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Of clerks & cleaners: the heterogeneous impact of monetary policy on the US labor market*

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Abstract

In this paper we estimate the effect of monetary policy on the US labor market using disaggregated data based on large scale micro surveys. By employing a Bayesian factor-augmented vector autoregression framework, we investigate the impact of an unanticipated interest rate change on the unemployment rate in 32 occupation groups. Our results on the aggregate level are in line with the literature and point towards a strong influence of monetary policy on economic activity, overall unemployment and investment. A closer look on the disaggregated level reveals heterogeneous impacts across occupation groups. This heterogeneity can partially be explained by the amount of routine tasks and the degree of offshorability of an particular occupation group. These results suggest that workers who are highly vulnerable to medium-term and long-term developments such as automatization and offshoring are also hit disproportionately hard by short-term economic fluctuations.

Keywords: Monetary Policy, Unemployment, FAVAR, Occupation-level, Bayesian Analysis.

JEL Codes: C11, C32, E24, E52

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1 Introduction

Among the majority of economists there is a consensus that monetary policy has indeed effects on the real economy. However, the full understanding of transmission mechanisms and propagation as well as amplification processes of monetary policy measures are still subject to intensive research. In addition, due to the high relevance for policymakers, it has been a particularly active field during the past decades. As a result, the effect of monetary policy on a broad variety of macroeconomic aggregates is well explored and has been analyzed thoroughly in various theoretical and empirical studies. An extensive review of the evolution of this literature is out of scope of this paper. However, some important empirical core contributions include, among others, Cochrane and Piazzesi (2002), Romer and Romer (2004), Bernanke *et al.* (2005) and Gertler and Karadi (2015).

Recently, a number of interesting contributions puts more emphasis on the understanding of possibly *heterogeneous* impacts that monetary policy may exert. For instance, Primiceri (2005) analyze heterogeneous monetary policy effects in different historical time periods in his seminal contribution on multivariate time-varying parameter frameworks. Using a more dissagregated perspective, Boivin *et al.* (2009) analyzes the impact of monetary policy on a large set of price variables. The influential contribution by Coibion *et al.* (2017) focuses on the heterogeneity of monetary policy responses along the income distribution. This gave rise to a variety of studies explaining monetary policy impacts on a distributional level, such as Cravino *et al.* (2018) or Furceri *et al.* (2018). From a spatial perspective, Beraja *et al.* (2017) explore geographical heterogeneity and analyze the effect of regional differences in housing equity on the impact of central bank policy. All of these studies implicitly tackle the issue of the oversimplifying assumption of an identical monetary policy impact across various economic dimensions.

Despite the growing interest in central bank policy activities over time, some aspects of the macroeconomy have received rather limited attention from researchers. In particular, the effects of interest rate changes on the labor market and specifically on employment are usually discussed in a rather superficial manner. From a theoretical perspective, the simplest classical macroeconomic models suggest that disinflationary monetary policy will dampen investment and production. With a reduced level of production, employment will decrease as well, at least in the short term. This is also a rather robust empirical finding, commonly reported in a variety of empirical studies on monetary policy (e.g. in Bernanke *et al.*, 2005 for the US economy and Potjagailo, 2017 for the Euro area).

However, taking into account that an aggregated view of the labor market conceals a set of possibly very heterogeneous dynamics, it seems highly unlikely that the aggregate, average effect of monetary policy on unemployment tells us the full story. Differential effects across industries and occupation groups, depending on e.g. the sluggishness of the local labor market, the specific demand for skills within a given industry or the task profile of a specific occupation group are at least thinkable. At the same time, the labor market is directly connected to important socioeconomic phenomena such as poverty, individual well-being and social mobility. Therefore, an in-depth analysis of the heterogeneous effect of monetary policy on employment is likely to generate highly relevant insights for both the academic discourse and policymakers.

Hence, it comes as no surprise that researchers have become interested in the disaggregated effects that monetary policy might have on the labor market. For instance, Thorbecke (2001) investigates the differential impact of central bank policy on employment across labor market groups that are considered as minorities. A similar idea is brought forward in Carpenter and Rodgers III (2004), who specifically analyze the employment response of teenagers, minorities, out-of-school youth and less-skilled individuals following changes in the federal funds rate. Both studies arrive at conclusions that are broadly in line with the theoretical concepts developed in Blanchard (1995): Put briefly, there exist groups of labor market participants that are likely to exhibit above average vulnerability to economic shocks and thus react more strongly to monetary policy as well. These empirical and theoretical contributions offer a valuable starting point which we will pick up and extend in what follows.

Building on previous literature, we offer explicit analysis of the heterogeneous occupation-level effect of monetary policy on the US labor market. Aggregating microdata from the US current population survey (CPS) allows us to explore the effect that changes in the federal funds rate have on employment in 32 occupation groups. In addition, using detailed information on the task profile of the workers within a given occupation group enables us to utilize a more detailed characterization for each occupation group in further empirical analysis. This in turn deepens our understanding of the transmission of central bank policy on the labor market. 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 several challenges that arise when dealing with disaggregated data.

We find that there is indeed occupation level heterogeneity in the responses of unemployment to interest rate hikes, despite most occupation groups showing strong and significant reactions to monetary policy. On the one hand, these results are in line with the commonly reported finding of an aggregate impact of interest rates on unemployment rates, which is reassuring. On the other hand, it is clearly the case that not all occupation groups show similar reactions to monetary policy innovations. This naturally raises the question of the specific characteristics driving the effectiveness of monetary policy on the occupation level.

Such characteristics are analyzed in a large body of research on the occupational structure of the US labor market. Important contributions include, among others, Autor *et al.* (2003), Acemoglu and Autor (2011) and Autor and Dorn (2013). Broadly speaking, a main insight of this literature is that the skill level and task content of occupations are highly relevant when trying to explain certain labor market dynamics. For instance, occupations characterized by repetitive, well-defined and standardized tasks are prone to be pushed out of their occupations due to medium-term and long-term developments such as technological change and automatization. In an additional empirical exercise, we connect to this literature to deliver a possible explanation of heterogeneous monetary policy impacts on an occupational level. We find that the degree of offshorability as well as the amount of routine tasks of a given occupation group are strong predictors of the effectiveness of monetary policy within this group.

This suggests that occupation groups that are particularly vulnerable to automatization and offshoring are also likely to suffer disproportionately from short-term economic fluctuations such as interest rate hikes.

