The Distributional Effects of Oil Shocks*

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Abstract

Negative oil supply shocks since the 1980s have increased German inflation and reduced aggregate economic activity, and prompted moderate monetary tightening to counter these inflationary effects. Using 45 years of high-frequency German administrative data, we find that these shocks disproportionally harm low-income individuals: their earnings growth falls by two percentage points two years after a 10-percent exogenous oil price rise, while high-income individuals are largely unaffected. Job-finding probabilities for low-income workers also decline significantly. This contrasts with the distributional effects of monetary policy shocks, which, while also stronger at the bottom, primarily impact job-separation probabilities. To understand the role of monetary policy in shaping these outcomes, we analyze counterfactual scenarios of policy non-response. Because the actual policy response to oil shocks involves an initial rate rise followed by a fall, a fully anticipated non-response (estimated following McKay and Wolf, 2023) leaves the oil shock's aggregate and distributional effects little changed.. When monetary policy repeatedly surprises by not reacting (following Sims and Zha, 2006), in contrast, the implied initial monetary loosening dominates, boosting activity, inflation, and particularly employment prospects for low-income individuals.

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1 Introduction

The economic challenges of the early 2020s, such as supply-chain disruptions following the COVID-19 pandemic and sudden commodity price spikes triggered by Russia's invasion of Ukraine, have reignited debates on how supply-side shocks propagate and affect different segments of society. While the distributional effects of demand-side shocks, particularly monetary policy, are increasingly understood (e.g., Broer et al., 2022), the distributional consequences of supply-side shocks remain less explored. This paper fills this gap by studying how oil supply shocks affect labor market outcomes across the income distribution, leveraging nearly half a century of granular administrative data from Germany.

Identifying supply shocks and their distributional implications is challenging, requiring robust identification strategies and high-frequency, long-run panel data. We address this challenge by focusing on exogenous oil supply shocks that move a key input price to Western economies—that of oil (Känzig, 2021)—and leveraging 45 years of high-frequency German administrative data on worker earnings and employment. Our primary contribution is to provide novel evidence on the heterogeneous labor market consequences of oil shocks across the income distribution. We then uniquely contrast these with the distributional effects of monetary policy shocks in Germany, elucidating differing transmission channels. Finally, we investigate the role of Germany's systematic monetary policy response in shaping the ultimate impact of oil shocks.

First, we confirm the textbook view of supply shocks: an increase in the oil price significantly increases inflation and reduces aggregate activity in the German economy. Next, we find significant and persistent negative effects of oil price increases on employment stability, job-finding probabilities, and earnings of German workers. Importantly, this contractionary effect on the labor market disproportionately harms workers at the lower end of the income distribution. Specifically, a small estimated negative effect of oil price increases on the average earnings of employed individuals is dominated by the small effects of oil prices on the income-rich. Earnings of individuals at the bottom of the income distribution, in contrast, decline substantially more, by about two percentage points two years after a 10 percent increase in the oil price. The probabilities of job-finding and of (future) employment for the currently employed also decline substantially more at the bottom of the distribution (although the effects are imprecisely estimated for the latter). In contrast, while monetary contractions also affect low-income individuals more, their impact is primarily through separation probabilities (Broer et al., 2022). We complement our previous estimates with an analysis of the distributional impacts of monetary policy shocks before Germany acceded to the European Monetary Union. We find monetary policy shocks during the Bundesbank period (Cloyne et al., 2022) have a more homogeneous impact on German labor-market outcomes. By directly comparing the impacts of oil supply shocks to those of monetary policy shocks, we thus elucidate similarities and differences in how demand and supply shocks affect employment, job transitions, and earnings growth.

Our empirical analysis also reveals the systematic monetary policy response to oil shocks. We find that, on average, policymakers in Germany responded to negative oil supply news and its inflationary consequences with a moderate increase in interest rates in the short run, followed by lower interest rates later. Armed with our estimates of the effects of monetary policy innovations as well as oil supply news, we take a step towards identifying the impact of oil shocks in the absence of such monetary contraction. How this is best done depends on the particular policy scenario one is interested in: on the one hand, policymakers might be interested in the economy's path should they decide to keep delaying their monetary response indefinitely, implying repeated surprises of non-reaction. Alternatively, they might want to know what path the economy would take if they were to credibly commit to not reacting to oil shocks ex-ante. We examine these two policy scenarios by employing the methodologies of Sims and Zha (2006) and McKay and Wolf (2023), respectively.

These two counterfactual scenarios yield distinct insights: A credible commitment to not responding (the McKay and Wolf (2023) scenario) eliminates both the short-run tightening and the eventual easing of monetary policy, with overall small effects on the baseline path of activity and a moderate, delayed increase in that of inflation. A continued, surprising delay of the monetary response (the Sims and Zha (2006) scenario), in contrast, means that while the immediate tightening is offset, the expectation of eventual policy easing (characteristic of the actual oil shock response) persists. This results in a substantially less contractionary impact of the oil shock on activity, and a substantially stronger inflationary effect. Consequently, the heterogeneous effects of oil shocks along the income distribution remain largely unchanged under a credible, anticipated non-response. Repeatedly delaying the response (the Sims and Zha (2006) scenario), however, dampens these adverse distributional effects, particularly for employment probabilities in the bottom half of the income distribution.

Related Literature

Our study relates, first, to previous work on the aggregate and individual-level effects of oil shocks. Many studies have tried to overcome the endogeneity problem arising from the response of oil prices to economic conditions, mostly using structural-vector-regression techniques (see Zhou (2020) for a recent contribution and a survey of the literature). Känzig (2021) investigates how news about oil supply, identified from high-frequency price changes around OPEC-announcements, affect the U.S. economy. He shows, using a vector autoregression (VAR) model, that U.S. aggregate activity falls and inflation rises in response to an increase in the price of oil. Relatedly, Känzig (2023) shows that carbon-price induced energy-price increases reduce aggregate activity in the EU. Further, he finds that, in UK data, they particularly reduce consumption of poor-income households, whose consumption baskets feature a higher share of energy. Relatedly, Pieroni (2023) and Labrousse and Perdereau

(2023), among others, theoretically study the heterogeneous incidence of, respectively, energy shocks and carbon taxation, in dynamic general-equilibrium models with heterogeneous consumers.

Second, our study contributes to a growing literature on the distributional effects of aggregate shocks. Much of this literature has focused on monetary policy, including our own previous work (Broer et al., 2022). That study uses the same dataset as the present paper to investigate the incidence of monetary policy along the income distribution in Germany during the ECB period.[1] Four contemporaneous papers—Holm et al. (2021), Andersen et al. (2023), Amberg et al. (2022) and Hubert and Savignac (2024) investigate this question for the cases of Norway, Denmark, Sweden, and France, respectively.

Two contemporaneous papers study the distributional consequences of oil shocks, Drossidis et al. (2024) and Del Canto et al. (2023). While Drossidis et al. (2024) also examine the distributional effects of Känzig (2021)'s oil-supply news using U.S. data, our study differs by focusing on German labor market earnings and transitions, directly comparing oil and monetary policy shock incidence, and analyzing counterfactual policy responses within the German context.[2] Del Canto et al. (2023) study the welfare effects of oil shocks throughout the distribution of households and find the oil-shock induced fall in equity prices to be an important determinant of its welfare effects. What sets our paper further apart is the comparison of the distributional effects of monetary policy and oil shocks. While both shocks affect the bottom of the income distribution more strongly, we demonstrate that the incidence of oil shocks is substantially heterogeneous, both for earnings among the employed and for transitions in and out of unemployment. The heterogeneous incidence of monetary policy shocks, in contrast, is concentrated in the probability of transitioning into unemployment.

Finally, our results relate to the literature that aims at separating the direct effects of supply shocks from those due to any monetary response. Following Sims and Zha (2006) (first published as a working paper 10 years earlier), Bernanke et al. (1997) study the effect of oil shocks (identified using the "net oil price increase" suggested by Hamilton (1996)) under a counterfactual scenario where monetary policy repeatedly surprises economic agents by not responding.[3] They find that much of the recession that follows oil-shocks is due to a contractionary monetary response (and could thus have been avoided with more expansionary policy). Their approach has been criticised by, e.g., Hamilton and Herrera (2004) as not being robust to the Lucas (1976)-critique that private-sector decision rules would change in response to an altered monetary policy reaction. Related, Kilian (2009) argues that the main

[1]See also Groiss (2023) for a similar analysis.

[2]We thank a referee for drawing our attention to this relevant paper. They also employ a different empirical method (they use a factor-augmented VAR with oil-supply news as an external instrument) and focus only on attached workers covered by Blanchet et al. (2022)'s distributional accounts).

[3]In contrast to Sims and Zha (2006), Bernanke et al. (1997) allow the counterfactual federal-funds rate shocks to affect the market interest rates that affect economic activity and inflation. Antolin-Diaz et al. (2021) provide a general framework for conditional forecasts based on structural VARs and discuss the link between conditioning paths for endogenous variables and the future structural shocks consistent with these.

episode underlying Bernanke et al. (1997)'s result, the oil shock in the late 1970s, coincides with the major change in monetary policy regime when Paul Volcker became chairman of the board of governors. Finally, Kilian (2009) argues that oil-price-based measures as those used by Bernanke et al. (1997), confound supply and demand factors.

To adress the Lucas (1976)-critique without a fully structural model, McKay and Wolf (2023) and Caravello et al. (2024) have shown how one can describe (conditional and unconditional) economic fluctuations under counterfactual policy rules based on VAR evidence. They use the shocks to U.S. monetary policy identified, respectively, by Romer and Romer (2004) and Gertler and Karadi (2015) together with simulated effects of oil shocks on the U.S. economy to estimate their effects under a counterfactual policy. Castelnuovo et al. (2024) use this methodology to study the monetary-policy response to several commodity-price shocks including oil. Contrary to Bernanke et al. (1997) they find an expansionary monetary-policy reaction to oil price increases, and accordingly a stronger fall in output and inflation absent monetary reaction. Together with the contemporaneous Ider et al. (2024), we are, to our knowledge, the first to compare the McKay and Wolf (2023) approach to that proposed by Sims and Zha (2006) in an empirical study of the role of monetary policy for the effects of oil supply shocks. What sets us apart from that paper is our focus on the distributional effects. We find that the monetary response to oil shocks contributes only moderately to the employment contraction and inflation increase after oil shocks, with a larger share identified by the Sims and Zha (2006) method. Similar to Ider et al. (2024), we thus find a smaller role of contractionay monetary policy responses for the overall effect of oil-price increases in Europe than in the U.S. (Bernanke et al., 1997). In particular, the distributional effects of oil shocks only differ very mildly in the counterfactual non-response scenario.

The rest of the paper is organized as follows: Section 2 introduces the administrative data we use to compute labor market transitions and earnings, the monetary and oil shock variables, as well as the aggregate variables we use in our regressions. Section 3 presents the effects of oil supply shocks on the German economy, both in terms of aggregates and along the income distribution. Section 4 discusses our estimation of the counterfactual impulse responses to an oil shock without a monetary policy response. Section 5 concludes.

2 Data

Sample of Integrated Labor Market Biographies

Our source of administrative data on the German labor market is the Sample of Integrated Labor Market Biographies (SIAB), a two-percent subsample of all labor-market biographies in Germany, provided to us by the Research Data Center (FDZ) of the German Federal

Employment Agency.[4] It covers the entire labor market history for all individuals included in our dataset, between 1975 and 2021. The data comprises information reported to the German tax authority and social-security administration, and includes information on employment status, job changes, unemployment benefit receipts, and average daily earnings within an ongoing employment relationship. The data do not cover employment spells of civil servants and do not contain self-employed individuals, as both groups are covered by special social security systems.

The data is organized in labor market spells, which can, at most, be one year long, since an employer needs to report information to the German tax authority at least once per year (Schmucker et al., 2023). We convert our data to monthly observations of employment status and average monthly earnings. For individuals who hold multiple jobs during a single month, we keep the one with the highest remuneration. Information on pre-tax earnings is top censored. We impute it by using observable characteristics, using a Tobit regression (Dauth and Eppelsheimer, 2020).

We categorize an individual as unemployed if they receive unemployment benefit payments at the beginning of their non-employment spell. To the extent that changes in benefit eligibility over the course of our sample period were predominantly in terms of duration, this allows us to work with a relatively consistent unemployment definition.

We restrict attention to individuals who are closely attached to the labor market (i.e., employed or unemployed, according to the definition above), and between the ages of 25 and 60. We deflate pre-tax earnings using the German CPI. Further, we restrict our sample to only include individuals who have worked in West Germany, to avoid confounding effects from the German reunification in 1990.

Finally, when investigating the effects of oil shocks across the income distribution, we follow Guvenen et al. (2017) and sort individuals into deciles based on their average earnings over the previous five years. We view this as an approximation of permanent income.[5] When constructing the deciles, we condition on gender and five-year age brackets.

Table 1 provides summary statistics for relevant variables across deciles. As deciles are constructed conditional on age and gender, we do not report either of these statistics. Real monthly pre-tax earnings are expressed in 2015 Euros. Workers in the tenth decile of the permanent income distribution earn about 6 times more per month than those at the very bottom of the distribution.[6] The employment share rises from 75% in the lowest decile to 99% in the highest, but is already beyond 90% in the third decile. This pattern is accounted

[4]We rely on the factually anonymous version of the Sample of Integrated Labour Market Biographies (SIAB-Regionalfile) – Version 7521. Research Data Centre (FDZ) of the Federal Employment Agency (BA) at the Institute for Employment Research (IAB). Data access was provided via a Scientific Use File supplied by the FDZ of the BA at the IAB.

[5]Other measures of permanent income, such as the individual fixed effect in a Mincer regression, likely lead to similar results (Broer et al., 2022).

