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Distributional Effects of Monetary Policy Shocks on Wage and Hours: Evidence from the Czech labor market*

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Abstract

We investigate the heterogeneity in the effects of monetary policy shocks on the distribution of wages and hours worked, using unique contract-level data from the Czech labor market and identifying monetary policy shocks using a narrative approach based on market suprises in interest rate futures. The results suggest that low-wage groups are hit more profoundly by monetary policy shocks than high-wage groups, and the effect of restrictive shocks is stronger in the manufacturing sector than in any other. Exploring other dimensions of the data offers insights into the heterogeneity of the the impact of monetary policy on different demographic groups. We show that low-educated and also young workers are more affected by restrictive monetary policy shocks due to their higher shares in low-wage groups.

Keywords: monetary policy; heterogeneity; wage inequality; shock identification
JEL Classifications: E2, E3, E4, E5

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1 Introduction

The aftermath of the Covid-19 pandemic has translated into a period of extraordinary inflationary pressures, to which many central banks have responded by reversing their monetary policy stances from expansionary to restrictive. The pace and strength of the observed monetary tightening were almost inconceivable in previous decades. In addition to the unwinding of unconventional policies, the tightening again takes the form of interest rate hikes. Through various channels these policies aim to cool overheated labor markets, constrain aggregate demand, and ultimately mitigate inflationary pressures. However, a closer look at the data suggests that these effects are not uniform across different agents in the economy.

Our paper investigates the heterogeneity in the effects of monetary policy shocks on wage levels and hours worked across the wage distribution and for different demographic and sectoral groups. We employ a rich administrative dataset on wage contracts from the Czech labour market. This contrasts with conventionally available survey data on households, which typically suffers from a number of drawbacks. In typical surveys, the number of observations might be limited, and the representativeness of the data collected might be questionable, especially at the tails of the distribution. Using a rich administrative dataset of wage contracts enables us to avoid many of the shortcomings of survey data. The data offers a large information set along both the cross-sectional and time dimensions, which enables us to work with the percentiles of the wage distribution and explore in detail the varied sectoral and demographic impact of monetary policy shocks. We identify monetary policy shocks using a narrative approach similar to Gertler and Karadi (2015), Miranda-Agrippino (2016), and Jarocinski and Karadi (2020).

Numerous earlier studies investigate the distributional effects of monetary policy shocks. Coibion et al. (2017) highlight the earnings heterogeneity channel as an important driver of rising inequality resulting from expansionary monetary policies. Mumtaz and Theophilopoulou (2017) find that the heterogeneous response to economic development among individuals results in monetary policy primarily affecting the lower end of the income distribution. These findings are supported by Ampudia et al. (2018) and Lenza and Slacalek (2022), who examine the distributional impacts of conventional and unconventional monetary policies in the Euro Area.

Our work is closely related to several recent papers using administrative individual-level data. Andersen et al. (2020) examine Danish data and suggest that the income response to an expansionary monetary policy shock increases monotonically across the wage distribution. Amberg et al. (2021) and Hubert and Savignac (2023) look at the individual-level income data in Sweden and France respectively and find that the income effects are U-shaped over the income distribution.

Our findings echo these results, which we then extend by analyzing the effect on various demographic and sectoral groups. We confirm that the redistribution of labor income resulting from a restrictive monetary policy shock disadvantages individuals at the bottom of the distribution. We also show that this effect is driven by gender, age, and education, as well as jobs that are rigid in terms of working hours; typically, low-paid, low-educated workers and those working in the manufacturing sector are hit by shocks stronger. On the other hand, in service sectors, flexibility of working hours allows for adjustment to shocks with less impact on labor earnings. The explanation of the latter findings traces back to a theoretical argument from Kaplan and Zoch (2020), according to which the effect of a negative aggregate shock is more pronounced for the typical worker in the manufacturing sector.

The rest of this paper is organized as follows. The next section describes the data and illustrates some stylized facts. Section 3 details the estimation methods and the construction of the monetary policy shock series. We present and discuss the results in Section 4. Section 5 concludes.

2 Data – labor market characteristics

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[2] frequency from 2002 up to the most recent vintages. Our sample used in the following analysis ends in 2020. In each data vintage, the variables include the average wage 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, number of employees (full-time-equivalent), total hours worked, and total wages paid. To gather more information on employers, we merge the data with the RES[3]

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

[2] Biannual frequency is available starting in 2012. However, because of some issues related to the seasonality of wages reported mid-year, we stick to the annual data vintages. The data reported mid-year covers only the first half of the year, while the annual data covers the full year. Among other issues, the mid-year data typically does not include year-end bonuses, making any seasonal factor estimates unstable. The biannual frequency seemed to induce more noise into the estimations rather than additional precision.

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

Business Register database, which provides information on the prevailing business sector in which the employer operates.

The panel covers a large amount of Czech labor market contracts, with around 1.5 million cross-sectional units (contracts) in the most recent data vintages. The panel is unbalanced, as many contracts appear and disappear during the observed time sample. We can still see the duration of each contract, which is a separate data entry. Not all contracts are covered; the inclusion of a contract in the sample depends on the size of the firm. Firms with 250+ employees are included in each vintage (fully covered), 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 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.

