad pattern as the benchmark case.

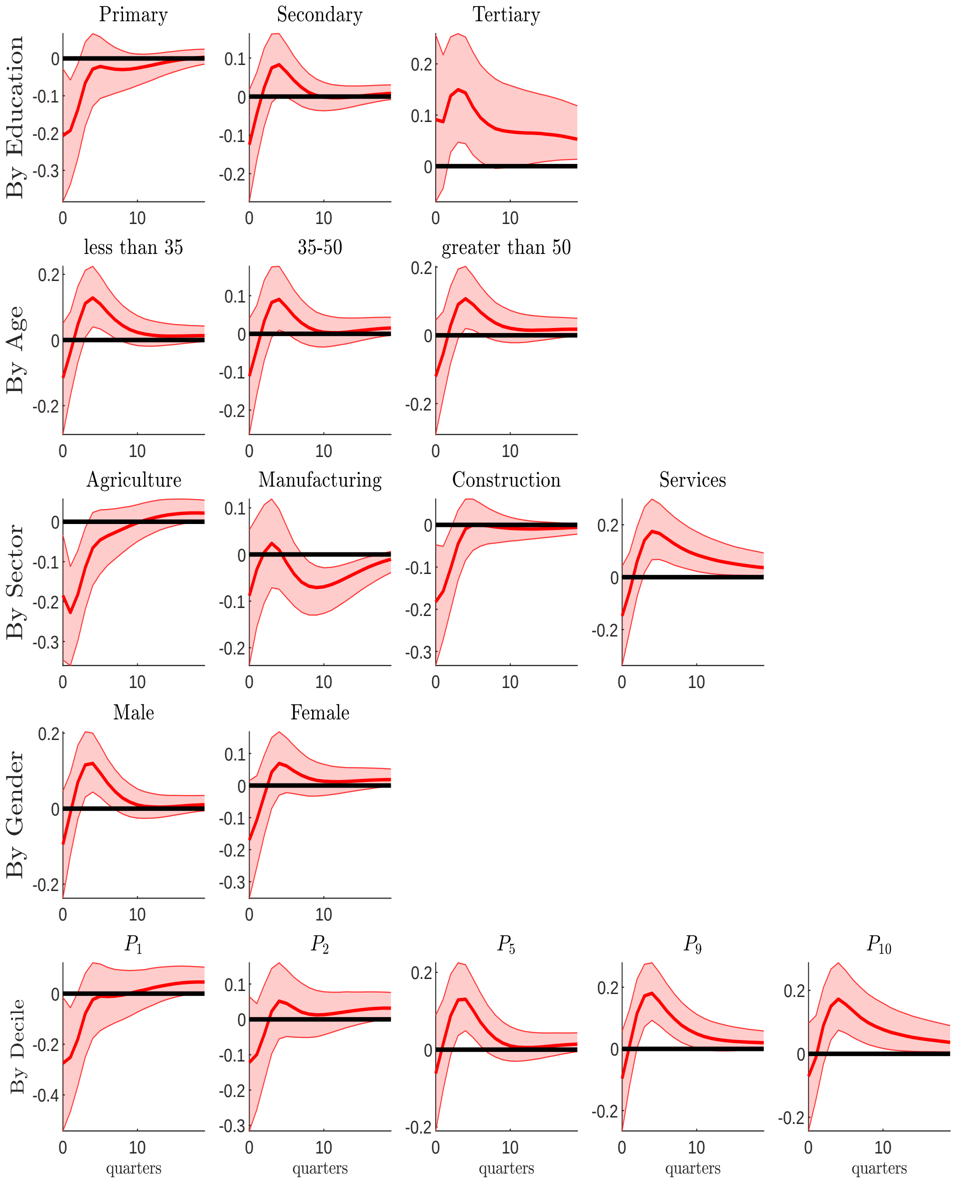

Figure 10: Response of hours for different demographic groups and sectors using 8 factors. The shaded area displays the 68% error bands

Number of factors Figure 10 shows that the main results are preserved if the number of factors is increased 8.