[6]The earnings figures are roughly in line with those reported by the Global Repository for Income Dynamics, which uses the same dataset for Germany (Guvenen et al., 2022).

Table 1: Descriptive statistics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Real monthly 2015 earnings	1260.09	1625.26	1952.03	2211.17	2457.56	2731.87	3065.66	3523.73	4360.08	5988.14
Employed	0.75	0.83	0.90	0.94	0.96	0.97	0.98	0.98	0.99	0.99
Job finding	0.26	0.28	0.30	0.32	0.33	0.33	0.34	0.33	0.33	0.34
Job loss	0.07	0.06	0.04	0.03	0.02	0.02	0.02	0.01	0.01	0.01
Observations	19575381	19563906	19571034	19544030	19538793	19541837	19528828	19502656	19532413	19524582

Note: The table summarizes decile-specific descriptive statistics in our sample. Deciles are constructed conditionally on age and gender. Real monthly pre-tax earnings are computed by dividing nominal monthly earnings by the price index, which is normalised to one in 2015. The variable *Employed* represents the employment share in each decile. The job-finding probability is computed as the share of unemployed individuals in period $t-1$ who are employed in period $t+12$, The job-loss probability is defined as the share of employed individuals in period $t-1$ who are observed as unemployed in period $t+12$. The sample period is 1975-2018.

for by both an increasing job-finding probability (which averages about 30 percent in our sample) and a falling probability to move into unemployment (which averages 3 percent). The job-finding rates reported in the table are constructed as the share of unemployed workers in period $t-1$ who are employed in period $t+12$, i.e., one year later. The job-loss rates are calculated analogously. The total size of our dataset is close to 200 million person-month observations.

Regarding economic aggregates, we utilize the West Texas Intermediate crude oil price in U.S. dollars (Federal Reserve Bank of St. Louis, 2025b), deflated using the U.S. CPI (U.S. Bureau of Labor Statistics, 2025), the West German unemployment rate (OECD, 2023) and the German consumer price index (OECD, 2025). From the German registry data, we construct average pre-tax labor earnings of the employed and the aggregate employment share each month. We obtain the Bundesbank's discount rate and the ECB's rate for main refinancing operations from the Bundesbank's databank (Deutsche Bundesbank, 2023, 2024). In the appendix, we show the impact of an oil price shock on oil production and oil inventories, both of these come from the replication package in Känzig (2021). The real exchange rate between the German currency and the dollar is calculated by (i) translating the exchange rate between the German mark and the dollar into euros by dividing by 1.95583 (Federal Reserve Bank of St. Louis, 2025a) and (ii) by appending this with the euro-dollar exchange rate after 1998 (Board of Governors of the Federal Reserve System, 2025). Finally, we obtain data for the oil supply surprises from Känzig (2024) and use the series starting from 1983..

Oil shocks and monetary policy surprises

To quantify the effect of unexpected oil supply shocks on macroeconomic outcomes, we use the series of oil supply surprises from Känzig (2021) as an instrument for changes in the price of oil in U.S. dollars.[7] We compare the economic effects of these shocks to those of monetary policy surprises. Känzig (2021) shows that the oil supply surprises, when employed as external instruments in a VAR, suggest that an oil supply shock that raises the price of oil by 10% leads to a significant economic contraction in the U.S. and across the world, and an increase in U.S. inflation.

To quantify the effects of monetary policy, we take account of the fact that German monetary policy during our estimation sample was controlled by two central banks: the Bundesbank (until 1998) and the ECB. For each of these two institutions, we construct the impulse responses to monetary policy surprises separately.

For the Bundesbank, we use a series of variations in monetary policy constructed by Cloyne et al. (2022) as an instrument for the monetary policy rate for the period from 1975 to the end of 1998.[8] In the spirit of Romer and Romer (2004), Cloyne et al. (2022) construct a series of monetary shocks by regressing the monetary policy rate on the information available to policy makers at the time, in addition to other variables.

For the time interval during which the ECB was responsible for German monetary policy, as well as the policy for other European countries, we construct the monetary policy impulse responses of our variables of interest by instrumenting the monetary policy rate using monetary policy surprises from Altavilla et al. (2019). More specifically, we utilize changes in the 3-month overnight indexed swap (OIS) rates during a narrow window around ECB monetary policy announcements.

3 The effects of oil supply shocks on the German economy

3.1 Aggregate effects of oil supply news shocks in Germany

To study the effect of oil shocks on aggregate economic conditions in Germany during our sample period, we estimate the following regression at the monthly frequency:

$$y_{t+h} - y_{t-1} = \alpha_h + \beta_h POIL_t + \sum_{l=1}^{L} \gamma_{h,l} X_{t-l} + \varepsilon_{t+h}, \tag{1}$$

where y is the variable of interest, $POIL_t$ is the real price of oil in period t in U.S. dollars, instrumented using the oil price surprise series from Känzig (2021), and X is a control vector containing lags of aggregate earnings and aggregate employment in our registry data sample, inflation, industrial production, unemployment, the oil price and the monetary policy rate.

[7]We instrument changes in the price of oil (and the monetary policy rate below) due to the concern that measures of surprises are merely correlated with the structural shock, and do not represent the structural shock itself (Stock and Watson, 2018).

[8]We extract the shock series from Cloyne et al. (2022) using a PDF graph reader. Each point was manually marked to obtain the time-series values. We confirmed that the series closely reproduces the graphs in the original paper.

We set the number of lags to 6, as suggested by the Aikaike Information Criterion (AIC). For this specification, the robust F-statistic of the first stage regression is 9.947, very close to 10, as suggested by Stock and Yogo (2005).

Figure 1 shows the results of this exercise. The oil price increase causes a contractionary monetary policy reaction, which peaks after 3 months at about 20 basis points, and then declines to turn expansionary during the second year of the response period. Unemployment rises slowly but persistently, with a peak response of 50 basis points after about 2.5 years. The employment response is an approximate mirror image of this, while industrial production follows a more volatile but declining path up to year 3. Average earnings of the employed in our micro-data also decline, with a trough response of about minus 80 basis points after two years. As expected after a negative supply shock, inflation rises and remains elevated by about 50 basis points throughout year 2. Together with the small response of policy interest rates, this implies only a weak response of monetary policy to the inflationary consequences of oil shocks.

The results are in line with those reported by Känzig (2021) for the U.S. economy, where a negative oil supply shock causes inflation to rise and industrial production to fall; the magnitudes are similar. Figure 12 reports the impulse responses of oil-related variables such as oil inventories and oil production. In these regressions, for consistency, we do not alter the right-hand side control variables. Consistent with a supply shock, oil production decreases during the first year after the oil price increase.

In order to rule out large effects of exchange rate movements driving the effects reported in Figure 1, we estimate Equation (1) with (i) the real exchange rate (German currency/dollar) and (ii) the real oil price in German currency as the dependent variables. The results are reported in Figure 13. The oil shock has no significant effect on the real exchange rate for the first 2.5 years after impact. Towards the three-year mark, the euro depreciates slightly. Hence, the impulse response of the real oil price in German currency is very similar to that reported in Figure 1.

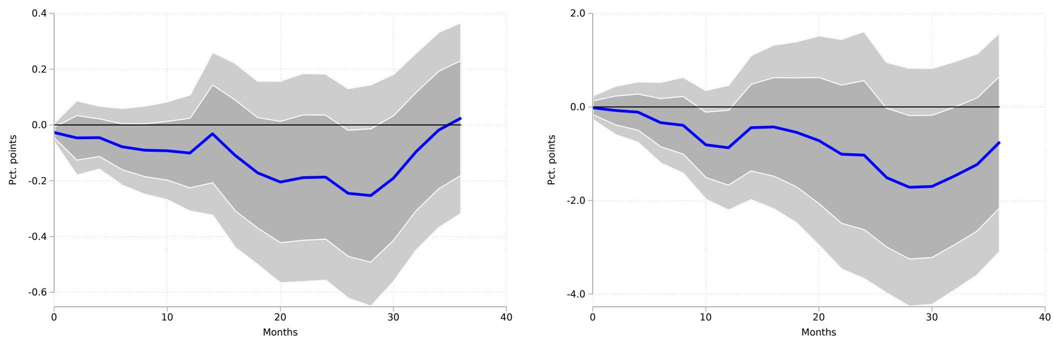
We also conduct our analysis with a modified oil supply surprise series, as suggested by Kilian (2024). In short, he raises two issues: (i) due to time aggregation issues in the monthly oil price series, the surprises from Känzig (2021) should be assigned to the months in which they affect the oil price, which are not necessarily the ones in which they occur; and (ii) due to limited liquidity in the oil futures market, the sample should start in 1989 instead of 1983. Figure 14 reports the results of this exercise; they closely match those in the baseline.[9] The impulse responses of inflation, industrial production and (un)employment are almost identical to the baseline estimates, exhibiting very similar shapes and magnitudes. The monetary policy response is, as in the baseline, contractionary on impact, but slightly less so. Further, it is more expansionary after three years. Overall, however, the results

[9]The robust F-statistic of the first stage when using the shock series suggested by Kilian (2024) is 20.149.

Figure 1: The aggregate effects of oil price news

Note: The Figure shows estimates of coefficients β_h in Equation (1) for different dependent variables y. We instrument the price of oil using the oil price surprises from Känzig (2021). Standard errors are heteroskedasticity robust. The shaded areas represent 68% and 90% confidence intervals. Impulse responses are scaled to a 10% increase in the monthly price of oil. Employment and average real earnings are constructed using German administrative data. The sample period is 1983-2018.

Figure 2: The labor market effects of oil price news



(a) Employment probability

(b) Job-finding probability

Note: The Figure shows estimates of coefficients β_h in Equation (1) for different dependent variables y. We instrument the price of oil using the oil price surprises from Känzig (2021). Standard errors are heteroskedasticity robust. The shaded areas represent 68% and 90% confidence intervals. Impulse responses are scaled to a 10% increase in the monthly price of oil. The *Left Panel* shows the aggregate response of the probability of observing an individual as employed in periods $t-1$ and $t+h$. The *Right Panel* depicts the response of the probability of an unemployed individual in $t-1$ having a job in period $t+h$. The sample period is 1983-2018.

closely mirror those of the baseline estimation.

3.2 The effects of oil shocks on labor market transitions

In addition to the aggregate responses reported above, our data allow us to analyze the impulse responses of labor market transitions to oil supply shocks. Specifically, at the individual level, we can track monthly labor market transitions between employment and unemployment. By aggregating these individual transitions, we construct a time series of labor market transition probabilities over different horizons. Specifically, for a given horizon $t+h$ we are interested in the "job-finding probability", defined as the observed share of transitions to employment in $t+h$ for those unemployed in $t-1$; and in the "employment probability for the currently employed", defined as the share of transitions to employment in $t+h$ for those in employment in $t-1$.

To operationalize this, we record each individual's labor market status $e \in \{U, E\}$ in period $t-1$ and again in period $t+h$, where h represents the impulse response horizon. Aggregating across all individuals enables us to estimate the effect of an oil price shock on labor market transition probabilities between $t-1$ and $t+h$, for each h, separately.

Figure 2 reports the estimated coefficients β_h from Equation (1). The left panel of Figure 2 illustrates the response of the employment probability for the currently employed . Following a 10% increase in oil prices due to a supply shock, this probability declines, reaching its lowest point (approximately -0.3 percentage points) after about 2.5 years. The right panel shows the job-finding probability, which also declines, reaching a trough of -2 percentage points. Note that, as a percentage of the unconditional probabilities depicted in Table 1, the two effects are approximately similar in size. Neither of them is precisely estimated.

3.3 Incidence of oil shocks across the income distribution

In this section, we investigate whether the aggregate labor market responses in Figure 2 mask heterogeneous incidences of oil supply shocks across the income distribution. To that end, as discussed in Section 2, we split individuals in our registry data into ten deciles, based on their average earnings over the previous five years. Subsequently, we estimate the following regression, for each decile separately:

$$y_{t+h,i,d} - y_{t-1,i,d} = \alpha_{h,d} + \beta_{h,d} POIL_t + \sum_{l=1}^{L} \gamma_{h,l} X_{t-l} + \varepsilon_{t+h,i,d}. \tag{2}$$

Our variables of interest y are individual level employment status $e \in \{U, E\}$ and earnings, $earn$. As before, we instrument the price of oil using the oil supply surprise series from Känzig (2021), X_{t-l} represents the same control variables as before, and, for consistency across estimations, we employ six lags, as in Equation (1). For the estimation of earnings changes of the employed, the estimation includes individuals employed in period $t-1$ and $t+h$, but does not require continuous employment.[10]

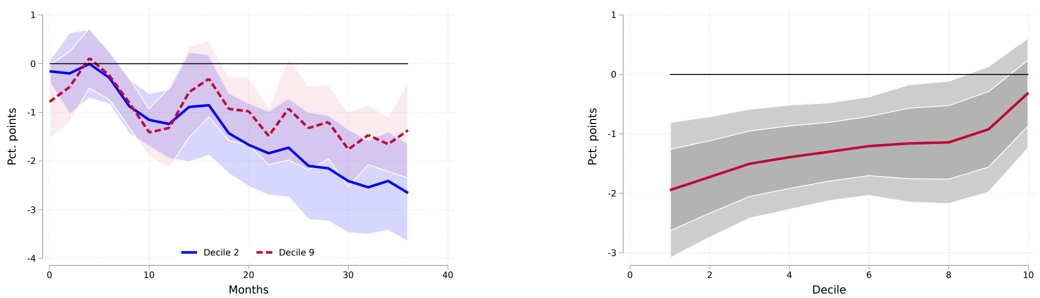
Figure 3 shows that the average response of earnings of the employed in response to an oil supply shock in Figure 1 masks important differences across the income distribution. The left panel plots the full impulse responses for the second and ninth deciles, in order not to clutter the figure. While earnings fall across the distribution, the fall in decile two is more pronounced, especially after two years. After three years, the earnings change for individuals at the bottom of the distribution is almost twice as large as the fall for individuals at the top.