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 nature and anonymization 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

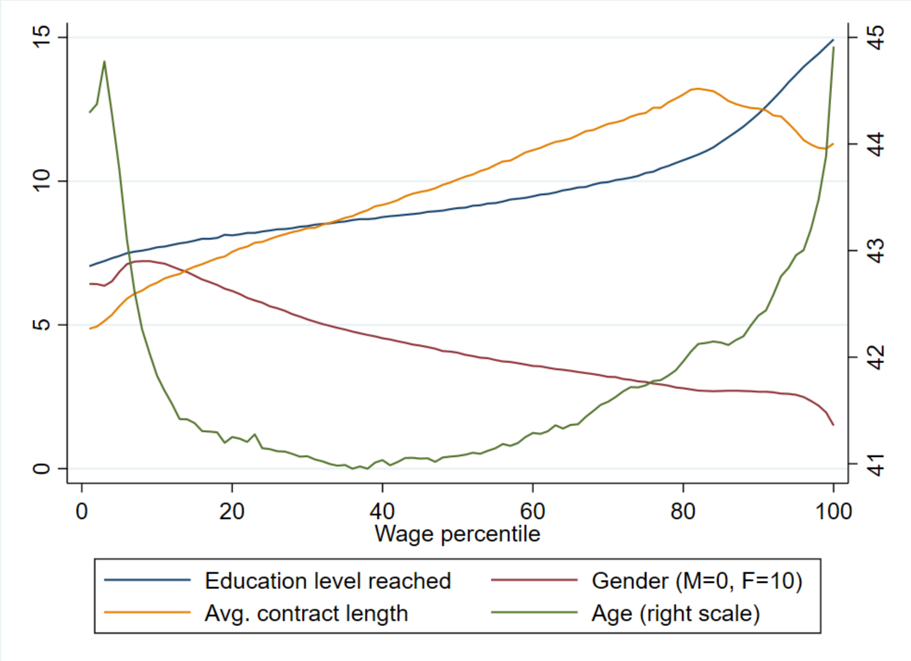
Figure 1: Log average hourly wage distribution in 2020

length of the present contract.

The data offers many interesting insights into the structure of the Czech labor market. Figure 1 shows the histogram of the log average hourly wage distribution in the last data vintage used in this paper – 2020.

In what follows, we shrink the wide cross-sectional dimension to percentiles of the average hourly wage. Figure 2 shows the characteristics of employees and respective contracts along the wage distribution, averaged over the whole time sample (2002–2020). Higher wage percentiles are associated with a higher education level, and the relationship is strictly increasing. Apparent gender inequality is illustrated not only by lower shares of females in most wage percentiles (the blue line below 5 in Figure 2), but also 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 those workers who were

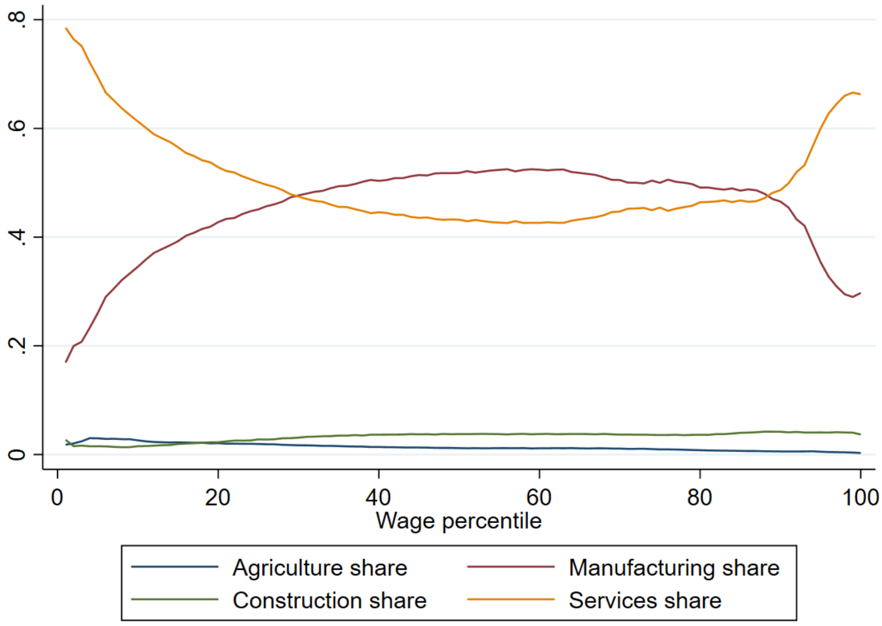
Figure 2: Characteristics of employees and contracts along the wage distribution



able to climb the seniority ladder and increase their wages, 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. Finally, higher wage percentiles are generally associated with longer duration of current contracts, indicating lower employee turnover rates. However, this regularity breaks down at the upper tail, where the observed contracts for the top percentiles have slightly shorter average durations than those around the 80th wage percentile.

Figure 3 illustrates the wage distribution in different sectors. The service sector has a higher share in the lowest and the highest wage percentiles. This may be related on the one hand to the high share of female workers (not shown in the figure), and on the other to the high average level of education in services compared to other sectors. The highest average wage is generally reported in the construction sector, closely followed by services and industry (manufacturing). In construction, however, the reporting might have been

Figure 3: Characteristics of employees across sectors along the wage distribution



skewed upward by the presumably large share of the shadow economy. There is not much sectoral diversity regarding the average age of employees or the length of their contracts.

3 Empirical model

Our benchmark model is the following mixed-frequency Vector Autoregression (VAR):

$$Y_t = c + \sum_{p=1}^{P} B_p Y_{t-p} + \upsilon_t \tag{1}$$

where $\upsilon_t \tilde{} N(0, \Sigma)$ and Y_t is a $1 \times N$ matrix of endogenous variables that includes the following variables:

$$Y_t = \begin{pmatrix} m_t & r_t & y_t & p_t & u_t & s_t & \hat{z}_t \end{pmatrix}' \tag{2}$$

where m_t is a measure of the monetary policy shock described below. The short-term interest rate, the log of GDP, the log of the GDP deflator, the unemployment rate, and the log of the dollar exchange rate are denoted by r_t, y_t, p_t, u_t, and s_t, respectively. The data for these variables is quarterly and runs from 2002Q1 to 2019Q4.[4] Finally, z_t denotes wages or hours worked averaged for the survey participants, who fall within groups defined either by percentile of the wage distribution, or characteristics such as industry of employment, gender, and education. We provide details on the definition of the groups in the empirical analysis below.

