The heterogeneous impact of monetary policy on the US labor market*

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Abstract

We empirically investigate the role of central banks in the context of heterogeneous labor markets, jobless recoveries and job polarization. Specifically, we estimate the effect of monetary policy on the US labor market using disaggregated time series based on large scale survey data. The impact of interest rate changes on unemployment in 32 occupation groups is explored in a Bayesian factor-augmented vector autoregression framework. The results suggest largely heterogeneous impacts across various occupation groups. This heterogeneity can be explained by differential task profiles of the workers in their respective occupations. Workers with tasks that are easily automated or offshored as well as workers at the bottom of the skill distribution are disproportionately affected following a monetary policy shock. This implies that labor market participants that are highly vulnerable to structural developments such as skill-biased technological change and the globalization of labor markets are also most sensitive to conventional monetary policy measures. From a policy perspective, we conclude that central banks are unlikely to be able to take on a stabilizing role in the context of labor market polarization.

Keywords: Monetary policy, Job polarization, Jobless recoveries, Occupation-level, FAVAR.

JEL Codes: C11, C32, E24, E52

Acknowledgments

Thomas Zörner gratefully acknowledges financial support by funds of the Oesterreichische Nationalbank (Austrian Central Bank, Anniversary Fund, project number: 17650).

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1 Introduction

In the past 40 years, labor markets have been shaped by long-term dynamics and medium-term business cycle forces alike. While structural change on labor markets has operated mainly through channels such as skill-biased technological change (Acemoglu and Autor, 2011), business cycles have largely driven these dynamics over time. This holds true for economic occurences such as increasing earnings inequality (Heathcote *et al.*, 2020) and job polarization (Jaimovich and Siu, 2020) that have been in the focus of economists for more than two decades now. This article aims to analyze the extent to which a central bank may influence or stabilize labor market dynamics in this context. With this in mind, we provide an empirical assessment of the impact of monetary policy on occupation-level unemployment. On the one hand, analyzing whether monetary policy has a constant effect across occupations complements existing empirical literature. At the same time, the analysis aims to provide helpful insights for the development of theoretical models focused on household heterogeneity.

A major economic theory that explains long-term developments on labor markets is that of skill-biased technological change (Acemoglu and Autor, 2011), tightly connected to labor market polarization dynamics (Autor *et al.*, 2003). A main insight of this literature is that the skill level of workers and the task content of their occupations are highly relevant to explain structural dynamics such as job polarization on labor markets. A tenet of this framework is that workers in occupations characterized by a low to medium level of skills and repetitive, standardized tasks (so-called *routine* tasks) are prone to be pushed out of the labor market due to long-term developments such as automation and offshoring. On the contrary, high-skilled workers are often seen as a complement to new technology as opposed to running the danger of being substituted (Dolado *et al.*, 2020).

Focusing more on short- and medium-term developments, economists have recently started to investigate so-called *jobless recoveries*. This term describes the phenomenon in which certain jobs that have been lost during recessions have not recovered at the same rate as overall macroeconomic activity. Jaimovich and Siu (2020) connect jobless recoveries to polarization dynamics and conclude that long-term US labor market developments are not decoupled from business cycle forces. They argue that recessions have hit routine workers especially hard, with mostly routine jobs not recovering after the trough. These cyclical dynamics largely explain the overall decline of the share of routine workers on the US labor market. More empirical support for this observation is provided by Gaggl and Kaufmann (2019). Arriving at similar conclusions, Heathcote *et al.* (2020) show that long-term earnings inequality trends can be explained by business cycle fluctuations.

In light of these contributions, this article empirically explores the role of central banks on the labor market. In general, evaluating the effects and the relevance of monetary policy authorities in this setting can be justified through a number of arguments. As regards the US, the Federal Reserve (Fed) is concerned with aggregate economic stability and hence has a strong focus on stable employment and labor market dynamics. Moreover, tackling jobless recovery episodes is an explicit part of the Fed's policy agenda (Bernanke, 2009; Powell, 2016). Finally, a more holistic understanding of the consequences of monetary policy enriches the information set of policy makers, who aim to reach a well-informed decision when deciding on a monetary policy stance.

Taking the general relevance of central banks on the labor market into account, it is unsurprising that a number of contributions have already explored the effects of monetary policy changes on labor market aggregates. The commonly encountered interest rate channel takes effect through dampening investment and production. With a reduced level of production, employment will decrease as well, at least in the short term. This has been attributed to wage rigidities which may arise from union bargaining (Zanetti, 2007), search frictions (Trigari, 2009), matching frictions (Faccini *et al.*, 2013) or wage inertia due to the bargaining process between firms and workers (Christiano *et al.*, 2016). This channel is also commonly reported in a variety of empirical studies on monetary policy in the US (e.g. Bernanke *et al.*, 2005) and elsewhere (e.g. Potjagailo, 2017 for the Euro area).

The labor market effects of monetary policy have typically been analyzed using highly aggregated data. This stands in sharp contrast to recent contributions underlining the importance of taking into account heterogeneity when analyzing macroeconomic shocks on the labor market. For instance, certain labor market participants may be easily replaced by cheaper, possibly foreign workers (Firpo *et al.*, 2011) while others may be replaced by capital more easily (Autor and Dorn, 2013). This is also documented in Dolado *et al.* (2020), who emphasize that capital-skill complementarity makes high-skilled workers comparatively well-off following expansionary monetary policy shocks. At the same time, a varying level of matching efficiency (Barnichon and Figura, 2015) makes re-entering the labor market more difficult for certain types of workers after economic downturns. Re-entering efforts may be further complicated by so-called *scarring* effects where workers lose skills during unemployment spells (Heathcote *et al.*, 2020). In addition, it is highly probable that bargaining power is unequally distributed among workers (Dumont *et al.*, 2012). Taken together, these channels are likely to cause heterogeneous effects of macroeconomic fluctuations on labor supply and labor demand on a disaggregated level. Hence, analyzing average, aggregate responses of unemployment following monetary policy shocks will most likely mask heterogeneity between groups of workers. More specifically, unemployment in certain labor market segments is expected to react more strongly to interest rate changes than in others.[1]

From an empirical perspective, these considerations with respect to heterogeneous agents are usually operationalized using one of two distinct ways of dividing the labor market. A skill-based approach as in Heathcote *et al.* (2020) utilizes households or individuals that differ by their *level of education*. These groups may be broadly defined. For instance, Dolado *et al.* (2020) classify all workers without college degrees as low-skilled. Opposed to that, a task-based approach in the style of Autor *et al.* (2003) uses the characteristics of the tasks within *occupations* to differentiate between individuals. For example, Autor and Dorn (2013) show that workers in occupations with a high level of well-defined, standardized tasks are affected significantly more strongly by structural phenomena such as automation when compared to other occupations. In this article, we employ a task-based, occupation-level approach for a number of reasons. From an academic perspective, this approach complements similar studies that use educational attainment as target variable. This is expected to generate valuable empirical results that can provide insights for future theoretical contributions. Moreover, the occupation level is arguably a more relevant perspective for policy makers in general, who may find it more convenient to design policies for e.g. all workers in the food industry, as opposed to designing a policy for e.g. all workers without a college degree. Finally, recent empirical literature suggests that task-based clusters naturally arise in the labor market data we use (Gaggl and Kaufmann, 2019).[2]

Our analysis aims to explore the effect that exogenous changes in the federal funds rate have on unemployment in 32 occupation groups. Specifically, we analyze whether the impact of conventional monetary policy on unemployment is constant across these occupations. For this, we aggregate microeconomic data from the current population survey (CPS) and combine the resulting time series with detailed information on the task profile of workers within a given occupation group. Using this approach allows us to bridge the vast literature on occupation-level analysis of the US labor market, the literature on jobless recoveries and the empirical literature evaluating the policy actions of the Federal Reserve. At the same time, we connect our results to recent theoretical and empirical contributions exploiting skill-based labor market heterogeneity.

[1] Other related articles on the possibly *heterogeneous* impact of monetary policy in general include Primiceri (2005) and Boivin *et al.* (2009). Mumtaz and Zanetti (2015) emphasize the importance of accounting for time variation when analyzing the effect of technology shocks on labor market aggregates. Coibion *et al.* (2017) argues that monetary policy may influence income and consumption inequality through a number of channels. These results are extended to more general welfare measures in Gornemann *et al.* (2016) who argue that the wealthy are relatively well-insured against unemployment spells following monetary contractions.

[2] Nevertheless, there is a clear translation from tasks to skills and vice versa. So-called *manual tasks* are mostly found at the bottom of the skill distribution, while *abstract tasks* are located at the top of the distribution. *Routine tasks* are most likely to be encountered in the middle of the skill distribution. For a more detailed discussion of these task profiles, refer to Sec. 5.

From an econometric point of view, we employ a Bayesian factor-augmented vector autoregression (FAVAR) approach in the spirit of Bernanke *et al.* (2005) to cope with a number of challenges that arise when analyzing disaggregated data.[3]

We find that there is strong occupation-level heterogeneity in the response of unemployment to interest rate changes. Nevertheless, most occupation groups show significant reactions to monetary policy interventions. On the one hand, these results are in line with the widespread finding of an impact of interest rate policy on aggregate unemployment. On the other hand, not all occupation groups show similar reactions to monetary policy innovations. This raises the question of which specific characteristics drive the effectiveness of monetary policy on the occupation level. In a further empirical exercise, we show that the task content of occupations is a relevant predictor of the impact of monetary policy on a given occupation. Finally, these results are connected to recent theoretical considerations to deepen the understanding of the transmission of conventional monetary policy interventions on the labor market.

The remainder of this article is organized as follows. Section 2 briefly describes the econometric framework of the FAVAR model employed in the empirical analysis and provides an overview of the data set we use. In section 3, we analyze persistence and volatility patterns in unemployment time series. Section 4 presents the effect of monetary policy on several variables of interest, including unemployment in a set of US occupation groups. Further discussion of the results is provided in section 5, while section 6 concludes the paper.

2 A multivariate econometric time-series framework for disaggregated data

This section introduces an econometric framework to cope with the peculiarities of more granular data than the commonly encountered macroeconomic aggregates. We rely on a Factor-Augmented Vector Autoregression (FAVAR) framework as proposed in Bernanke *et al.* (2005) for two reasons. First, since it is likely that the underlying occupation-specific unemployment series are strongly driven by a common component, a factor model based approach is a natural modeling choice. Furthermore, the FAVAR approach can span a high-dimensional information set, which helps with the identification of macroeconomic shocks (Forni and Gambetti, 2011). This econometric specification overcomes several issues frequently encountered in low dimensional models (Stock and Watson, 2012).[4]

2.1 Econometric Framework

Let $\boldsymbol{X}_t$ $(t = 1, \dots, T)$ be a $N \times 1$ vector representing a large information set that captures different aspects of an economy. These variables are assumed to contain relevant information on q economic factors which are not directly observable, whereby $q << N$. The FAVAR model can then be recast in a state-space representation where the measurement equation takes the following form:

$$\boldsymbol{X}_t = \boldsymbol{\Lambda}^f \boldsymbol{F}_t + \boldsymbol{\Lambda}^y \boldsymbol{Y}_t + \boldsymbol{\eta}_t, \quad \boldsymbol{\eta}_t \sim \mathcal{N}_N(\boldsymbol{0}, \boldsymbol{\Omega}), \tag{2.1}$$

[3] In this sense, this article constitutes a methodological extension to De Giorgi and Gambetti (2017), who model disaggregated data from the US consumer expenditure survey using dynamic factor models.