The right panel of Figure 3 shows the coefficients for all deciles, two years after the shock ($h = 24$). The point estimates fall strongly in magnitude along the distribution, from an estimated two percentage point reduction at the bottom to a small and insignificant effect in the top decile.

Figure 4 plots the response to the oil price shock of the employment probability for the currently employed at horizon $t+h$. Again, there is substantial heterogeneity around the average response in Figure 2. The left panel of Figure 4 plots the impulse responses of that probability for deciles 2 and 9. The responses are imprecisely estimated, but suggest that the probability of being observed employed at horizons $t-1$ and $t+h$ falls most for

[10] To save on computational resources, we estimate only every second horizon for Equations (2) and (4), i.e., $h \in \{0, 2, ..., 36\}$ and interpolate between the values.

Figure 3: The earnings response to oil price news



(a) Earnings response for deciles 2 and 9

(b) Earnings response at h=24, across deciles

Note: The Figure shows estimates of coefficients $\beta_{h,d}$ in Equation (2) for the earnings of the employed. We instrument the price of oil using the oil price surprises from Känzig (2021). Standard errors are heteroskedasticity robust. The coefficients are scaled to a 10% increase in the monthly price of oil. The *Left Panel* plots the coefficients for deciles 2 and 9 for all horizons. The shaded areas represent 68% confidence intervals. The *Right Panel* plots the coefficients across deciles at horizon $h = 24$. The shaded areas represent 68% and 90% confidence intervals. The sample period is 1983-2018.

individuals at the low end of the income distribution. For the ninth decile, on the other hand, the probability barely decreases. The same picture emerges from the right panel of Figure 4: after 24 months, the probability of employment decreases by half of a percentage point below the median of the income distribution; above the median, the probability falls by less than half of that number.

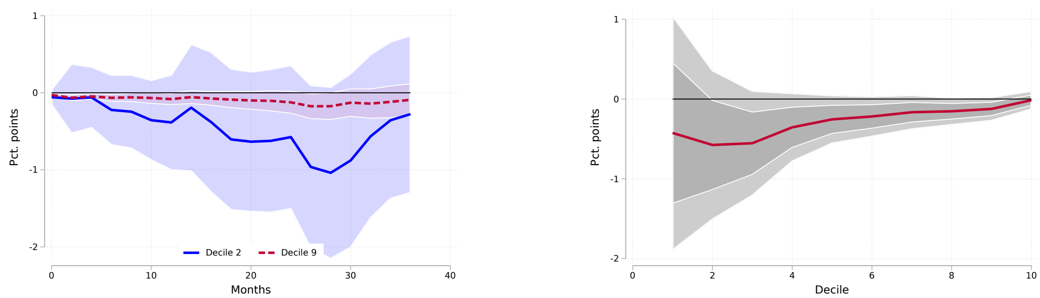
Finally, we conduct an analogous analysis for the job-finding probability. The left panel of Figure 5 shows that job-finding probabilities decrease across the distribution, but, again, more so at the bottom. The impulse responses for the second and ninth decile move in parallel over the first 24 months, with a difference of about a percentage point. At the 24 months horizon, as shown in the right panel of Figure 5, job-finding probabilities are reduced across the whole distribution, but again substantially more at the bottom of the distribution: a siginificant decrease by four percentage points in the bottom quintile contrasts with a zero effect in the top quintile and with the smaller and insignificant average effect in Figure 2.

Our estimates thus paint a consistent picture on the distributional effects of oil shocks on the German labor market: although the average magnitudes and precise patterns across the income distributions differ, their contractionary effects are consistently felt more strongly below the median of the income distribution.

4 The effects of oil shocks without monetary policy

The response of aggregate economic conditions in Germany to a surprise oil supply contraction in Figure 1 includes the consequences of any monetary policy response to rising inflation or

Figure 4: Employment probability response to oil price news

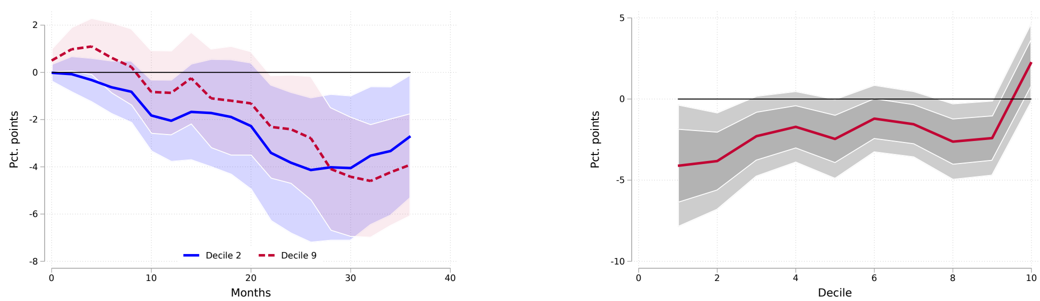


(a) Pr(E-to-E) response for deciles 2 and 9

(b) Pr(E-to-E) at h=24, across deciles

Note: The Figure shows estimates of coefficients $\beta_{h,d}$ in Equation (2) for the probability of being employed in periods $t-1$ and $t+h$. We instrument the price of oil using the oil price surprises from Känzig (2021). Standard errors are heteroskedasticity robust. The coefficients are scaled to a 10% increase in the monthly price of oil. The *Left Panel* plots the coefficients for deciles 2 and 9 for all horizons. The shaded areas represent 68% confidence intervals. The *Right Panel* plots the coefficients across deciles at horizon $h = 24$. The shaded areas represent 68% and 90% confidence intervals. The sample period is 1983-2018.

Figure 5: Job-finding probability response to oil price news



(a) Pr(U-to-E) response for deciles 2 and 9

(b) Pr(U-to-E) at h=24, across deciles

Note: The Figure shows estimates of coefficients $\beta_{h,d}$ in Equation (2) for the probability of being unemployed in period $t-1$ and employed in period $t+h$. We instrument the price of oil using the oil price surprises from Känzig (2021). Standard errors are heteroskedasticity robust. The coefficients are scaled to a 10% increase in the monthly price of oil. The *Left Panel* plots the coefficients for deciles 2 and 9 for all horizons. The shaded areas represent 68% confidence intervals. The *Right Panel* plots the coefficients across deciles at horizon $h = 24$. The shaded areas represent 68% and 90% confidence intervals. The sample period is 1983-2018.

falling output. In this section, we aim to "clean" the responses from this systematic response using two different approaches.

A sequence of non-response surprises: Sims and Zha (2006)

The first approach relies on a method proposed by Sims and Zha (2006) and applied to oil shocks in Bernanke et al. (1997): each period after the oil price shock, there is a monetary policy surprise such that the policy rate remains at zero. All other variables in the economy evolve according to the combined effect of the oil price news shock *and* the sequence of surprising monetary (non-) responses. We conduct this exercise for monetary-policy shocks associated with the ECB period.

Anticipated non-response: McKay and Wolf (2023)

The second approach follows McKay and Wolf (2023) and Caravello et al. (2024): in period zero, in addition to being hit by an oil supply news shock, the economy is hit by several different monetary policy shocks, calibrated to bring the policy rate's impulse response as close to zero as possible.[11] The appealing feature of this approach is that it does not rely on an economy continuously being surprised, as all unexpected monetary policy actions happen in period zero. The downside is that the ability to implement a given counterfactual policy scenario improves with the number of different identified policy shocks, and their estimated responses. We use the shocks identified, respectively, in Cloyne et al. (2022) for the Bundesbank from 1975 until 1998, and Altavilla et al. (2019), for the ECB period. Like McKay and Wolf (2023), who use the shocks to U.S. monetary policy identified, respectively, by Romer and Romer (2004) and Gertler and Karadi (2015), we thus use shocks identified by two different methods (narrative vs. based on high-frequency asset prices). In contrast to their work, we also consider shocks to the policies of different central banks but for the same economy. Specifically, we estimate the impulse responses of all variables of interest to monetary policy changes for the Bundesbank subsample (before 1999) and the ECB subsample, using local projections.

This way of proceeding relies on two maintained assumptions: first, that the relevant structural features of the German economy are approximately identical over the two subsamples, an assumption implicit also in the choice of estimation sample for the effects of oil shocks in Sections 3.[12] To make this more likely, we only include data on West Germany

[11] In practice, we calibrate the shocks to minimize the policy rate's sum of squared deviations from zero over the 36 month horizon.

[12] This assumption of parameter stability is maintained in previous studies of the effects of oil shocks, with the exception of Bruns and Lütkepohl (2023), who in their VAR analysis maintain the assumption of stable slope coefficients but find some evidence of changing within-period impacts of oil shocks identified using the Känzig (2021)-instrument.

in our calculations, including after 1990.[13] Second, our strategy requires that the main assumption underlying McKay and Wolf (2023)'s method, that monetary policy innovations affect the economy only through the current level and expected path of the policy instrument, holds in both subperiods. This aligns with the common view that the ECB's mandate was modeled after the Bundesbank (see, e.g., Kaltenthaler, 2005), and that the interest rate was the key policy instrument for both.[14]

For our strategy to be valid, we thus need to assume that the structural features of the German economy across the two estimation periods, and the monetary policies of the two central banks, are sufficiently similar. For it to be interesting, however, we need the instrument paths following monetary policy shocks to be sufficiently different between the two central banks such that their linear combination substantially augments the ability to implement counterfactual policies relative to a single shock. Even though we consider two shocks to the current stance of monetary policy (as opposed to, for example, the forward-guidance shocks considered in Altavilla et al. (2019)) their implied instrument paths may still differ for at least two reasons. First, the exogenous part of the instrument may differ, e.g. due to different levels of persistence of the shocks. Second, the endogenous response of monetary policy to the evolution of the economy following the shock (the "policy rule") may not be the same. The estimated responses we present in the next section identify the sum of both components.

Comparing the two methods to evaluate counterfactual policy

In the two approaches we consider, monetary non-response is implemented in fundamentally different ways. Sims and Zha (2006) calculate repeated surprises that keep the policy path exactly at zero during the response period, which maintains the assumption that economic agents do not update their expectations about future policy, making this exercise plainly subject to the Lucas (1976)-critique. We find it nevertheless interesting in particular at shorter horizons to the extent that it captures the effects of temporary, exceptional, and unanticipated changes in policy. McKay and Wolf (2023)'s method, in contrast implements monetary non-response through a combination of period-zero shocks, without any further change in policy. This make this exercise immune to the Lucas (1976)-critique, but requires that the current change in policy is perfectly understood, and its consequences anticipated.

[13]This first assumption also presumes an alignment to German monetary policy by today's Euro Area countries, many but not all of whom followed the Bundesbank closely in its rate setting.

[14]This view goes against monetary targeting being a central element of Bundesbank policy, and is sustained, for example, by Clarida and Gertler (1997), who argue that "As is commonly understood by close observers of the Bundesbank, the [monetary] targets are meant as guidelines. In no sense do they define a strict policy rule. In terms of operating procedures, the Bundesbank chooses a path for short-term interest rates to meet its policy objectives, similar in spirit to the Federal Reserve Board."

4.1 Aggregate effects of monetary policy in Germany

In order to implement the two approaches outlined above, we first need to estimate the impulse responses of all relevant variables, most importantly the monetary policy rate, to monetary policy shocks. We do so using an analogous regression to Equation (1), estimated at the monthly frequency:

$$y_{t+h} - y_{t-1} = \alpha_h + \beta_h i_t + \sum_{l=1}^{L} \gamma_{h,l} X_{t-l} + \varepsilon_{t+h}, \tag{3}$$

where i_t is the monetary policy rate, instrumented either using the Bundesbank surprises from Cloyne et al. (2022), or the ECB surprises from Altavilla et al. (2019), y_t is an outcome variable of interest, and X is a vector of control variables. For consistency across estimations, we use six lags, as in Equation (1), and include all control variables from above: the price of oil, the German CPI, the German unemployment and employment rates, German industrial production, average earnings and the monetary policy rate.[15] We also add six lags of the instrument. For the Bundesbank period, the robust F-statistic of the first stage regression is 358.35, for the ECB period, it is 18.75, both comfortably above 10 (Stock and Yogo, 2005).

