Equalising Monetary Policy – the Earnings Heterogeneity Channel in Action

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Abstract

This paper examines how conventional and unconventional monetary policies affect wage distribution using administrative German labour market data from 1999 to 2019. The study finds that policy rate cuts and quantitative easing (QE) increase wages across the distribution three to six quarters after implementation. QE notably raises wages at the bottom more than at the top, reducing wage inequality significantly and persistently. Policy rate cuts also reduce inequality, but less so. These effects occur because low-income workers, especially young men, benefit more from job finding or switching after an expansionary policy shock compared to high-income workers.
Keywords: monetary policy, quantitative easing, wage inequality, temporal disaggregation, administrative data

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1 Introduction

With the onset of the Global Financial Crisis (GFC), central banks around the world began to implement exceptionally accommodative monetary policies. While these efforts prevented a more severe crisis, concerns were raised about possible unintended side-effects, in particular the promotion of already rising inequality among advanced economies. Since high-income households are more likely to own stocks and real estate, boosting asset returns and rents through monetary policy interventions such as quantitative easing could increase income inequality (Montecino and Epstein, 2015). At the same time, by improving financial conditions, expansionary monetary policy provides incentives for households to consume and firms to invest, thereby accelerating job creation and raising wages (Kaplan et al., 2018). As these effects potentially vary along the earnings distribution and due to the importance of labour income for household consumption, knowledge of the effects of conventional and unconventional monetary policies on the wage distribution is crucial for central banks.[1]

The current theoretical and empirical evidence on the effects of expansionary monetary policy on earnings inequality is, nonetheless, inconclusive and focuses on the period of conventional measures. Quantitative models predict a declining wage inequality due to lower unemployment (Gornemann et al., 2016) or increasing inequality due to compositional changes (Faia et al., 2022) and a larger skill premium following more technological investments (Dolado et al., 2021). The seminal empirical contribution by Coibion et al. (2017) finds a significant reduction in income inequality after expansionary monetary policy shocks, but the small sample size and problems with the exact timing does not allow for robust conclusions on the impact on earnings inequality. Other studies based on survey data report significant unequalising effects on wages in Japan (Inui et al., 2020) as well as significant equalising effects in the UK, at least prior to 1993 (Mumtaz and Theophilopoulou, 2017). Only recently, also administrative data were used to shed light on the distributional effects of monetary policy (Amberg et al., 2022; Andersen et al., 2023) with the limitation of annual data, no distinction between different policy tools, and a focus on the overall income inequality, encompassing the effects on transfers, capital

[1] Note that the terms wages and earnings are used interchangeably throughout the text, except where specifically characterised, such as hourly wages.

income and wages.

This paper contributes to the literature by shedding light on the different effects of conventional and unconventional monetary policy measures on quarterly wage inequality, and by decomposing the so-called *earnings heterogeneity channel* along several dimensions using reliable administrative labour market data. Based on the large Sample of Integrated Labour Market Biographies (SIAB) from Germany, I describe wage dynamics using high-quality data at a quarterly frequency that is not subject to survey bias or small sample problems. The quarterly analysis is possible because the SIAB allows to observe not only annual wage and inequality measures, but also within-year measures for sub-samples of workers. The quarterly frequency is relevant for an assessment of monetary policy, because macroeconomic projections are presented once a quarter and monetary policy decisions are taken every six weeks at the European Central Bank (ECB). Therefore, annual observations could blur the actual effects. Consequently, I create a quarterly measure of wage inequality that can be used to inform quarterly models and analyse the diffusion of economic shocks. In particular, I compare the effects of interest rate changes and asset purchases of the ECB on the wage distribution and assess the relevance of the earnings heterogeneity channel (see Colciago et al., 2019) and possible sub-channels.

All types of monetary policy affect wages only indirectly. An expansionary adjustment in policy tools improves financial conditions and may trigger increased spending and investment, leading to higher prices, employment and wages. As these indirect effects may differ across households, monetary policy has distributional effects in addition to its aggregate effects. Contributing to the literature about the different distributional monetary policy channels, this paper focuses on the earnings heterogeneity channel. It describes the effects of monetary policy on earnings inequality due to different wage responses along the wage distribution. These heterogeneities result from different wage rigidities, labour supply elasticities and unemployment rates at different wage levels.[2] In addition to describing the overall impact of monetary policy on wage inequality, this paper analyses the sub-channels that describe the sources of wage changes, such as job creation, changes

[2]Another indirect distributional channel is the income composition channel. Since households acquire income from different sources (labour, capital or transfers) and these react differently to monetary policy, the effects vary along the distribution. Examples of direct channels are the savings redistribution channel or the portfolio composition channel. See Coibion et al. (2017) or Colciago et al. (2019) for a detailed description of these distributional monetary transmission channels.

in hourly wages, changes in hours worked and job changes. Moreover, gender, age and educational differences reveal further distributional consequences of monetary policy.

Previous research has shown that both conventional and unconventional monetary policies are capable of stimulating the economy and that there are several similarities (e.g. Boeckx et al., 2017; Inoue and Rossi, 2018). At the same time, there are also relevant differences when looking at the detailed impact on financial markets and beyond (Haitsma et al., 2016; Galariotis et al., 2018). Not only is the implementation of policy rate changes different from the expansion of asset purchases, but they also target different maturities in the yield structure. Policy rate cuts have a stronger immediate impact via short-term rates, while asset purchases target long-term rates (Altavilla et al., 2019) via imperfect substitutability of assets, signalling about future policy and improving balance sheets. Therefore, it is relevant to analyse the effects of different types of monetary policy separately to see whether the differences are transmitted to the labour market and, in particular, to wage inequality.

In order to estimate the causal effects of monetary policy on wages and inequality, I apply the state-of-the-art high-frequency shock identification following Altavilla et al. (2019). I extract and disentangle factors representing conventional and unconventional monetary policies from changes in financial market variables observed in a narrow window around policy announcements. Since these shocks can hardly capture the full quarterly impact, I use them as exogenous instruments for changes in the policy rate and the balance sheet. The responses of inequality to conventional and unconventional monetary policy measures are then estimated using IV local projections (Jordà et al., 2015). This flexible approach allows me to describe quarterly distributional dynamics of wages in detail.

The estimates reveal that both expansionary interest rate (IR) policies and quantitative easing (QE) have significant positive effects on real gross wages, in line with former research. In contrast to the previous literature, I find statistically significant equalising effects on wage inequality. IR cuts lead to higher wages along the whole wage distribution with slightly larger effects at the bottom of the distribution than at the top. In comparison, QE raises wages especially at the bottom and has almost no effect at the top. Moreover, low wages respond faster to both monetary policy tools than high wages, which leads to additional temporary reductions in wage inequality. Thus, the ECB's unconventional measures not only affected the wealth distribution, but also led to a reduction in wage inequality between the GFC and 2020. This dynamic can be mainly explained by two sub-channels. Monetary policy has a much stronger effect on the wages of unemployed and job switchers at the bottom of the distribution than at the top. Thus, the job creation channel and the job switching channel are the main sources of the observed equalising effects, dominating the effects of the changes in hours worked or hourly wages. While expansionary monetary policy reduces wage inequality in general, it widens the inequality between certain groups. Young, low-educated and male workers benefit more from expansionary monetary policy, which slightly increases the differences within wage groups. Moreover, I find that policy changes take time to pass through the economy, as the effects on all wage deciles start with a lag. The responses reach their maximum after eight to twelve quarters. In terms of magnitude, the effects on the wage distribution of a one percentage point reduction in the policy rate are comparable to the effects of an expansion of the ECB's balance sheet by one trillion Euro.[3]

The paper by Mitman et al. (2022) is the closest analysis to this article in that it also uses the information collected in the SIAB to analyse the impact of monetary policy. However, there are important differences. First, their data ends in 2014, which does not allow for a comparison of different monetary policy instruments. Second, they assume that all relevant wage information for a monthly analysis is captured in the data, while for more than 80% of (incumbent) workers only average wages over the last year are reported. Therefore, they only report the timely wage effects of job changers, which could bias the results, as suggested by the different wage pattern of the national accounts data (Figure A.1). My temporal disaggregation approach aims to solve this problem. Finally, they examine the *average* wages and transition rates per ventile, while I decompose the earnings heterogeneity channel and analyse *individual* wage gains from job creation and job change, as well as from changing working hours and staying in the same job, in addition to differences across socio-economic groups.

After a closer look at the literature, the paper is structured as follows. Section 2 discusses the data used in the analysis, in particular the SIAB, and the selection of samples. Section 3 explains the construction of quarterly inequality measures and describes their

[3]Between 2007 and 2018 the ECB reduced its policy rate by four pp and expanded its balance sheet by three trillion Euro.

evolution since 1975. Section 4 focuses on the identification of exogenous monetary policy shocks. Section 5 describes the local projection approach and compares the effects of conventional and unconventional monetary policies on the wage distribution. Section 6 takes a closer look at the earnings heterogeneity channel and its sub-channels. Finally, Section 7 concludes.