As described in the previous section, the survey data is available only at annual frequency before 2012 and at biannual frequency thereafter. The unobserved quarterly data z_t is treated as unknown along with the other VAR parameters.

3.1 Mixed frequency

The vector of endogenous variables contains quarterly macroeconomic variables and survey-based variables, which are available at a lower frequency. The survey-based variables z_t are observed in the fourth quarter of every year before 2012 and are then available twice a year. Following Schorfheide and Song (2015), we treat the quarterly observations of $\hat{z}_t$ as

[4] All series are obtained from the FRED data base. The Fred mnemonics are CLVMNACSCAB1GQCZ, CZECPIALLQINMEI, IR3TIB01CZM156N and CCUSMA02CZM618N for real GDP, CPI, short-term interest rate and the exchange rate, respectively.

unobserved states. The model is augmented with the following observation equation:

$$Z_t = H \underbrace{\begin{pmatrix} Y_t \\ Y_{t-1} \\ Y_{t-2} \\ Y_{t-3} \end{pmatrix}}_{\beta_t} + \begin{pmatrix} E_t \\ 0 \\ 0 \\ 0 \end{pmatrix} \tag{3}$$

where $Z_t = \begin{pmatrix} m_t & r_t & y_t & p_t & u_t & s_t & z_t \end{pmatrix}'$ and $E_t = \begin{pmatrix} 0 & 0 & 0 & 0 & 0 & 0 & \tilde{v}_t \end{pmatrix}'$. Note that the last element in Z_t equals the missing value in $Q1$ to $Q3$ of each year in the sample before 2012 and is observed only in $Q4$. After 2012, Z_t equals the missing value in $Q1$ and $Q3$ and is observed in the remaining quarters. If z_t is missing, then $H = \begin{pmatrix} I_{N-1} & 0_{N-1,N} & 0_{N-1,N} & 0_{N-1.N} \\ 0_{1,N} & 0_{1,N} & 0_{1,N} & 0_{1,N} \end{pmatrix}$ where I_N and $0_{N,N}$ denote the $N \times N$ identity matrix and an $N \times N$ matrix of zeros, respectively. Note that $var(\tilde{v})$ is set to a large number in this case. When z_t is observed once a year, $H = \begin{pmatrix} I_{N-1} & 0_{N-1,N} & 0_{N-1,N} & 0_{N-1.N} \\ e_N & e_N & e_N & e_N \end{pmatrix}$ with $e_N = \begin{pmatrix} 0 & 0 & 0 & 0 & 0 & 0 & \frac{1}{4} \end{pmatrix}$ and $var(\tilde{v})$ is set to 0. In this case, the observation equation implies that $z_t = \sum_{i=0}^{3} \frac{\hat{z}_{t-i}}{4}$ – i.e., the observed value is assumed to be the average of the unobserved values in the current and the last three quarters. When z_t is observed twice a year, $H = \begin{pmatrix} I_{N-1} & 0_{N-1,N} & 0_{N-1,N} & 0_{N-1.N} \\ e_N & e_N & 0 & 0 \end{pmatrix}$ with $e_N = \begin{pmatrix} 0 & 0 & 0 & 0 & 0 & 0 & \frac{1}{2} \end{pmatrix}$ and $var(\tilde{v})$ is set to 0. In this case, the observed value is the average of the current and previous quarter.

Figure 4: Changes in Pribor futures around meetings of the monetary policy committee

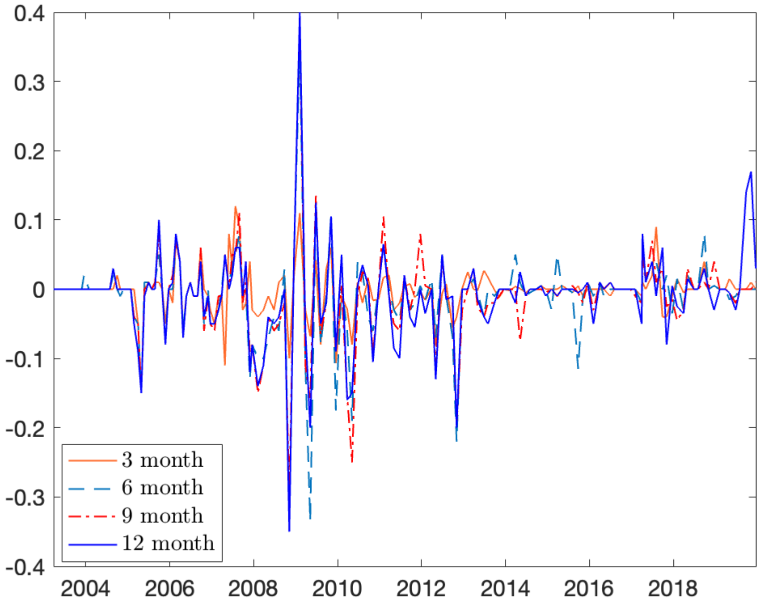
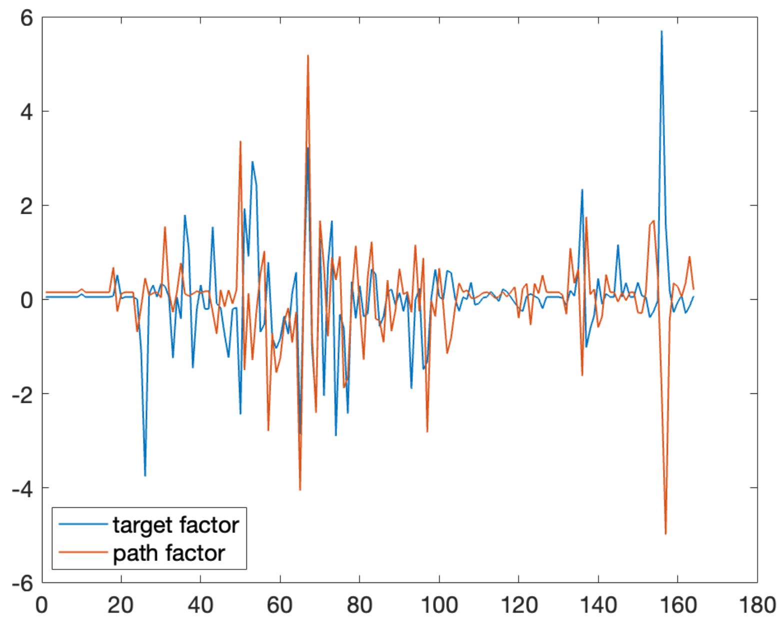