[4] In principle, it is possible to estimate separate, small-scale VAR models for each disaggregated time series. That is, one could estimate separate VARs for each occupation in the data set. This corresponds to analyzing the effects of monetary policy in each subsection of the labor market separately. However, this procedure has a few drawbacks. Besides being a particularly cumbersome exercise from a computational point of view, it would ultimately boil down to an unconditional analysis. That is, separately estimating small scale VARs for each occupation group does not take into account possible employment fluctuations *between* occupation groups. However, it is likely that such inter-occupation employment flows take place following monetary policy interventions. Hence, separate small scale VARs implicitly assume that no workers flow from other occupations to the occupation of interest. This biases the analysis upwards and higher impact estimates may result.

where $\boldsymbol{\Lambda}^f$ and $\boldsymbol{\Lambda}^Y$ are factor loading matrices with dimensions $N \times q$ and $N \times l$, respectively. The latent factors are denoted by the q-dimensional vector $\boldsymbol{F}_t$. The error term $\boldsymbol{\eta}_t$ is normally distributed with zero mean and variance-covariance matrix $\boldsymbol{\Omega} = \text{diag}(\omega_1, \dots, \omega_N)$, ultimately translating into N independent regressions. The unobserved and observed factors are gathered in $\boldsymbol{f}_t = (\boldsymbol{F}_t', \boldsymbol{Y}_t')'$. Then, the dynamic state equation may be written as

$$\boldsymbol{f}_t = \boldsymbol{c} + \sum_{j=1}^{p} \boldsymbol{\Phi}_j \boldsymbol{f}_{t-j} + \boldsymbol{\varepsilon}_t, \quad \boldsymbol{\varepsilon}_t \sim \mathcal{N}_M(\boldsymbol{0}, \boldsymbol{\Sigma}_t), \tag{2.2}$$

where $\boldsymbol{\Phi}_j$ denotes the $M \times M$ coefficient matrix of lag j and $\boldsymbol{\varepsilon}_t$ is an error term of dimension $M = l + q$. The variance-covariance matrix $\boldsymbol{\Sigma}_t$ of the state equation innovations is assumed to evolve over time. This has been shown to improve model fit when the period under scrutiny exhibits volatile macroeconomic behavior (Clark, 2011). Following Carriero *et al.* (2019), a simple factorization of the $M \times M$ variance-covariance matrix $\boldsymbol{\Sigma}_t$ is employed to introduce stochastic volatility:

$$\boldsymbol{\Sigma}_t = \boldsymbol{L}^{-1} \boldsymbol{D}_t \boldsymbol{L}^{-1\prime}, \tag{2.3}$$

where $\boldsymbol{L}^{-1}$ is a lower-triangular matrix with ones on the main diagonal and $\boldsymbol{D}_t$ is a diagonal matrix containing the log-volatilities, i.e. $\boldsymbol{D}_t = \text{diag}\left(\exp(h_{1,t}), \dots, \exp(h_{M,t})\right)$. Finally, the log-volatilities are assumed to follow a centered AR(1) process

$$h_{i,t} = \mu_i + \phi_i(h_{i,t-1} - \mu_i) + \xi_i, \quad \xi_i \sim \mathcal{N}(0, \delta_i^2), \quad i = 1, \dots, M. \tag{2.4}$$

Estimation is carried out in a semi-Bayesian fashion. Similar to Bernanke *et al.* (2005), a two-step approach is implemented, where the latent factors are extracted through a principal component analysis prior to estimation. To handle the high number of parameters in the model, Normal-Gamma shrinkage priors are implemented to introduce regularization (Huber and Feldkircher, 2019). More details on the estimation procedure are found in App. A.

2.2 Identification

In terms of identification, this paper is concerned with recovering the dynamic effects of exogenous variation in the monetary policy instrument. Specifically, the focus lies on an increase in the federal funds rate[5], which has been identified as valid monetary policy instrument (Bernanke and Mihov, 1998). The Federal Reserve observes a large set of macroeconomic quantities with utmost attention and conducts monetary policy according to a Taylor rule (Clarida *et al.*, 2000). It aims to conduct a stabilization policy with respect to prices and employment. Any deviation that is not attributable to this systematic policy rule is considered as an exogenous monetary policy movement. This exogenous variation can largely be attributed to measurement errors or to different preferences/strategic considerations within the Federal Open Market Committee (FOMC). In this article, we identify such exogenous variation using two distinct strategies to make sure that the results do not strongly depend on a specific identification scheme.[6] Recently, Wolf (2020)

[5] More specifically, the main specification is estimated using the *shadow* federal funds rate constructed by Wu and Xia (2016) to account for the zero lower bound episode within our sample period. For convenience, we refer to the policy instrument as ”federal funds rate” throughout the article. The presented results are generally robust to using the effective federal funds rate as policy instrument.

[6] Note that in the proposed framework, the identified monetary policy shock is symmetric, i.e. a monetary expansion and a monetary contraction will generate responses with flipped signs, but otherwise equal in expectation. We acknowledge that a structural look on the asymmetric effects of expansionary and contractionary monetary policy may reveal a more holistic picture of monetary policy impacts on the labor market (see e.g. the considerations in Dolado *et al.*, 2020). However, as the main focus of this article is concerned with empirical analysis, we rely on well-known, macroeconometric methods like the FAVAR methodology. Within this framework, shocks are symmetric by construction.

has shown that both employed identification schemes are able to recover structural shocks generated from a New Keynesian model.

Regardless of the specific identification strategy, the policy instrument has to be included in the list of observed factors $\boldsymbol{Y}_t'$, in order to identify a monetary policy shock after model estimation. Furthermore, industrial production, unemployment and the GDP deflator are assumed to be observed factors. That is, the list of observable factors includes a set of classical variables the Federal Reserve monitors carefully. Another argument in favor of this set of observables is that misspecification may arise when not including measures of economic activity and prices (Bernanke *et al.*, 2005).

Recursive identification

Following Bernanke *et al.* (2005), the first identification strategy is based on a recursive structure, where all factors respond to a change in the monetary policy instrument with a lag. Therefore, the federal funds rate is ordered last in Y_t.[7] The main assumption is that unobserved factors do not respond to monetary policy shocks within a quarter. This corresponds to the idea that the Federal Reserve is observing macroeconomic quantities in real time, but that these quantities do not react to a monetary policy shock contemporaneously. However, this assumption is not imposed on the idiosyncratic components of the variables in the information set. As is standard in the literature on empirical monetary policy evaluation, we define two categories of variables: "slow-moving" and "fast-moving". Slow-moving variables are assumed to react to interest rate changes *after* one quarter, whereas fast-moving variables are allowed to react *within* one quarter. Common examples of slow-moving variables include real activity or price variables, while fast-moving variables include financial market measures or expectations. The classification of slow- and fast-moving variables can be found in App. C.

Sign-restricted identification

The second identification strategy is based on sign restrictions. The main idea of this identification scheme is to restrict the impulse response functions of several variables using theoretical considerations. From a computational point of view, the algorithm proposed by Rubio-Ramirez *et al.* (2010) and adapted to FAVARs in Ahmadi and Uhlig (2015) is implemented. Two sets of restrictions are used to identify a monetary policy shock. In both strategies, industrial production, unemployment, the GDP deflator and the federal funds rate are restricted for up to six months. Output and prices are expected to decrease, while unemployment is expected to increase after a monetary policy tightening. This set of restrictions is labeled *small set*. In a second set of restrictions (labeled *big set*), the money stock, 3-months treasury bill rates and various price deflators and commodity price indices are additionally restricted to refine the identification of the monetary policy shock. In both scenarios, no labor market variables except for aggregate unemployment are restricted. The restrictions are summarized in Tab. 1. The results do not depend on the specific set of signs implemented. For brevity, only results based on the less restrictive, smaller set of signs are presented below.

2.3 Data

We use a high-dimensional data set of 146 macroeconomic indicators based on Korobilis (2013) that runs from 1978Q1 to 2019Q1. Appending unemployment rates for 32 occupation groups results in a total of 178 time series. The set of macroeconomic indicators covers the most important aspects of the US economy and includes, among others, real activity measures, interest rates, financial market variables and price data. This

[7] Since we recover the latent factors from the full information set, they could contain information contained in Y_t. Thus, it is not valid to estimate the VAR using the principal component estimates and Y_t and identify the shock recursively. It is necessary to remove the dependence of the initial factor estimates on Y_t prior to the estimation. To achieve this, the following linear regression is estimated: $F_t^{PCA} = b_{F0} F0_t^{PCA} + b_Y Y_t + e_t$, where F_t^{PCA} and $F0_t^{PCA}$ denote the principal component estimates of the factors extracted from the complete data set and the factors extracted from the slow-moving variables, respectively. It is then possible to construct the appropriately rotated factors via $F_t = F_t^{PCA} - \hat{b}_Y Y_t$. The adjusted factor estimates F_t are then used to estimate the FAVAR model. The same procedure is used in Bernanke *et al.* (2005).

Table 1: Sign restrictions.

Shock	y	p	ur	i	m	tb	$p_{115-126}$
Monetary policy (*small set*)	$\downarrow_3$	$\downarrow_3$	$\uparrow_3$	$\uparrow_3$	–	–	–
Monetary policy (*large set*)	$\downarrow_3$	$\downarrow_3$	$\uparrow_3$	$\uparrow_3$	$\uparrow_1$	$\uparrow_1$	$\downarrow_1$

Notes: The restrictions are imposed as $\geq$ / $\leq$. Constraints are put on industrial production (y), GDP deflator (p), unemployment rate (ur), federal funds rate (i), money stock M1 (m), 3-months treasury bill rate (tb) and various price indicators (#115 − 126 in App. C). Restrictions are either binding only on impact (denoted by 1 period) or half a year (denoted by 3 periods). This identification strategy follows Ahmadi and Uhlig (2015).

set is expected to contain the vast majority of US macroeconomic behavior. When necessary, the series are seasonally adjusted and appropriately transformed to ensure stationarity.[8] Before extracting the factors, the data is standardized to obtain a mean of zero as well as a unit variance. A detailed description of the dataset and the applied transformations is found in App. C.

The unemployment data is extracted from detailed monthly public use microdata files of the US current population survey (IPUMS-CPS). These data files are the most important source of US statistics on labor market specific topics such as employment, earnings and demographics as approximately 60,000 households are surveyed each month (Flood *et al.*, 2018). In this paper, we focus on individuals that are between 15 and 64 years of age. For each individual, the employment status as well as the census occupation classification is extracted using the monthly survey files. To guarantee a maximum of comparability over time, we translate the census classification to the *occ1990dd* occupation classification scheme first introduced by Dorn (2009). This classification scheme is specifically developed to enable researchers to exploit a consistent long-term classification of occupations, and is commonly encountered in related articles such as Autor and Dorn (2013) or Gaggl and Kaufmann (2019). The occupations are binned into broader occupation groups to facilitate further analysis. After classification, the individual employment status data is aggregated from monthly to quarterly frequency to reduce noise. Within these quarterly occupation group clusters, weighted employment to population ratios are computed.[9] From these, the occupation-specific unemployment rates are derived. App. B provides more information on the occupation groups we construct and offers a detailed crosswalk to the *occ1990dd* occupation classification system.