1.1 Related Literature

My analysis relates to the expanding literature on the interplay between monetary policy and inequality, and contributes along three dimensions. First, I explicitly distinguish and compare the effects of conventional and unconventional monetary policy on wage inequality. While the data of the seminal contributions from Coibion et al. (2017) and Mumtaz and Theophilopoulou (2017) end before QE was implemented, later studies deliberately look at overall monetary policy effects (e.g. Furceri et al., 2018; Mitman et al., 2022). An exception is Guerello (2018) who analyses interest rate and balance sheet changes in the euro area. However, she uses an inequality indicator based on qualitative answers of the European Commission's Consumer Survey that captures disposable income but no components thereof. Lenza and Slacalek (2018) specifically analyse the effects of QE on income (and wage) inequality. Their results stem from a simulation exercise, which assumes the same effect-size along the income distribution and a fixed portfolio over time. They find equalising effects of QE at the beginning of its implementation, mainly by bringing people into employment.

Second, I analyse wage responses at the quarterly frequency using reliable administrative data. Due to the limited availability of earnings data, researchers usually face the trade-off between quarterly survey data (Coibion et al., 2017; Inui et al., 2020) and annual administrative data (Amberg et al., 2022; Andersen et al., 2023). While the first captures the within-year dynamics of monetary policy and business cycles, it suffers from small sample sizes and survey bias. The latter allows for a more detailed analysis but at risk of biased monetary policy effects due to annual aggregation, which potentially leads to conflicting results. Amberg et al. (2022) use annual tax information from Sweden to show that accommodative monetary policy shocks increase the incomes of individuals at the top and bottom of the distribution more than in the middle. While the effects at the bottom can be explained by the earnings response, the top is mainly due to a capital income response. The former effect points towards the relevance of the earnings heterogeneity channel. In contrast, Andersen et al. (2023) find monotonically increasing effects of monetary policy shocks on income along the income distribution in Denmark, implying an increase in income inequality. The earnings heterogeneity channel plays no role. While both papers describe the income responses across the distribution in detail, the framework does not allow for a quarterly analysis of the distributional dynamics. In addition, the policy impact on inequality is only described by a simulation exercise based on disposable income and does not distinguish between different types of monetary policy.

In order to overcome the trade-off between quarterly survey data and annual administrative data, researchers focused on interpolation methods. Samarina and Nguyen (2023) and Mumtaz and Theophilopoulou (2017) use mixed frequency VARs to estimate quarterly inequality dynamics, but those interpolation estimates are based on other aggregate variables. Mitman et al. (2022) use the spell structure of SIAB data and analyse the effects on monetary policy on wages similar to my approach. While their results are in line with my findings by showing significantly higher wages and a reduction in wage inequality after expansionary monetary policy shocks, their results are only statistically significant at the 68% confidence level. Moreover, they do not correct for the unobserved within-year wage dynamics of incumbents, which account for more than 80% of the observations. A comparison between the average wages from the SIAB data and the national accounts (see Figure A.1) show a significantly different pattern between these measures with the main difference stemming from the frequency of the incumbents' wage changes. Moreover, their analysis is limited to conventional monetary policy and focuses on the transition rates between labour market status.

Third, I contribute to the literature by focusing specifically on the earnings heterogeneity channel and its sub-channels that might explain the equalising effects and differences across policy tools. In line with the research that considered the job creation channel (Lenza and Slacalek, 2018; Mitman et al., 2022; Faia et al., 2022), I include unemployed workers in later analyses to show the different effects of monetary policy on unemployed workers. In addition, I decompose the sample of employed workers to understand the effects of job switching, changes in working hours and wage changes. I also distinguish between socio-economic characteristics, like gender, age groups and educational level to extend the heterogeneity analysis conducted by Andersen et al. (2023) on the role of age.

This paper also relates to the growing number of quantitative models of the interplay between monetary policy and inequality. Kaplan et al. (2018) show the relevance of indirect channels for monetary policy transmission and Auclert (2019) defines potential distributional channels, such as the earnings heterogeneity channel, to test their aggregate implications. More specifically, Gornemann et al. (2016) argues for the importance of getting people into employment. In line with my findings, expansionary monetary policy reduces inequality because it increases the chances of the unemployed to find a job, and the effects in terms of wage gains are largest at the bottom of the distribution. In contrast, I do not find an increase in the skill premium due to more technological investment after expansionary monetary policy changes as predicted by Dolado et al. (2021).[4] While Gornemann et al. (2016) suggest a simple heterogeneous agent model that accounts for unemployment effects, they do not directly relate to the emerging HANK literature. Moreover, my findings point to the job switching channel as another relevant sub-channel to describe declining wage inequality, which has not yet been incorporated.

2 Data

This study builds on a combination of several data sources. First, I use the factually anonymized data of the Sample of Integrated Labour Market Biographies (SIAB) to describe the wage distribution at a quarterly frequency. In addition, the euro area monetary policy event-study database (EA-MPD) by Altavilla et al. (2019) provides high frequency financial market data to identify monetary policy shocks. Finally, the ECB's Statistical Data Warehouse is the source of most quarterly macroeconomic variables. An overview of all macroeconomic variables, their sources and their definition is in Appendix A.1.

[4] The role of compositional changes, as suggested by Faia et al. (2022), cannot be properly analysed with the data at hand, as they do not include non-employed workers and do not identify whether workers leave for retirement or self-employment.

2.1 SIAB

The SIAB is a 2% random sample of German labour market participants provided by the German Institute for Employment Research (Frodermann et al., 2021). It contains the labour market biographies of individuals reported to social security providers since 1975 and includes observations from 1.9 million workers (in SIAB 2019). In Germany, it is mandatory for employers to report the employment status and other information to social security providers, which increases the reliability of the data compared to household responses in surveys, which are often subject to measurement errors. Further, the data is with daily precision and provides gross wages. This avoids errors that would otherwise be caused by cleaning the data of taxes and transfers. Moreover, the sample is representative (up to the exclusion of civil servants and self-employed individuals[5]) as it is a random sample of all social security records available and it is updated every year. Starting in 1992, the sample also contains East German workers. The long and large data set results in 80 million worker-quarter observations with at least 330,000 observations per quarter

The SIAB also has limitations, like top-coded wages and the non-reporting of hours worked. The social security providers only report wages up to the social security contribution limit. This implies that 7% to 15% of the wages in each quarter are higher than stated in the data. Hence, I use the 80-20 percentile ratio as the main measure of inequality. It describes the gap between the 80th wage percentile and the 20th wage percentile and is unaffected by the censoring. In addition, I report wage deciles separately and I calculate the Gini coefficient based on imputed wages with robust findings.[6] Another disadvantage is the non-reporting of hours worked. The SIAB only contains the average daily gross wage earned between two reports handed in by the employer. Therefore, the effects presented in the upcoming chapters can arise from changes in hourly wages as well as hours worked. Finally, for employees who neither change their labour market status nor their social security provider, employers are obliged to hand in a report only once a year in the first quarter. Hence, for these incumbent workers, the SIAB only reports

[5] These groups of people are subject to a different social security system and hence not covered by the data.

[6] The wage imputation follows the suggestion of Dauth and Eppelsheimer (2020) who adapt the censored regression models of Dustmann et al. (2009) and Card et al. (2013). Since Andersen et al. (2023) and Holm et al. (2021) find the largest earnings elasticities at the bottom of the income distribution and little differences between the median and the top, the choice of the top percentiles should not affect my conclusions.

annual average wages. The wage inequality can be described directly for each year but not the quarterly inequality. However, there are many reports handed in within the year to report changes relevant to the social security providers and these within-year changes offer valuable insights. I use them in a temporal disaggregation setting to estimate higher frequency wage deciles.

2.2 Sample preparation

In order to make use of the quarterly dynamics captured in the SIAB, I have to identify the workers who face a change in their labour market status. For this purpose, the SIAB data are split into different samples. Beside an overall sample to describe the annual wage distribution, I create sub-samples of workers for whom their employer handed-in an additional report during the year. I use this wages to infer the quarterly dynamics not directly observed in the overall sample.