In summary, our main contribution is the utilization of disaggregated data on US employment across time and occupations in a state-of-the-art macroeconometric framework to evaluate the impacts of monetary policy on the labor market. This article therefore bridges the vast literature on occupation level analysis of the US labor market and the empirical literature evaluating the policy actions of the Federal Reserve. In doing so, we shed light on the employment dynamics on the US labor market following changes in the effective federal funds rate and help to deepen the understanding of the transmission of conventional monetary policy interventions.

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 as well as Bayesian estimation of the model using Markov Chain Monte Carlo (MCMC) methods. Section 3 thoroughly documents the data set employed in the analysis. In section 4, the effect of monetary policy on several variables of interest, including unemployment in a set of US occupation groups, is presented. 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 the econometric framework to cope with the peculiarities accompanying data that is more granular than the commonly encountered macroeconomic aggregates. For a number of reasons laid out subsequently, a Factor-Augmented VAR (FAVAR) framework is employed.

First, standard macroeconometric analysis using VAR models is usually not able to incorporate large information sets due to overparametrization problems. However, at the same time it is not advisable to confine the model to a relatively small amount of information. When using small information sets, it is rather likely that private sector information that is not present in the analysis becomes a major issue. A classical illustration of this potential shortcoming is the so-called ”price puzzle”. This commonly encountered empirical result suggests that a contractionary monetary policy shock is accompanied by inflation, rather than a decrease in the price level, as standard economic theory would predict. This is most likely due to a missspecified model that does not incorporate data on future expectations about inflation (Sims, 1986; 1992). However, since expectation data is actually available to policy makers, central banks will systematically take expectations into account when conducting monetary policy (Leeper *et al.*, 1996), leading to ultimately puzzling empirical results.

Second, theoretical and vague economic concepts like ”economic activity” or ”prices” are often not ideally captured by a single variable like industrial production or a given consumer price index. In addition, most often a set of variables capturing a similar concept is available. Choosing a single variable out of this set is a rather arbitrary process and most likely increases measurement error, leading to estimation problems. The employed FAVAR approach extracts a small set of factors out of a large data set by capturing comovements among variables describing broadly similar concepts. Thus, the FAVAR avoids the issues outlined above (Stock and Watson, 2012).

Finally, the FAVAR framework has desirable properties when using disaggregated data as proposed in this article. 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 group 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, it would ultimately boil down to an *unconditional* analysis. That is, separately estimating small scale VARs for each occupation group will 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 will result. Further on, estimating separate, small VARs also neglects the possibility of exploiting the strong comovements of various disaggregated unemployment rates. Both issues are comprehensively tackled using the FAVAR approach, thus making it the model of choice for this application.

2.1 General Framework

Let X_t $(t = 1, \ldots, T)$ be a $N \times 1$ vector comprised of non-trending observed economic variables. Let X_t represent a large information set capturing different aspects of an economy, in particular providing extensive knowledge on unemployment on a disaggregated scale. These variables are assumed to contain relevant information on q economic factors, whereby $q << N$, which are not directly observable. Moreover, a set of time series playing the role of observed factors is captured in a $l \times 1$ vector Y_t. In the estimation setup outlined below, the processes we consider as observed factors are industrial production, the unemployment rate, the GDP deflator and the federal funds rate acting as monetary policy target variable. The information set considered in this article is rather large and contains a total of $N = 178$ macroeconomic time-series. The FAVAR model can then be recast in a state-space representation where the measurement equation takes the following form:

$$\begin{bmatrix} X_t \\ Y_t \end{bmatrix} = \begin{bmatrix} \Lambda^f & \Lambda^y \\ 0_{l\times q} & I_l \end{bmatrix} \begin{bmatrix} F_t \\ Y_t \end{bmatrix} + \begin{bmatrix} \eta_t \\ 0_{l\times 1} \end{bmatrix}, \quad \eta_t \sim N_N(0, \Omega), \tag{2.1}$$

where Λ^f and Λ^Y are factor loading matrices with dimension $N \times q$ and $N \times l$, respectively. I_l denotes the identity matrix of dimension l, while $0_{l\times q}$ denotes the zero matrix of dimension $l \times q$. The latent factors are denoted by the q-dimensional vector F_t. The error term η_t is normally distributed with zero mean and variance-covariance matrix $\Omega = \text{diag}(\omega_1, \ldots, \omega_N)$, ultimately translating into N independent regressions. The state equation may be written as

$$\begin{bmatrix} F_t \\ Y_t \end{bmatrix} = \Phi(L) \begin{bmatrix} F_{t-1} \\ Y_{t-1} \end{bmatrix} + \varepsilon_t, \quad \varepsilon_t \sim N_M(0, \Sigma_t), \tag{2.2}$$

where $\Phi(L)$ is the lag polynomial of finite order p and ϵ_t is an error term of dimension $M = l + q$. The variance-covariance matrix Σ_t of the state equation innovations is assumed to evolve over time to capture changes in the second moment of the VAR system. Cogley and Sargent (2005) and Primiceri (2005) conclude that capturing time variation may be important both with respect to the coefficients and the variance-covariance matrix. Nevertheless, both studies point out that modeling time variation in the volatilities is more important than capturing time variation in the coefficients. A natural extension for the FAVAR is hence to include time variation in the coefficients as well (Korobilis, 2013). We abstain from doing so in order to keep the model parsimonious. Following Carriero *et al.* (2019), we use the a simple factorization for the $M \times M$ variance-covariance matrix Σ_t to introduce stochastic volatility:

$$\Sigma_t = L^{-1} D_t L^{-1\intercal}, \tag{2.3}$$

where L_t is a lower-triangular matrix with ones on the main diagonal and D_t is a diagonal matrix $D = \text{diag}\left(\exp(h_{1,t)}, \ldots, \exp(h_{M,t})\right)$. Finally, the log-volatilities are assumed to follow a centered AR(1) process

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

2.2 A Bayesian Approach to Estimation

Estimation is carried out in a Bayesian fashion and a Markov Chain Monte Carlo (MCMC) algorithm is implemented 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. In the following, we discuss our prior choices and sketch the employed algorithm.

In general, recovering the latent factors in a FAVAR setting is possible using two distinct estimation strategies. Most commonly, principal components analysis is used to estimate the unobservable factors. However, a fully Bayesian approach would preferably estimate the factors via Kalman filtering (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. Furthermore, Bernanke *et al.* (2005) argue that the two-step approach based on principal components estimation 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 X_t and Y_t (Stock and Watson, 2002).