The extracted unemployment rates exhibit an interquartile range of [0.040, 0.098] with an average of 0.075. The majority of 99% of observations lie between 0.015 and 0.217. Only a very small number of observations take more extreme values. The minimum unemployment rate is 0.003 whereas the maximum observed unemployment rate is 0.394. Lowest average unemployment is observed for the group of "medical professionals" whereas mean unemployment is highest for workers in "recreational services". A first impression of the occupation group unemployment rates is provided in Fig. 1. Most occupations exhibit strong co-movements over time. Surprisingly, occupations related to extractive activities such as miners and explosive workers evolve differently and show extensively high unemployment rates over a prolonged period of time.

3 Labor market fluctuations: Macroeconomic versus occupation-specific influences

The estimation of the model outlined in Sec. 2 allows to shed some light on volatility and persistence patterns in aggregated and disaggregated unemployment measures. Specifically, it is possible to analyze the degree

[8] Stationarity is checked via applying Augmented Dickey-Fuller tests to each series individually.

[9] Note that only the extensive margin (i.e. employed vs. not employed) is considered in this article. Several valuable insights may be produced by analyzing the intensive margin (i.e. the number of hours worked). However, generally only limited data on the hours worked is available by occupation groups, resulting in noisy time series for some occupations. As a result, the extensive margin is the focus of our analysis.

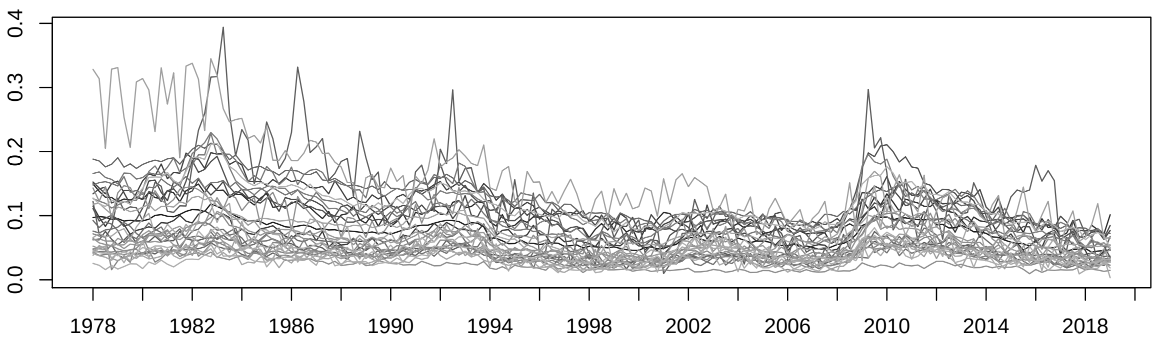

Figure 1: Deseasonalized occupation-level unemployment rates over time. Each line corresponds to one of the 32 occupation groups under analysis.

to which fluctuations in unemployment time series are explained by macroeconomic shocks and the extent to which their dynamics are the result of the idiosyncrasies of each time series. Consider the equation

$$X_{it} = \lambda_i' \boldsymbol{f}_t + \eta_{it}, \quad \eta_{it} \sim \mathcal{N}(0, \omega_i), \tag{3.1}$$

where X_{it} denotes a specific labor market series that may be measured on the aggregated or occupation-specific level.[10] Note that Eq. (3.1) corresponds to a single equation in the system summarized in Eq. (2.1). From this, it becomes possible to analyze the importance of aggregated macroeconomic shocks – represented by the common component $\boldsymbol{C}_t = \lambda_i' \boldsymbol{f}_t$ – and disaggregated, idiosyncratic shocks – represented by the error term η_{it} – for each of the unemployment series included in the estimation.

The main results are based on a model specification with four lags and three latent factors based on standard model selection criteria. However, experimenting with different specifications suggests that the model and the derived conclusions are insensitive to the lag order and the number of factors. Furthermore, the results are robust to the specific identification scheme employed.[11]

3.1 Volatility and persistence of unemployment series

In Tab. 2, empirical results on the volatility and persistence of all labor market measures included in the modeling framework are summarized. Columns 1 to 3 report the volatility of the overall time series, of its common component and of its respective idiosyncratic component. These volatilities are reported in two blocks, corresponding to the aggregate and occupation-level time series. The rows of the table contain summary measures of the corresponding volatilities.[12]

Column 4 provides the variance share that is explained by the common component (R^2). We generally observe a consistently high share of variance explained within the aggregate unemployment time series. On the contrary, occupation-level unemployment measures are not as well captured by the common component,

[10] Here, "aggregate series" refers to unemployment growth rates by unemployment duration across all industries and occupations, see App. C, series 36 to 40. "Occupation-level" refers to the occupation-specific unemployment rates introduced in Sec. 2.3.

[11] Selected sign restriction-based results are presented in the next section. Additional sign restriction results may be found in App. D.

[12] Note that e.g. the minimum volatility of the unemployment rates within the occupation level does not necessarily stem from the same equation as the minimum volatility of the common component within the occupation level. That is, a given row does not necessarily correspond to one equation.

Table 2: Volatility and persistence of unemployment time series.

	Standard deviations				Persistence		
	Unemp. rate	Common component	Idio-syncratic	R^2	Unemp. rate	Common component	Idio-syncratic
Aggregate series							
Mean	7.22	5.78	4.21	0.61	0.41	0.62	−0.16
Median	8.32	6.43	3.73	0.65	0.45	0.66	−0.30
Minimum	3.81	2.21	3.10	0.34	0.03	0.43	−0.41
Maximum	10.09	8.53	5.71	0.80	0.67	0.75	0.14
Standard deviation	2.59	2.54	1.25	0.18	0.26	0.14	0.27
Occupation-specific							
Mean	1.56	0.97	1.15	0.43	0.41	0.77	−0.05
Median	1.34	0.85	0.89	0.38	0.46	0.78	−0.03
Minimum	0.44	0.12	0.31	0.06	−0.35	0.70	−0.53
Maximum	6.70	4.03	5.35	0.85	0.78	0.79	0.31
Standard deviation	1.12	0.74	0.93	0.25	0.27	0.02	0.20

Notes: The sample runs from 1978Q1 to 2019Q1 and the common component corresponds to $\boldsymbol{C}_t$ while the idiosyncratic component corresponds to η_{it}. R^2 measures the fraction of the variance of X_{it} explained by $\boldsymbol{C}_t$. The reported persistence measure is based on the sum over the estimated AR(4) coefficients.

although the level of heterogeneity compared to the aggregated series is rather high. This implies that occupation-level unemployment rates are often relatively strongly driven by idiosyncratic shocks. Such occupation-specific shocks can be thought of as economic developments or changes in the immediate business environment that affect only a given occupation group at hand. For instance, certain changes in an occupation-specific legislation may only impact the wage and employment structure of an isolated occupation. Hence, the resulting employment dynamics are distinct to this specific occupation group. On the contrary, common component shocks are macroeconomic shocks that are common across all occupations. Some examples include technological innovations leading to automation, an overall recessionary state of the economy as well as aggregate demand and supply side distortions like oil price shocks or a monetary policy shock. For the latter we provide a deeper discussion in Sec. 4. This decomposition exercise reveals that macroeconomic fluctuations explain an average of 43% of the variance of the occupation-specific series. To specifically quantify the importance of a monetary policy shock in this context, a forecast error variance decomposition is conducted. This reveals that 13.8 % of the variance of aggregate unemployment and on average 10.5% of the occupation-level unemployment forecast error are explained by the policy shock under investigation. This corroborates Bernanke *et al.* (2005), who report 8.4% for aggregate unemployment between 1959 to 2001. While these are only moderate shares of the overall variance, they are nonetheless relevant from a macroeconomic perspective.

To further investigate the dynamics of the unemployment time series, we examine the degree of flexibility and persistence within the labor market. For this, we proceed to compute a simple measure to quantify the degree of persistence of the common component, the idiosyncratic component, and the overall time series. We fit an AR process with four lags to each of the three components for all labor market time series. Taking the sum over the autoregressive coefficients serves as the reported measure of persistence, where higher values indicate a larger degree of persistence.[13] Columns 5 to 8 of Tab. 2 report this persistence measure for the aggregate and the occupation-level unemployment measures.

The results suggest that aggregate and occupation-level unemployment series share similar dynamics and appear to be persistent. From a macroeconomic perspective, this phenomenon is subject to extensive research;

[13]See Boivin *et al.* (2009) for a similar analysis using disaggregated price data.

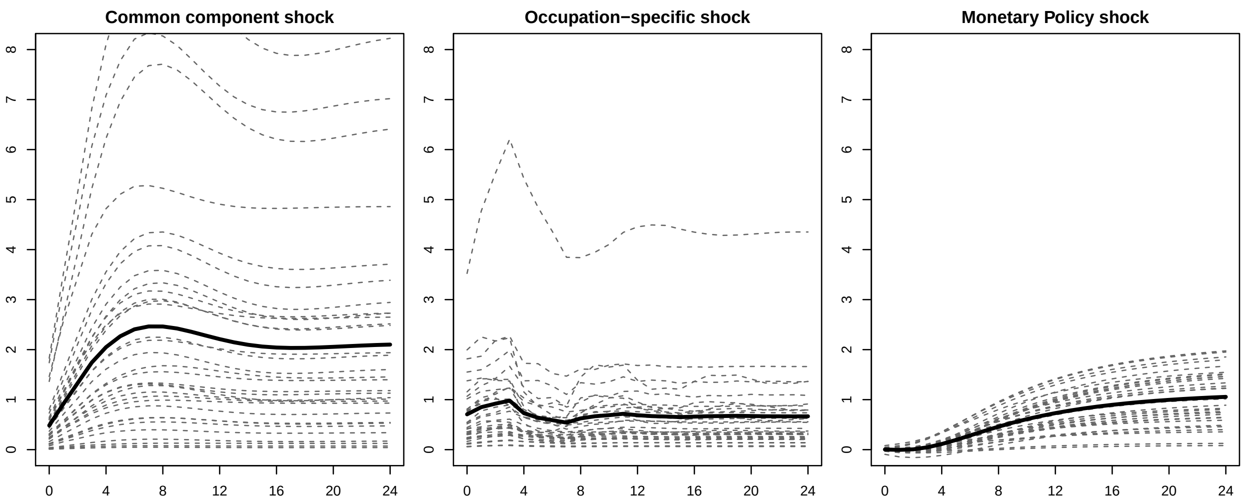

Figure 2: Cumulative reaction of occupation-level unemployment to an exogenous shock to the common component (left) and the idiosyncratic component (middle) as well as the reaction of occupation-specific unemployment to a monetary policy tightening (right) over a period of six years. Dashed grey lines correspond to occupation-specific responses and the solid black line is the average response across occupations. Each shock is scaled to a shock of one standard deviation of the respective series. Note that the y-axis is not comparable across panels.

see for instance the early considerations on unemployment persistence in Clark *et al.* (1979) and the empirical examinations in Barro (1988). Three classical arguments for this phenomenon include sticky real wages (Blanchard and Summers, 1986), capital shortage in long economic downturns (Sachs, 1986) and human capital depreciation of the long-term unemployed (Budd *et al.*, 1988, Heathcote *et al.*, 2020). In addition, empirical studies on the microeconomic level regularly report that individual unemployment history is a strong indicator of the current probability of unemployment, indicating persistent unemployment (e.g. Arulampalam *et al.*, 2000). In terms of decomposition, the common component exhibits a higher degree of persistence relative to the idiosyncratic component. This translates into macroeconomic shocks having persistent effects on both aggregate and occupation-level unemployment measures. To summarize, macroeconomic shocks explain a significant amount of variation of occupation-specific unemployment measures. In addition, the effects of these macroeconomic fluctuations manifest themselves in a persistent fashion.