The spell structure of the SIAB data requires a first adjustment to a panel structure. Following Dauth and Eppelsheimer (2020), the main spell per person and quarter is determined. Details can be found in Appendix A.1. Then, I deflate the average daily gross wages by the quarterly German CPI provided by the German Bundesbank.[7] The overall sample consists of all workers between 20 and 60 years who are subject to social security and whose working place location is known. Marginal workers, i.e., workers who earn gross wages below the social security contribution threshold (450€ per month in 2019) are excluded.[8] I consider both part-time workers and full-time workers to describe the wage distribution in a broad sense. This is particularly relevant because the definition of part-time workers was refined in 2011. Thus, excluding part-time workers would lead to a temporal inconsistency in the wage distribution (Fitzenberger and Seidlitz, 2020).

The main sample can be split into two large groups: "incumbents" and "changers". Incumbents are workers who neither change their job nor provide any other reason to send a report to a social security provider in a respective quarter. The rest of the sample (around 15%) are changers, for whom within-year wage dynamics are observed. These

[7]Inflation differentials along the income distribution were marginal during the period of observation (Charalampakis et al., 2022). Hence, I do not consider potential inflation heterogeneity across individuals.

[8]This also excludes unemployed workers with no wage/work place in the baseline specification.

changers consist of workers who start a new job, leave their job or for whom the employer submits a report during the year due to other reasons. These reasons include change of health insurance company, change of contribution group, change of payroll accounting system, external wage compensation, parental leave, statutory official duties (e.g. jury duty) and extra payment. In order to estimate the quarterly dynamics of the overall sample, using all changers could, however, introduce a selection bias as the decisions to start or end a job are not orthogonal to monetary policy shocks. In addition, individuals who start or end a job are on average younger, less educated, and their wages react much stronger to the business cycle.

In contrast, the sub-sample of all workers reported to social security providers due to other reasons (than starting/leaving their job) is representative for the overall sample along several dimensions (see Table 1) and hence, informative regarding the quarterly wage dynamics. These reporting reasons are more equally distributed in the population and less subject to monetary policy than starting a new job. There is a clear seasonal pattern as changes happen more often at the year end, but there are no cyclical movements among these reasons as shown in Figure A.2. This sub-sample termed "employed changers" consists of even fewer observations, but due to the large main sample there are 19,000 observations per quarter on average (see Table A.2). Moreover, I create a sample called "restricted employed changers" which additionally excludes parental leave and extra payment reasons due to their women-specific and seasonal characteristics. Having the various samples defined, I calculate the quarterly wage deciles for the main sample and all sub-samples. Note that the main sample includes incumbent workers for whom only annual wage changes are reported. Hence, the true values for the overall sample are not known at a quarterly frequency.[9]

3 Measuring inequality

A common limitation of inequality measures is their annual (or lower) frequency. This becomes a drawback when analyses focus on higher-frequency polices such as monetary

[9]Before I estimate the unknown quarterly wage deciles for the overall sample, I remove structural breaks and outliers from the wage deciles. As this only affects periods not covered in my analysis, details are shifted to the Appendix.

policy. Since I am interested in the within-year propagation of monetary policy effects, I derive quarterly wage deciles via temporal disaggregation. This section starts with an explanation of the interpolation approach and the indicator series used, before presenting the resulting inequality pattern for Germany. As the analysis is carried out at a quarterly frequency, the wage deciles as well as the inequality measures are seasonally adjusted whenever I deviate from annual averages. This is necessary because the time-series show seasonal patterns due to holiday payments and calendar effects of employment, which obscure the effect of monetary policy on wages (Buono et al., 2018).[10]

3.1 Temporal disaggregation

The overall sample of the SIAB only captures the annual average wage percentiles completely. By means of temporal disaggregation, however, it is possible to interpolate the missing wage values at a higher frequency for a monetary policy analysis. Regression-based interpolation methods use high-frequency indicator series to inform the low-frequency series of interest. Prominent examples are the method developed by Chow and Lin (1971) and its extensions to interpolate, for example, quarterly GDP by the monthly industrial production index or triennial wealth data by quarterly financial accounts (Batty et al., 2019).

The approach by Chow and Lin (1971) estimates an unknown high frequency series Y_h, whose averages (alternatively: sums, first values or last values) are consistent with a known low frequency series Y. To estimate Y_h one or more high frequency indicator series X are required. In this analysis, I estimate the overall *quarterly* wage percentiles by regressing the overall *annual* wage percentiles on the *quarterly* wage percentiles of specific *subsamples* and an intercept. For this purpose a generalized least squares (GLS) regression of the annual values Y on the annualized quarterly indicator series CX is performed,

[10] I apply the X-13ARIMA-SEATS software package, which is used by many statistical offices in Europe, in its version for R provided by Sax and Eddelbuettel (2018). Due to the German Reunification, East Germans enter the SIAB in 1992. Hence, I include a level shift in 1992-Q1 and allow for different seasonal patterns before and after 1992. Otherwise, I follow the default options. Including calendar effect covariates (length of quarter, trading day, Easter) has no effect on the seasonal adjustment.

where C is a conversion matrix that performs the annualization of the quarterly series.

$$C = \begin{bmatrix} 1/4 & 1/4 & 1/4 & 1/4 & 0 & 0 & 0 & 0 & \cdots & 0 \\ 0 & 0 & 0 & 0 & 1/4 & 1/4 & 1/4 & 1/4 & \cdots & 0 \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \cdots & 1/4 \end{bmatrix} \tag{1}$$

The GLS regression has the form:

$$Y = CX\beta + Cu \tag{2}$$

Chow and Lin (1971) demonstrate that for a given variance-covariance matrix, $V = \mathbb{E}[uu']$, the consistent GLS estimator, $\hat{\beta}$, is calculated by:

$$\hat{\beta} = \left[X'C'(CVC')^{-1}CX\right]^{-1} X'C'(CVC')^{-1}Y, \tag{3}$$

and the linear unbiased estimate of Y_h is given by:

$$\hat{Y_h} = X\hat{\beta} + VC'(CVC')^{-1}[Y - CX\hat{\beta}], \tag{4}$$

which consists of two components: $X\hat{\beta}$ represents the predicted values of the unknown high frequency series Y_h given the high frequency indicator series X; the second term distributes the low frequency residuals across quarters. The critical assumption of this method is that the estimated linear relationship between the annual series CX and Y_h also holds between the quarterly series X and Y_h (Sax and Steiner, 2013). Since the wage percentiles are relatively persistent and the sub-sample characteristics closely follow the characteristics of the main sample, this assumption seems reasonable. For the estimation of the variance-covariance matrix, Chow and Lin (1971) assume that the quarterly residuals follow an AR(1) process, while Litterman (1983) generalizes the residual process to a random walk to capture series that are not cointegrated:

$$u_t = u_{t-1} + \epsilon_t \qquad \epsilon_t = \rho\epsilon_{t-1} + \eta_t \qquad (0 < \rho < 1) \tag{5}$$

This latter approach is used to estimate the quarterly German wage deciles.[11]

To estimate the missing observations of a low-frequency series reliably, a suitable indicator series is required. The indicator series usually applied for temporal disaggregation describe different but related outcomes to the low-frequency series (e.g. industrial production index - overall GDP). Also the previous inequality literature applies other macro variables in mixed frequency VARs to interpolate missing inequality observations (see Samarina and Nguyen, 2023; Mumtaz and Theophilopoulou, 2017). In contrast, it is possible to infer the overall wage percentiles by wage percentiles of a restricted sample from the same data set, since the SIAB contains suitable sub-samples with observations at quarterly frequency. In particular, I use the wage deciles of the sub-sample "employed changers" (defined in Section 2.2) as indicator series for the annual average wage deciles of the overall sample.

The suitability of an indicator series for a regression-based temporal disaggregation can be evaluated along several criteria. First, the high-frequency series has to cover the whole period of the low-frequency series. Second, the correlation between the low-frequency series and the annualized high-frequency series should be high, and the high-frequency series should have explanatory power for the low-frequency series. Third, in case of the same outcome variable, the sample and sub-sample characteristics should be similar. These criteria are largely met by the "employed changers" sub-sample. In addition to the coverage of the whole period, similar sample characteristics, as shown by the differences to the overall sample in Table 1, argue in favour of "employed changers". Other sub-samples like all "changers" or "restricted employed changers" are less similar along the dimensions of average tenure, age and the share of higher educated workers. Moreover, Figure 1 shows the 20th, the 50th and the 80th wage percentile of the annual low-frequency series as well as the percentiles of the competing indicator series. The blue line representing the "employed changers" sample is closest to the overall wage deciles and shows a high annualized correlation.[12] Finally, Fukuda (2009) suggests to compare the explanatory power of different indicator series against a baseline scenario with just an intercept and a

[11] For details, see Sax and Steiner (2013) and the original papers by Chow and Lin (1971) and Litterman (1983).

[12] A comparison of the seasonally unadjusted mean wages of the sub-samples and the mean wages according to German National Accounts data also favours the "employed changers" sample regarding the representativeness of its dynamics (Figure A.1).