Figure 5: Filtered target and path factors



3.2 Narrative identification of the monetary policy shock

We acknowledge a distinction between monetary policy changes, monetary policy shocks, and monetary policy surprises. Not every change to the monetary policy rate is a shock, as many policy changes are in accordance with both macroeconomic fundamentals and expectations. Along with the majority of the literature, we understand monetary policy shock to mean a deviation from the systematic monetary policy reaction. Further, shocks can be either unexpected (surprises) or expected (news about future events). For a discussion on the nature and treatment of expected vs. unexpected shocks, see Musil, Tvrz, and Vlcek (2021). However, in empirical practice, true monetary policy shocks remain unobserved and need to be identified or estimated. Recent literature has been relying increasingly on financial market surprises around monetary policy meetings as a useful proxy for the identification of monetary policy shocks.

Following recent papers such as Gertler and Karadi (2015b), Miranda-Agrippino and Ricco (2015), and Jarocinski and Karadi (2020), we adopt a narrative approach to identify the monetary policy shock. In particular, we use daily data on three-month Prague interbank Libor rate futures (Pribor) at maturities of 1, 3, 6, and 9 months. We calculate the daily changes in these futures around monetary policy meetings. As shown in Figure 4, the change in future rates at the nine-month horizon shows the largest volatility, with large spikes occurring during the 2008–2010 period. It is also noticeable that the change in future rates is highly correlated. Infact, 91 percent of the cross-sectional variation in the futures is explained by the first two principal components of these futures. Given this feature, we follow Gürkaynak, Sack, and Swanson (2005) and use linear combinations of these futures to characterize monetary policy shocks. As discussed in Gürkaynak, Sack, and Swanson (2005), the cross-section of futures captures multiple dimensions of monetary policy and contains information regarding the market reaction to expected changes in current rates and their future path. We follow the approach of Gürkaynak, Sack, and Swanson (2005) and rotate the principal components $\mathcal{P}_t$ to obtain factors $\mathcal{P}_t^*$. This orthogonal rotation imposes the restriction that the second factor in $\mathcal{P}_t^*$ has a zero loading at the one-month maturity. Therefore, this factor can be interpreted as a "statement" or a "path" factor that captures changes in guidance on future policy rates. In contrast, the first factor in $\mathcal{P}_t^*$ that is allowed to load at the one-month maturity is the "target" factor and is a proxy for current policy surprise.

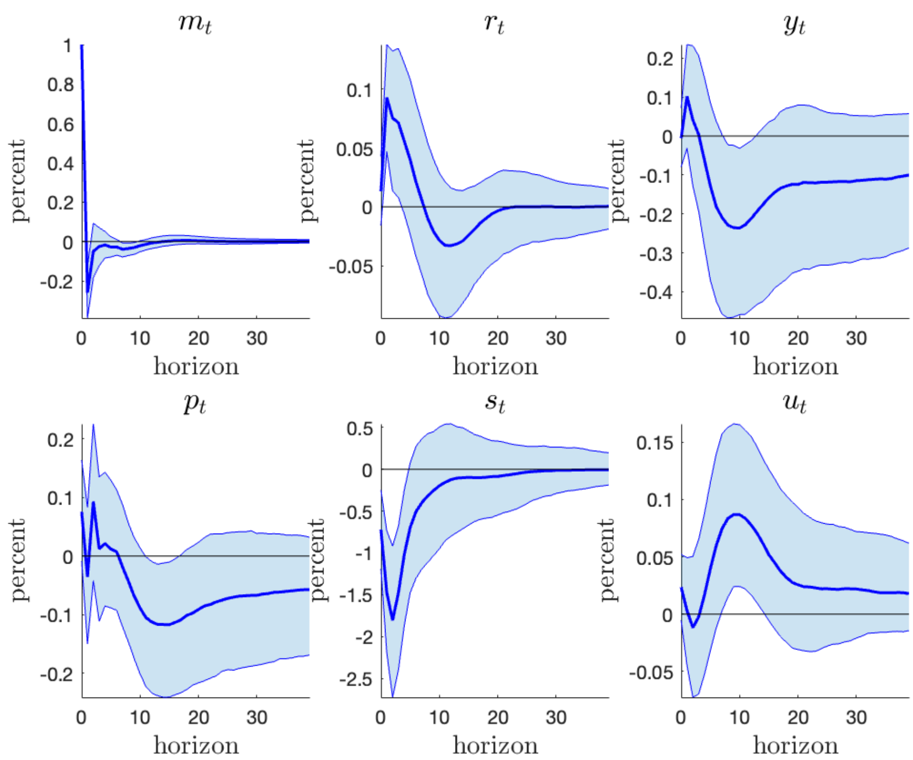
The movements of $\mathcal{P}_t^*$ (Figure 5) accord well with the narrative of monetary policy events in the Czech Republic. The extreme values of the target and path factors identified from interest rate futures can be directly linked to surprising decisions at the relevant monetary policy meetings. For example, the monetary policy meeting on Feb 6, 2020 brought an unexpected 25 bp hike (a spike in the target factor), and the market expected this move to be corrected later on (a concurrent drop in the path factor). To give another example, the meeting on Feb 5, 2009 resulted in a cut of 50 bp, but a larger amount of easing had been expected, leading to a restrictive shock captured by a spike in the target factor. Additionally, a surprisingly hawkish rate forecast led to a positive spike in the path factor as well.