To introduce sparsity and reduce noise in the estimates, shrinkage priors are utilized. Hereby, variants of the Normal-Gamma (NG) shrinkage prior in the spirit of Griffin and Brown (2010) are specified for the elements of the factor loading matrices $\Lambda = (\Lambda^f, \Lambda^y)$ and L as well as for the VAR coefficients in $\Phi(L)$. For the sake of brevity, Eq. (2.5) gives the general specification of the NG prior, where $\beta_{i,k}$ denotes a typical element in one of the system matrices indicated with $k \in \{\Lambda, L, \Phi\}$. In the general form, the NG prior can be written as

$$\beta_{i,k} \mid \tau_{i,k} \sim \mathcal{N}(0, 2/\lambda_k^2 \tau_{i,k}), \quad \lambda_k^2 \sim G(c_{j,k}, d_{j,k}), \quad \tau_{i,k} \sim \mathcal{G}(\vartheta_k, \vartheta_k), \tag{2.5}$$

with ϑ_k being a hyperparameter chosen by the researcher. λ_k^2 refers to the *global* and $\tau_{i,k}$ to the *local* shrinkage parameters. The global shrinkage parameters induce shrinkage on specific groups of variables, whereas the local shrinkage parameters induce shrinkage on specific variables (Polson *et al.*, 2012). Some clarifying comments are in order with respect to specific idiosyncrasies in the variants of the NG prior we implement. Following Kastner (2019), a set of row-wise global shrinkage parameters for the factor loadings matrix Λ is specified. This corresponds to a setup where each time series has a high a priori probability to *not* load on any factor. Thus, this prior setting can be thought of as series-specific shrinkage. Concerning the prior for the VAR coefficients, a lag-wise variant of the NG prior outlined in Huber and Feldkircher (2019) is adopted. The main idea here is to specify the global shrinkage parameters such that more shrinkage is introduced on higher order lagged coefficients.

In terms of hyperparameters, we set $\vartheta_k = 0.6$, which induces a moderate amount of shrinkage. The case $\vartheta_k = 1$ corresponds to the Bayesian variant of the LASSO shrinkage prior (Park and Casella, 2008). Lower values of ϑ_k impose stronger shrinkage since this parameter controls the excess kurtosis of the imposed conditional normal distribution of the variables of interest. Huber and Feldkircher (2019) also discuss estimating ϑ_k from the data via an additional, hierarchical structure on this hyperparameter. However, since this calls for the introduction of an computationally rather intensive Metropolis-Hastings-step, we opt for a fixed value of ϑ_k. The hyperparameters of the Gamma prior on λ_k^2 are set to $c_{j,k} = d_{j,k} = 0.01$ in a quite uninformative manner.

The remaining prior choices are standard and thus discussed rather briefly. On the individual variances in the measurement equation, $\Omega = \text{diag}(\omega_1, \ldots, \omega_N)$, an Inverse-Gamma prior is specified for each $\omega_i \sim IG(a_0, b_0)$, where $a_0 = b_0 = 0.01$, for $i = 1, \ldots, N$. Concerning the priors on the time varying state equation variances, we follow Kastner (2016) and specify a Gaussian prior $\mu_i \sim N(b_\mu, B_\mu)$ for the level and a Beta prior $(\phi_i + 1)/2 \sim B(a_1, b_1)$ for the persistence parameter to ensure that $\phi_i \in (-1, 1)$. Finally, a Gamma prior $\sigma_i^2 \sim G(1/2, 1/(2B_\sigma))$ is specified on the volatility of the log-volatilities where $i = 1, \ldots, M$. The associated hyperparameters are again chosen in an uninformative manner, where $b_\mu = 0$ and $B_\mu = 100$ for the level parameter μ_i. For the persistence parameter ϕ_i, we set $a_1 = 5$ and $b_1 = 1.5$, which corresponds to an a priori mean of the persistence of about 0.54 and corresponding variance of 0.6. The choice of the hyperparameter B_σ has only a minor influence in empirical applications and is set to $B_\sigma = 1$.[1] This completes the prior setup.

To conclude, a brief sketch of the posterior sampling procedure is provided. After obtaining an initial estimate for the latent factors F_t using principal components analysis, samples from the conditional Gaussian posterior of the VAR coefficients in $\Phi(L)$ are generated in a straightforward manner. To sample from the posterior distribution of the time varying volatilities of the state equation, we rely on the algorithm developed in Kastner and Frühwirth-Schnatter (2014), available in the R package stochvol (Kastner, 2016). Conditional on knowing the remaining variables, the loadings in Λ represent N independent linear regressions with standard posterior moments.

2.3 Identification

Following Bernanke *et al.* (2005), it is necessary to impose two different sets of restrictions on the system in Eq. (2.1) and Eq. (2.2). The first set is concerned with the identification of the factor model, where a minimum set of normalization restrictions on the observation equation in Eq. (2.1) is needed to identify the model. Furthermore, identifying the monetary policy shock requires additional restrictions on the variance-covariance matrix of the transition equation Eq. (2.2).

The assumptions that Ω is diagonal and $\mathbb{E}[\eta_t, \varepsilon_t] = 0$ are not sufficient to identify the model in Eq. (2.1). Assume that $\hat{\Lambda} = (\hat{\Lambda}^f, \hat{\Lambda}^y)$ and $\hat{f}_t = (\hat{F}_t^\intercal, \hat{Y}_t^\intercal)^\intercal$ is a solution to the estimation problem. Then, for any nonsingular $M \times M$ matrix H, there is an observationally equivalent model such that $\tilde{\Lambda} = \hat{\Lambda}H$ and $\tilde{f}_t = H^{-1}\hat{f}_t$ holds. In order to identify the model we have to choose a nonsingular matrix H. Since it consists of M^2 elements, we also need M^2 identifying restrictions to pin down Λ and f_t. In the literature on dynamic factor models (Kaufmann and Schumacher, 2017), a fairly often encountered standard identification scheme sets the upper diagonal elements of the $M \times M$ leading matrix in Λ to zero, which provides $M(M-1)/2$ restrictions. If, additionally, Σ_t is set to the identity matrix, $\Sigma_t = I_M$, another $M(M+1)/2)$ restrictions are set. We deviate from this approach to identify the full variance-covariance matrix Σ_t in the transition equation. This is important since we are interested in structural analysis and contemporaneous relationships are captured in the variance covariance matrix Σ_t. We follow Bernanke *et al.* (2005) and set the upper $q \times q$ block of Λ^f to an identity matrix and the upper $q \times l$ block of Λ^y to zero. This set of restrictions is sufficient for identification of the FAVAR model.