Table 1: Sub-sample comparison by summary statistics

	1975-1991	1992-1998	1999-2008	2009-2019	qtr corr
Average Age					
All	38.13	39.08	40.40	42.04	1.00
Changers	-4.42	-3.22	-3.39	-4.31	0.82
Employed Changers	-0.32	-0.54	-0.80	-0.79	0.87
Restricted Empl. Changers	-0.26	-0.50	-1.22	-1.18	0.77
Average Tenure					
All	1,641.69	2,312.43	2,672.18	2,968.48	1.00
Changers	-949.54	-1,362.84	-1,438.79	-1,738.13	0.78
Employed Changers	-28.99	-95.22	-59.65	-111.78	0.98
Restricted Empl. Changers	-46.25	-183.55	-31.77	-143.37	0.95
Higher Education Share					
All	5.81	10.02	13.49	18.54	1.00
Changers	0.05	-0.13	-0.29	-1.02	0.97
Employed Changers	-1.06	-0.61	0.68	0.25	0.92
Restricted Empl. Changers	2.62	5.37	3.77	3.62	0.83
(Average) Median Wage					
All	83.14	89.29	90.35	89.07	1.00
Changers	-13.49	-16.82	-17.70	-20.94	0.51
Employed Changers	-3.51	-2.67	-1.08	-4.44	0.67
Restricted Empl. Changers	1.49	5.09	8.74	6.67	0.48

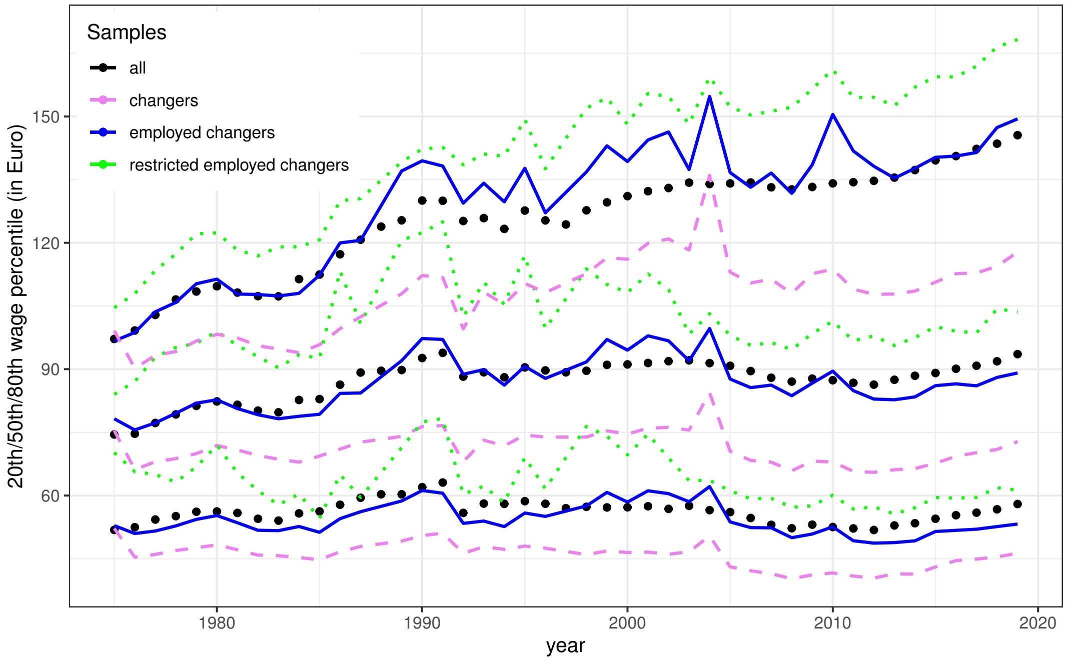
Note: This table compares age, tenure, higher education share and median wage of the sub-samples "Changers", "Employed Changers" and "Restricted Employed Changers" to the main sample (All) as defined in 2.2. Tenure counts the days a worker is employed at a firm. The higher education share shows the sample share of workers with a university or Fachhochschul degree. Wages are the daily gross real wages. The average values are reported for the period 1975-1991 (pre Reunification in SIAB), 1992-1998 (pre Euro), 1999-2008 (pre GFC) and 2009-2019. The last column shows the quarterly correlation with "All" over the whole period. Source: factually anonymized SIAB 2019

trend. The seasonally adjusted wage percentiles of the "employed changers" sub-sample beat the baseline scenario and the other sub-samples in generating low values of the Bayesian Information Criterion (BIC) in the Chow-Lin regression framework (see Table A.3). Due to its explanatory power and similarity to the main sample, I use the "employed changers" wage percentiles as indicator series.

3.2 Quarterly wage inequality

In this paper, the preferred measures of wage inequality are percentile ratios. These ratios describe the gap between wages at different positions of the wage distribution. Beside the 80-20 percentile ratio, I report the 80-50 percentile ratio and the 50-20 percentile ratio, as well as the development of individual wage deciles to identify changes specific to the top

Figure 1: Comparison of annual wage percentiles

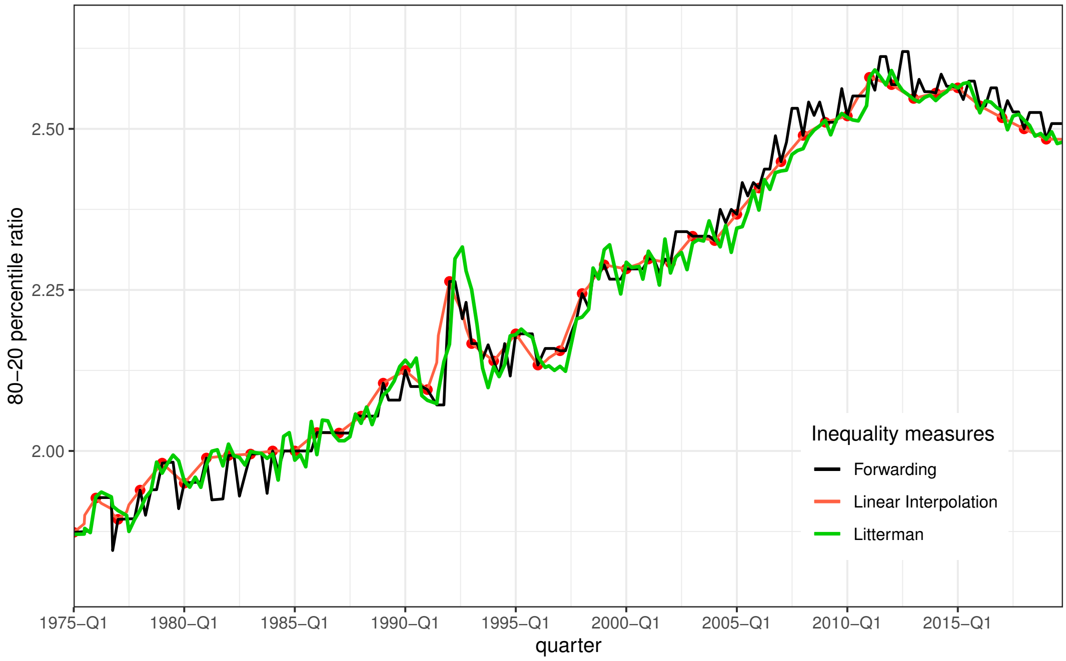


Note: This figure plots the annual average wage percentile of the main sample (black large dots) and the sub-samples "changers" (pink, dashed), "employed changers" (blue, solid) and "restricted employed changers" (green, dotted). The lowest line of each sample represents the 20th percentile, the middle line the median and the highest line the 80th percentile.

or bottom of the distribution. All inequality measures are based on the real gross daily wage deciles.

The application of temporal disaggregation leads to a wage development known from the inequality research based on annual SIAB data (e.g. Dustmann et al., 2009; Fitzenberger and Seidlitz, 2020) with the important addition of quarterly movements (see Figure A.3). The focus of this section is on the 80-20 ratio based on the interpolated quarterly 80th and 20th wage percentile. Figure 2 shows its quarterly development (green line) between 1975-Q1 and 2019-Q4. Until 1991 the ratio only captures data from West Germany, while it describes the wage inequality of whole Germany afterwards. The economic shock of the German Reunification is represented by the spike in inequality in 1991. The 80-20 ratio shows a stable inequality level during the late 1970s and the 1980s. It then starts to rise and continues to do so until 2010 with a short decline in inequality due to the convergence after the Reunification. Only recently, German wage inequality has reached a plateau and it seems that inequality has been declining during the last years, a period of extremely expansionary monetary policy.