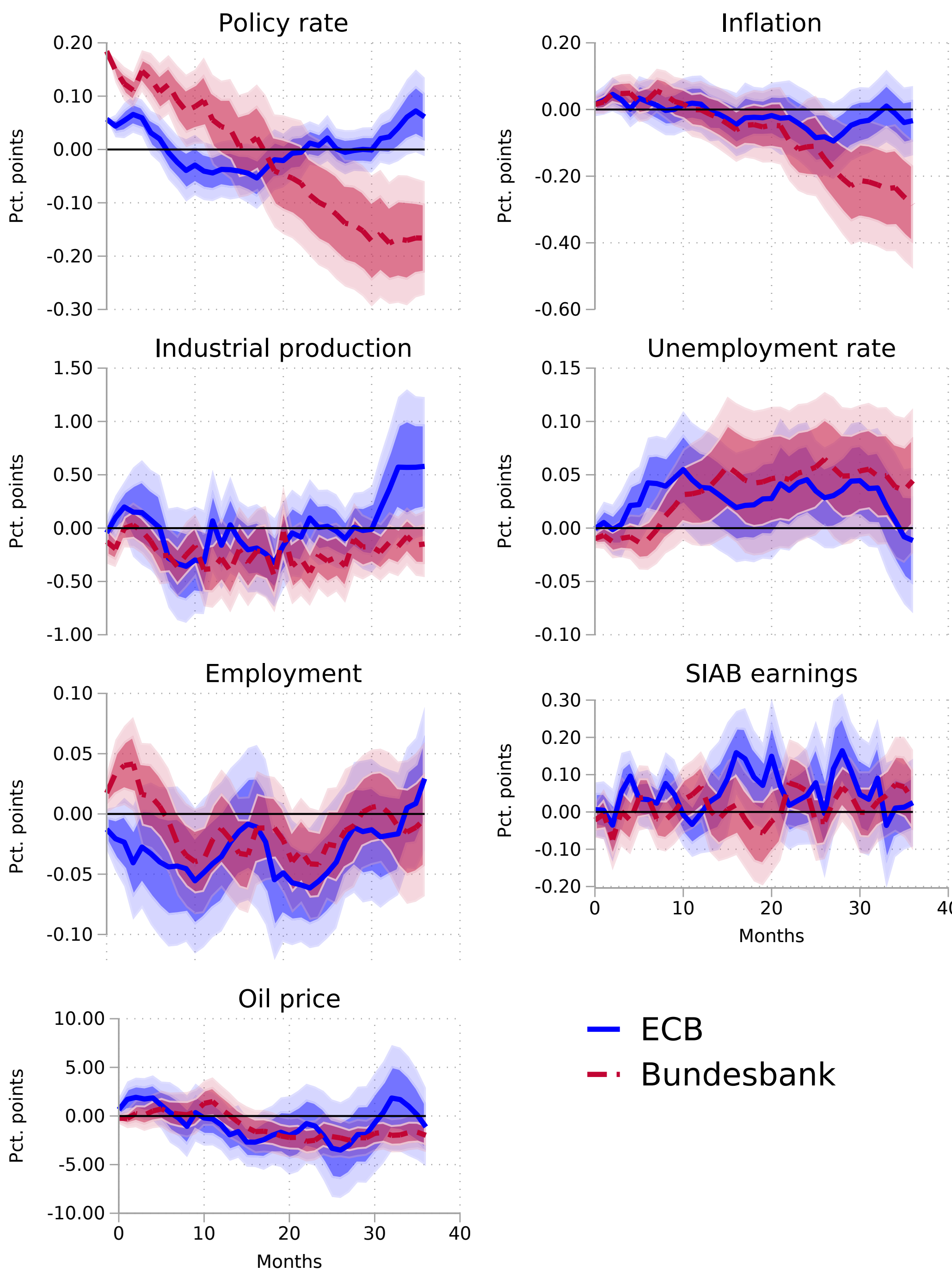
Figure 6 depicts the estimated responses to monetary shocks in the periods associated with, respectively, the Bundesbank (1975-1998, red lines and shaded areas) and the ECB (1999-2014, in blue). The innovations are scaled to correspond to one standard deviation of the identified shocks, equal to 19 and 5 basis points for, respectively, the Bundesbank and ECB period.[16]

For the ECB, the policy rate remains elevated at around the initial level for about half a year, then declines rapidly, turning negative seven months after the shock, before it returns to zero after about two years. After a brief initial increase, inflation starts falling in response to the tightening with a considerable lag, by close to 10 basis points after two years. Economic activity, in contrast responds somewhat faster: the growth rate of industrial production is reduced by about 40 basis points one year after the shock. The official unemployment rate starts to increase after about 5 months and attains its peak after about one year, at about 10 basis points. It remains elevated for the next two years before falling back towards zero. The response of the employment rate of workers closely attached to the labor market is an approximate mirror image of this. The response of average earnings growth of the employed in our micro data is noisy and suggests that the earnings of the employed rise significantly but briefly after about 1.5 years. We attribute this to a selection effect, as low-earnings individuals are more likely to become unemployed. Finally, the impact of European monetary

[15] The results are robust to the inclusion of only 5 or 8 lags for the ECB and Bundesbank, respectively, which is the optimal number according to the AIC. The results are reported in Figures 21 and 22

[16] The standard deviation of the instrument for the ECB period, for example, is $\sigma_z = 3.93$, while the first stage coefficient on the instrument is $\beta_z = 0.014$, hence, a one standard deviation contraction would lead to an increase in the policy rate by about 5 basis points.

Figure 6: The aggregate effects of monetary policy



Note: The Figure shows estimates of coefficients β_h in Equation (3) for different dependent variables y and different monetary policy instruments. For the ECB, we instrument the monetary policy rate using the changes in 3-month OIS rates in a narrow window around monetary policy announcements from Altavilla et al. (2019); for the Bundesbank, we instrument using the surprises from Cloyne et al. (2022). Standard errors are heteroskedasticity robust. The shaded areas represent 68% and 90% confidence intervals. For comparability, impulse responses are scaled to a 1 standard deviation monetary policy shock for both banks. Employment and average real earnings are constructed using German administrative data. For the ECB, the sample period is 1999-2018, for the Bundesbank it is 1975-1998.

policy on the oil price is estimated to be initially positive before it turns negative. As in Ider et al. (2024) the point estimates are large, but very imprecisely estimated.

The estimated response of the policy indicator to a monetary policy shock by the Bundesbank differs substantially from that estimated for the ECB. The initial one-standard-deviation increase - three times larger than that for the ECB - is followed by a steady decline over almost the entire response period.[17] The policy indicator thus stays elevated for longer than after an ECB shock, but also turns substantially more negative over the entire second half of the response period. The rate of inflation reacts with a lag of about two years, but then falls significantly, by substantially more compared to the ECB period. Industrial production also falls more persistently. The unemployment rate rises by a similar amount, but somewhat later and more persistently than after an ECB shock. Apart from an initial short-lived increase after a Bundesbank shock, the employment rate, as measured in our individual-level dataset, shows a similar response in both cases. Aggregate earnings changes are volatile and not significantly different from zero. Finally, the oil price decreases by a similar magnitude compared to the ECB shock, but with a longer lag. Figure 15 shows the impact of monetary policy on the real exchange rate between the euro and the dollar.[18] Upon impact, the euro appreciates, but only briefly. After one year, the real exchange rate has returned to its initial value. Hence, the effect of German monetary policy on the oil price is similar when the oil price is measured in euros.

The responses of inflation and activity to ECB and Bundesbank policy are thus broadly similar, including in magnitude. The responses of the policy rate, in contrast, differ substantially. In particular, for the Bundesbank, a larger initial increase is followed by a delayed but substantially more pronounced and more persistent policy loosening. Taken together, stronger tightening followed by a stronger policy reversal may explain an overall similar response in inflation and activity. This will be important for the counterfactual policy scenarios in Section 4, where these shock paths are used to offset the monetary policy response to the oil shock.

4.2 The effects of monetary policy shocks on labor market transitions

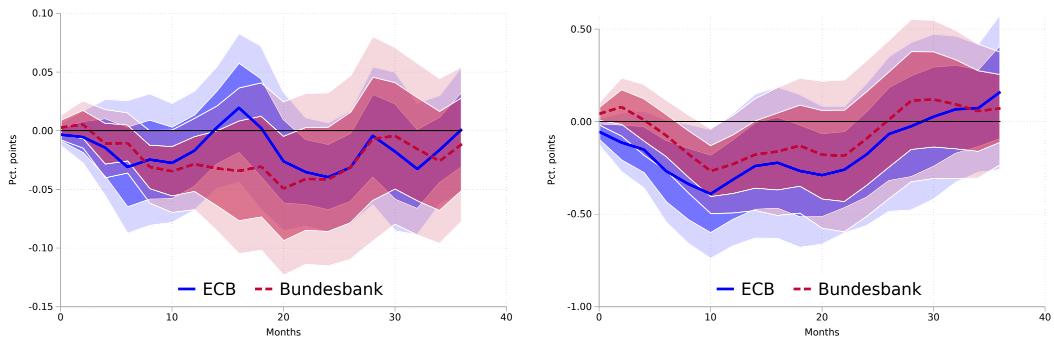
Similar to Section 3.2 for oil shocks, we use our administrative data to compute the effect of monetary policy shocks on the likelihood of different labor market transitions. The results are reported in Figure 7.

The figure shows that the two contractionary one-standard-deviation monetary policy shocks reduce by similar amounts the employment probability for both the currently employed and the unemployed, although the latter effect is concentrated in the first half of the response

[17] The standard deviation of the monetary policy shocks from Cloyne et al. (2022) is $\sigma_z = 21.67$, and the first stage coefficient is $\beta_z = 0.009$. Thus, a one standard deviation monetary policy shock would induce a 19 basis point contraction.

[18] We report euro exchange rates as implied by the Euro-Deutschmark conversion rate for ease of comparison.

Figure 7: The labor market effects of monetary policy



(a) Employment probability

(b) Job-finding probability

Note: The Figure shows estimates of coefficients β_h in Equation (1) for different dependent variables y. For the ECB, we instrument the monetary policy rate using the changes in 3-month OIS rates in a narrow window around monetary policy announcements from Altavilla et al. (2019); for the Bundesbank, we instrument using the surprises from Cloyne et al. (2022). Standard errors are heteroskedasticity robust. Standard errors are heteroskedasticity robust. The shaded areas represent 68% and 90% confidence intervals. Impulse responses are scaled to a 1 standard deviation monetary policy shock. For the ECB, the sample period is 1999-2018, for the Bundesbank it is 1975-1998. The *Left Panel* shows the response of the average employment probability of the currently employed at horizon $t+h$. The *Right Panel* depicts the response of the average job-finding probability.

horizon. The point estimates amount to about one percent the average probabilities of changing labor-market status in Table 1, but imprecisely estimated and, in the case of the employment probability of the currently employed, volatile.

4.3 Incidence of monetary policy across the income distribution

To estimate the impact of monetary policy on earnings and employment across the income distribution, we run the following regression, mirroring Equation (2):

$$y_{t+h,i,d} - y_{t-1,i,d} = \alpha_{h,d} + \beta_{h,d} i_t + \sum_{l=1}^{L} \gamma_{h,l} X_{t-l} + \varepsilon_{t+h,i,d}. \tag{4}$$

where, as in Equation (3), we instrument the policy rate i_t using either the monetary shocks from Cloyne et al. (2022), for the Bundesbank, or the surprises from Altavilla et al. (2019), for the ECB. We employ the same control variables as before and use six lags. The coefficient $\beta_{h,d}$ measures the effect of monetary policy on y (employment status or individual log-earnings), for each horizon h and decile d.

The top left panel of Figure 8 reports the effect of a one standard deviation monetary policy shock on the earnings growth of the employed, two years after the shock, for both central banks. In line with the volatile and insignificant responses of average earnings in Figure 6, the impact of contractionary ECB monetary policy on earnings is small and insignificant, with positive point estimates for deciles 9 and 10. The full impulse responses for deciles 2 and 9 in Figure 17 confirm this. The Bundesbank shocks yield an effect on earnings growth that is positive and significant for the first seven deciles at the 24 months horizon, but negative for the top deciles. We attribute these contrasting effects to the presence of two offsetting forces: an effect on earnings of continuously employed workers; and a seclection effect, whereby lower-earnings workers within deciles have lower employment probabilities.

The top right panel of Figure 8 shows that the insignificant effect of ECB monetary policy on the average employment probability for the currently employed in Figure 7 masks significant but heterogeneous effects across the income distribution: Two years after a monetary policy shock, the probability of being employed (for individuals who were employed before the shock) has fallen by more than 10 basis points for workers below the median. Moving further up the distribution, the effect diminishes strongly. The results are in line with those reported in Broer et al. (2022), who, despite different sample selection, sample period and monetary policy surprises, find that ECB monetary policy significantly reduces separation probabilities (the complement of our estimate) especially at the bottom of the income distribution. The pattern for contractionary Bundesbank policy is similar: employment probabilities at the low end of the distribution drop by about 30% more than those at the top.

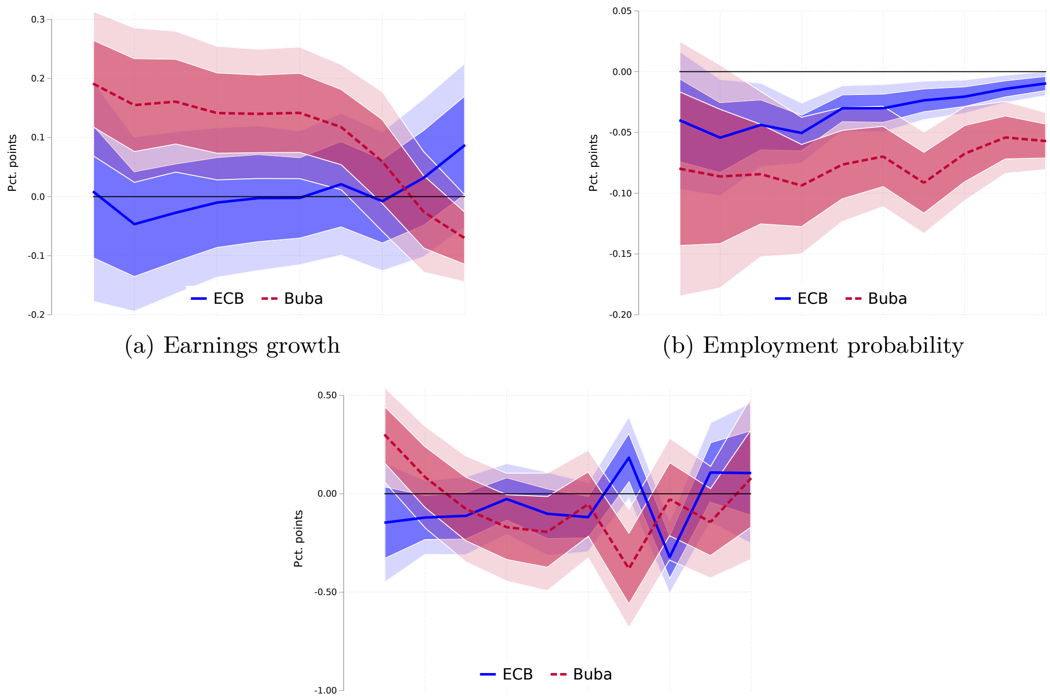
The point estimates of the effect of ECB monetary policy on the job-finding probability (of an initially unemployed individual being employed at horizon h) are negative below the median (and even rise above zero at the top of the distribution). At the 24-months-horizon shown in Figure 8, the effects are mostly insignificant, but there are significant reductions below the median at shorter horizons, with mostly insignificant effects above (see Figure 17). The responses for deciles 2 and 9 in Figure 18, and the 24-months snapshot in Figure 8 show that the effects of monetary policy shocks on job-finding rates during the Bundesbank period was less concentrated on the bottom of the distribution.