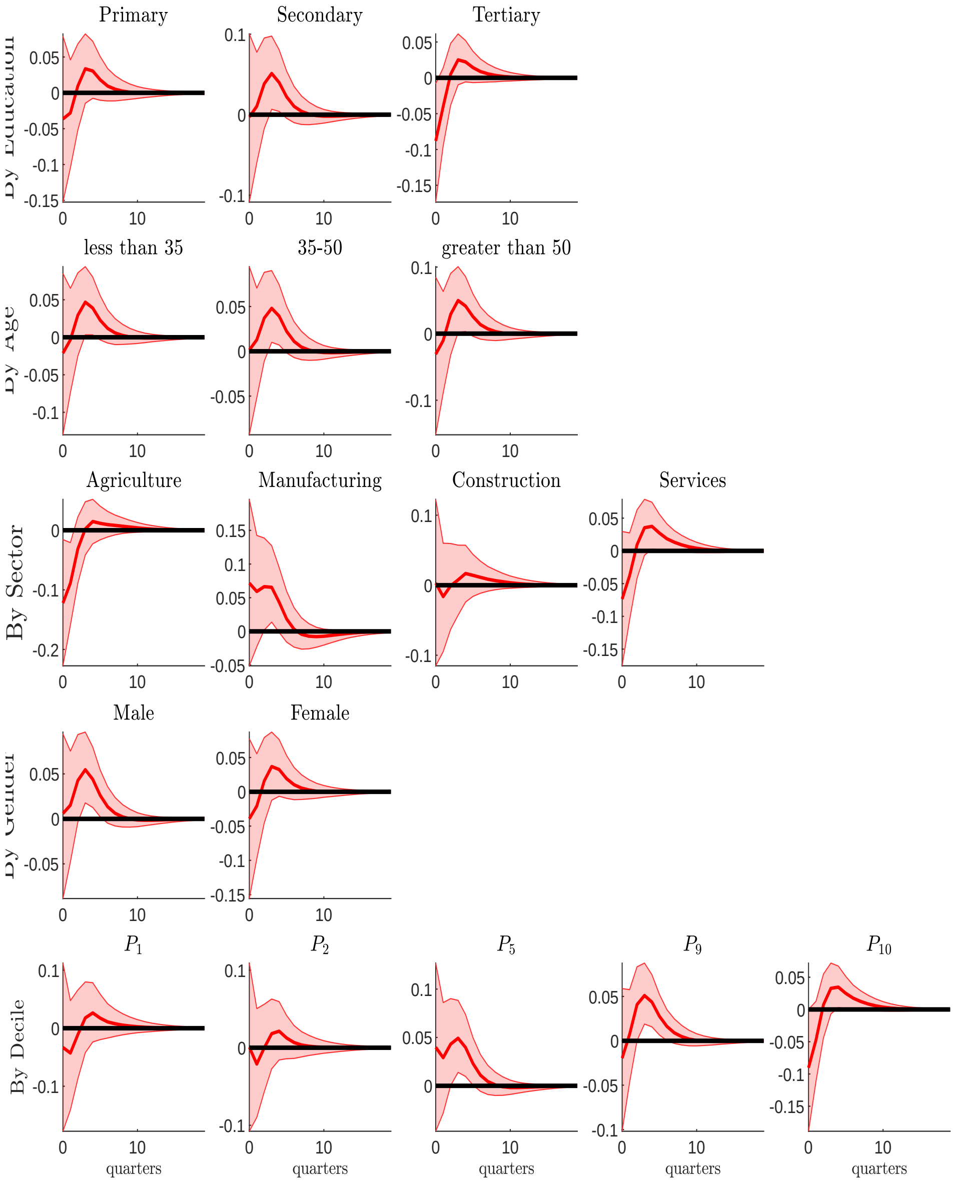

Figure 11: Response of hours for different demographic groups and sectors using hours in growth rates. The shaded area displays the 68% error bands

De-trended Hours Figure 11 shows that the main results are preserved if the hours data log-differenced before estimation. In this case we assume that observed annual/sem-annual growth rates are a sum of unobserved quarterly growth rates that are treated as latent. The estimated responses are less precise but show an increase in hours towards the right tail of the wage distribution, in services, for males and those with higher than primary eduction.