Figure 2: Quarterly inequality in Germany (interpolated)



Note: This figure shows the development of the 80-20 percentile ratio according to different interpolation methods: linear interpolation (orange), wage forwarding (black), Litterman regression-based approach (green). The interpolation is always applied to the percentiles before the ratio is calculated. For a comparison with the annual frequency literature, the values of the first quarters (red dots) are depicted.

Figure 2 compares the chosen disaggregation method to more mechanic interpolation methods. The orange line shows a linear interpolation between first quarters, which are represented by red dots. Since most of the labour market changes, the annual reporting and the extension of the random sample take place in the first quarter, the period from January to March is used as benchmark. This implies that the inequality changes steadily over the three missing observations with no possibility to deviate in the short-run. A simple visual inspection shows that the pattern is too static and far less volatile than the interpolated 80-20 ratio. Another possibility to derive quarterly inequality is to simply take the quarterly wage values of each individual as derived by the preparations of Dauth and Eppelsheimer (2020); this is done by Mitman et al. (2022). This interpolation strategy forwards all wages until a new report is handed in by the employer and ignores the fact that more than 80% of the workers are incumbents with unobserved within-year wage dynamics. The black line represents the 80-20 ratio based on forwarded wages. It has within-year plateaus and jumps due to the large share of incumbents. In contrast, my interpolated time-series follows a path that is neither restricted by a linear or cubic pattern nor does it show plateaus. Moreover, I do not assume that the values in Q1 are correct, as they might also ignore wage changes of incumbents. The temporal disaggregation method targets the annual average wage distribution, so that the annual average of the quarterly values is equal to the annual values. This improves the quarterly time-series compared to mechanic approaches, and the results are robust to many methodological adjustments as shown in Section 5.4 (and Appendix A.3).

4 Identification of monetary policy shocks

In order to describe a causal relationship between monetary policy and labour market outcomes, it is necessary to derive exogenous variation monetary policy. This is relevant as monetary tools not only affect economic output and inflation, they are also influenced by these macroeconomic conditions. Kuttner (2001) derives exogenous monetary policy shocks[13] by changes of financial markets in a tight window around the announcement of central bank actions. Thereby, any anticipated change in market rates is captured until a few minutes before the policy decision is made. This high-frequency identification builds on the assumption that new information which arises within the window does not affect the policy decision. Hence, after checking for potential other sources of information around the announcement, it is plausible to state that the effects observed in this window are only due to monetary policy decisions and these shocks are exogenous. While this approach is well equipped to measure instantaneous effects of a policy surprise due to its event study framework, it is difficult to identify the persistence of shocks. Moreover, the shocks potentially contain measurement errors as financial markets do not always incorporate all information correctly or within the announcement window (Gertler and Karadi, 2015). Therefore, I will not use these policy shocks directly in local projections, but as instruments for changes in the policy rate and the balance sheet size.

I derive and disentangle different types of monetary policy shocks by applying a Principle Component Analysis (PCA) on risk free interest rate changes, following Altavilla et al. (2019). They provide changes of a wide range of financial market indicators around the policy announcements of the ECB in the EA-MPD. The Governing Council meets

[13]A shock is considered exogenous, if it is neither contaminated by other economic shocks and news nor anticipated due to forecasts and predicted central bank behaviour.

every six weeks to make policy decisions. On these days, the changes in financial market rates between 13:25 and 15:50 are documented to capture the press release of the policy decision as well as the ECB President's press conference. I use Overnight Index Swap (OIS) rates, a proxy for risk-free interest rates, at different maturities in a PCA to capture several dimensions of monetary policy in terms of instruments and objectives (Gürkaynak, 2005).[14]

The PCA identifies two relevant factors before the introduction of QE and three factors afterwards, as described in detail by Altavilla et al. (2019). Unfortunately, principal components do not have a clean interpretation. However, it is possible to apply an orthogonal rotation to create an interpretable distinction between these shocks. The rotation matrix applied in this context captures the following identifying restrictions: i+ii) the second and third factor do not load on the one-month OIS rates and iii) the third factor has the smallest variance before the GFC started (Swanson, 2021). Thereby, I find a factor that mainly loads on the short-term OIS rates, one with its main impact after two years (the forecast horizon of the ECB) and one with longer term effects that is only significantly relevant after the GFC. Thus, these factors are termed "Target Rate" shock, "Forward Guidance" shock and "QE" shock according to the different target horizons of the most relevant monetary policy tools. In this way, it is possible to create exogenous monetary policy shocks and to disentangle the effects of conventional and unconventional policy measures so that they are orthogonal to each other.

To refine the interpretation, I scale the three monetary policy shocks to unit effects on the OIS maturities with the largest loading, respectively. The temporal pattern of the different central bank tools are as expected (see Figure A.4a-A.4c): a short-run impact of the Target Rate, hump-shaped loadings with a peak after two years in the case of Forward Guidance and an increasing impact of QE over time. After the scaling, the Target Rate shock has a unit effect on the one-month OIS rate, the Forward Guidance shock has a unit effect on the two-year OIS rate and the QE shock has a unit effect on the ten-year OIS rate. This implies that a positive QE shock increases OIS rates and hence has contractionary effects, while an expansion of the balance sheet is expansionary.

[14] I use OIS rates with 1, 3, 6 month and 1, 2, 5, 10 year maturities. Before 2011 no OIS rates with maturities longer than 2 years are available. I use German sovereign yields as proxy for risk-free rates for this period as done by Altavilla et al. (2019).

Target Rate shocks and policy rate changes work in the same direction.

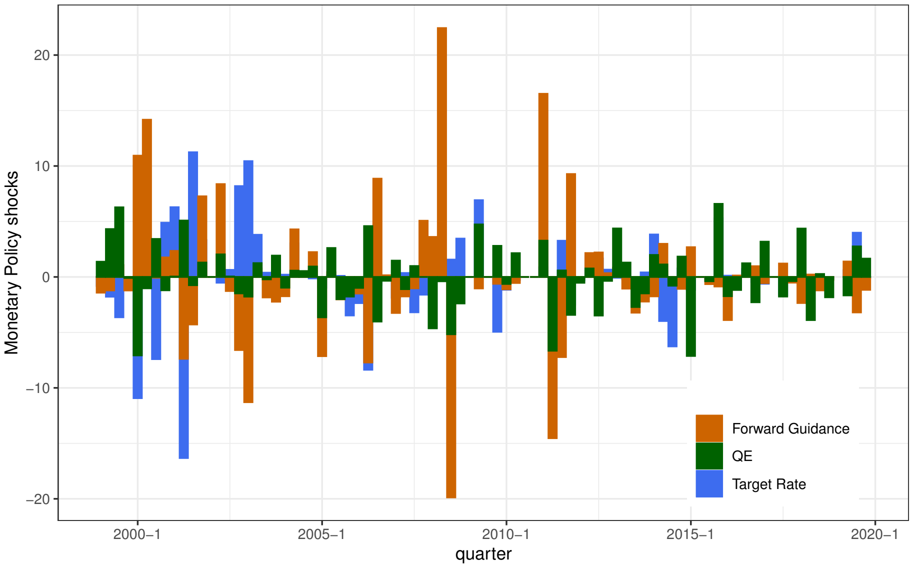
Jarociński and Karadi (2020) show that the surprises derived from the high-frequency identification approach are not pure monetary policy shocks. Central bank announcements reveal information about the central bank's economic outlook in addition to the information about the policy tools. Thus, I follow Jarociński and Karadi (2020) and apply their "poor man's sign restriction" to remove information shocks. Each policy meeting is classified as a monetary policy shock or information shock depending on the direction of changes of the three-month OIS rate (policy shock) and the EUROSTOXX 50 (stock price change) in the window around the policy announcement. Based on monetary theory, stock prices are expected to decline after a monetary policy tightening and to increase after monetary easing. If the policy shock and the stock prices move, however, in the same direction, it is likely that the information captured in the decision dominates. A central bank usually decides for contractionary measures if inflation is expected to be too high. This can be caused by a good economic development from which companies and their stocks benefit, so that a contractionary surprise is followed by an increase in stock prices. The poor man's sign restriction identifies dominating information effects at a third of the decision dates in my sample and sets these shocks to zero.