In summary, we find stronger incidence of monetary policy and oil shocks at the bottom of the income distribution. For monetary policy, however, this heterogeneity materialises through its effect on labor market transitions, in particular the employment probabilities of the employed, and more so during the ECB period. This contrasts with the incidence of oil shocks that is strongly heterogeneous in particular on earnings.

4.4 Aggregate responses without monetary contraction

In this section we identify the effects of oil shocks on the German economy when monetary policy does not react. When applying the method of Sims and Zha (2006), we concentrate on the ECB subperiod and solve for a series of monetary policy shocks that maintains the policy rate exactly at zero for all $t \in \{0, 36\}$. When following McKay and Wolf (2023) we

Figure 8: Responses to ECB monetary policy across the distribution – $h = 24$



(a) Earnings growth

(b) Employment probability

(c) Job-finding probability

Note: The Figure shows estimates of coefficients $\beta_{h,d}$ in Equation (4) for different dependent variables y, at horizon $h = 24$. Standard errors are heteroskedasticity robust. The shaded areas represent 68% and 90% confidence intervals. Impulse responses are scaled to a 1 standard deviation monetary policy shock. For the ECB, we instrument the monetary policy rate using the changes in 3-month OIS rates in a narrow window around monetary policy announcements from Altavilla et al. (2019); for the Bundesbank, we instrument using the surprises from Cloyne et al. (2022). Standard errors are heteroskedasticity robust. For the ECB, the sample period is 1999-2018, for the Bundesbank it is 1975-1998. The *Top Left* panel shows the change in earnings growth across deciles, conditional on employment. The *Top Right* panel shows the change in the probability of a worker employed at $t-1$ to be employed at $t = 24$. The *Bottom* panel shows the change in the probability of an unemployed individual in period $t-1$ to be employed in period $t = 24$.

proceed as follows: to the oil shock responses in Figure 1, we add a weighted sum of the responses to monetary policy shocks in Figures 6 (ECB and Bundesbank). The weights are chosen to attain a monetary policy rate as close to zero as possible over the first 36 months in response to the oil shock.

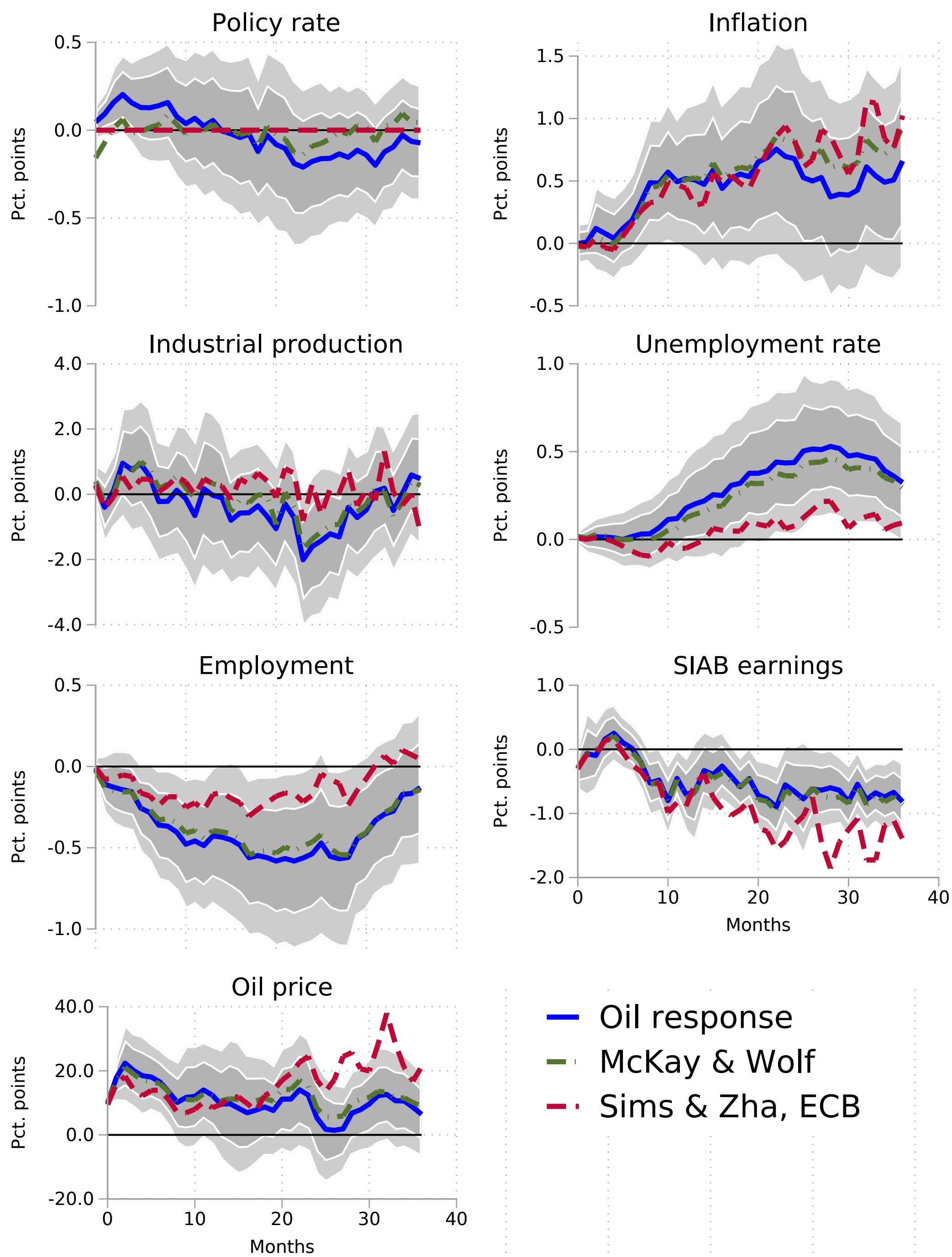
Figure 19 in the Appendix plots the shocks associated with the two exercises that offset the policy response to oil shocks in Figure 11. Importantly, that response combines an initial tightening with a substantial loosening in the second half of the response horizon. Accordingly, the repeated surprises that implement the monetary non-respose following Sims and Zha (2006) are on average expansionary in the first 24 months (where they average -2.5 BP in the first 12 months, and -1.4 BP in the second), turning contractionary during the last year of the response horizon (with an average of 2 BP, almost a standard deviation greater than in the first year). The estimated shocks are, however, volatile, because the ECB-period shock, in response to which the policy rate rises upon impact and remains high for 6 months before declining rapidly, struggles to offset the hump-shaped response of monetary policy to oil shocks.

When following McKay and Wolf (2023), to undo the contractionary response to the oil price shock using $t = 0$ shocks, the weight given to Bundesbank shocks (equal to -17 basis points, or close to one standard deviation) strongly exceeds that of ECB shocks (-3.3 basis points, or 2/3 of a standard deviation). This is because the protracted decline in the policy instrument that follows the Bundesbank shock is better placed to offset the policy response to oil shocks, relative to the ECB shock that falls back towards zero after an initial plateau.

Figure 9 displays the original responses to the oil supply shock jointly with the two counterfactual responses. Under the approach of Sims and Zha (2006), the policy rate is exactly zero by construction, for the entire response horizon. The McKay and Wolf (2023)-approach yields a substantially dampened policy path. During the year following the oil shock, both approaches imply a mildly more expansionary monetary policy, with an average reduction of the policy rate of 10 basis points. Figure 20 depicts the difference between the estimated responses of policy and other variables to the oil-price shock and those under the counterfactual scenarios. Figure 9 shows how both counterfactuals dampen the decline in activity throughout the entire reponse period, and amplify the inflation increase in the second and third year. The difference with respect to the baseline responses, depicted in Figure 20, is, however, substantially larger for the Sims and Zha (2006)-counterfactual. In particular, the Sims and Zha (2006)-method implies a substantially stronger boost to employment (of about 35 basis points during year 2) and to industrial production (which rises by about a percentage point on average during year 2).

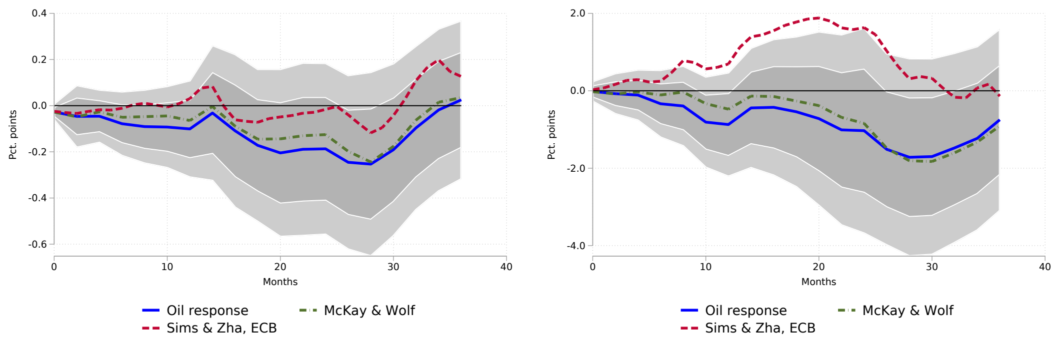
This divergence arises from two main factors. First, the accumulated policy rate changes implied by the Sims and Zha (2006) method are considerably larger mid-horizon than the one-time adjustments in the McKay and Wolf (2023) approach. More importantly, both

Figure 9: The aggregate effects of counterfactual monetary policy



Note: The Figure shows estimates of coefficients β_h in Equation (1) for different dependent variables y as blue solid lines. Standard errors are heteroskedasticity robust. The shaded areas represent 68% and 90% confidence intervals. Impulse responses are scaled to a 10 percent increase in the oil price upon impact. The green dash-dotted lines represent the counterfactual responses of the variables estimated according to McKay and Wolf (2023). The red dashed line represents counterfactual responses estimated according to Sims and Zha (2006), using ECB monetary policy.

Figure 10: The labor market effects of counterfactual monetary policy



(a) Employment probability

(b) Job-finding probability

Note: The Figure shows estimates of coefficients β_h in Equation (1) for different dependent variables y. We instrument the price of oil using the oil price surprises from Känzig (2021). Standard errors are heteroskedasticity robust. The shaded areas represent 68% and 90% confidence intervals. Impulse responses are scaled to a 10% increase in the monthly price of oil. The green dash-dotted lines represent the counterfactual responses of the variables estimated according to McKay and Wolf (2023). The red dashed lines represent counterfactual responses estimated according to Sims and Zha (2006), using ECB monetary policy.

methods must account for the eventual policy reversal observed in the actual oil shock response when it turns expansionary. This reversal is inherent in both underlying monetary shocks (see Figure 6) but is substantially weaker for ECB shocks. Consequently, in the Sims and Zha (2006) (ECB) exercise, much of the necessary later reversal manifests as unanticipated contractionary surprises in year three. These, being unanticipated, do not dampen the earlier expansionary effect, thereby amplifying the overall counterfactual impact. Conversely, the McKay and Wolf (2023) counterfactual achieves its reversal largely through the initial Bundesbank shock, which incorporates a significant, anticipated contractionary phase during year three. This anticipation inherently mutes the initial expansionary effect of the Bundesbank shock when used to construct the "no policy reaction" scenario for oil shocks.

4.5 The labor market effects of counterfactual monetary policy

Figure 10 shows the response of average employment probabilities to oil shocks when monetary policy follows the counterfactual policy paths discussed in the previous section. The employment probability for the currently employed is higher in the counterfactuals. The effect is largest for the Sims and Zha (2006) counterfactual, equal to about 20 basis points on average in year 2 of the response. The McKay and Wolf (2023) counterfactuals, which load heavily on the Bundesbank, increase the probability by less than half as much. The effects of muted monetary policy on the job-finding probability materialize earlier, are larger in absolute terms, and again more important with repeated surprises of monetary non-response (Sims and Zha (2006)), where they imply a rise in the average job-finding probability after oil shocks in the absence of a monetary response.

4.6 Distributional effects without monetary contraction

In this section we present counterfactual responses of earnings and employment probabilities to oil shocks across the income distribution when monetary policy follows the counterfactual policy paths discussed in the previous section.

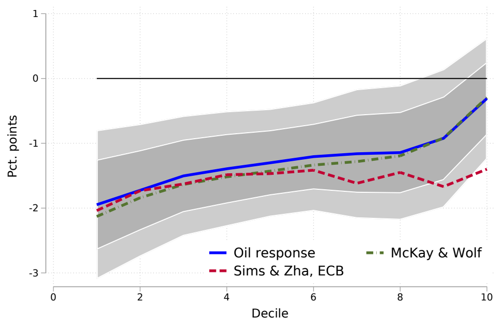
Figure 11 presents the results, across deciles, at horizon $h = 24$. Starting with the bottom panel, because the Bundesbank monetary policy shocks have a small effect on job-finding probabilities, the McKay and Wolf (2023) counterfactual policies, which rely more heavily on them, leave their baseline response essentially unchanged. Using the ECB-shocks to implement the Sims and Zha (2006)-method, in contrast, implies a substantial boost to job-finding, by between 1.5 and 2.5 percentage points, below the median of the income distribution. This is because job-finding responds strongly and quickly to ECB shocks (see the impulse responses in Figure 17). This increases the cumulative effect of the shocks depicted in Figure 19.