In our empirical analysis, our interest lies in conventional monetary policy. We therefore use the target factor as our instrument m_t. As in Jarocinski and Karadi (2020), the instrument is added directly to the VAR model, and impulse responses are calculated using a Cholesky decomposition with m_t ordered first. Plagborg-Møller and Wolf (2021) prove that the impulse responses obtained via this approach are asymptotically equivalent to those obtained using the instrumental variable or proxy VAR approach. Given our small sample size and the presence of missing data, we prefer the simpler approach of recursive VAR.

3.3 Model specification and estimation

Based on the Schwarz information criterion, the lag length of the VAR model is set to 2. The mixed frequency VAR model is estimated using Bayesian techniques. In particular, we use the Gibbs sampling algorithm devised by Schorfheide and Song (2015). In short, each iteration involves sampling from the conditional posterior distributions of b, Σ, and β_t, respectively, where b denotes the VAR coefficients in vectorized form. The first two conditional posterior distributions are standard in the Bayesian VAR literature. Draws from the conditional posterior distribution of the state variables β_t can be obtained using the simulation smoother of Durbin and Koopman (2002). The technical appendix provides details of the conditional posteriors and prior distributions that are standard. We use 21,000 iterations, dropping the first 1,000 as burn-in. Every fifth remaining iteration is saved for inference. We provide evidence for convergence of the algorithm in the appendix.

Figure 6: Response of macroeconomic variables to a monetary policy shock



4 Results

4.1 The macroeconomic effects of a monetary policy shock

Before describing the impact of monetary policy shocks on the distribution of wages and hours worked, we show that the responses of the main macroeconomic variables are plausible and accord well with the theory and with previous estimates for the Czech Republic.

Figure 6 shows that a contractionary shock leads to an increase in the short-term interest rate r_t of about 0.1 percent. Both GDP and the GDP deflator fall in response to the shock, while the unemployment rate rises. The decline in GDP is sharp, with the peak response occurring at a three-year horizon. The fall in the price index occurs more slowly, with prices declining by about 0.2 percent after four years. The exchange rate appreciates sharply and s_t declines by 1.5 percent one quarter after the shock. To sum up, a contractionary monetary policy shock impacts the interest rate and exchange rate variation mostly in the short run; the effect on GDP and the price index peaks after a longer time.

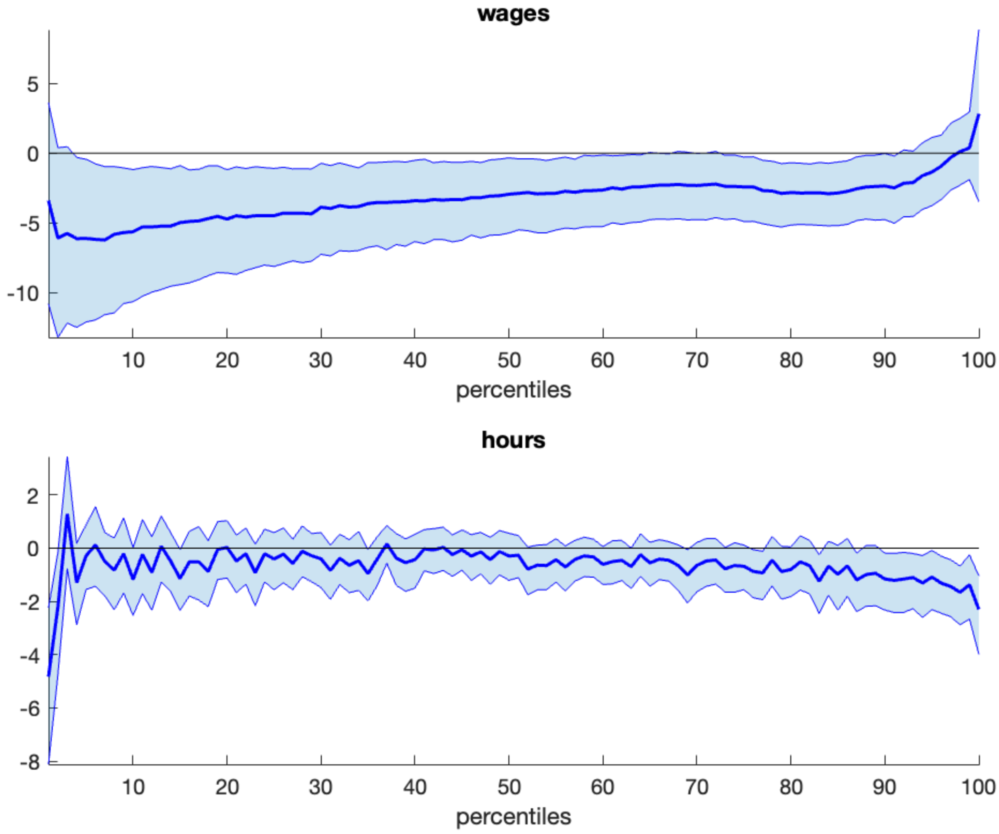
4.2 Monetary policy shocks and the distribution of wages

We augment the benchmark model with data on average wages and hours in each percentile. These variables are added one by one and the VAR model is estimated in each case.[5] The granular nature and number of observations included in our dataset means that average wages and hours worked within each percentile are estimated precisely. Therefore, unlike survey-based studies, we can examine the impulse responses at a finer level and, importantly, we can illustrate the behavior of the distribution at the tails, which may not be evident from a more aggregate analysis.