After the identification of Target Rate, Forward Guidance and QE shocks for each policy meeting of the Governing Council, aggregation harmonizes the six-week frequency of the shocks with the quarterly frequency of the labour market variables. In accordance with Gertler and Karadi (2015), I calculate a weighted aggregate where the timing of the policy meeting is considered.[15] Figure 3 depicts the quarterly time series of the policy shocks (for the detailed shock series see Figure A.5). While the policy surprises were larger in the first years of the Euro and dominated by the Target Rate shocks, the relative importance shifted to the QE shocks in later years. Over time, market participants became more used to the ECB's decision-making, so that the volatility declined. The largest shocks occurred during the GFC and they are dominated by the Forward Guidance shock

[15] The Governing Council meetings are not at the same time every quarter, so it is likely that earlier decisions affect a quarter stronger than later ones. The weighting is realized in two steps. First, I sum over all shocks from a specific type during the last 92 days (e.g. on August 10 I consider all shocks since May 10, the duration of a quarter) to obtain an aggregate for each day. Then, I use these values to calculate the average for each specific quarter (e.g. Q2-2010). Thereby, earlier shocks are weighted higher, since they affect a quarter longer than those shocks realized at the end.

series. Note that the policy shocks can be contractionary even if interest rates were cut or QE was expanded when a stronger central bank reaction was expected by the market participants.[16]

Figure 3: Monetary Policy shocks



Note: Quarterly monetary policy shocks decomposed into Target Rate, Forward Guidance and QE shocks and corrected for information effects. The monetary policy shocks are denoted in basis point changes of the respective OIS rate.

In order to show that the different shocks capture information on monetary policy in line with economic intuition, I analyse their effects on financial market variables. Specifically, I regress the intraday changes of OIS rates, government bond yields, stock returns and the Euro-USD exchange rate on the shock series. Table 2 shows the estimated coefficients for expansionary monetary policy shocks. While Target Rate shocks have a strong influence on the short-run OIS rates, Forward Guidance shocks capture the impact in the medium run and QE shocks increase their influence with maturity. The effects are similar for German bond yields, but even at ten-year maturity the Target Rate shocks show a significant impact. The expansionary shocks have a significantly positive influence on the stock returns after controlling for the information effect as monetary policy is expected to boost demand and hence firm profits. The Euro is depreciating in line with the uncovered interest rate parity theory.

[16]The QE shocks before 2008 stem from the explorative approach of the PCA. Monetary policy already affected long-term rates before QE was conducted and the balance sheet size changed as well, so that I cannot exclude shocks before 2008. This is another reason why I use the shocks only as instruments and not directly in the local projection. Setting the values of the QE shocks before 2008 to 0 manually does not change the results.

Table 2: Effects of monetary policy surprises on financial market variables

	Dependent variable:							
	OIS_1M	OIS_6M	OIS_2Y	OIS_10Y	DE2Y	DE10Y	STOXX50	EURUSD
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Target shock	-0.577^{***}	-0.747^{***}	-0.482^{***}	-0.349	-0.632^{***}	-0.334^{***}	0.164^{***}	-0.068^{***}
	(0.116)	(0.096)	(0.134)	(0.242)	(0.141)	(0.090)	(0.026)	(0.019)
FG shock	0.054	-0.587^{***}	-0.967^{***}	-0.137	-1.064^{***}	-0.289^{***}	0.012	-0.037^{***}
	(0.080)	(0.066)	(0.089)	(0.189)	(0.097)	(0.062)	(0.017)	(0.013)
QE Shock	-0.270	-0.351^{**}	-1.135^{***}	-1.019^{***}	-1.093^{***}	-1.206^{***}	0.019	-0.106^{***}
	(0.163)	(0.134)	(0.194)	(0.184)	(0.198)	(0.127)	(0.036)	(0.026)
Constant	0.419	0.199	-0.107	-0.101	0.086	-0.133	-0.255^{**}	-0.164^{**}
	(0.442)	(0.364)	(0.509)	(0.433)	(0.537)	(0.343)	(0.097)	(0.070)
Observations	84	84	79	34	84	84	84	84
R^2	0.257	0.639	0.692	0.606	0.679	0.610	0.342	0.319
Adjusted R^2	0.229	0.626	0.680	0.566	0.667	0.596	0.318	0.293

Note: The table reports the effects of monetary policy surprises on financial market variables at different maturities using intraday data. The OIS rate at one-month, six-month, two-year and ten-year maturity is used as dependent variable. In addition, the effects on the two-year and ten-year German Government bond yields (DE2Y, DE10Y), the Euro Stoxx50 and the EUR-USD exchange rate are shown. Robust standard errors in parentheses. *p<0.1; **p<0.05; ***p<0.01

5 Monetary policy effects

In the following section I combine the quarterly wage percentiles and monetary policy shocks for my econometric analysis in a local projection (LP) framework (Jordà, 2005). More specifically, I use an instrumental variable LP framework due to the potential measurement error in high-frequency monetary policy shocks. Therefore, I will present the concept of IV LP and test the validity of the instruments, before I present the effects of conventional and unconventional monetary policy on wages and inequality.

5.1 IV local projection

In order to quantify the responses of wages and inequality to changes in monetary policy tools between 1999-Q1 and 2019-Q4, I estimate equation (6) at different horizons h as suggested by Jordà et al. (2015).

$$ln(y_{t+h}) - ln(y_{t-1}) = c^h + \sum_{p=1}^{P} \alpha_p^h ln(y_{t-p}) + \beta^h \widehat{policy_t^i} + \phi^h X_t^i + u_{t+h}^h, \quad h = 0, 1, ..., H \tag{6}$$

where y_t is the variable of interest, like the 80-20 percentile ratio or a wage decile, at time t. The dependent variable is constructed as a growth rate between the period $t+h$ and the period before a shock happened $(t-1)$ to isolate the effect similar to a Difference-in-Difference approach. H equals 12 to estimate the quarterly dynamics over a three-year horizon. In contrast to VAR frameworks, the equation is estimated at each horizon h to derive Impulse Response Functions (IRF) directly. c^h represents the constant at horizon h and u_{t+h} is the respective error term. Further, $policy_t^i$ represents the change in the ECB's policy rate (i=IR) or the change in the volume of the ECB's balance sheet (i=QE). The IRFs are generated by the estimated β^h, i.e., the expected policy effect on the dependent variable at horizon h. Since the policy variables are subject to endogeneity, they are instrumented by exogenous monetary shocks. Moreover, equation (6) includes the lags of the variable of interest up to lag P to control for the persistency of the left-hand side variables. I choose the number of lags according to the BIC, so that $P = 8$ if i = IR and $P = 4$ if i = QE, but the results are similar if two, four or eight quarters of lags are employed. X_t^i contains control variables. In particular, the policy rate specification includes lagged Target Rate shocks, the current change in the balance sheet and the lagged Harmonized Index of Consumer Prices (HICP) of the euro area. The QE specification includes lagged QE shocks and current and lagged policy rate changes.[17] The baseline specifications contain four lags of each lagged control variable.

Three conditions need to be fulfilled for a valid IV local projection that controls for endogeneity and does not introduce another bias (Stock and Watson, 2018). Let Z_t^i be a vector of instrumental variables specific to policy i. Then, this set of instruments is valid to estimate the dynamic causal effects if:

$$(i) \quad \mathbb{E}(\epsilon_t^i Z_t^i) = \alpha \neq 0 \quad (relevance); \tag{7}$$

$$(ii) \quad \mathbb{E}(\epsilon_t^o Z_t^i) = 0 \quad (contemporaneous\, exogeneity); \tag{8}$$

$$(iii) \quad \mathbb{E}(\epsilon_{t+j} Z_t^i) = 0 \quad for \quad j \neq 0 \quad (lead-lag\, exogeneity) \tag{9}$$

where ϵ_t^i is the true (unobserved) policy shock i, which is approximated by the contemporaneous change in monetary policy i and controlled for the covariates in X and the

[17] Since inflation was low and flat during the implementation of QE, HICP does not have significant explanatory power in this setup and hence is not included in this specification.

lagged endogenous variable. ϵ_t^o represents all other shocks at time t and ϵ_{t+j} captures all future and past shocks. While (i) and (ii) are the usual IV conditions known from microeconometric applications, (iii) arises from the dynamics of y_{t+h} as it usually depends on the whole history of shocks. Thus, a clear identification of ϵ_t^i is only possible, if there is exogeneity at all leads and lags (Stock and Watson, 2018).

Contemporaneous exogeneity holds true by the construction of monetary policy shocks described in the previous section. Since Target Rate, Forward Guidance and QE shocks are measured in a narrow window around policy announcements, it is very unlikely that other shocks systematically occur at the same time. Similarly, lead exogeneity is justified by the definition of shocks as unexpected innovations as long as Z_t^i does not contain variables realized in the future. This is underpinned by an augmented Dickey-Fuller test for autocorrelation of the shock series, which does not find any temporal relation. The assumption of lag exogeneity is more restrictive, since y_{t+h} is the result of current and past shocks. Hence, Stock and Watson (2018) suggest a regression of Z_t^i on lags of y_t to test the lag-exogeneity condition, whereby Z_t^i should not be forecastable. None of the monetary policy shocks is predictable by lagged values of the 80-20 ratio or the wage deciles (see Table A.7 in the Appendix). Thus, the exogeneity conditions (ii) and (iii) hold true.