Figure 11 presents the results, across deciles, at horizon $h = 24$. Starting with the bottom panel, because the Bundesbank monetary policy shocks have a small effect on job-finding probabilities, the McKay and Wolf (2023) counterfactual policies, which rely more heavily on them, leave their baseline response essentially unchanged. Using the ECB-shocks to implement the Sims and Zha (2006)-method, in contrast, implies a substantial boost to job-finding, by between 1.5 and 2.5 percentage points, below the median of the income distribution. This is because job-finding responds strongly and quickly to ECB shocks (see the impulse responses in Figure 17). This increases the cumulative effect of the shocks depicted in Figure 19. The effect of more expansionary monetary policy on separation rates is more similar across the two methods: a mild reduction that falls in magnitude along the income distribution. For earnings growth, anticipated non-response (McKay and Wolf (2023)) again leaves the baseline response almost unchanged at the 24-months horizon, while the alternative Sims and Zha (2006)-counterfactual predicts a *stronger* fall in earnings above the median, explained by the significant *positive* response of earnings to contractionary ECB shocks in that part of the income distribution during year two of the response (Figure 17), which, again, may be interpreted as a selection effect of lower-paid workers being laid off.

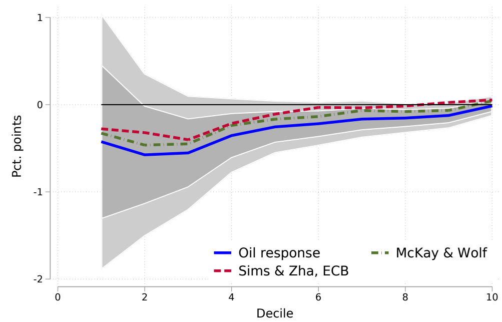
5 Conclusion

This paper demonstrates that oil price shocks inflict significant and unequally distributed economic pain in Germany, with low-income workers bearing the brunt through reduced

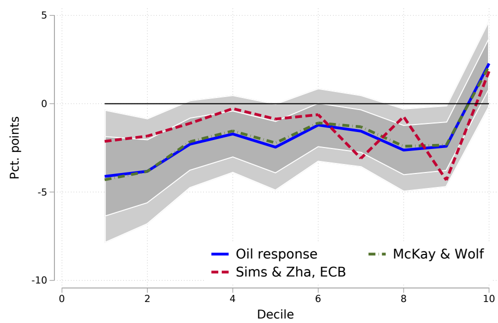
Figure 11: Responses to counterfactual monetary policy across the distribution – h=24



(a) Earnings growth of the employed



(b) Employment probability of the employed



(c) Job-finding probability of the unemployed

Note: The Figure shows estimates of coefficients $\beta_{h,d}$ in Equation (2) for different dependent variables y as blue solid lines, across deciles, for $h = 24$ months after the initial shock. Standard errors are heteroskedasticity robust. The shaded areas represent 68% and 90% confidence intervals. Impulse responses are scaled to a 10 percent increase in oil prices upon impact. The green dash-dotted lines represent the counterfactual responses of the variables estimated according to McKay and Wolf (2023). The red dashed line represents counterfactual responses estimated according to Sims and Zha (2006), using ECB monetary policy. The *Top Left Panel* shows the responses of the earnings growth of the employed, the *Top Right Panel* shows the response of the probability of an individual employed at $t-1$ to be employed at $t+24$, the *Bottom Panel* shows the response of the probability that an individual who was unemployed at $t-1$ is employed at $t+24$.

earnings and deteriorating employment prospects. In contrast, we show that the transmission of these oil shocks differs from that of monetary policy shocks. While both disproportionately affect the income-poor, oil shocks erode earnings directly and reduce job-finding, whereas monetary tightening primarily operates through increased job separations for this group.

Our analysis further identifies the contribution of Germany's systematic monetary policy response to the propagation of oil shocks. This contribution depends largely on the counterfactual one has in mind. Because the actual policy response to oil shocks involves an initial rate rise followed by a fall, a commitment to not responding at all (estimated following McKay and Wolf, 2023) does little to alter the oil shock's aggregate and distributional effects. A surprise lack of monetary reaction, (following Sims and Zha, 2006), in contrast, provides a substantial boost to activity, inflation, and employment prospects for low-income individuals (but remains subject to the Lucas (1976)-critique, particularly at longer horizons). Policymakers concerned with equity may therefore need to consider more targeted fiscal or structural measures in response to adverse supply shocks.

Future research should further explore the interplay between supply shocks and monetary policy. In particular, the different magnitudes of monetary-policy effects across different periods of our data sample deserve further investigation. Different types of supply shocks do as well.

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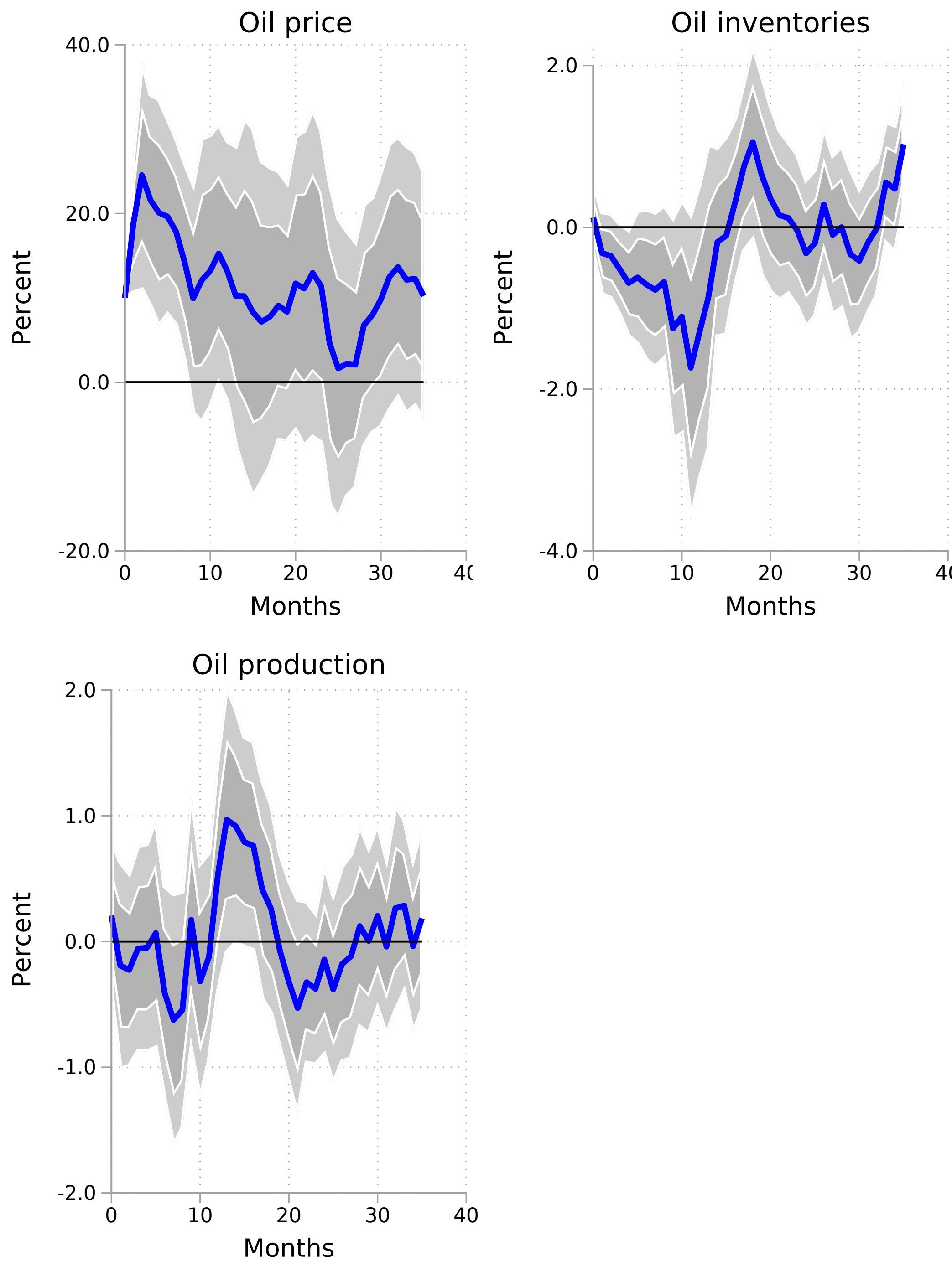
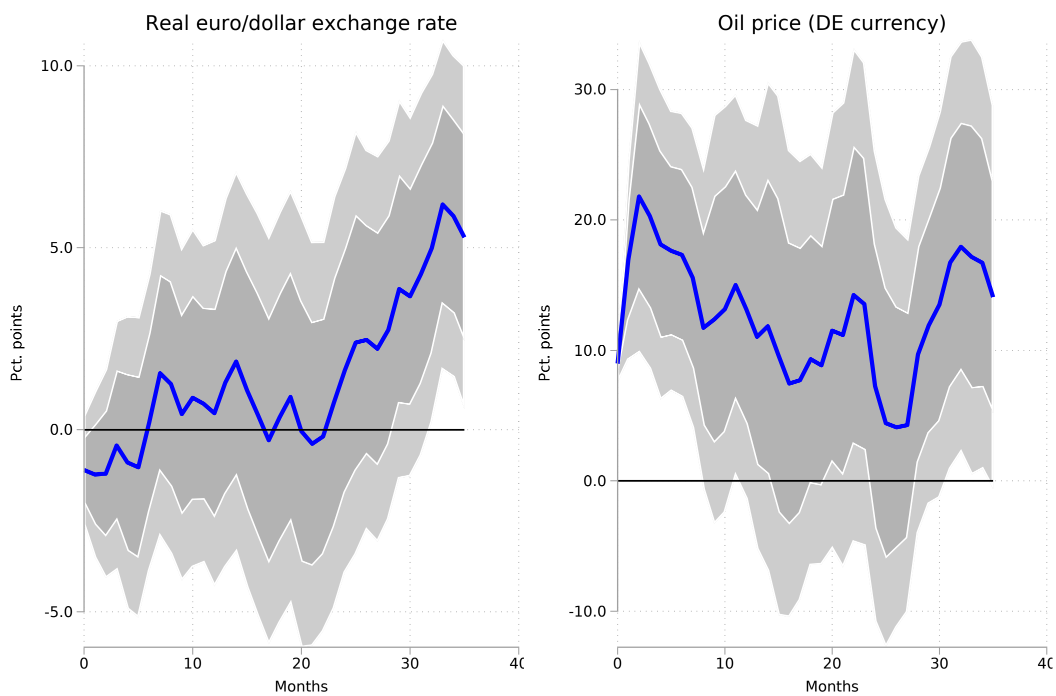
A Additional Figures

Figure 12: The aggregate effects of Oil price shocks – oil variables



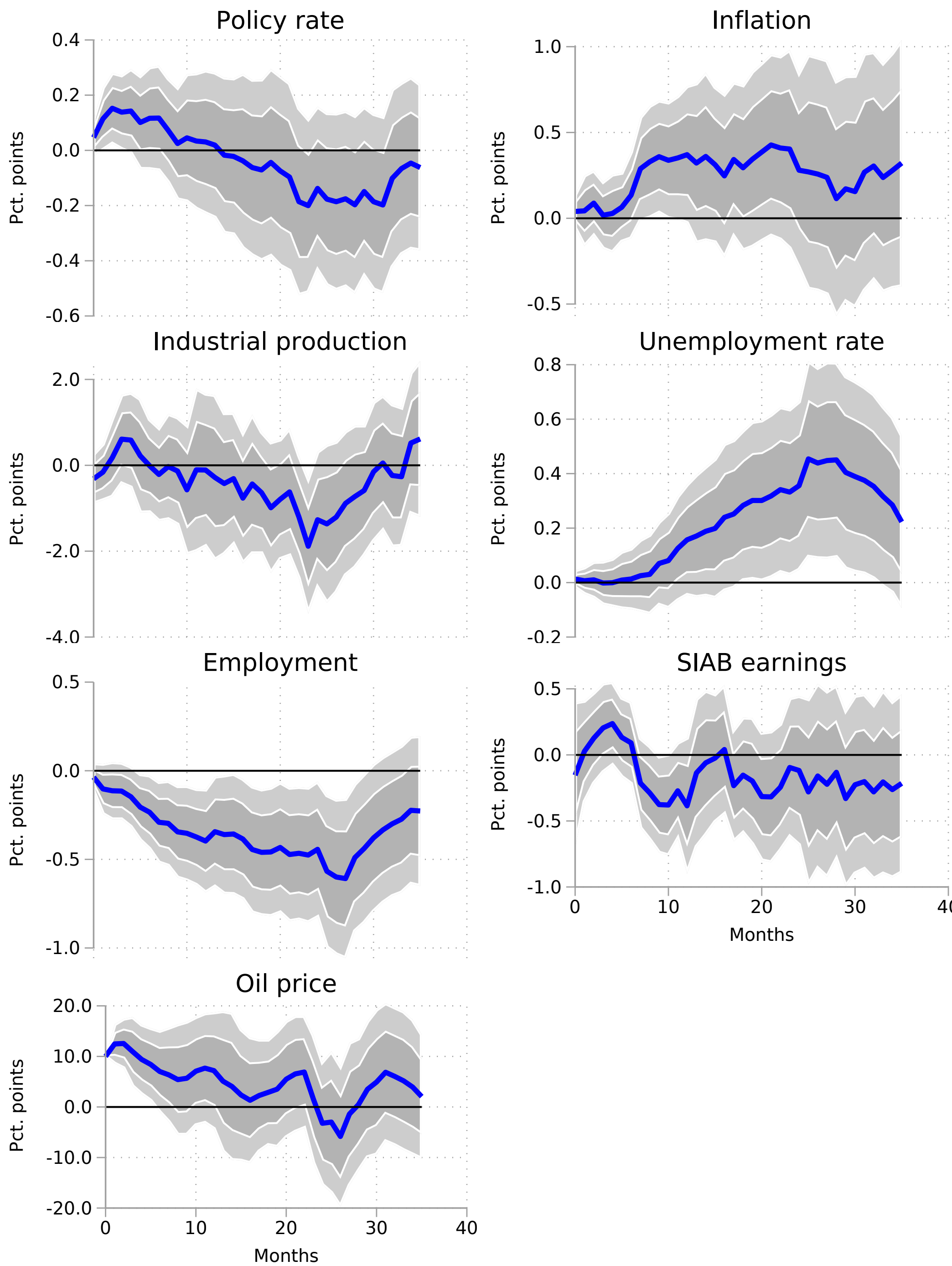
Note: The Figure shows estimates of coefficients β_h in Equation (1) for different dependent variables y. We instrument the price of oil using the oil price surprises from Känzig (2021). Standard errors are heteroskedasticity robust. The shaded areas represent 68% and 90% confidence intervals. Impulse responses are scaled to a 10% increase in the monthly price of oil. The sample period is 1983-2018.