Figure 7 displays the cumulative response of wages and working hours over 20 quarters to the contractionary monetary policy shock in each percentile group. The shock is normalized to increase the short-term interest rate by 100 basis points. The figure shows that within five years after the monetary contraction, the wage is depressed across almost the whole distribution. The largest adverse effect occurs at the left tail of the distribution. For low earners, the wage declines cumulatively by about 5 percent, while the wage of top earners is largely unaffected. In contrast, a closer look at working hours shows that the contractionary policy shock tends to reduce the number of working hours across the whole

[5] While it would be preferable to add these variables jointly, the small sample size and large number of unobserved state variables make this computationally infeasible.

Figure 7: Cumulated response of wage and working hours to monetary policy shock



distribution, being strongest at both ends of the distribution. These are not only new findings in the context of the Czech labor market, but might extend to labor markets in many other countries (e.g., Amberg et al., 2022). It is therefore important to understand what drives this apparent heterogeneity in the reaction to monetary policy shocks. To conduct a more thorough examination of these questions, in the following subsection we explore the reaction by sectoral and demographic groups.

As shown in Appendix A.3, the monetary policy shock also contributes to the forecast error variance for wages and working hours mainly at the tails of the distributions.

4.2.1 Demographic and sectoral analysis

The structure of our dataset allows us to extract primary demographic characteristics of employees, such as gender, age, and education. We also know the prevailing business sector in which the employer operates. In this section, we consider the role played by these characteristics in driving the heterogeneous response of wages and hours worked. In particular, we estimate the VAR model by adding one by one wages or hours worked averaged across different demographic and sectoral characteristics.[6]

Interestingly, the results indicate that while services jobs are more likely to react with restriction of hours worked, jobs in the industry sector are more prone to a decline in wages. The negative reaction of wages to the shock is larger for those who are less educated, young workers, and those working in manufacturing. The higher the level of education, the smaller the reaction of wages to monetary policy shocks. Moreover, female workers seem to experience a marginally stronger response to the shock, although the differences are not significant. Contract length does not seem to play a significant role.

In relation to Figure 7 and the characteristics of employees discussed in Section 2, we can hypothesize that the stronger response of the left tail might be driven by lower age, lower education level, and higher share of female workers. We can summarize our findings as follows.

Main findings: stylized facts about the distributional effects of monetary policy shocks on wages and hours worked

1. Workers with higher education are more resistant to the effects of monetary policy

[6] For example, we estimate the VARs for different age groups, adding their average wages or hours.

Figure 8: Response for different groups (quantiles of contract length)

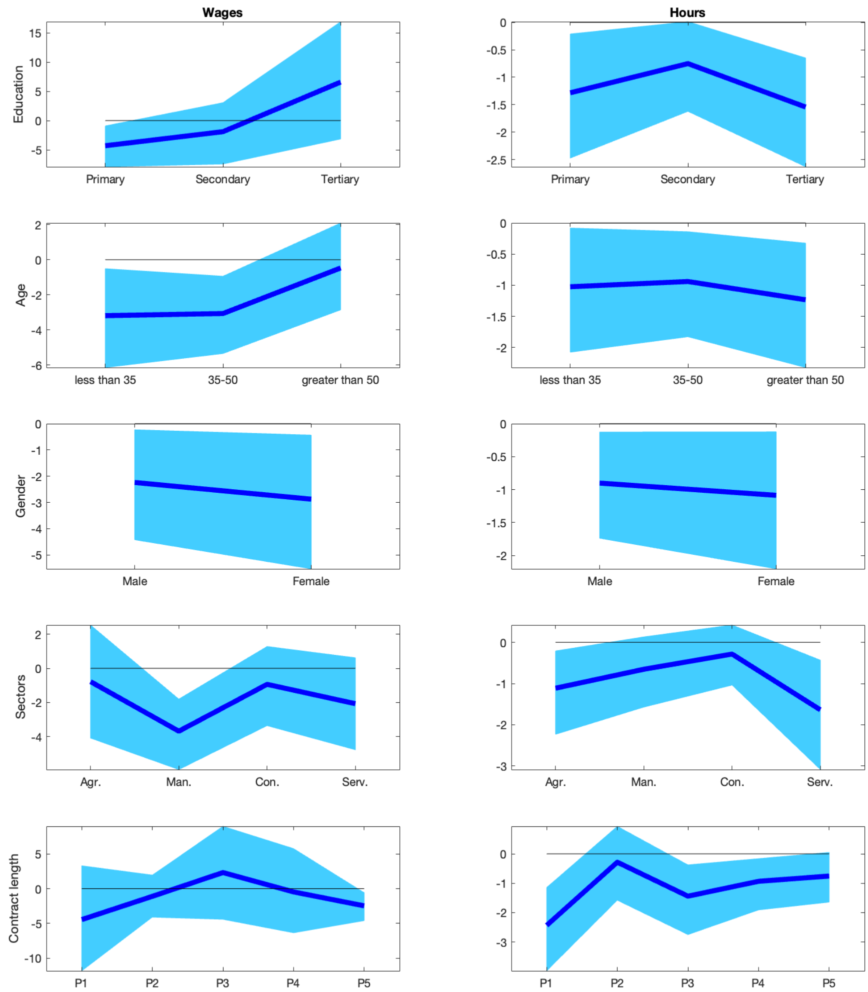


Figure 9:

shocks. High-income jobs of well-educated workers are typically more stable. These workers might also have higher bargaining power and be more able to keep their wages unchanged in the event of negative shocks. The response of hours worked shows a marginally stronger decline for the well-educated than for the rest, but the wage raise seems to compensate for the decline in hours worked at the upper end of the earnings distribution.

2. The wage of young workers responds more to a contractionary monetary policy shock. This might be because senior workers have relatively stable working conditions, including wages, and their contracts are renegotiated less often. Older workers also show marginally higher flexibility in hours worked.