The second issue deals with identification of the monetary policy shock. We assume a recursive structure where all factors respond with a lag to a change in the monetary policy instrument, ordered last in Y_t. Therefore, the main assumption is that unobserved factors do not respond within a quarter to monetary policy shocks. 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

[1] This corresponds to the standard values suggested in the R package stochvol that is utilized for estimating the model.

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.[2]

Similar to Bernanke *et al.* (2005) and subsequent contributions using FAVAR models, we rely on a two-step estimation approach using principal components without explicitly imposing Y_t as being observable in the first step.[3] Principal components consistently recover q independent, but arbitrary, linear combinations of F_t and Y_t. Therefore, any linear combination of the space spanned by the information set could involve information contained in Y_t. Thus, it is not valid to estimate the VAR in F_t and Y_t and identify the shock recursively. It is necessary to remove the dependence of F_t on Y_t prior to estimation. To achieve this, the following regression is estimated

$$F_t^{PCA} = b_{F0} F0_t^{PCA} + b_Y Y_t + e_t, \qquad e_t \sim N(0, \sigma_f^2), \tag{2.6}$$

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.

3 Data

This section is dedicated to a detailed data set description. After providing information on the occupation level unemployment data base, we move over to a discussion of the remaining macroeconomic variables included in the estimation process.

The unemployment data for the analysis outlined below 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 part of the survey each month. This survey data has led to a tremendous amount of research, providing highly relevant insights in a broad variety of social sciences. All data files are available online and provided in readily available form through IPUMS-CPS (Flood *et al.*, 2018).

For the present paper, we focus on individuals that are between 15 and 64 years of age and are part of the labor force. 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

[2] The classification of slow- and fast-moving variables can be found in App. B.

[3] A slightly different approach is chosen by Boivin *et al.* (2009), who directly impose this restriction. However, they point out that the results of both their approach and the approach outlined here are very similar.

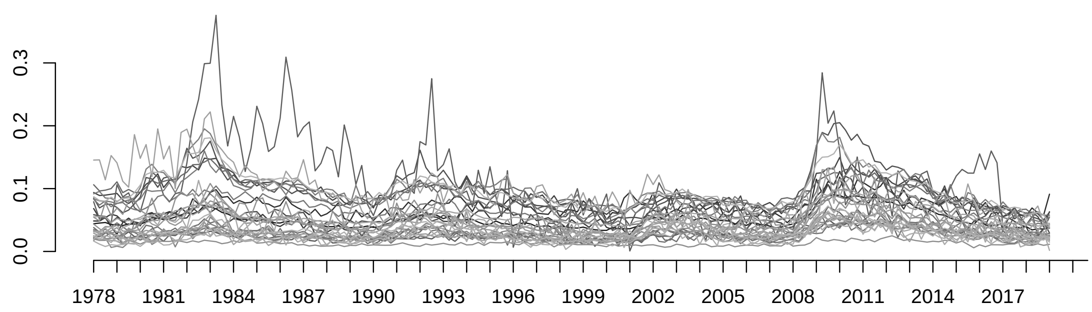

Figure 1: Deseasonalized occupation level unemployment rates over time. Each line corresponds to one of the 32 occupation groups under analysis.

to exploit a consistent long-term classification of occupations and is commonly encountered in related works such as Autor and Dorn (2013) or Gaggl and Kaufmann (2019). These 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 unemployment rates are computed. All unemployment time series are deseasonalized prior to analysis. The resulting data set includes unemployment rates for 32 occupation groups in 164 quarters covering 1978Q1 to 2019Q1. App. A 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 [0.028, 0.074] with an average of 0.054. A staggering 99% of observations lie between 0.010 and 0.169. Only a very small number of observations takes more extreme values such that the minimum unemployment rate is 0.001 whereas the maximum observed unemployment rate is 0.376. Lowest average unemployment is observed for the group of ”Medical Professionals” whereas mean unemployment is highest for workers in the extractive sector. A first impression of the occupation group unemployment rates is provided in Fig. 1. Most occupations exhibit a rather common pattern across time. Interestingly, occupations related to extractive activities such as miners and explosive workers seem to evolve differently and show extensively high unemployment rates during certain time periods.

In general, it has to be noted that aggregating data to the occupation level is a somewhat arbitrary choice. In principle, it is possible to use other target variables to aggregate individual employment data from the CPS.[4] However, we choose the occupation level as it is arguably an aggregation level

[4] For instance, Thorbecke (2001) and Carpenter and Rodgers III (2004) use aggregated employment data based on educational attainment, among other variables.

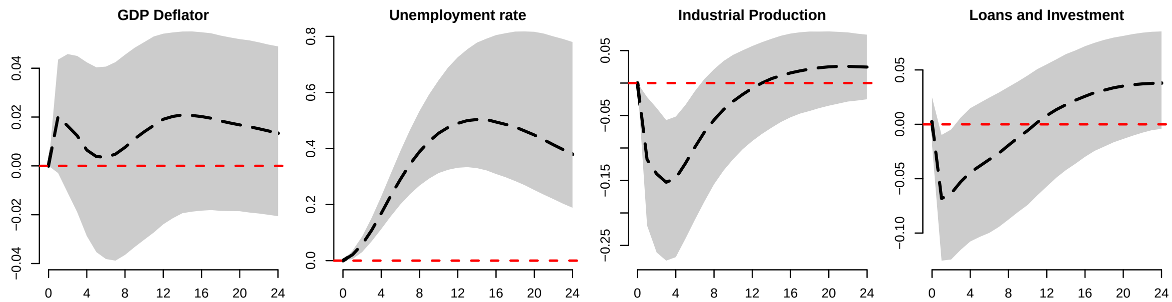

Figure 2: Impulse response functions of selected macroeconomic aggregates following an unexpected monetary policy innovation of 100bp. The dashed lines corresponds to the posterior median while the grey area gives the 16/84 highest posterior density interval.

specifically relevant to policy makers. Furthermore, the direct connection to the vast literature on labor market dynamics in the US makes the occupation level a sensible choice.