3.2 Aggregated and disaggregated shocks to occupation-level unemployment series

As outlined above, unemployment rates are subject to a bandwidth of different shocks, including macroeconomic shocks such as monetary policy or technology shocks as well as disaggregated, idiosyncratic shocks. Aggregate shocks result in structural dynamics that affect the majority of workers across industries and occupations. On the contrary, idiosyncratic shocks may only be relevant for a single specific occupation group. To disentangle the effects of these two types of fluctuations, we proceed to shock the residuals of the autoregressive process of the common component C_t and the idiosyncratic component η_{it} introduced above. To enable a direct comparison of the duration of the adjustment process, the resulting impulse response functions are plotted over a period of six years in Fig. 2. In addition, the impulse response functions of occupation-specific unemployment rates to monetary policy shock of one standard deviation, identified in Sec. 4, are provided.

We find significant differences in the adjustment timing following the three different types of shocks. Occupation-specific shocks (middle panel) are followed by rapid adjustments in unemployment rates, where the new steady-state level is reached after approximately one to two years. Interestingly, macroeconomic shocks – represented by the common component (left panel) – lead to a significantly slower adjustment

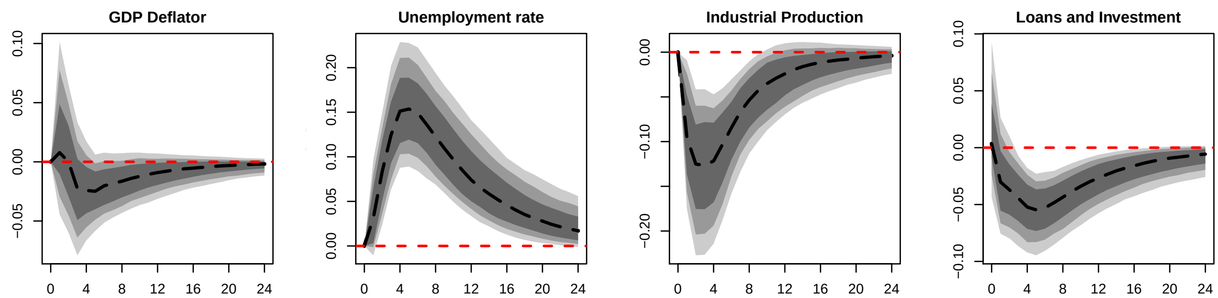

Figure 3: Impulse response functions of selected macroeconomic aggregates (change in the growth rate of the GDP deflator, change in the unemployment rate, growth rate of industrial production and change in the growth rate of loans and investment) following an exogenous monetary policy innovation of one standard deviation. The dashed lines correspond to the posterior median while the grey areas show the 50/68/80% highest posterior density mass. Identification is based on a Cholesky decomposition.

process, where the new level of unemployment is reached only after two to three years. These shocks include shifts in aggregate demand, where consumers take time to adjust their consumption behavior or where new technologies have to be adopted. The slowest adjustment is observed for a monetary policy shock (right panel), where the adjustment process takes three or more years. This may be a result of a slow monetary transmission channel on unemployment. After the federal funds rate changes, banks have to adjust their effective credit rates and firms have to adjust their investment behavior in addition to the relatively slow aggregate economic activity changes. Many investments are expected to come into effect with high latency, leading to the slow adjustment in unemployment rates observed here.

After this preliminary analysis of aggregated and disaggregated unemployment time series, we will now specifically focus on the macroeconomic and labor market specific effects of a monetary policy tightening. We focus on the reaction of occupation-level unemployment and potential explanations of the observed dynamics. We choose a monetary policy shock as this is arguably one of the most relevant macroeconomic shocks from the perspective of policy makers. However, in principle, an analysis of other macroeconomic shocks within this framework is straightforward.

4 The Effects of Monetary Policy on Unemployment

We present the main FAVAR estimation results in three steps. First, the impulse response functions (IRFs) of some classical macroeconomic aggregates to an exogenous tightening of monetary policy are discussed. The second step focusses on the IRFs of selected labor market aggregates. Finally, the reaction of unemployment within 32 occupation groups is presented.

To analyze the response of the variables of interest following monetary policy innovations, a simulated one standard deviation increase of the federal funds rate is imposed upon the estimated FAVAR framework. In Fig. 3 the resulting reactions of a set of classical macroeconomic aggregates are provided. The results of this empirical analysis are similar to the findings in related literature: Monetary tightening leads to decreasing loans and investment and therefore to decreasing real activity. With reduced real activity, unemployment rises. Eventually, prices will decrease. These aggregate findings are also in line with the predictions offered by standard theoretical macroeconomic frameworks.

An examination of the response of labor market variables following the simulated monetary tightening is crucial for the further analysis in this article. While the significant reaction of aggregate unemployment is promising, a more specific focus on relevant labor market measures is required to discuss the results within

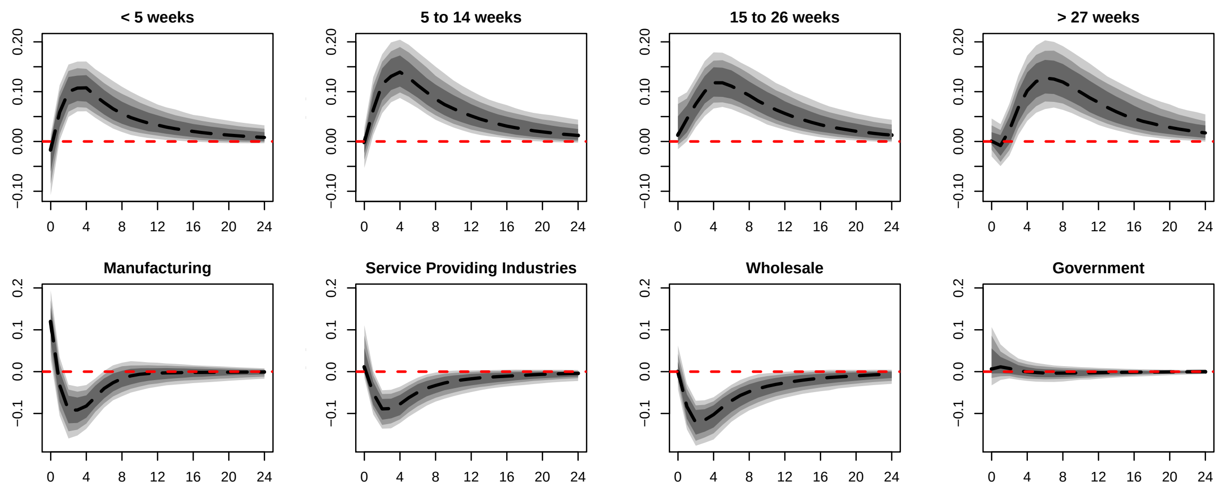

Figure 4: Impulse response functions of various labor market aggregates following an exogenous monetary policy innovation of one standard deviation. Upper row: Growth rate of unemployment headcounts for different unemployment durations. Bottom row: Change in growth rate of employment headcounts in different sectors of the economy. The dashed lines correspond to the posterior median and the grey areas show the 50/68/80% highest posterior density mass. Identification is based on a Cholesky decomposition.

the respective occupational groups. This provides insights into how well the model is able to capture overall labor market dynamics and underlines the credibility of the reported findings.

The resulting labor market IRFs, depicted in Fig. 4, are split into two groups. The first group in the upper row contains the IRFs of unemployment headcount growth across various unemployment durations. For instance, "< 5 weeks" corresponds to the reaction of the growth rate of unemployed civilians who have been in unemployment for under five weeks. The results show that monetary tightening increases unemployment, irrespective of the specific duration that an individual has already spent in unemployment. The second group of IRFs in the bottom row corresponds to the response of the change of employment growth in various major sectors of the US economy. We find that an interest rate hike leads to decreasing employment among manufacturing workers, within the service providing sector as well as in the wholesale industry. Notably, government employment shows a muted response to monetary policy interventions. This is expected given that government spending and employment in the public sector are unlikely to react to changing interest rate environments. These first findings are summarized as follows: Besides weak effects on government employment, monetary policy has rather homogeneous effects along the sectoral dimension and across various unemployment duration groups.

The final step increases the level of granularity further to focus on the labor market reactions to a monetary policy shock on the occupational level. Fig. 5 (Cholesky-based identification) and Fig. 6 (sign restrictions) depict the IRFs of changes in the unemployment rate within 32 occupational groups following an interest rate hike. Two interim conclusions can be drawn from this figure: first, monetary policy affects unemployment in most of the analyzed occupation groups. The groups that show significant reactions account for the majority of the working age population of the United States. This is in line with the consensus in literature suggesting that monetary policy indeed affects real activity and therefore aggregate unemployment measures. Second, despite strong impacts on most occupation groups, a large degree of heterogeneity is present. On the one hand, some occupation groups react significantly to the simulated interest rate hike, others do not. On the other hand, even within groups that react significantly, effect sizes vary strongly. In terms of timing, the largest differences in impulses are observed after approximately one to two years, whereas almost no heterogeneity is observed after six years where all occupation group specific IRFs return to zero. The largest effects across occupations are estimated for the group of ”transport & material moving” workers, which includes taxi and truck drivers as well as freight and cargo movers. On the contrary, occupations belonging to the medical sector exhibit extremely small reactions to interest rate changes.

We conclude that monetary policy exerts strong labor market effects, in line with empirical and theoretical literature suggesting real economic effects following interest rate hikes. However, the degree of ”vulnerability” to conventional monetary policy varies across occupation groups. In the next section, we therefore shed light on possible determinants of this varying sensitivity to monetary policy through an additional empirical analysis. To link our results to the broad literature on polarization, task profiles and skill-biased technological change on the labor market, we analyze characteristics that have shown to be key determinants of labor market dynamics across occupational groups.

5 The heterogeneous impact of monetary policy on the occupation-level

The section aims to reveal possible predictors of the sensitivity of unemployment to interest rate hikes across different occupation profiles. Following previous literature, we expect task profiles to exhibit predictive power when analyzing occupation-level reactions to macroeconomic fluctuations. Therefore, a number of tasks and their relevance within a monetary policy context is discussed in further detail. Afterwards, the FAVAR estimation results are related to several task measures on the occupational level in an additional empirical exercise. Finally, the empirical results are connected to a number of theoretical channels to deepen the understanding of monetary policy transmission on a disaggregated labor market.