3. While jobs in manufacturing react to the restrictive shock with a reduction in wages, in services the response is more likely to materialize via fewer hours worked. This might be explained by the different nature of jobs across sectors. It is difficult to adjust working hours individually in factories operating in standardized shifts. In contrast, the flexibility of schedules is naturally much higher in services, which respond strongly to demand conditions and possibly to the employer's financial situation. This might relate to the two types of labor proposed by Kaplan and Zoch (2020), (production-type and expansionary-type) and their different reactions to shocks.

4. Despite the sizable gender pay gap, we do not find a significant difference in the reaction to monetary policy shocks. The reaction of wages to monetary policy shocks seems to be of similar size regardless of gender. This may result from two counteracting forces, as men are typically more represented in industrial jobs, which show a more

pronounced wage response to the shock, while women are more present in the low-income bracket, where the reaction to the shock is stronger.

In addition to illustrating the heterogeneity in the transmission of monetary policy shocks, the above stylized facts broadly relate to the debate on potential changes in the slope of the Phillips curve, in conjunction with the observed secular changes in the economy. According to what we outline above, both population aging and a structural transformation from manufacturing to services would lead to a weaker response of wages to monetary policy shocks and maybe also a flatter Phillips curve. This view aligns with the conclusions of Szafranek (2017), who shows that the slope of the curve in Poland has decreased over the last few decades.

4.3 Sensitivity analysis

We carry out an extensive sensitivity analysis. In particular, we show in the technical appendix A.4 that the results are robust to the following:

1. Sign restrictions: We identify the monetary policy shock using contemporaneous sign restrictions. We assume that a contractionary monetary policy shock is associated with an increase in short-term interest rates, a decline in output and prices, a real exchange rate appreciation, and a rise in the unemployment rate. Figure 12(i) in the appendix shows the estimated response of hours and wages. As in the benchmark case, wages decline substantially at the left tail of the distribution and wage inequality rises.

2. Model specification: We add the following variables to the benchmark model: (1) Euro-area GDP, (2) Euro-area CPI and (3) Oil prices. As shown in Figure 12(ii) in

the appendix, the key results are unaffected. The contractionary monetary policy shock still has a disproportionately large effect on wages at the left tail of the wage distribution.

5 Concluding Remarks

This paper analyzed the heterogeneous effects of monetary policy on labor markets (the distribution of wages and hours worked), with a particular focus on the sectoral and demographic characteristics of workers. We used unique, contract-level administrative data on wages and hours worked from the Czech labor market. The data covers more than one million contracts in recent data vintages. In order to identify monetary policy shocks, we employed the narrative approach, deriving surprises from interest rate futures data around monetary policy meetings. Exploring the maturity spectrum of futures, one can differentiate between the interest rate target factor (surprise in rate decisions) and the path factor (surprise in guidance). We used the target factor as a measure of conventional monetary policy shocks.

We embedded this information in a standard monetary policy VAR model to document new facts about the distributional effects of monetary policy shocks. The results suggest that monetary policy shocks affect low-wage workers disproportionately more, a finding in line with most of the recent empirical literature. The response of higher wage bins is often insignificant, suggesting that the effects of monetary policy materialize mainly through low-income workers, who also have a higher propensity to consume. However, at the very upper tail of the wage distribution, managerial compensation schemes tied to financial results seem to lead to an immediate and robust response of wages to monetary policy shocks.

A more detailed demographic analysis showed that the negative reaction of wages to a contractionary monetary policy shock is larger for young and less educated workers, while there is no significant redistribution regarding gender or contract length. We observe a significant reaction of wages in the manufacturing sector, while the reactions to monetary policy shocks in other sectors, especially in the service sector, are somewhat muted. On the other hand, contracts in services seem to be more flexible in their reaction via adjusting hours worked.

Many of these findings are new not only in the context of the Czech labor market, but also from the international perspective. Further research is needed to confirm or relativize our results using granular data from other economies. A theoretical explanation of the apparently heterogeneous reaction to monetary policy shocks across the wage distribution and for different demographic and sectoral groups would be another welcome contribution.

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A Technical Appendix

The observation equation of the model is defined as:

$$Z_t = H \underbrace{\begin{pmatrix} Y_t \\ Y_{t-1} \\ Y_{t-2} \\ Y_{t-3} \end{pmatrix}}_{\beta_t} + \begin{pmatrix} E_t \\ 0 \\ 0 \\ 0 \end{pmatrix} \tag{4}$$

The transition equation is

$$\beta_t = \mu + F\beta_{t-1} + V_t \tag{5}$$

Note that the transition equation is the companion form of the VAR model given in equation 6.

$$Y_t = c + \sum_{p=1}^{P} B_p Y_{t-p} + v_t \tag{6}$$

where $v_t \tilde{} N(0, \Sigma)$.

The disturbances are normally distributed:

$$E_t \tilde{} N(0, R)$$
$$V_t \tilde{} N(0, Q)$$

As discussed above, R is a known parameter and $Q = diag\left(\Sigma, 0_{3N,3N}\right)$

A.1 Priors

1. Let b denote the coefficients of the VAR model given in equation 1 in vectorized form. We use a Minnesota type prior for b implemented using dummy observations (see Banbura, Giannone, and Reichlin (2010)): $p(b) \tilde{} N(b_0, S_0)$. The parameter that controls the tightness of the prior is set to the typical value of 0.1.

2. The prior for Σ is inverse Wishart: $IW\left(\Sigma_0, t_0\right)$ where the scale matrix $\Sigma_0 = I_N$ and degrees of freedom $t_0 = N + 2$.

A.2 Gibbs algorithm

The Gibbs algorithm samples from the following conditional posterior distributions in each iteration:

1. $G(\hat{z}_t|b,\Sigma)$. Conditional on b, Σ, the model is a linear Gaussian state-space model. We use the simulation smoother of Durbin and Koopman (2002) to draw the state $\hat{z}_t$ from its conditional posterior distribution.