To obtain a large macroeconomic information set for analysis, we compile quarterly macroeconomic indicators based on the data set outlined in Korobilis (2013). We extend the data to the first quarter of 2019 and add some variables of interest. In total, a set of 150 macroeconomic variables is compiled for the subsequent analysis. These series describe the most important aspects of the US economy and include, among others, real activity measures, interest rates, financial market variables and price data. In general, we expect that the vast majority of information on US macroeconomic behavior is spanned by this information set. When necessary, the series are seasonally adjusted and appropriately transformed to ensure (approximate) stationarity. Afterwards, the data is demeaned and standardized before extracting the factors. A detailed description of the dataset and the applied transformations can be found in App. B.

4 Monetary Policy & Unemployment

The Gibbs sampler outlined in Sec. 2 is iterated 20,000 times where the first 10,000 iterations are discarded as burn-in phase. Every second draw is kept for further analysis to reduce autocorrelation of the posterior draws. In line with Primiceri (2005) and Korobilis (2013), the main results presented here correspond to a model specification with two lags and three latent factors. However, experimenting with different specifications suggests that the model is not very sensitive to the lag order and the number of factors. We proceed to present the main FAVAR estimation results in three steps. First, the impulse response functions (IRFs) of some classical macroeconomic aggregates to an unexpected tightening of monetary policy are discussed. In a second step, the focus lies on the IRFs of selected labor market aggregates. Finally, the reaction of unemployment within 32 occupation groups is presented.

To analyze the reaction of the variables of interest following monetary policy innovations, a simulated 100 basis point increase of the effective federal funds rate is imposed upon the estimated FAVAR framework. Fig. 2 provides the resulting reactions of a set of classical macroeconomic

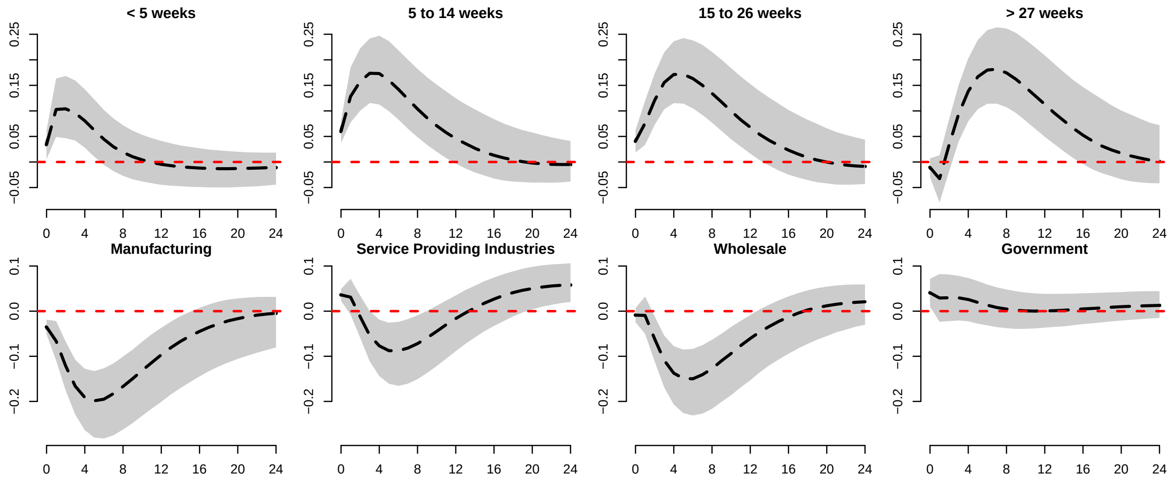

Figure 3: Impulse response functions of various labor market aggregates following an unexpected monetary policy innovation of 100bp. Upper row: Unemployment headcounts for different unemployment durations. Bottom row: Employment headcounts in different sectors of the economy. The dashed lines corresponds to the posterior median and the grey area gives the 16/84 highest posterior density interval.

aggregates. The results of this empirical analysis are similar to the findings in related literature: Monetary tightening leads to decreasing investment and therefore to decreasing real activity. With reduced real activity, unemployment rises. These aggregate findings are also in line with the predictions standard theoretical macroeconomic frameworks offer. Interestingly, the response of the GDP deflator does not correspond to classical theoretical predictions.[5]

A careful look on the response of various labor market variables following the simulated monetary tightening is crucial for the further analysis laid out in this article. While the significant reaction of aggregate unemployment is promising, a more specific focus on relevant labor market measures is in order before discussing the results within the respective occupational groups. This gives an insight into how well the model is able to capture overall labor market dynamics and is supposed to underline the credibility of the reported findings.

The resulting labor market IRFs, depicted in Fig. 3, are split into two groups. The first group in the upper row gives 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 clearly that monetary tightening increases unemployment, irrespective of the specific duration that an individual has already spent in unemployment. The rate of long-term unemployed (> 27 weeks) shows a short but pronounced drop on impact, which may be explained through long-term unemployed individuals actually leaving the labor

[5] This is most likely due to the small number of expectation time series included in the macroeconomic data set at hand, ultimately leading to the insignificant price reaction discussed in Sec. 2. Theoretically, the inclusion of more time series on expectations is likely to improve the reaction of prices, compare for instance the data set and results in Korobilis (2013). However, in practice, many expectation variables included in Korobilis (2013) stem from a restricted access database and are therefore not included in the present version of this paper.

force following monetary tightening. The second group of IRFs in the bottom row corresponds to the response 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. It is interesting to note that government employment shows a muted reaction and seems to be largely unaffected by monetary policy interventions. This comes at no surprise as government spending and employment in the public sector is unlikely to react to changing interest rate environments. These first findings can be summarized as follows: the labor market effects of monetary policy do strongly and significantly stand when investigating beyond the aggregate level. Besides weak effects on government employment, monetary policy appears to have rather homogeneous effects along the sectoral dimension and across various unemployment duration groups.