5.1 Task-based approaches to occupation-level dynamics

Following Autor and Dorn (2013), *routine tasks* describe highly standardized, well-defined and repetitive operations performed by a worker. Such tasks are typically encountered in the middle of the skill distribution. A main feature of routine tasks is that they might be performed similarly by a suitable computer or robotic device. Hence, the number of routine tasks an occupation entails is an important measure in labor economics as it provides insights into the likelihood of being automated. Occupations featuring a high degree of repetitive, routine tasks have a higher probability of reallocating into unemployment or other occupations due to automation. On the contrary, *abstract tasks* are performed using mainly cognitive input to solve complex problems. These tasks are often found in high-skill occupations that may be seen as complementary to capital as opposed to being easily replaced by new technologies (Dolado *et al.*, 2020). So-called *manual tasks* are concentrated at the bottom of the skill distribution. These tasks are mainly performed using manual input, where automation is often difficult.

In addition to these classical types of tasks, Firpo *et al.* (2011) introduce the *degree of offshorability* of tasks as a relevant occupation characteristic. Offshorability attaches a number to the likelihood of an occupation being offshored. High offshorability is a characteristic of occupations that mainly involve tasks that do not require workers to be on-site during working hours and occupations where local interaction is not particularly important. Such occupations feature an above-average probability to be offshored. Hence, workers within these occupation groups are at risk of being replaced by a possibly foreign workforce or cheaper labor in general. Note that the term offshoring typically implies replacing a domestic workforce with a foreign workforce. In the context presented here, domestic workers may, however, also be replaced by a cheaper *domestic* workforce in the form of temporary workers or similar.

5.2 The relation of occupation characteristics and the impact of monetary policy

In summary, the specific task structure within occupation groups is an important predictor of the dynamics of occupation groups following medium-term and long-term labor market developments such as globalization

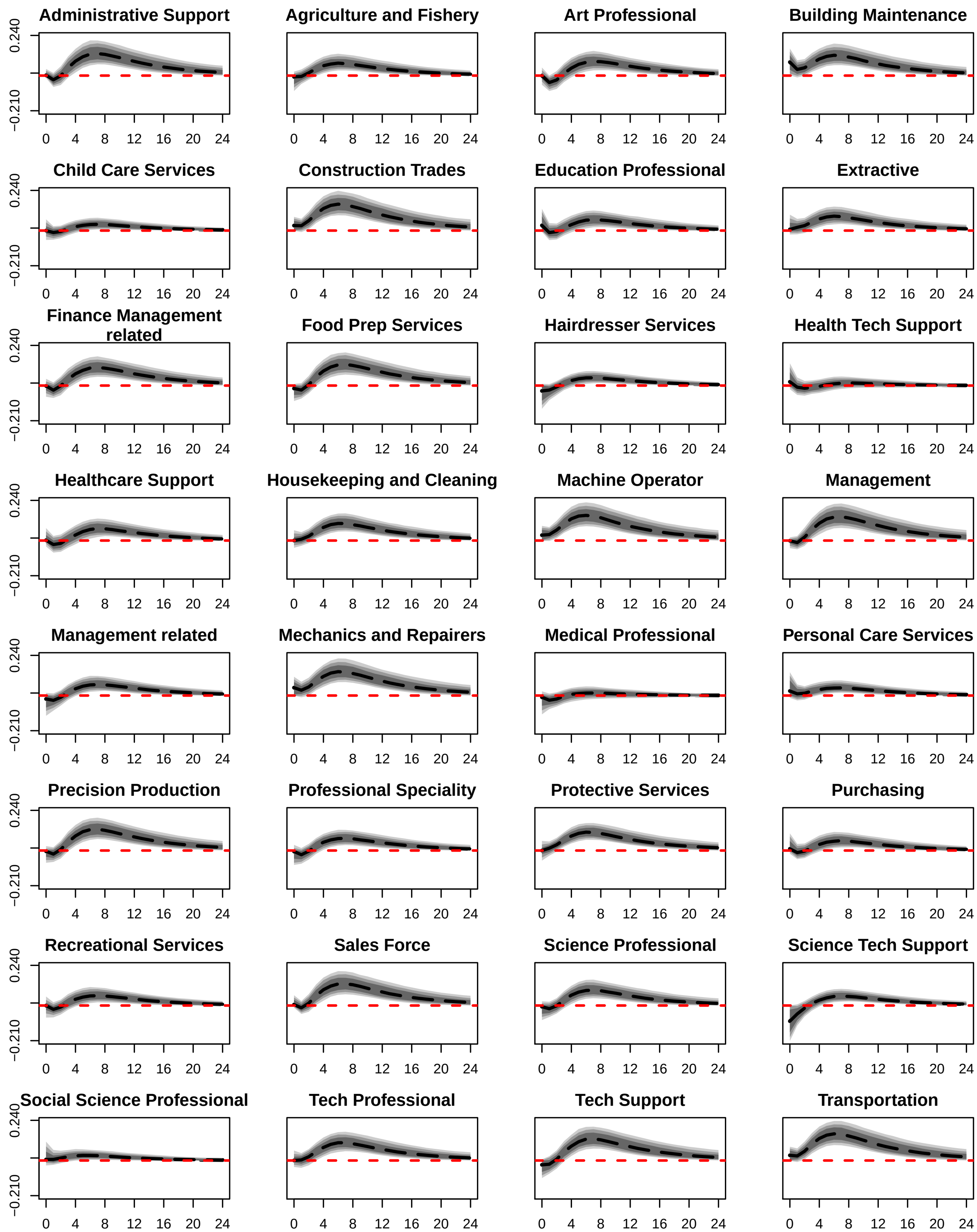

Figure 5: Impulse response functions of the change of the unemployment rate in 32 occupational groups following an exogenous monetary policy innovation of one standard deviation identified via a Cholesky decomposition. The dashed lines correspond to the posterior median and the grey areas show the 50/68/80% highest posterior density mass.

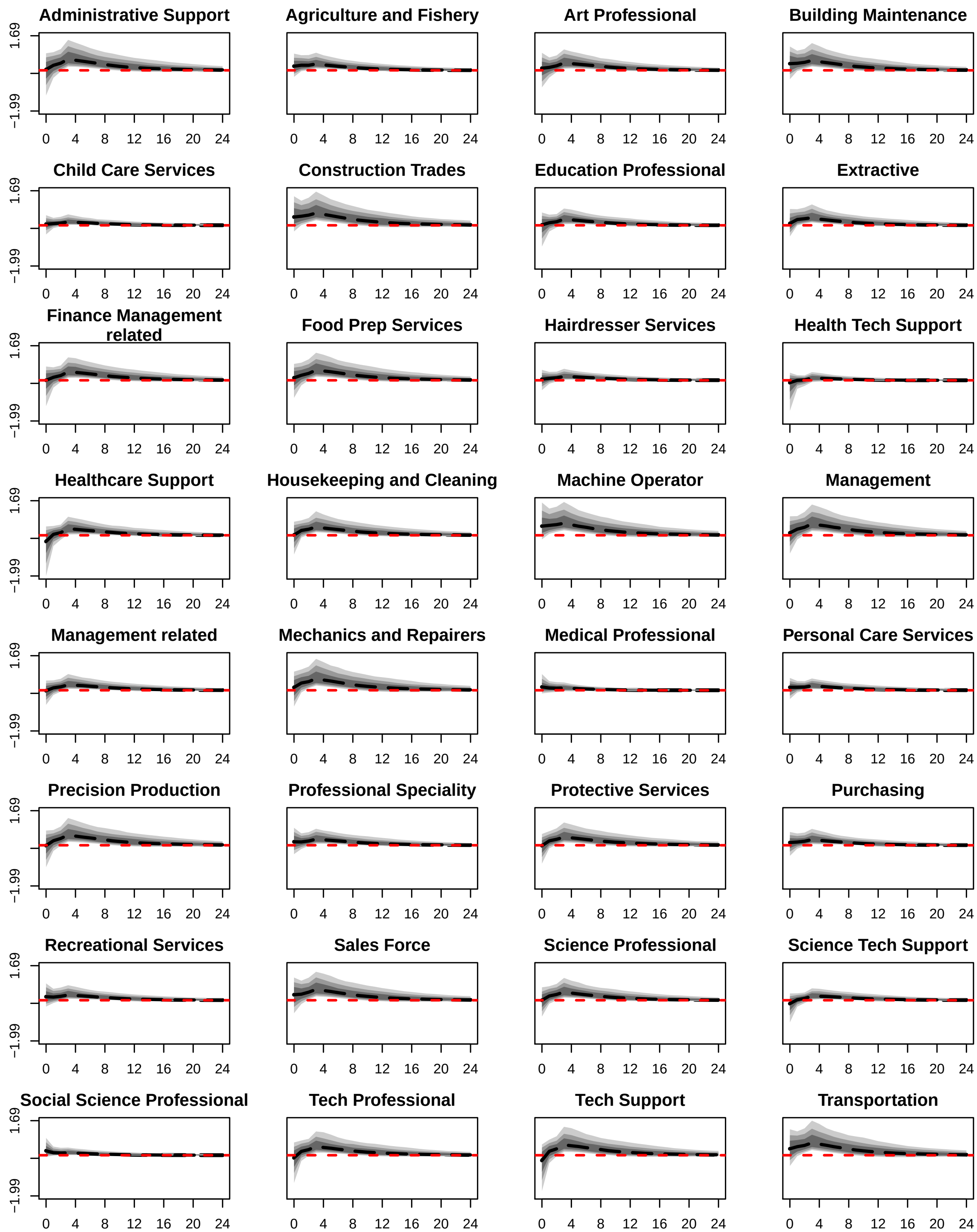

Figure 6: Impulse response functions of the change of the unemployment rate in 32 occupational groups following an exogenous monetary policy innovation of one standard deviation identified via sign restrictions. The dashed lines correspond to the posterior median and the grey areas show the 50/68/80% highest posterior density mass.

and technological change. In this section, we test whether an empirical relationship can also be established between task profiles and short-term economic fluctuations such as monetary policy shocks. To test the connection of a specific task profile and the response to monetary policy, we first compute several measures quantifying the impact that interest rate hikes have on unemployment in each occupation group: the median impulse response function after zero, four and eight quarters measures the instantaneous impact of monetary policy and the effect after one and after two years. In addition, we compute the maximum of the median impulse response function. These four measures are used as dependent variables in four separate linear regressions with the goal of disentangling possible channels behind the heterogeneous responses in the empirical exercise in Sec. 4.

The task structure of each occupation group is operationalized using the data compiled and analyzed in Autor and Dorn (2013) and Firpo *et al.* (2011). The job task requirements collected in the fourth edition of the *US Department of Labor's Dictionary of Occupational Titles* are matched to the census occupation classification system to generate an index measuring routine, abstract and manual task content by occupation. To derive a measure of potential offshorability, Firpo *et al.* (2011) take data from the *US Department of Labor's Occupational Information Network database* (O*NET). They compute a simple index of potential offshorability from the categories "face-to-face contact" and "on-site job". This summary index can then be matched to the census occupation groups.[14] These measures are then used as explanatory variables to disentangle the impact monetary policy has on unemployment within occupation groups.

In addition, it has to be taken into account that occupations are dispersed across industries. If certain occupations are concentrated in durable manufacturing or other cyclically sensitive industries, these occupations might be more sensitive to monetary policy and the business cycle in general. To control for this, we construct an occupation-level cyclicality index as follows. Using the industry classification system of the CPS, we derive industry-level unemployment rate time series from 1976 to 2019. Similar to Berman and Pfleeger (1997), we compute the correlation of each industry-level unemployment rate with quarterly GDP. Then, for each occupation, we take the weighted average of these correlations across all industries. The weights correspond to the share of an occupation within an industry's total employment.