2. $G(b|\hat{z}_t,\Sigma)$. Conditional on $\hat{z}_t$ the model collapses to a Bayesian VAR. Given a normal prior for b, the conditional posterior is also normal: $N(M,V)$:

$$M = \left(S_0^{-1} + \Sigma^{-1} \otimes X_t'X_t\right)^{-1}\left(S_0^{-1}b_0 + \Sigma^{-1} \otimes X_t'X_t\hat{b}\right)$$

$$V = \left(S_0^{-1} + \Sigma^{-1} \otimes X_t'X_t\right)^{-1}$$

where $\hat{b}$ denotes the OLS estimates of the coefficients in vectorized form and X collects the regressors on the RHS of the equations in the VAR model 6.

3. $G(\Sigma|b,\hat{z}_t)$. The conditional posterior is inverse Wishart: $IW(\Sigma_1, t_1)$

$$\Sigma_1 = \Sigma_0 + v_t'v_t$$
$$t_1 = t_0 + T$$

   We employ 21,000 iterations, with 1,000 discarded as burn-in. We save every fifth of the remaining draws for inference.

A.3 FEVD

Figure 10 shows the contribution of the monetary policy shock to the variance of the forecast error of the main macroeconomic variables. The shock is significantly important in explaining the variation of all observed variables. The shock contributes more to the interest rate variation (around 7 percent) and the exchange rate variation (up to 12 percent) in the short run. The contribution to GDP and the price index peaks rather in the long run (2.5 years) at 5 percent.

Figure 11 shows the contribution of the monetary policy shock to the forecast error variance of wages and hours worked in each percentile of the distribution. It is noticeable that the monetary policy shock contributes more to wages and to hours worked at the right and left tails of the distribution. It explains up to 9 percent in the low income percentile and up to 7 percent in the top income percentile.

The contribution of the monetary policy shock to the variation in hours worked is even more profound. It explains more than one third of the variance at the right tail and about 10 percent at the left tail, particularly at early horizons of up to two years.

Figure 10: Forecast error variance decomposition of the monetary policy schock to the main macroeconomic variables

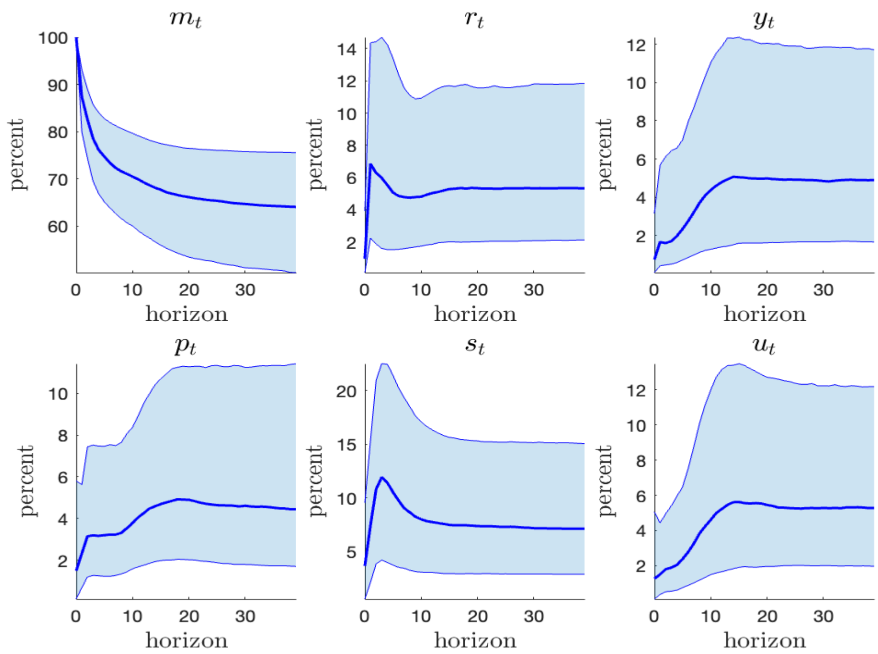
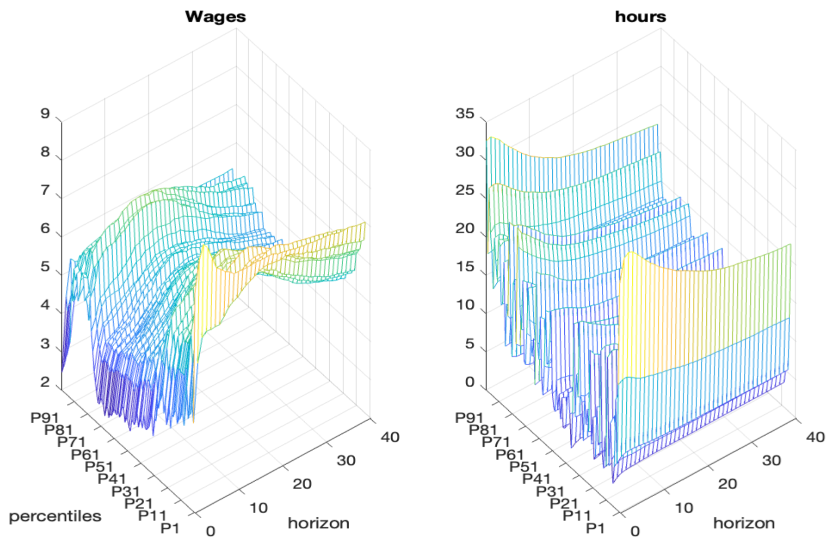


Figure 11: Forecast error variance decomposition of the monetary policy schock to the wages and hours worked



A.4 Robustness Check

Figure 12: Shock identification using
(i) contemporaneous sign restrictions (top panel)
(ii) additional exogenous variables (bottom panel)