In a final step, we will now proceed to increase the level of granularity even further and focus on the labor market reactions to a monetary policy shock on the occupational level. Fig. 4 depicts the IRFs of unemployment within 32 occupational groups following the simulated interest rate hike discussed above. Two interim conclusions can be drawn from this figure: First, it is striking that monetary policy has effects on employment in most of the analyzed occupation groups. The occupation groups that show significant reactions account for, on average, more than 75% of individuals in the US labor force. This is in line with the vast majority of literature suggesting that monetary policy has indeed effects on real activity and therefore on aggregate unemployment measures. Second, despite strong impacts on most occupation groups, a large degree of heterogeneity can be observed. 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 summary, the results of this empirical exercise have shown that interest rate changes exert strong labor market effects, in line with empirical and theoretical literature suggesting real economic effects following monetary policy changes. However, the degree of ”vulnerability” to interest rate hikes varies across occupation groups. In the next section, we therefore shed some 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 Monetary policy, automatization & offshoring

In this section, we discuss the heterogeneous impact that monetary policy has on the occupation level. The aim of this analysis is to reveal possible occupation characteristics that predict the sensitivity of employment to interest rate hikes within occupational groups. For this, we try to stay close to the vast literature on US labor market dynamics on an occupational level. Following Autor *et al.* (2003), Dorn (2009), Acemoglu and Autor (2011) and Autor and Dorn (2013), we expect task profiles of

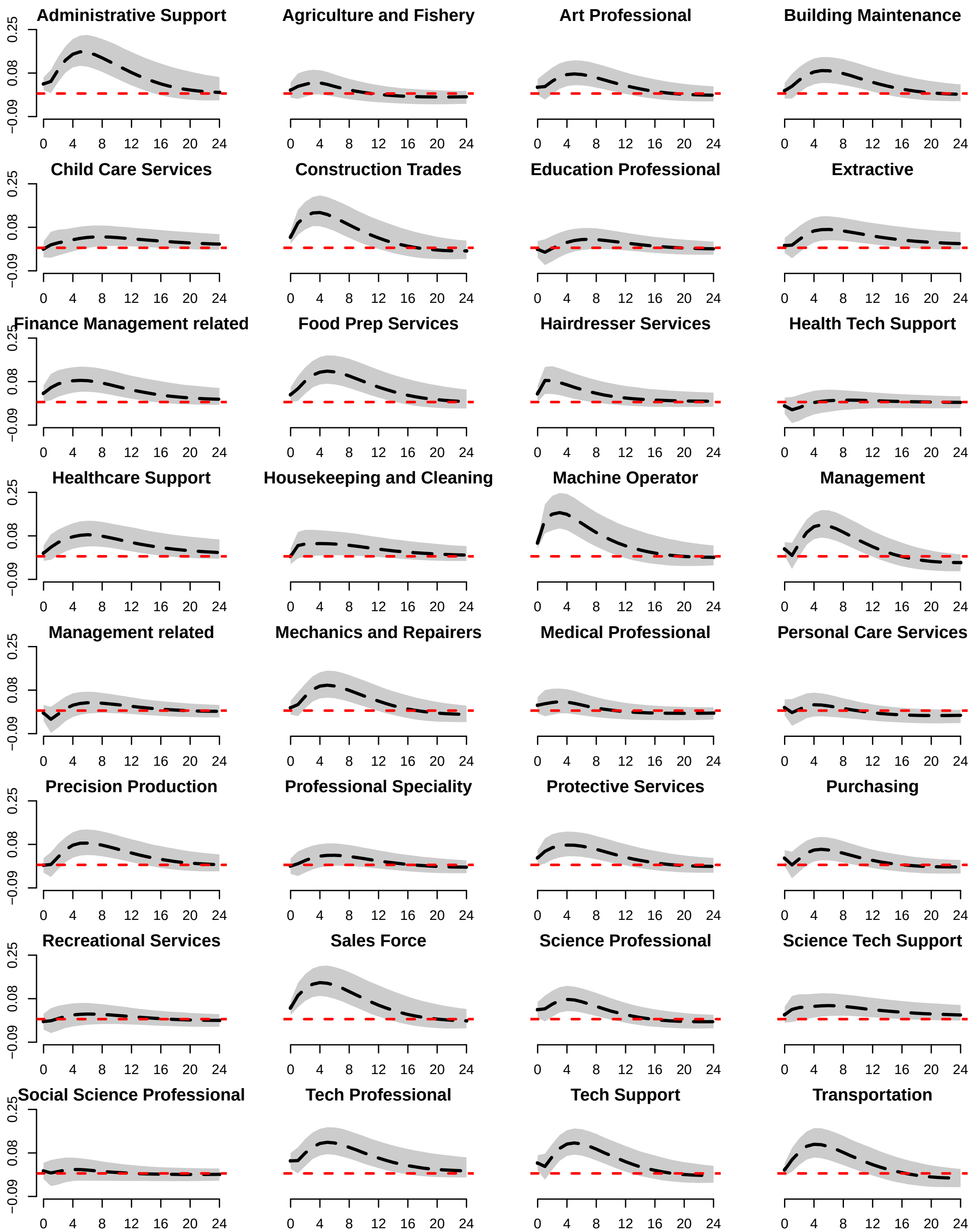

Figure 4: Impulse response functions of unemployment in 32 occupational groups following an unexpected monetary policy innovation of 100bp. The dashed lines corresponds to the posterior median and the grey area gives the 16/84 highest posterior density interval.

occupations to be highly relevant when analyzing an occupation's reaction to economic fluctuations. Two specific characterizations of occupation task profiles are promising candidates that might help to explain the empirical results in Sec. 4: the amount of routine tasks and potential offshorability of a given occupation group. Therefore, these characteristics and their relevance will be discussed in further detail subsequently.

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, as high skill jobs usually involve mostly *abstract* tasks whereas low skill jobs involve a large amount of *manual* tasks. A main feature of routine tasks is that they might similarly be performed by a suitable computer or robot. Hence, the amount of routine tasks in an occupation is an important measure in labor economics because it provides insights into the likelihood of an occupation being automatized. Obviously, occupations featuring a high degree of repetitive, routine tasks have a higher probability of reallocating into unemployment or other occupations due to automatization.

Similarly, the *degree of 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 actually 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 foreign workforce and reallocate into unemployment or occupations with a lower degree of offshorability.

To facilitate understanding and provide a business world narrative we would like to draw attention to two specific groups of workers: clerks & cleaners. Consider the example of office clerks. A commonly encountered task profile of clerks consists of typing documents and filling in records. In general, these tasks are standardized, well-defined and therefore have an increased probability of automatization. Similarly, these tasks may not be directly tied to specific workplaces and could therefore be easily outsourced. On the other side of the spectrum, consider the occupation group of cleaners. Their task profile typically consists of non-automatizable duties. In addition, cleaners are usually completely confined to on-site work. As a result, the degree of offshorability and automatization is rather low for this occupation group.