The first stage regression (10) and a related weak instrument test adjusted for heteroscedasticity evaluate the instruments' relevance and hence, condition (i).

$$policy_t^i = c + \sum_{p=1}^{P} \alpha_p ln(y_{t-p}) + \phi X_t^i + \gamma Z_t^i + e_t \tag{10}$$

The Target Rate shocks adjusted by the poor man's sign restriction are used as instrument for the endogenous changes of the ECB policy rate. In the baseline specification $P = 8$ and X_t contains four lags of the HICP, four lags of the Target Rate shocks and the current change in the ECB's balance sheet. In this specification, the Target Rate shocks have a statistically significant impact on policy rate changes and the heteroscedasticity and autocorrelation robust first-stage F-Statistic is significantly different from zero at the 1% confidence level.[18] Hence, I reject the null hypothesis that Target Rate shocks are weak

[18]The first-stage F-Statistic for y being the median wage is 15.4 and for the 80-20 percentile ratio it is also 15.4 as shown in Table A.4.

instruments, which confirms the validity of the IV LP framework.

The relationship between ECB balance sheet changes and QE shocks is not strong and so the LP estimation could suffer from weak instruments (as depicted in Table A.5). There are two problems regarding this policy-instrument combination. First, the announcements of QE are not exclusively related to one point in time like policy rate changes, but imply adjustments in the balance sheet over the coming months, usually six to twelve months. Hence, I will use the difference between the balance sheet size two quarters ahead ($t + 2$) and the balance sheet in the previous quarter ($t - 1$) as measure of unconventional monetary policy in all my regressions. Second, QE was not conducted over the whole period. While assets were purchased for fine-tuning only in the first ten years of the Euro, the majority was bought after 2014. At the same time, the QE shocks show that monetary policy already had long-term effects before large-scale asset purchases began. Thus, Dedola et al. (2021) use a QE announcement dummy in their IV analysis to specifically capture large-scale asset purchases. The application of the QE shocks adjusted by the poor man's sign restriction and QE announcement dummies as instruments for ECB balance sheet changes result in F-Statistics that reject the weak instrument hypothesis at the 1% confidence level for all specifications.[19] Moreover, the exogeneity of the instruments can be verified by an overidentification test due to the application of several instruments. There is no statistical indication that the QE shocks or the newly added QE announcements are endogenous variables. Hence, valid instruments also exist for balance sheet policies.[20]

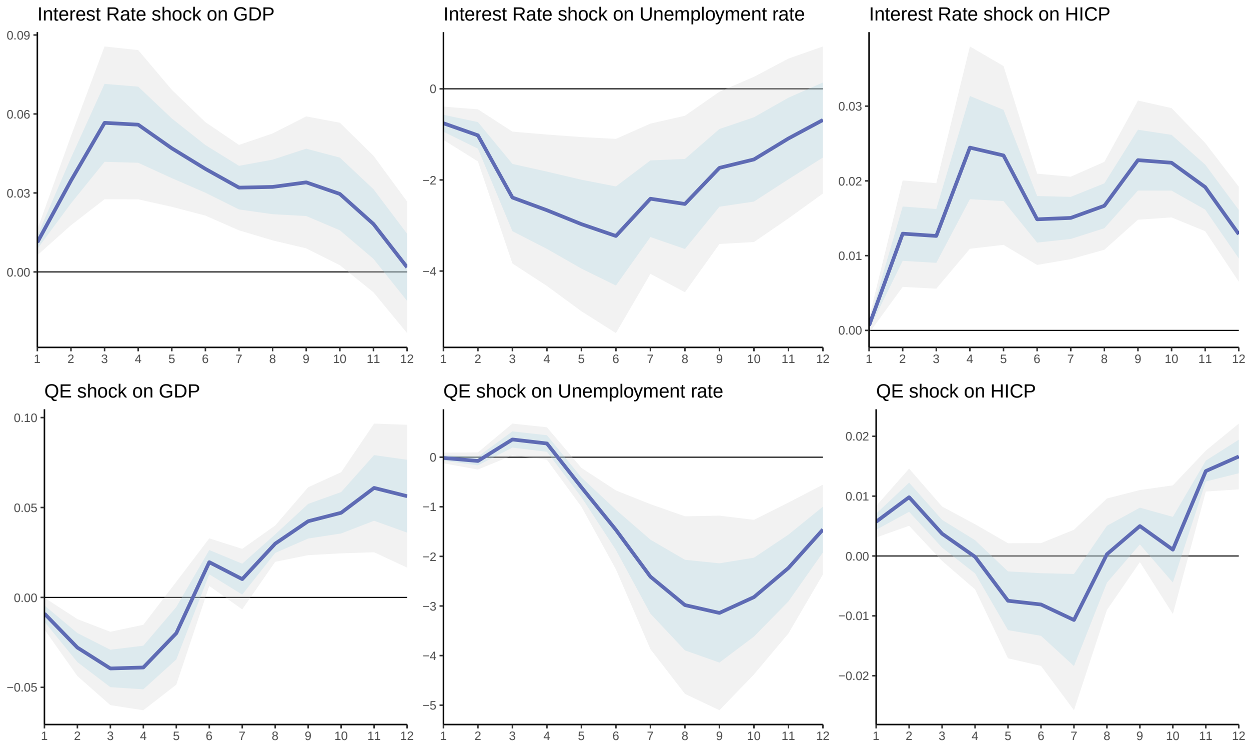
The validity of the chosen instruments and the consistency of the IV LP framework can also be shown by a comparison to the existing empirical macro literature. I estimate equation (6) with the dependent variable being the growth rate of the seasonally adjusted real GDP, the change in the seasonally adjusted unemployment rate and the growth rate of the seasonally adjusted HICP. Each variable contains the values of the euro area. The upper row of Figure 4 shows the statistically significant impulse responses of GDP, unemployment and inflation to a one pp interest rate decline. The lower row shows

[19]The first-stage F-Statistic is 15.3 for specifications with the median wage and 15.9 for the 80-20 percentile ratio as shown in Table A.6.

[20]Forward Guidance shocks are neither a strong instrument for policy rate changes nor for balance sheet changes, and quantifying forward guidance is less clear-cut than interest rates and balance sheets that are directly manipulated by the central bank. Therefore, I will present the effects of forward guidance, proxied by 2-year OIS rates and (weakly) instrumented by Forward Guidance shocks, only in the Appendix.

the respective IRFs to an expansion of the ECB's balance sheet by one trillion Euro. The confidence bands depict heteroscedasticity and autocorrelation consistent standard errors (Newey and West, 1987). In both cases GDP and inflation increase significantly and unemployment declines over the medium-run as known from the monetary policy literature. The positive responses of seasonally adjusted investment and employment is depicted in Figure A.6. This shows the suitability of the empirical strategy and the policy indicators.