The results of the regression exercise are provided in Tab. 3 where results for both employed identification schemes are summarized. Across specifications, it becomes clear that the amount of manual tasks, routine tasks and offshorable tasks have strong and positive influence on the effect that interest rate hikes have on unemployment within occupation groups. Occupations with a largely abstract task profile, corresponding mostly to high-skill jobs, show smaller effect sizes compared to the average. However, the estimates of the abstract task coefficients are generally noisy. Finally, more cyclical sensitive occupations show larger effect sizes on average, corresponding to economic intuition.[15]

5.3 Monetary transmission on a heterogeneous labor market

To conclude the empirical analysis, this subsection connects the presented results to a number of possible theoretical channels and focuses on what academics and policy makers may learn from the empirical exercises. This question is approached in two steps. First, the results from Tab. 3 are related to a number of theoretical results from related literature. Second, the derived theoretical channels are put into the context of central banking in the age of jobless recoveries.

To better understand the outcomes in Tab. 3, it is helpful to think of a representative firm that is profit-maximizing (or, at least, cost-minimizing). Interest rate policy directly affects the investment decisions of

[14]David Dorn made both data sets available on his personal webpage.

[15]As a sensitivity check, these regressions have been computed for a number of alternative FAVAR specifications and after including additional control variables such as average education, average wage level, average age, the share of workers in the public sector or the share of self-employed within an occupation group. The overall picture remains unchanged, while statistical significance of some coefficient estimates is sometimes weaker or stronger than in Tab. 3. Taking into account that these regressions merely include 32 observations, this outcome is to be expected.

Table 3: The effect of occupation characteristics on the impact of monetary policy.

	On Impact		After One Year		After Two Years		Maximum IRF	
	Chol.	Signs	Chol.	Signs	Chol.	Signs	Chol.	Signs
Routine Tasks	−0.002	−0.013	0.003	0.016*	0.004	0.010*	0.005*	0.017*
	(0.003)	(0.017)	(0.003)	(0.009)	(0.003)	(0.005)	(0.003)	(0.010)
Offshorability	−0.003	−0.010	0.016***	0.067***	0.020***	0.042***	0.021***	0.070***
	(0.006)	(0.035)	(0.006)	(0.019)	(0.005)	(0.011)	(0.006)	(0.021)
Abstract Tasks	−0.003	−0.013	−0.002	−0.003	−0.001	−0.002	−0.001	−0.002
	(0.003)	(0.018)	(0.003)	(0.010)	(0.003)	(0.006)	(0.003)	(0.010)
Manual Tasks	0.006	0.025	0.019***	0.063**	0.018**	0.033**	0.020**	0.069**
	(0.007)	(0.043)	(0.007)	(0.023)	(0.007)	(0.014)	(0.007)	(0.025)
Cyclicality Index	0.231	1.988	0.826***	3.716***	1.003***	2.104***	1.053***	4.035***
	(0.227)	(1.397)	(0.221)	(0.751)	(0.218)	(0.439)	(0.235)	(0.815)
Constant	0.006	0.105	0.015	0.120*	0.028	0.067*	0.029	0.143*
	(0.020)	(0.124)	(0.020)	(0.067)	(0.019)	(0.039)	(0.021)	(0.072)
N	32	32	32	32	32	32	32	32
R^2	0.185	0.158	0.525	0.618	0.594	0.611	0.591	0.612

Notes: The dependent variable is the value of the impulse response function on impact, after one year, after two years and at its maximum. Explanatory variables are indices measuring routine, abstract, manual tasks and the degree of potential offshorability as well as the constructed cyclicality index. Standard errors in parentheses. *, ** and *** denote significance on the 10%, 5% and 1% level.

firms through the price of investment, and therefore through expected profits. Hence, in the context of conventional monetary policy, firms are the most relevant decision makers on the microeconomic level. Consider now an increase in interest rates, i.e. contractionary monetary policy which decreases the expected profits of firms. Hence, firms now have an incentive to substitute relatively costly workers with cheaper alternatives that are able to fulfil the same tasks. If they can find such cheaper alternatives, expected profits will increase again.

One such alternative is capital in the form of robots or computers. This is most relevant for workers with a large amount of routine tasks as they are relatively easily replaced by capital, as outlined above. However, this channel is likely to be counteracted through the increased price of capital as interest rates have gone up (Dolado *et al.*, 2020). Taken together, these channels may result in a positive or negative relationship between the impact of monetary policy and routine tasks within occupations, depending on which channel is stronger. The weakly significant, positive coefficient of routine tasks in Tab. 3 suggests that the increased price of capital is not completely offsetting the incentive to replace workers with capital in our sample. A second alternative is to replace expensive workers by a cheaper, possibly foreign work force (Firpo *et al.*, 2011). As the price of these workers does not directly depend on interest rates, no strong counteracting force is present here. This is reflected in a highly significant, positive relationship between offshorability and the impact of monetary policy.

Abstracting from microeconomic decision making, a contractionary monetary policy shock is accompanied by an aggregate economic downturn due to decreasing aggregate investment. For a number of reasons, this recessionary period is highly likely to disproportionately affect manual workers, usually located at the bottom of the skill distribution. First, separation rates in the low-skill labor market segment are generally high (Wolcott, 2018), while bargaining power is low (Dumont *et al.*, 2012), resulting in a generally low level of job security. After losing their job, matching efficiency is often rather low as well (Barnichon and Figura, 2015). Moreover, unemployment spells may lead to *scarring*, i.e. workers losing their skills over time, making them less likely to be re-employed (Heathcote *et al.*, 2020). At the same time, prolonged periods of unemployment of medium-skilled, routine workers may lead to these workers losing their skills as well. This process can potentially create a feedback loop, where even more competition in the low-skill labor market segment results. These considerations provide a possible explanation for the significant positive relationship between manual tasks and the impact of interest rate policy.

On the contrary, workers with abstract tasks in the high-skill labor segment are generally considered to have high bargaining power and a higher level of job security (Dumont *et al.*, 2012). Moreover, workers in this segment are seen as complementary to capital and technology, to some degree protecting them from automation (Dolado *et al.*, 2020). In addition, abstract workers are likely to be able to attend to other types of tasks as well (Dolado *et al.*, 2009), resulting in a higher level of matching efficiency (Barnichon and Figura, 2015) in case they lose their job. However, abstract workers are most likely to be offshorable, with the correlation between abstract tasks and offshorability being around 0.3 across occupations. Nevertheless, the degree of offshorability is already controlled for in Tab. 3, resulting in an overall negative, but non-significant relationship between abstract tasks and the vulnerability to monetary policy.

From an academic point of view, these results complement and confirm previous findings in three points. First, as emphasized in a large body of literature on macroeconomic modeling, we find that it is important to shed light on heterogeneity in a given population when analyzing the effects of macroeconomic shocks. Second, in line with the literature focusing on skill-based household heterogeneity, we find that workers further down the skill distribution, which are more likely to attend to manual and routine tasks are more strongly affected by monetary policy shocks (Gornemann *et al.*, 2016). Finally, as recently brought forward in Heathcote *et al.* (2020) and Jaimovich and Siu (2020), our results suggest that understanding long-term structural change in the macroeconomic environment may well be facilitated by analyzing cyclical fluctuations.

From a policy maker's perspective, these results suggest that conventional monetary policy generally plays only a limited role in counteracting jobless recoveries and job polarization. This is mainly due to the impact of monetary policy on the labor market being of limited quantitative importance. However, even in a scenario where the impact of monetary policy on occupation-specific unemployment is larger, we expect that a central bank will not be able to sufficiently stabilize long-term labor market developments through monitoring and steering the business cycle. When interest rates go up, routine and manual workers are likely to lose out as discussed above. However, at the same time, actively steering against jobless recoveries by providing firms with cheap investments is not a viable solution either. At best, this will counteract the job loss of routine and manual workers through an increase in profit expectations and through lowered incentives for firms to dismiss workers. At the same time, cheap capital increases the incentive to automate, counteracting this channel for routine workers that suffer strongest from jobless recoveries and job polarization dynamics in general. Moreover, earnings inequality may surge following a monetary expansion due to an increasing skill premium as high-skilled, abstract workers become more "valuable" due to their high level of capital-skill complementarity (Dolado *et al.*, 2020).

6 Concluding remarks

In this paper, we aim to evaluate the role of central banks on the labor market in the context of jobless recoveries and job polarization. For this, we link a broad data set of macroeconomic variables to disaggregated labor market data extracted from the US current population survey (CPS). This allows us to explore the effect that exogenous changes in the federal funds rate have on unemployment in 32 occupation groups. To enable efficient and reliable estimation we opt for a factor-augmented vector autoregressive model (FAVAR) in a Bayesian estimation framework. The FAVAR implicitly imposes a VAR process on the macroeconomic aggregates and the disaggregated labor market data that is the focus of this article. The proposed model allows us not only to bypass dimensionality problems and overparametrization, but also enables us to incorporate a large information set spanning major parts of the US macroeconomy. Moreover, the FAVAR approach makes it possible to capture essential dynamics between occupation groups.

The results on the aggregate level corroborate both the findings of previous empirical literature and implications of theoretical frameworks. The main findings are summarized as follows. First, an increase of the federal funds rate (i.e. a contractionary monetary policy shock) sharply decreases aggregate economic measures like output and investment, while aggregate unemployment surges. Moreover, the overall response of aggregate labor market variables is in line with previous empirical studies and theoretical macroeconomic frameworks. From a disaggregated perspective, the results on the occupational level reveal a more heterogeneous picture. First, not all occupations experience a significant increase in unemployment. Second, heterogeneity with respect to the magnitude and persistence of reactions is observed.

These findings are explained using previous theoretical and empirical studies on household heterogeneity on the labor market. However, as opposed to the majority of contributions, which focus on the skill level of workers, our main findings emphasize particularities in the task profile of occupation groups. Specifically, we find that the number of manual and routine tasks as well as the potential to offshore certain professions are predictors of the effectiveness of monetary policy in this occupation group. Finally, we discuss these results in the context of the causes and consequences of job polarization dynamics to shed further light on the transmission of monetary policy on the labor market. We conclude that conventional monetary policy is unlikely to sufficiently stabilize long-term structural developments such as job polarization. In general, we show that the use of readily available disaggregated data and the application of macroeconometric frameworks to microeconomic data sets can be an important source of insights into the functionality of the economy in the future.

To conclude, a large number of potential theoretical and empirical extensions to the work presented in this article is easily found. Ideally, the presented findings and the suggested theoretical channels should be further underpinned by thorough empirical analysis on a microeconomic level. In addition, developing structural theoretical models that link task profiles and heterogeneous transmission of monetary policy may produce relevant findings. Moreover, although an approximate crosswalk between skill-based and task-based approaches to heterogeneity exists, it would be insightful to explore in which applications which perspective delivers more useful results. A major conceptual question that arises is whether unexpected interest rate changes are the most important shock to analyze in the context of jobless recoveries and job polarization. From the perspective of central banks that most often follow policy rules (Primiceri, 2005), an arguably more dominant issue is to what extent a monetary policy authority can influence or stabilize the labor market in the context of *systematic* monetary policy interventions. While acknowledging the importance of this distinction, we leave this open for future analysis. On a more empirical note, the effects of macroeconomic shocks on the labor market may change over time (Mumtaz and Zanetti, 2015), which warrants further investigation considering that jobless recoveries are observed after 1990, but not before (Jaimovich and Siu, 2020). Finally, analyzing whether the presented patterns hold with respect to the vulnerability of specific occupations to other types of macroeconomic distortions, such as oil price or uncertainty shocks is a direct extension of the framework in this article and may produce valuable empirical and theoretical insights.