Hence, the specific task structure within occupation groups is an important predictor of the dynamics of these occupation groups following medium-term and long-term labor market developments. 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 and after four quarters is utilized to measure the instantaneous impact of monetary policy and the effect after one year. In addition, we compute the maximum of the median impulse response function as well as the cumulative effect as two further measures of the reaction

Table 1: The effect of occupation characteristics on the impact of monetary policy.

	IRF On Impact (1)	IRF One Year (2)	IRF Maximum (3)	IRF Cumulative (4)
Routine Tasks	0.004	0.010	0.010	0.130
	(0.002)	(0.004)	(0.004)	(0.041)
Offshorability	0.006	0.017	0.016	0.209
	(0.004)	(0.008)	(0.008)	(0.085)
Abstract Tasks	0.0005	−0.007	−0.007	−0.087
	(0.002)	(0.004)	(0.004)	(0.042)
Manual Tasks	−0.001	−0.001	−0.005	−0.051
	(0.004)	(0.009)	(0.010)	(0.102)
Constant	0.003	0.053	0.069	0.486
	(0.011)	(0.025)	(0.026)	(0.270)
N	32	32	32	32
R^2	0.234	0.296	0.297	0.379

Notes: Standard errors in parentheses.

of each occupation group.[6] These four measures are used as dependent variables in four separate linear regressions with the goal of disentangling possible channels behind the heterogeneous responses presented in the empirical exercise in Sec. 4, shown in Fig. 4.

The task structure of each occupation group is operationalized corresponding to the data compiled and analyzed in Autor and Dorn (2013). Following Autor *et al.* (2003), 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.[7] These measures are then used as explanatory variables to disentangle the impact monetary policy has on unemployment within occupation groups.

[6] The cumulative effect is computed as the cumulative sum of the median impulse response over all ”significant” periods where ”significant” indicates that zero is not included in the 16/84 highest posterior density interval. The results are robust to using the cumulative effect over the full impulse response horizon.

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

The results of this exercise are provided in Tab. 1. Although there is no visible pattern with respect to the effect on impact, a few interesting observations can be made regarding the overall strength of the reactions to monetary policy. A rather robust observation is that the amount of routine tasks as well as the degree of offshorability have strong and positive impacts on the effect that interest rate hikes have on unemployment within occupation groups. No significant relationship can be established between effect sizes and the amount of manual tasks within an occupation group. Occupations with a largely abstract task profile, corresponding mostly to high-skill jobs, show significantly smaller effect sizes compared to the average. From a purely econometric point of view, this means that occupation groups that are easy to offshore or have tasks that are largely based on routine activities are hit more strongly following unanticipated interest rate hikes. Prime examples include for instance the group of ”Mechanics & Repairers” that show the highest amount of routine tasks within our sample. Similarly, individuals working in ”Tech Support” occupations, corresponding to e.g. programmers or software developers exhibit a high degree of offshorability.

The channels at work behind these results are rather intuitive and in line with other common findings in literature, already briefly outlined above. Blanchard (1995) was one of the first to mention that, in general, it is important to differentiate between different degrees of vulnerability in a given population when analyzing the effects of macroeconomic shocks. Thorbecke (2001) and Carpenter and Rodgers III (2004) show in early empirical studies that vulnerable labor market groups such as minorities are hit disproportionately hard by monetary policy. Autor *et al.* (2003), Autor and Dorn (2013) and Cortes *et al.* (2017) argue that specifically occupation groups characterized by high degrees of offshorability and a large amount of routine tasks are highly vulnerable to certain structural developments on the labor market, most prominently including automatization and globalization. Our results connect to this literature as they show that not only medium-term and long-term developments, but also short-term economic shocks such as interest rate hikes can disproportionately affect occupational groups with routine or easily offshorable task profiles. Following monetary shocks that dampen real activity, these occupation groups are likely to reallocate into unemployment.

Workers that attend to routine or easily offshorable tasks might thus play a special role when investment decisions are made. From the perspective of a firm, these workers are easy to replace by cheaper labor in foreign countries, by robots or by computers. When a firm makes decisions with respect to investment and therefore employment, two distinct paths may be taken. On the one hand, firms could decide to keep the relatively expensive workers performing routine or offshorable tasks. On the other hand, a firm could have the same tasks accomplished through the relatively cheaper options of automatization and offshoring. Assuming cost-minimizing firms, it is likely that workers in occupation groups that are characterized by routine tasks and a high degree of offshorability will lose out in this competition. From a theoretical point of view, we thus conclude that a significant fraction of the heterogeneous impact of monetary policy on the labor market is likely due to task-biased changes in investment behavior following interest rate changes. That is, new investment created via monetary policy easing is unlikely to be targeted towards occupational groups with routine tasks or groups with a high degree of offshorability. Similarly, if companies have to reduce investment due to monetary policy tightening, it is rather likely that the first group to be hit are individuals within routine and offshorable occupation groups.

6 Concluding remarks

In this paper, we link a broad dataset of macroeconomic variables to disaggregated labor market data extracted from the US current population survey (CPS). This allows us to explore the effect that unexpected 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 a large amount of variables, including 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, by choosing a FAVAR approach it is possible to capture essential dynamics between occupation groups.

The results on the aggregate level corroborate both the findings of previous literature and suggestions of theoretical frameworks. The main findings can be summarized as follows. First, an unexpected increase of the federal funds rate (i.e. a contractionary monetary policy shock) tends to sharply decrease 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. However, the results on the occupational level reveal a more heterogeneous picture. First, not all occupations experience a significant increase of unemployment. Second, heterogeneity with respect to the magnitude and persistence of reactions can be observed to a certain extent.

As an explanation, we rely on previous studies about the vulnerability to automatization and offshoring linked to specific job characteristics. The main findings concentrate on particularities in the task profile of occupation groups. Specifically, we find that the amount of routine tasks as well as the potential to offshore certain professions are predictors of the effectiveness of monetary policy in this occupation group. The easier a certain job can be outsourced, the higher is the reaction to a monetary policy shock. Moreover, occupations which consist predominately of well-defined, standardized and repetitive tasks react significantly stronger than occupation groups featuring e.g. a mostly abstract task profile. We conclude that this heterogeneous picture is the results of task-biased changes in investment behavior following monetary policy interventions. New investment is not directed to occupations that can be easily automatized or offshored. Vice versa, these occupations are disproportionately likely to be hit when investment is reduced following monetary tightening.