Figure 13: The aggregate effects of Oil price shocks – exchange rates



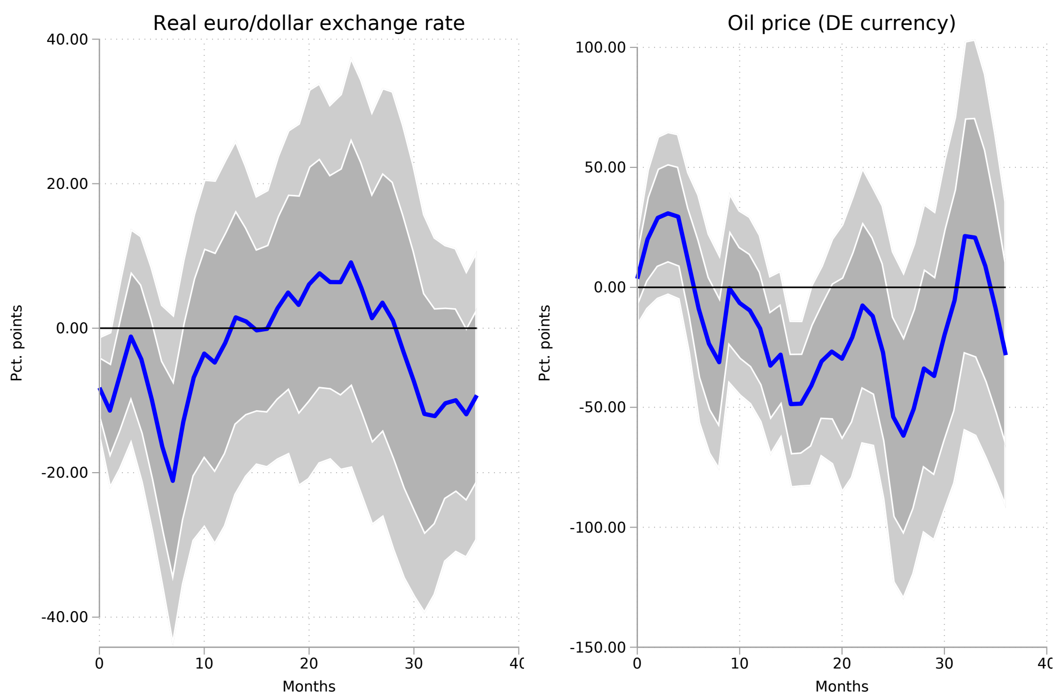
Note: The Figure shows estimates of coefficients β_h in Equation (1) for different dependent variables y. We instrument the price of oil using the oil price surprises from Känzig (2021). Standard errors are heteroskedasticity robust. The shaded areas represent 68% and 90% confidence intervals. Impulse responses are scaled to a 10% increase in the monthly price of oil. The sample period is 1983-2018.

Figure 14: The aggregate effects of Oil price shocks – Kilian (2024) instrument



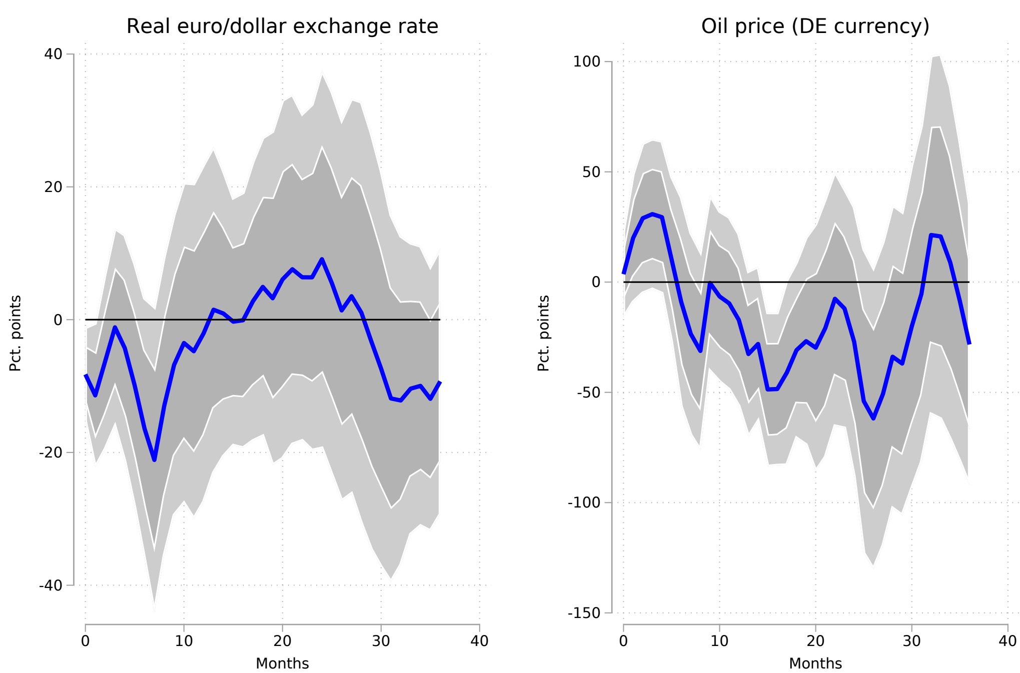
Note: The Figure shows estimates of coefficients β_h in Equation (1) for different dependent variables y. We instrument the price of oil using the oil price surprises constructed as in Kilian (2024). Standard errors are heteroskedasticity robust. The shaded areas represent 68% and 90% confidence intervals. Impulse responses are scaled to a 10% increase in the monthly price of oil. Employment and average real earnings are constructed using German administrative data. The sample period is 1989-2018.

Figure 15: The aggregate effects of ECB monetary policy – exchange rates



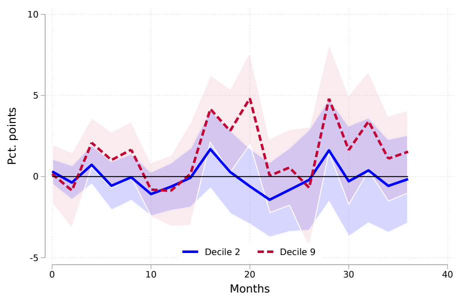
Note: The Figure shows estimates of coefficients β_h in Equation (3) for different dependent variables y. We instrument the monetary policy rate using the monetary policy surprises from Altavilla et al. (2019). Standard errors are heteroskedasticity robust. The shaded areas represent 68% and 90% confidence intervals. Impulse responses are scaled to a 100 basis point monetary policy shock. The sample period is 1999-2018.

Figure 16: The aggregate effects of Bundesbank monetary policy – exchange rates

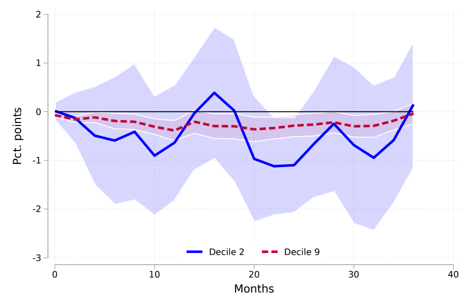


Note: The Figure shows estimates of coefficients β_h in Equation (3) for different dependent variables y. We instrument the monetary policy rate using the monetary policy surprises from Cloyne et al. (2022). Standard errors are heteroskedasticity robust. The shaded areas represent 68% and 90% confidence intervals. Impulse responses are scaled to a 100 basis point monetary policy shock. The sample period is 1975-1998.

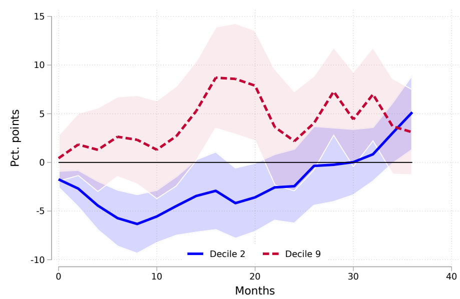
Figure 17: Responses to ECB monetary policy across the distribution – Deciles 2 & 9



(a) Earnings growth



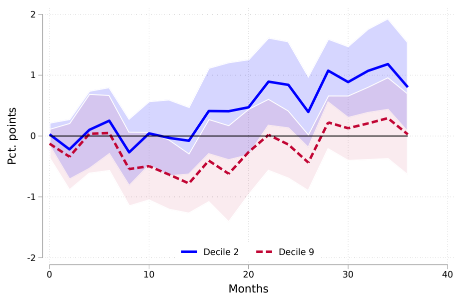
(b) Employment probability



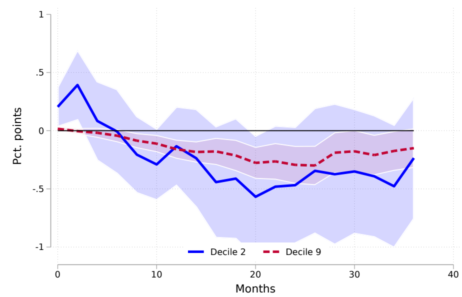
(c) Job-finding probability

Note: The Figure shows estimates of coefficients $\beta_{h,d}$ in Equation (4) for different dependent variables y, for deciles $d = \{2, 9\}$. Standard errors are heteroskedasticity robust. The shaded areas represent 68% and 90% confidence intervals. Impulse responses are scaled to a 100 basis point monetary policy shock. The policy rate is instrumented using monetary policy surprises from Altavilla et al. (2019). The sample period is 1999-2018. The *Top Left* panel shows the change in earnings growth over time, conditional on employment. The *Top Right* panel shows the change in the probability of a worker employed at $t-1$ to be employed in period $t+h$. The *Bottom* panel shows the change in the probability of an unemployed individual in period $t-1$ to be employed in period $t+h$.

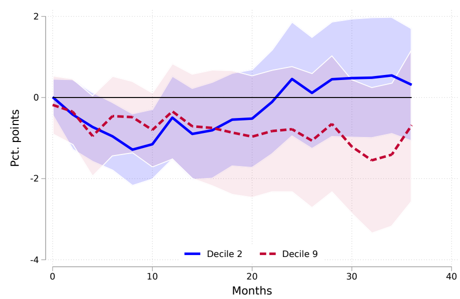
Figure 18: Responses to Bundesbank monetary policy across the distribution – Deciles 2 & 9