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A Bayesian Estimation

A two-step estimation approach is implemented. In the first step, the factors are estimated via principal component analysis (PCA). Then, a Markov Chain Monte Carlo (MCMC) algorithm is used to sample from the joint posterior distribution. However, since the joint posterior density is analytically intractable, we rely on Gibbs sampling to sample iteratively from the conditional posterior densities. The Gibbs sampler outlined in Sec. 2 is iterated 40,000 times where the first 20,000 iterations are discarded as burn-in phase. Every 20th draw is kept for further analysis to reduce autocorrelation of the posterior draws. In the following, some additional topics with respect to prior choices as well as the employed algorithm are briefly discussed.

Recovering the latent factors is also possible in a fully Bayesian approach via commonly encountered forward filtering backward sampling algorithms (Carter and Kohn, 1994; Frühwirth-Schnatter, 1994). In the application at hand, we abstain from doing so for two reasons. First, using principal components of the information set and observables reduces the computational burden in a setting with many variables by a large margin. Moreover, Bernanke *et al.* (2005) argue that the two-step approach based on principal components carries more information since factor estimation is less sensitive to the required identification structure of the model. Conveniently, if the number of variables in the information set is large, principal components consistently recover the space spanned by $\boldsymbol{X}_t$ and $\boldsymbol{Y}_t$ (Stock and Watson, 2002).

For *statistical* identification of the FAVAR, we follow Bernanke *et al.* (2005) and set the upper $q \times q$ block of $\boldsymbol{\Lambda}^f$ to an identity matrix as well as the upper $q \times l$ block of $\boldsymbol{\Lambda}^y$ to zero. This is sufficient for the identification and allows to recover a full variance-covariance matrix in the state equation.

Since VAR models are heavily parameterized, shrinkage priors may be employed to introduce sparsity. In this article, a Normal-Gamma (NG) type global local shrinkage prior originally proposed in Griffin and Brown (2010) and applied to the VAR context in Huber and Feldkircher (2019) is implemented. The prior setup may be summarized as

$$\beta_{ij} \mid \tau_{ij} \sim \mathcal{N}(0, 2\lambda_j^{-2}\tau_{ij}), \quad \lambda_j^2 \sim G(c_j, d_j), \quad \tau_{ij} \sim \mathcal{G}(\vartheta, \vartheta). \tag{A.1}$$

β_{ij} denotes a typical element of one of the system matrices $\{\boldsymbol{\Lambda}, \boldsymbol{L}, \boldsymbol{\Phi}\}$, where i refers to the coefficient and j to the lag. τ_{ij} denotes the *local* shrinkage parameter that is coefficient specific and λ_k^2 refers to the *lag-specific* shrinkage parameter pulling parameters associated with higher-order lags towards zero. ϑ_k is a hyperparameter chosen by the researcher that we set tp $\vartheta_k = 0.6$. This corresponds to a moderate amount of shrinkage. The case $\vartheta = 1$ corresponds to the Bayesian variant of the LASSO shrinkage prior (Park and Casella, 2008). Lower values of ϑ impose stronger shrinkage since this parameter controls the excess kurtosis of the imposed conditional normal distribution of the variables of interest. The hyperparameters of the Gamma prior on λ_j^2 are set to $c_j = d_j = 0.01$, allowing for moderately large amounts of global shrinkage.

For the remaining quantities in the model, standard priors are assumed. More precisely, the prior setup proposed in Kastner and Frühwirth-Schnatter (2014) is used for the coefficients in the log-volatility state equation.This corresponds to using a Gaussian prior on the unconditional mean of the log-volatility, $\mu_i \sim \mathcal{N}(0, 10)$, a Beta prior on the persistence parameter, $(\rho + 1)/2 \sim \mathcal{B}(25, 5)$, and a non-conjugate Gamma prior on the error variance of the log-volatility process $\sigma_i^2 \sim \mathcal{G}(1/2, 1/2)$. Estimation is carried out with the R package **stochvol** (Kastner, 2016).

B Occupation data

We use an extended version of the occupation groups provided in the *occ1990dd* occupational classification system. This classification has been introduced by David Dorn and has since been used in a variety of studies. Compared to the standard US census occupation classification, the *occ1990dd* enables a more balanced analysis of occupational groups over prolonged periods of time. More detailed information on the *occ1990dd* scheme can be found online on David Dorn's personal webpage.

The following table provides a crosswalk of the classification used in this paper to the standard *occ1990dd* classification system. Most of the broader occupational groups correspond exactly to the groups suggested in the original *occ1990dd* scheme. However, a few large groups have been split into smaller groups to permit a more differentiated look across occupation groups.

Table A1: Occupation Groups and Crosswalk

#	Name	Codes in *occ1990dd* scheme	Tcode	Scode
1	Administrative support	303 - 389	2	1
2	Agriculture & fishery	473 - 498	2	1
3	Art professional	185 - 194	2	1
4	Building maintenance	448 - 455	2	1
5	Child care services	468	2	1
6	Construction trades	558 - 599	2	1
7	Education professional	154 - 165	2	1
8	Extractive	614 - 617	2	1
9	Finance management related	23-25	2	1
10	Food preparation services	433 - 444	2	1
11	Hairdresser services	457, 458	2	1
12	Health tech support	203 - 208	2	1
13	Healthcare support	445 - 447	2	1
14	Housekeeping & cleaning	405, 408	2	1
15	Machine operator	703 - 799	2	1
16	Management	4 - 22	2	1
17	Management related	26-27, 34-37	2	1
18	Mechanics & repairers	503 - 549	2	1
19	Medical professional	83 - 106	2	1
20	Personal care services	469 - 472	2	1
21	Precision production	628 - 699	2	1
22	Professional speciality	173 - 184, 195 - 199	2	1
23	Protective services	415 - 427	2	1
24	Purchasing	28-29, 33	2	1
25	Recreational services	459 - 467	2	1
26	Sales force	243 - 283	2	1
27	Science professional	64 - 79	2	1
28	Science tech support	218, 223 - 225	2	1
29	Social science professional	166 - 169	2	1
30	Tech professional	43 - 59	2	1
31	Tech support	214, 217, 226-229,233-235	2	1
32	Transportation	803 - 889	2	1

C Macroeconomic data

All series were downloaded from the St. Louis' FRED database using the R-package `fredr` (Boysel and Vaughan, 2019) and cover the time period 1978Q1 to 2019Q1. The dataset is similar to the one used in Korobilis (2013), but extended in the time dimension. All series are seasonally adjusted, either by downloading the already adjusted series from FRED or by applying a quarterly X11 filter based on an AR(4) model to the unadjusted series. Some series in the database are observed only on a monthly basis and quarterly values are computed by obtaining quarterly averages. Furthermore, all variables are transformed to be approximately stationary. In particular, the column *Tcode* shows the transformation we applied to a series: 1 – no transformation (levels); 2 – first difference; 4 – logarithms; 5 – first difference of logarithms; 6 – second difference in logarithms. The same classification for *slow-moving* (Scode=1) and *fast-moving* (Scode=0) variables as in Bernanke *et al.* (2005) is employed. Slow-moving variables include real activity (output, employment/unemployment etc.) and consumer prices. Fast-moving variables include interest rates, stock returns, exchange rates and commodity prices.

Table B1: Real Activity Measures Part I

#	Mnemonic	Description	Tcode	Scode
1	GDPC1	Real Gross Domestic Product, 3 Decimal	5	1
2	CBI	Change in Private Inventories	1	1
3	FINSAL	Final Sales of Domestic Product	5	1
4	FSDP	Final Sales to Domestic Purchasers	5	1
5	FINSLC	Real Final Sales of Domestic Product, 3 Decimal	5	1
6	GGSAVE	Gross Government Saving	1	1
7	TGDEF	Net Government Saving	1	1
8	GSAVE	Gross Saving	5	1
9	FPI	Fixed Private Investment	5	1
10	PRFI	Private Residential Fixed Investment	5	1
11	GFDEBTN	Federal Debt: Total Public Debt	6	1
12	W068RCQ027SBEA	Government total expenditures	6	1
13	W006RC1Q027SBEA	Federal government current tax receipts	6	1
14	SLINV	State and Local Government Gross Investment	6	1
15	SLEXPND	State and Local Government Current Expenditure	6	1
16	EXPGSC1	Real Exports of Goods and Services, 3 Decimal	5	1
17	IMPGSC1	Real Imports of Goods and Services, 3 Decimal	5	1
18	CIVA	Corporate Inventory Valuation Adjustement	1	1
19	CP	Corporate Profits After Tax	5	1
20	CNCF	Corporate Net Cash Flow	5	1
21	DIVIDEND	Net Corporate Dividends	5	1
22	PCE	Personal Consumption Expenditure	6	1
23	PCES	Personal Consumption Expenditure: Servcies	6	1
24	PCEDG	Personal Consumption Expenditure: Durable Goods	6	1
25	PCEND	Personal Consumption Expenditure: Nondurable Goods	6	1
26	INDPRO	Industrial Production Index	5	1
27	HOABS	Business Sector: Hours of All Persons	5	1
28	HCOMPBS	Business Sector: Compensation per Hour	5	1
29	RCPHBS	Business Sector: Real Compensation per Hour	5	1
30	ULCBS	Business Sector: Unit Labor Cost	5	1

Table B2: Real Activity Measures Part II

#	Mnemonic	Description	Tcode	Scode
31	COMPNFB	Nonfarm Business Sector: Compensation per Hour	5	1
32	HOANBS	Nonfarm Business Sector: Hours of All Persons	5	1
33	COMPRNFB	Nonfarm Business Sector: Real Compensation per Hour	5	1
34	ULCNFB	Nonfarm Business Sector: Unit Labor Cost	5	1
35	UNRATE	Unemployment Rate	2	1
36	UEMPLT5	Civilians Unemployed for Less Than 5 Weeks	5	1
37	UEMP5TO14	Civilians Unemployed for 5-14 Weeks	5	1
38	UEMP15OV	Civilians Unemployed for Over 15 Weeks	5	1
39	UEMP15TO26	Civilians Unemployed for 15-26 Weeks	5	1
40	UEMP27OV	Civilians Unemployed for Over 27 Weeks	5	1
41	NDMANEMP	All Employees: Nondurable Goods	6	1
42	MANEMP	All Employees: Manufacturing	6	1
43	SRVPRD	All Employees: Service-Providing Industries	6	1
44	USTPU	All Employees: Trade, Transportation and Industries	6	1
45	USWTRADE	All Employees: Wholesale Trade	6	1
46	USTRADE	All Employees: Retail Trade	6	1
47	USFIRE	All Employees: Financial Activities	6	1
48	USEHS	All Employees: Education and Health Services	6	1
49	USPBS	All Employees: Professional and Business Services	6	1
50	USINFO	All Employees: Information Services	6	1
51	USSERV	All Employees: Other Services	6	1
52	USPRIV	All Employees: Total Private Industries	6	1
53	USGOVT	All Employees: Government	6	1
54	USLAH	All Employees: Leisure and Hospitality	6	1
55	AHECONS	Average Hourly Earnings: Construction	6	1
56	AHEMAN	Average Hourly Earnings: Manufacturing	6	1
57	AHETPI	Average Hourly Earnings: Total Private Industries	6	1
58	AWOTMAN	Average Weekly Hours: Overtime: Manufacturing	1	1
59	AWHMAN	Average Weekly Hours: Manufacturing	1	1
60	HOUST	Housing Starts: Total	4	1
61	HOUSTNE	Housing Starts: Northeast Census Region	4	1
62	HOUSTMW	Housing Starts: Midwest Census Region	4	1
63	HOUSTS	Housing Starts: South Census Region	4	1
64	HOUSTW	Housing Starts: West Census Region	4	1
65	HOUST1F	Housing Starts: 1-Unit Structures	4	1
66	PERMIT	New Private Housing Units Authorized by Building Permit	4	1