This finding and the suggested theoretical channel have to be underpinned by thorough empirical analysis into investment behavior on a microeconomic level, which would be an interesting avenue for further research. In addition, it would be interesting to explore whether similar patterns hold with respect to the vulnerability of specific occupations to other types of macroeconomic distortions, such as oil price or uncertainty shocks. Generally speaking, we are confident that the use of readily available disaggregated data and the application of macroeconometric frameworks to microeconomic data sets may be an important source of new insights into the functionality of the economy in the future.

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

B Macroeconomic data tables

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 averaging the monthly values to a quarter. 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 – logarithm; 5 – first difference of logarithm. We use the same classification for *slow-moving* (Scode=1) and *fast-moving* (Scode=0) variables as in Bernanke *et al.* (2005). 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	5	1
12	W068RCQ027SBEA	Government total expenditures	5	1
13	W006RC1Q027SBEA	Federal government current tax receipts	5	1
14	SLINV	State and Local Government Gross Investment	5	1
15	SLEXPND	State and Local Government Current Expenditure	5	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	5	1
23	PCES	Personal Consumption Expenditure: Servcies	5	1
24	PCEDG	Personal Consumption Expenditure: Durable Goods	5	1
25	PCEND	Personal Consumption Expenditure: Nondurable Goods	5	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	1	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	5	1
42	MANEMP	All Employees: Manufacturing	5	1
43	SRVPRD	All Employees: Service-Providing Industries	5	1
44	USTPU	All Employees: Trade, Transportation and Industries	5	1
45	USWTRADE	All Employees: Wholesale Trade	5	1
46	USTRADE	All Employees: Retail Trade	5	1
47	USFIRE	All Employees: Financial Activities	5	1
48	USEHS	All Employees: Education and Health Services	5	1
49	USPBS	All Employees: Professional and Business Services	5	1
50	USINFO	All Employees: Information Services	5	1
51	USSERV	All Employees: Other Services	5	1
52	USPRIV	All Employees: Total Private Industries	5	1
53	USGOVT	All Employees: Government	5	1
54	USLAH	All Employees: Leisure and Hospitality	5	1
55	AHECONS	Average Hourly Earnings: Construction	5	1
56	AHEMAN	Average Hourly Earnings: Manufacturing	5	1
57	AHETPI	Average Hourly Earnings: Total Private Industries	5	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	CMDEBT	Household Sector: Liabilities: Household Credit Market Debt Outstanding	5	0
72	BUSLOANS	Commercial and Industrial Loans at All Commercial Banks	5	0
73	CONSUMER	Consumer (Individual) Loans at All Commercial Banks	5	0
74	LOANS	Total Loans and Leases at Commercial Banks	5	0
75	LOANINV	Total Loans and Investments at All Commercial Banks	5	0
76	INVEST	Total Investments at All Commercial Banks	5	0
77	REALLN	Real Estate Loans at All Commercial Banks	5	0
78	AMBSL	Board of Governors Monetary Base, Adjusted for Changes in Reserve Requirements	5	0
79	NONBORRES	Non-Borrowed Reserves of Depository Institutions	5	0
80	REQRESNS	Required Reserves, Not Adjusted for Changes in Reserve Requirements	5	0
81	RESBALNS	Reserve Balances with Fed. Res. Banks, Not Adj. for Changes in Reserve Req.	5	0
82	BORROW	Total Borrowings of Depository Institutions from the Federal Reserve	5	0
83	M1SL	M1 Money Stock	5	0
84	CURRSL	Currency Component of M1	5	0
85	CURRDD	Currency Component of M1 Plus Demand Deposits	5	0
86	DEMDEPSL	Demand Deposits at Commercial Banks	5	0
87	TCDSL	Total Checkable Deposits	5	0
88	M2SL	M2 Money Stock	5	0
89	M2OWN	M2 Own Rate	5	0
90	M2MSL	M2 Minus Small Time Deposits	5	0
91	M2MOWN	M2 Minus Own Rate	5	0
92	MZMSL	MZM Money Stock	5	0
93	SVSTCBSL	Savings and Small Time Deposits at Commercial Banks	5	0
94	SVSTSL	Savings and Small Time Deposits - Total	5	0
95	SVGCBSL	Savings Deposits at Commercial Banks	5	0
96	SVGTI	Savings Deposits at Thrift Institutions	5	0
97	SAVINGSL	Savings Deposits - Total	5	0
98	STDCBSL	Small Time Deposits at Commercial Banks	5	0
99	STDTI	Small Time Deposits at Thrift Institutions	5	0
100	STDSL	Small Time Deposits - Total	5	0
101	USGVDDNS	US Government Demand Deposits and Note Balances - Total	5	0
102	USGDCB	US Government Demand Deposits at Commercial Banks	5	0
103	CURRCIR	Currency in Circulation	5	0

Table B4: Interest Rates

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

Table B5: Prices

#	Mnemonic	Description	Tcode	Scode
118	GDPDEF	Gross Domestic Product: Implicit Price Deflator	5	1
119	GDPCTPI	Gross Domestic Product: Chain-type Price Index	5	1
120	PCECTPI	Personal Consumption Expenditures: Chain-type Price Index	5	1
121	PPIACO	PPI: All Commodities	5	1
122	WPU0561	PPI by Commodity for Fuels and Related Products and Power: Crude Petroleum	5	1
123	WPUFD4111	PPI: Finished Consumer Foods	5	1
124	WPUFD49502	PPI: Finished Consumer Goods	5	1
125	WPSFD41311	PPI: Finished Consumer Goods Excluding Foods and Energy	5	1
126	WPSFD49207	PPI: Finished Goods	5	1
127	WPSFD41312	PPI: Finished Goods: Capital Equipment	5	1
128	PPIENG	PPI: Fuels and Related Products, Power	5	1
129	PPIIDC	PPI: Industrial Commodities	5	1
130	WPSID61	PPI by Commodity for Intermediate Demand by Commodity Type: Processed Goods for Intermediate Demand	5	1
131	CPIAUCSL	CPI for All Urban Consumers: All Items	5	1
132	CPIUFDSL	CPI for All Urban Consumers: Food	5	1
133	CPIENGSL	CPI for All Urban Consumers: Energy	5	1
134	CPILEGSL	CPI for All Urban Consumers: All Items Less Energy	5	1
135	CPIULFSL	CPI for All Urban Consumers: All Items Less Food	5	1
136	CPILFESL	CPI for All Urban Consumers: All Items Less Energy and Food	5	1
137	WTISPLC	Spot Oil Price: West Texas Intermediate	5	1

Table B6: Expectations

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