(a) Earnings growth



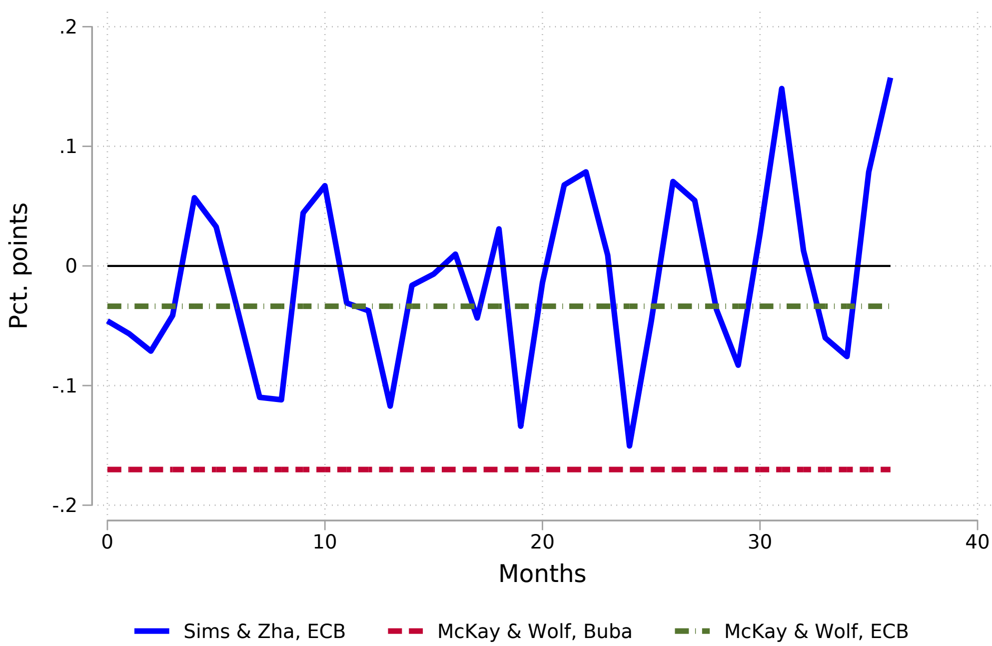
(b) Employment probability



(c) Job-finding probability

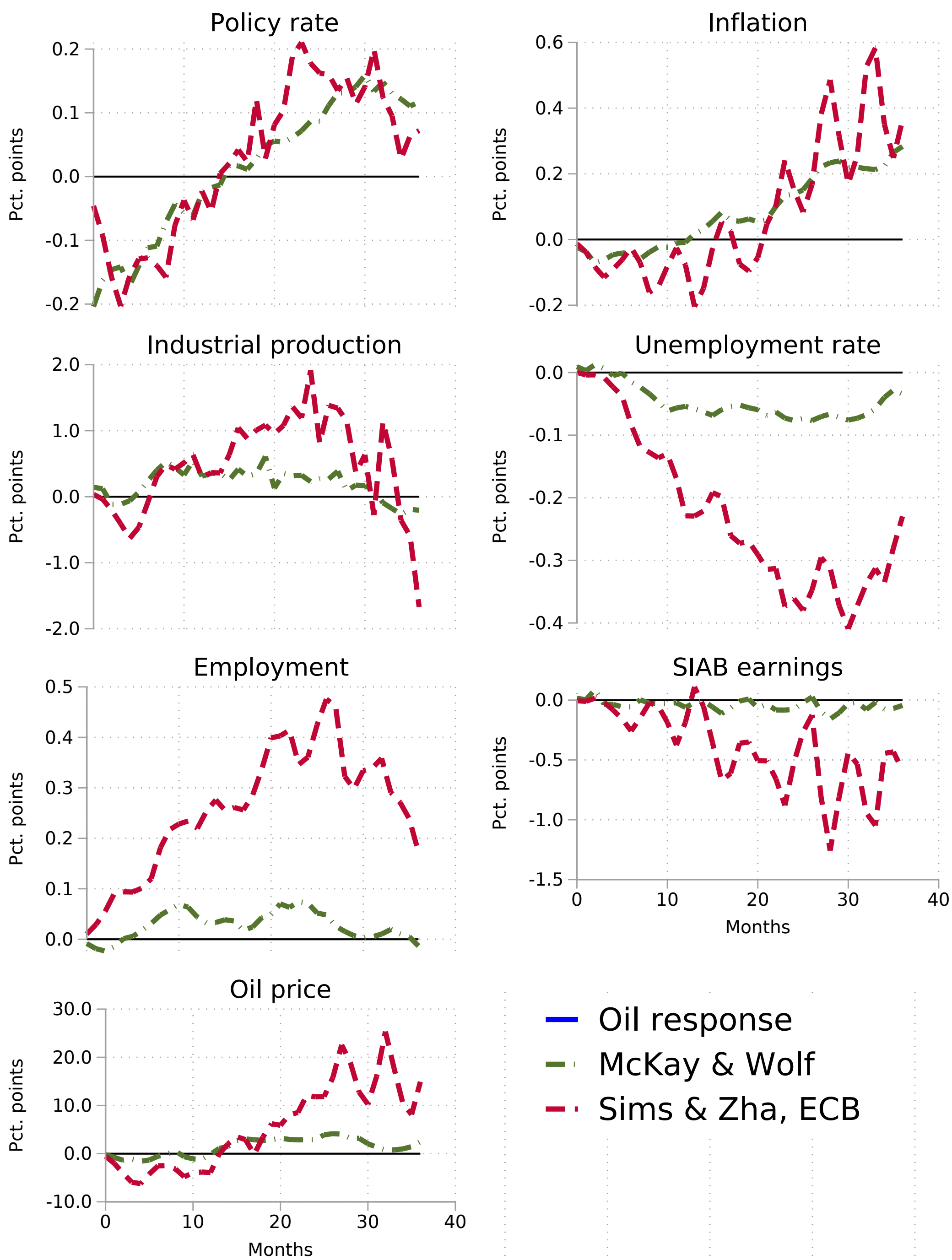
Note: The Figure shows estimates of coefficients $\beta_{h,d}$ in Equation (4) for different dependent variables y, for deciles $d = \{2, 9\}$. Standard errors are heteroskedasticity robust. The shaded areas represent 68% and 90% confidence intervals. Impulse responses are scaled to a 100 basis point monetary policy shock. The policy rate is instrumented using monetary policy surprises from Cloyne et al. (2022). The sample period is 1975-1998. The *Top Left* panel shows the change in earnings growth over time, conditional on employment. The *Top Right* panel shows the change in the probability of a worker employed at $t-1$ to be employed in period $t+h$. The *Bottom* panel shows the change in the probability of an unemployed individual in period $t-1$ to be employed in period $t+h$.

Figure 19: Implied shock series



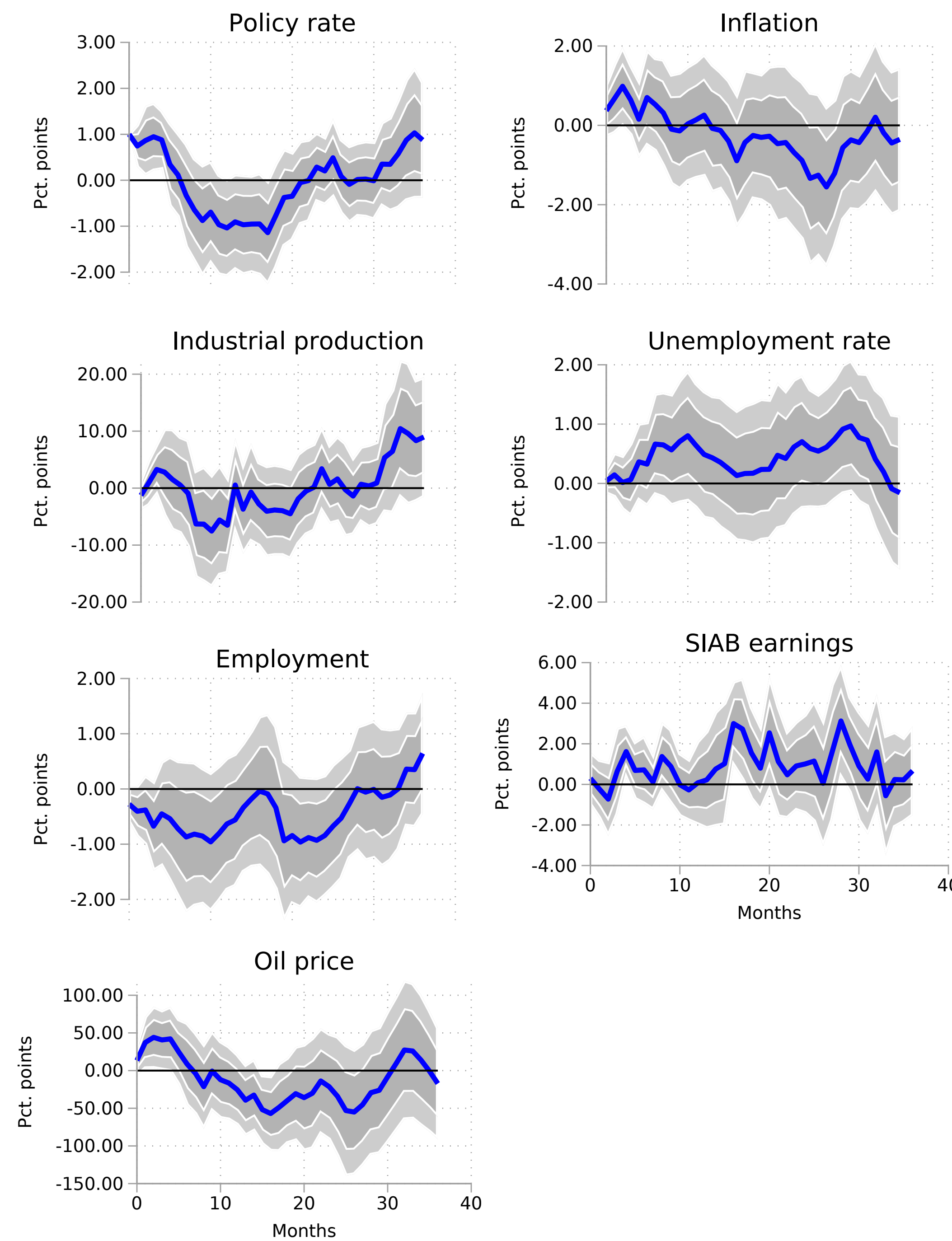
Note: The Figure shows the implied monetary policy shock series necessary for a zero response of the policy rate after an oil supply news shock (Sims and Zha, 2006), for both the Bundesbank and the ECB. In addition, it shows the period-0 shocks necessary to keep the policy rate response as small as possible, following McKay and Wolf (2023).

Figure 20: The aggregate effects of counterfactual monetary policy – relative



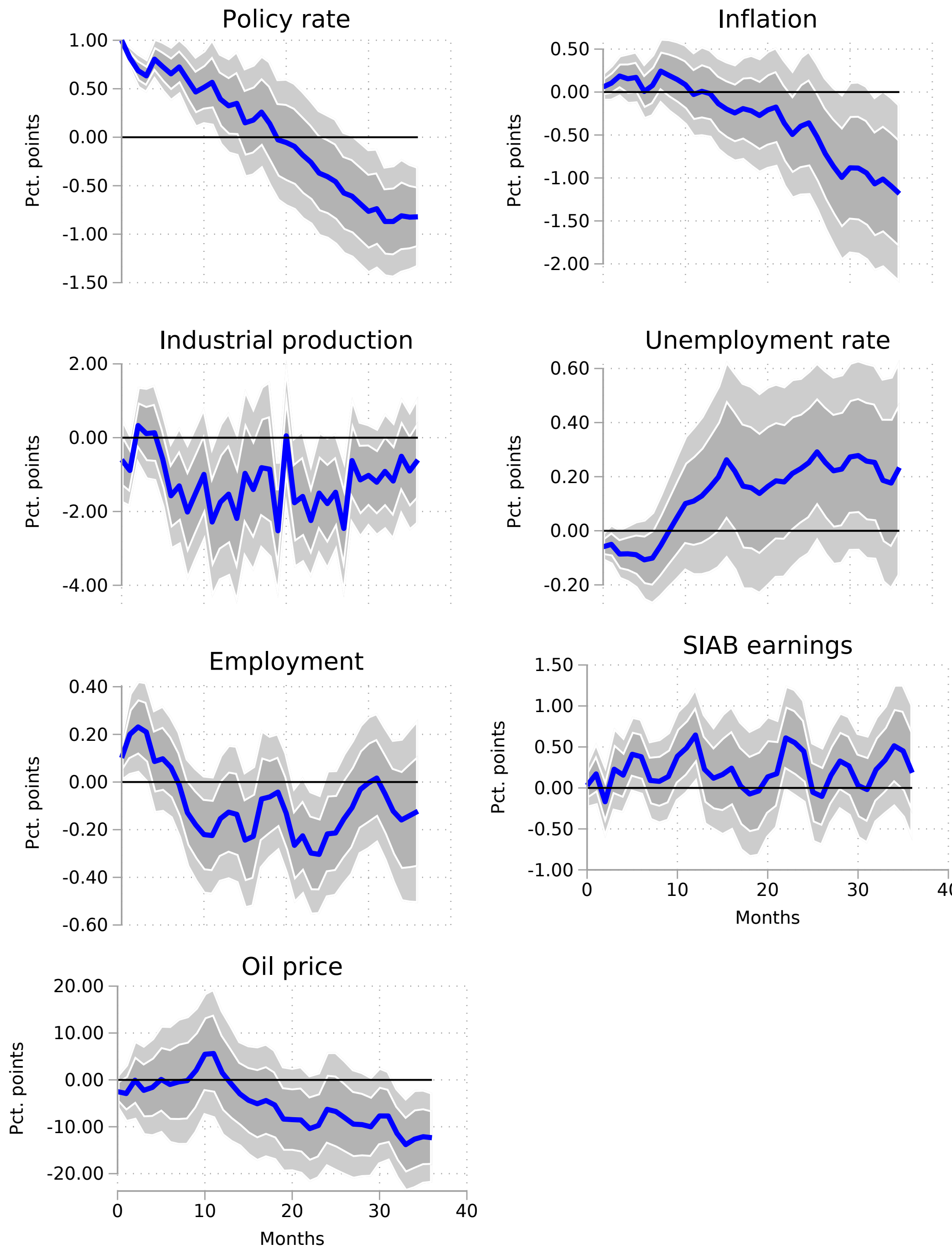
Note: The Figure shows **the difference** between estimates of coefficients β_h in Equation (1) and the counterfactual impulse responses, for different dependent variables y. Impulse responses are scaled to a shock that raises the oil price by 10 percent. The orange lines represent the counterfactual responses of the variables estimated according to McKay and Wolf (2023). The green dash-dotted line represents counterfactual responses estimated according to Sims and Zha (2006), using ECB monetary policy. The red long-dashed lines represent counterfactual responses estimated according to Sims and Zha (2006), using Bundesbank monetary policy.

Figure 21: The aggregate effects of ECB monetary policy – 5 lags



Note: The Figure shows estimates of coefficients β_h in Equation (3) for different dependent variables y. We instrument the monetary policy rate using the changes in 3-month OIS rates in a narrow window around monetary policy announcements from Altavilla et al. (2019). Standard errors are heteroskedasticity robust. The shaded areas represent 68% and 90% confidence intervals. Impulse responses are scaled to a 100 basis point monetary policy shock. Employment and average real earnings are constructed using German administrative data. The sample period is 1999-2018.

Figure 22: The aggregate effects of Bundesbank monetary policy – 8 lags



Note: The Figure shows estimates of coefficients β_h in Equation (3) for different dependent variables y. We instrument the monetary policy rate using the monetary policy surprises from Cloyne et al. (2022). Standard errors are heteroskedasticity robust. The shaded areas represent 68% and 90% confidence intervals. Impulse responses are scaled to a 100 basis point monetary policy shock. Employment and average real earnings are constructed using German administrative data. The sample period is 1975-1998.