Table B3: Money, Credit and Finance Measures

#	Mnemonic	Description	Tcode	Scode
67	NONREVSL	Total Nonrevolving Credit Outstanding, Billions of Dollars	5	0
68	USGSEC	US Government Securities at All Commercial Banks	5	0
69	OTHSEC	Other Securities at All Comercial Banks	5	0
70	TOTALSL	Total Consumer Credit Outstanding	5	0
71	BUSLOANS	Commercial and Industrial Loans at All Commercial Banks	5	0
72	CONSUMER	Consumer (Individual) Loans at All Commercial Banks	5	0
73	LOANS	Total Loans and Leases at Commercial Banks	6	0
74	LOANINV	Total Loans and Investments at All Commercial Banks	6	0
75	INVEST	Total Investments at All Commercial Banks	5	0
76	REALLN	Real Estate Loans at All Commercial Banks	6	0
77	AMBSL	Board of Governors Monetary Base, Adjusted for Changes in Reserve Requirements	5	0
78	REQRESNS	Required Reserves, Not Adjusted for Changes in Reserve Requirements	5	0
79	RESBALNS	Reserve Balances with Fed. Res. Banks, Not Adj. for Changes in Reserve Req.	5	0
80	BORROW	Total Borrowings of Depository Institutions from the Federal Reserve	5	0
81	M1SL	M1 Money Stock	6	0
82	CURRSL	Currency Component of M1	5	0
83	CURRDD	Currency Component of M1 Plus Demand Deposits	5	0
84	M2SL	M2 Money Stock	6	0
85	M2OWN	M2 Own Rate	6	0
86	M2MSL	M2 Minus Small Time Deposits	6	0
87	M2MOWN	M2 Minus Own Rate	6	0
88	MZMSL	MZM Money Stock	6	0
89	SVSTCBSL	Savings and Small Time Deposits at Commercial Banks	6	0
90	SVSTSL	Savings and Small Time Deposits - Total	6	0
91	SVGCBSL	Savings Deposits at Commercial Banks	6	0
92	SVGTI	Savings Deposits at Thrift Institutions	6	0
93	SAVINGSL	Savings Deposits - Total	6	0
94	STDCBSL	Small Time Deposits at Commercial Banks	6	0
95	STDTI	Small Time Deposits at Thrift Institutions	6	0
96	STDSL	Small Time Deposits - Total	6	0
97	USGVDDNS	US Government Demand Deposits and Note Balances - Total	5	0
98	USGDCB	US Government Demand Deposits at Commercial Banks	5	0
99	CURRCIR	Currency in Circulation	5	0

Table B4: Interest Rates

#	Mnemonic	Description	Tcode	Scode
100	FEDFUNDS	Effective Federal Funds Rate	1	1
101	TB3MS	3-month Treasury Bill: Secondary Market Rate	1	0
102	TB6MS	6-month Treasury Bill: Secondary Market Rate	1	0
103	GS1	1-year Treasury Constant Maturity Rate	1	0
104	GS3	3-year Treasury Constant Maturity Rate	1	0
105	GS5	5-year Treasury Constant Maturity Rate	1	0
106	GS10	10-year Treasury Constant Maturity Rate	1	0
107	MPRIME	Bank Prime Loan Rate	1	0
108	AAA	Moody's Seasoned Aaa Corporate Bond Yield	1	0
109	BAA	Moody's Seasoned Baa Corporate Bond Yield	1	0
110	EXSZUS	Switzerland / US Foreign Exchange Rate	5	0
111	EXJPUS	Japan / US Foreign Exchange Rate	5	0
112	EXUSUK	US / UK Foreign Exchange Rate	5	0
113	EXCAUS	Canada / US Foreign Exchange Rate	5	0

Table B5: Prices

#	Mnemonic	Description	Tcode	Scode
114	GDPDEF	Gross Domestic Product: Implicit Price Deflator	6	1
115	GDPCTPI	Gross Domestic Product: Chain-type Price Index	6	1
116	PCECTPI	Personal Consumption Expenditures: Chain-type Price Index	6	1
117	PPIACO	PPI: All Commodities	6	1
118	WPU0561	PPI by Commodity for Fuels and Related Products and Power: Crude Petroleum	6	1
119	WPUFD4111	PPI: Finished Consumer Foods	6	1
120	WPUFD49502	PPI: Finished Consumer Goods	6	1
121	WPSFD41311	PPI: Finished Consumer Goods Excluding Foods and Energy	6	1
122	WPSFD49207	PPI: Finished Goods	6	1
123	WPSFD41312	PPI: Finished Goods: Capital Equipment	6	1
124	PPIENG	PPI: Fuels and Related Products, Power	6	1
125	PPIIDC	PPI: Industrial Commodities	6	1
126	WPSID61	PPI by Commodity for Intermediate Demand by Commodity Type: Processed Goods for Intermediate Demand	6	1
127	CPIAUCSL	CPI for All Urban Consumers: All Items	6	1
128	CPIUFDSL	CPI for All Urban Consumers: Food	6	1
129	CPIENGSL	CPI for All Urban Consumers: Energy	6	1
130	CPILEGSL	CPI for All Urban Consumers: All Items Less Energy	6	1
131	CPIULFSL	CPI for All Urban Consumers: All Items Less Food	6	1
132	CPILFESL	CPI for All Urban Consumers: All Items Less Energy and Food	6	1
133	WTISPLC	Spot Oil Price: West Texas Intermediate	6	1

Table B6: Expectations

#	Mnemonic	Description	Tcode	Scode
134	sTB3MS	TB3MS - FEDFUNDS	1	0
135	sTB6MS	TB6MS - FEDFUNDS	1	0
136	sGS1	GS1 - FEDFUNDS	1	0
137	sGS3	GS3 - FEDFUNDS	1	0
138	sGS5	GS5 - FEDFUNDS	1	0
139	sGS10	GS10 - FEDFUNDS	1	0
140	sMPRIME	MPRIME - FEDFUNDS	1	0
141	sAAA	AAA - FEDFUNDS	1	0
142	sBAA	BBB - FEDFUNDS	1	0
143	MICH	University of Michigan: Inflation Expectation	1	0
144	BSCICP03USM665S	Business Tendency Surveys for Manufacturing: Confidence Indicators: Composite Indicators: OECD	1	0
145	CSINFT02USM460S	Consumer Opinion Surveys: Consumer Prices: Future Tendency of Inflation	1	0
146	BAA10Y	BAA - GS10	1	0

D Additional sign restriction results

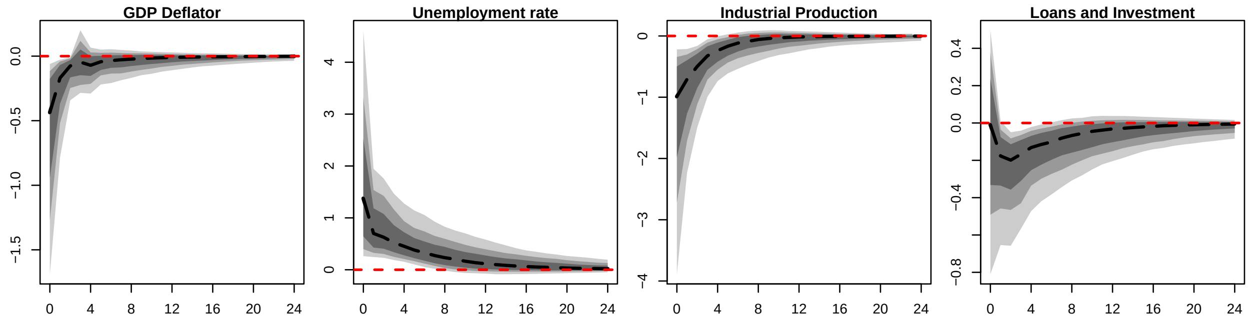

Figure 7: Impulse response functions of selected macroeconomic aggregates following an exogenous monetary policy innovation of one standard deviation. The dashed lines correspond to the posterior median while the grey areas show the 50/68/80% highest posterior density mass. The identification is based on sign restrictions.

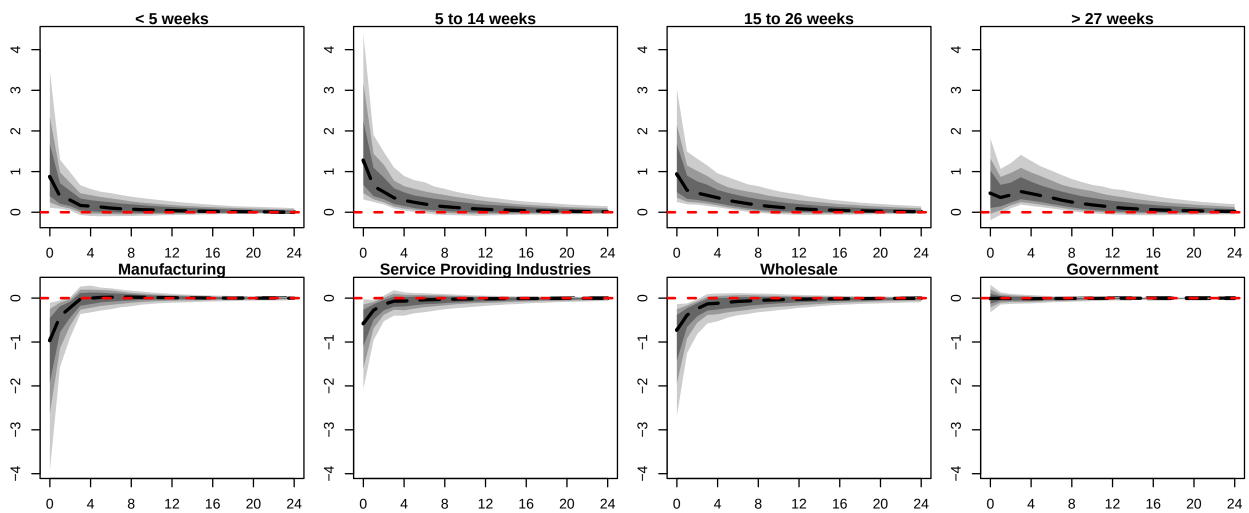

Figure 8: Impulse response functions of various labor market aggregates following an exogenous monetary policy innovation of one standard deviation. Upper row: Unemployment headcounts for different unemployment durations. Bottom row: Employment headcounts in different sectors of the economy. The dashed lines correspond to the posterior median and the grey areas show the 50/68/80% highest posterior density mass. The identification is based on sign restrictions.