Table 1: Aggregate variables included in the FAVAR

Variable	**Transformation**	**Source**
Industrial Production	LD	FRED
CPI Non-Food	LD	FRED
Retail Sales	LD	FRED
Total Credit to Non-Financial Corporations	LD	FRED
Mining	LD	FRED
Balance of Payments: Goods	LD	FRED
CPI Services	LD	FRED
Imports	LD	FRED
Unit Labour Costs	LD	FRED
Vacancies	LD	FRED
M3	LD	FRED
Exports	LD	FRED
World Uncertainty Index Czechia	LD	FRED
CPI Energy	LD	FRED
Unemployment Rate	N	FRED
Real Consumption	LD	FRED
CPI Alcohol Tobacco	LD	FRED
Share Prices	LD	FRED
Government Consumption	LD	FRED
PPI Food	LD	FRED
Real GDP	LD	FRED

Continued on next page

Table 1 – continued from previous page

Variable	Transformation	Source
US dollar exchange rate	LD	FRED
CPI	LD	FRED
3 mth T-Bill rate	LD	FRED
Real Effective Exchange Rate	LD	FRED
PPI Manufacturing	LD	FRED
CPI Food	LD	FRED
GDP deflator	LD	FRED
PPI industry	LD	FRED
Gross Capital formation	LD	FRED
CPI Restaurants hotels	LD	FRED
Labour Compensation	LD	FRED
Earnings Manufacturing	LD	FRED
CPI housing	LD	FRED
CPI education	LD	FRED
Unemployment 25 and over	LD	FRED
Unemployment 15-24	LD	FRED
Unemployment 25 and over females	LD	FRED
Unemployment 25 and over males	LD	FRED
Unemployment 15-24 males	LD	FRED
CPI Communication	LD	FRED
CPI culture	LD	FRED

Continued on next page

Table 1 – continued from previous page

Variable	Transformation	Source
Retail trade	LD	FRED
CPI Misc.	LD	FRED
Unemployment 15-24 females	LD	FRED
CPI transport	LD	FRED
10 Year rate	N	FRED
Net Acquisition Czechia	LD	FRED
Construction Dwellings	LD	FRED
Earnings Private Sector	LD	FRED
Employment Manufacturing	LD	FRED
Employment Rate total	LD	FRED
Employment Agriculture	LD	FRED
Permits for dwellings	LD	FRED
Employment Rate 15-74	N	FRED
Unemployment Rate 15-24	N	FRED
Leading indicator	LD	FRED
Unemployment Rate	N	FRED
Employment Rate 15-24	N	FRED
Employment Services	LD	FRED
CPI clothing	LD	FRED
Real Broad Effective ER	LD	FRED
NEER	LD	FRED

Continued on next page

Table 1 – continued from previous page

Variable	Transformation	Source
Dividend Yield	LD	GFD
Price Equity	LD	GFD
5 year yield	N	GFD
Lending Rate	LD	GFD
Lending Rate 1 year loans	LD	GFD
Lending Rate 4+ years	LD	GFD
Prices last 12 months	LD	GFD
Unemployment Expectations last 12 mths	LD	GFD
Consumer expectations	LD	GFD
Economic situation last 12mths	LD	GFD
Financial situation last 12mths	LD	GFD
Prices next 12 mths	LD	GFD
Financial situation next 12mths	LD	GFD
Time deposit rate	LD	GFD
Business Confidence	LD	GFD
Consumer Confidence	LD	GFD
Housing starts	LD	GFD
Housing Permits	LD	GFD
Stock market capitalization	LD	GFD
Import Prices	LD	GFD

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