Figure 4: Macro responses to monetary policy changes

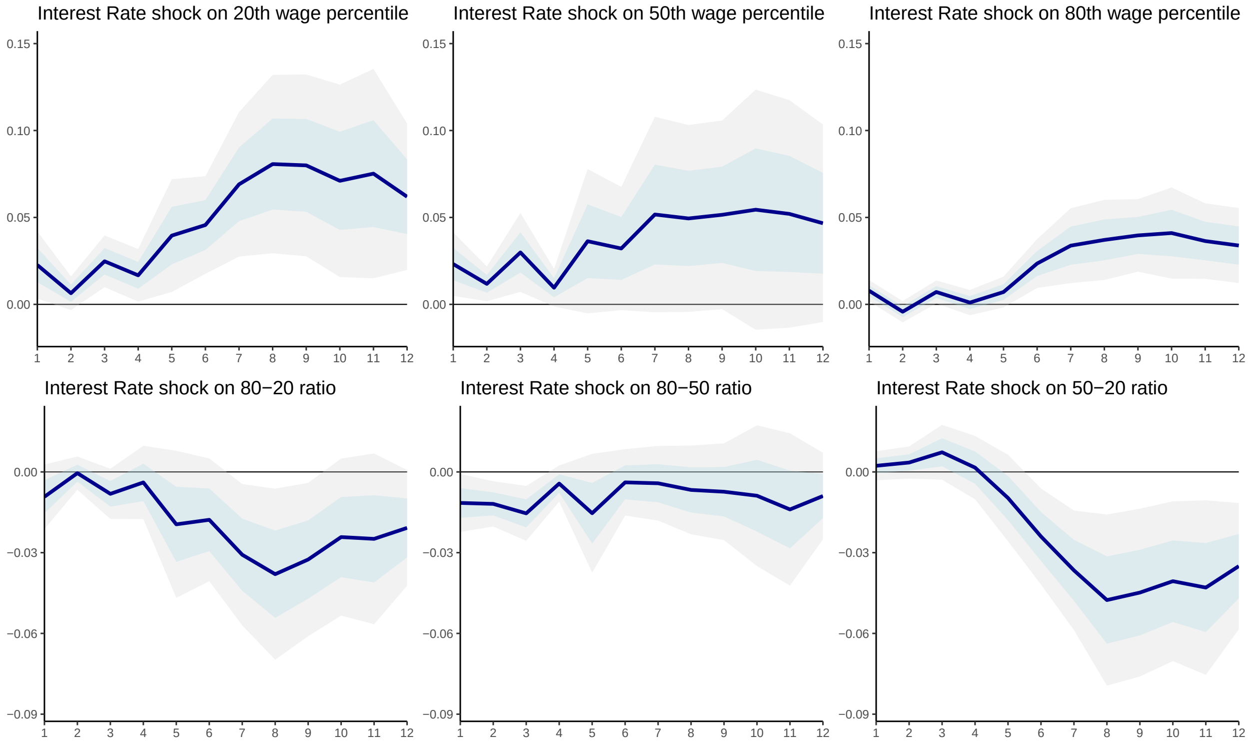


Note: The figure presents impulse responses of macroeconomic variables to a 1 pp expansionary policy rate change (upper row) and a 1 trillion Euro expansionary balance sheet change (lower row) instrumented by Target Rate shocks and QE shocks/QE announcements, respectively. Time is in quarters. The blue and grey shaded areas indicate 68% and 95% confidence intervals, respectively.

5.2 Conventional Monetary Policy

Figure 5 presents the impulse responses of selected German wage percentiles and inequality measures to a one percentage point (100 basis points) reduction in the ECB policy rate. More specifically, the upper row depicts effects on the wage components of the inequality ratios: the 20th, 50th and 80th wage percentile. The lower row shows the effects on wage inequality for the whole, the top half and the bottom half of the wage distribution by the 80-20, 80-50 and 50-20 percentile ratios. All plots describe relative changes.

Figure 5: Responses to expansionary conventional monetary policy



Note: The figure plots impulse responses as well as 68% and 95% confidence intervals (blue and grey shaded areas) of wage deciles (upper row) and inequality measures (lower row) to a 1 pp policy rate cut. Impulse responses are at the quarterly frequency using data from 1999-Q1 to 2019-Q4.

While an expansionary conventional monetary policy shock leads to an increase in wages across the whole wage distribution, there are notable and statistically significant differences along the distribution. The 20th wage percentile reacts quickly and is already significantly different from zero in the third quarter. In contrast, the top wages start to react with a delay of six quarters. The lower wages do not only react faster, but also slightly stronger compared to the median and the top wages.[21] These conclusions also hold true when all wage deciles are considered, as is done in Figure A.7. Especially for the 10th percentile, it is noteworthy that the pattern is very similar to that for the 20th percentile, and even quicker. This pattern implies a significant decline in inequality in the lower half of the German wage distribution after an expansionary monetary policy shock. At the same time, the decline in wage differences at the top is only short-lived,

[21]The statistical significance of the effect differences across the wage distribution are shown in Table A.8.

as the median wage adjusts quicker than the 80th wage percentile. Otherwise, the wage developments at the top and in the middle are very similar. The effect on the 80-20 percentile ratio indicates a reduction in overall inequality after an expansionary interest rate shock, which becomes statistically significant after seven quarters.

Due to the persistence and small variation in inequality, the impact shown in Table 5 is economically relevant. In particular, two years after a 100 basis points reduction in the policy rate, the 80-20 ratio has fallen by 3.9% on average. Given that the standard deviation of quarterly policy rate changes is 34 basis points, the size of the shock shown is reasonable in the medium run. Between 1999-Q1 and 2019-Q4, the 80-20 ratio has increased by 0.2 in Germany, which implies an average annual inequality growth rate of 0.4% over the last 21 years. The standard deviation of the annual inequality growth rate is 1.5%, which is approximately the same size as the inequality response one year after a one pp monetary policy shock. Thus, as expected, conventional monetary policy cannot explain all developments in inequality, and especially not the long-term trends, but the results indicate that interest rate changes are relevant in accounting for short- to medium-term movements in the German wage inequality. Moreover, the expansionary monetary policy of the last two decades has contributed to the slowdown in the increase and recent reduction in the 80-20 percentile ratio. Note, however, that the reverse is also true. Contractionary policies affect low wages quicker and slightly stronger than high wages, so that inequality will increase when the policy path is reversed, assuming symmetric policy responses. While there were hardly any interest rate increases in the 2010s, policy rates were raised in response to the surge in inflation in 2022, making an increase in wage inequality likely.

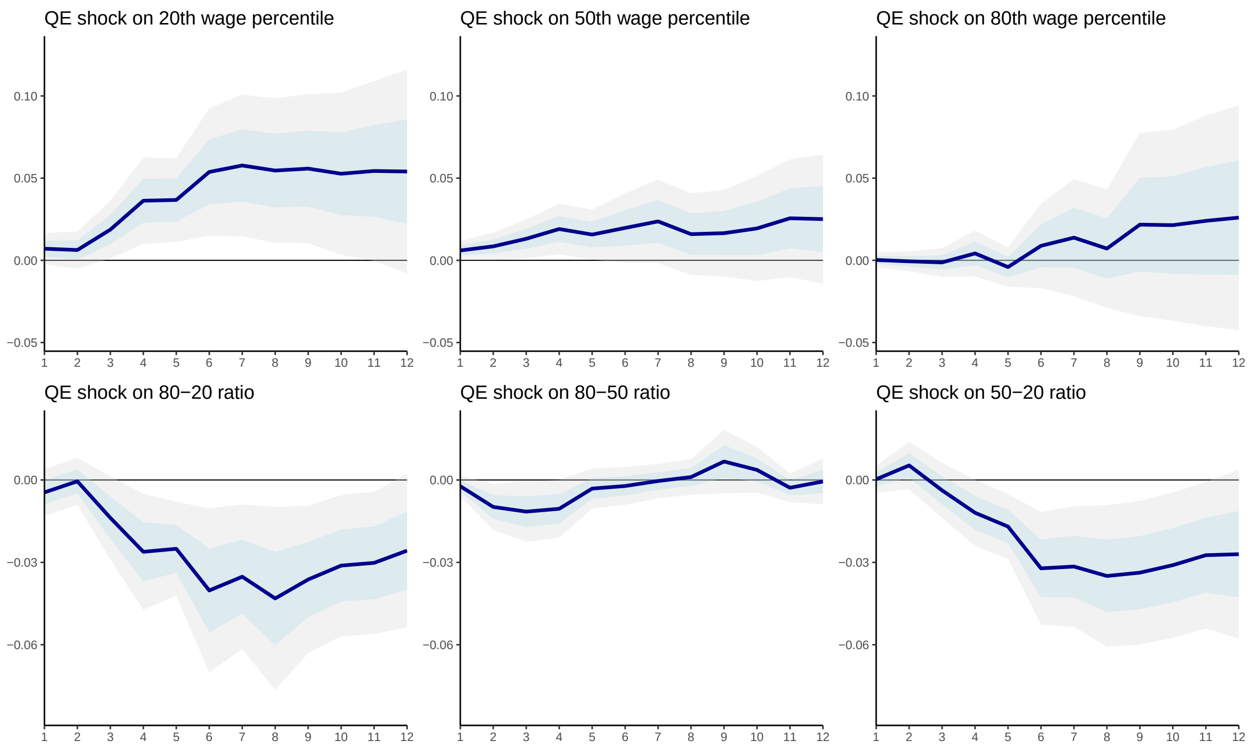
The wage responses to conventional monetary policy shocks are in line with the recent literature. Amberg et al. (2022) and Holm et al. (2021) find higher wage elasticities at the bottom of the earnings and wealth distribution and hence point to the relevance of the earnings heterogeneity channel in Sweden and Norway, respectively. Regarding wage inequality, these papers report, however, small to no changes. This difference with my results may be due to their annual aggregation of monetary policy changes. In addition, Holm et al. (2021) use household data which results in smoothed wage responses across household members and Amberg et al. (2022) do not estimate effects on inequality directly but calculate them by multiplying the estimated effects with individual wages. Inui et al. (2020) even find a persistent increase in earnings inequality after interest rate cuts in Japan before 2000. In contrast, I find equalising effects of expansionary policy rate changes for Germany and even significant equalising effects for the overall wage distribution pointing to the relevance of the earnings heterogeneity channel. Beside the different institutional framework in Japan that could explain these differences (more rigid labour market, even lower unemployment rate), Inui et al. (2020) do not use an IV approach or control for the potential endogeneity of monetary policy in another way. Samarina and Nguyen (2023) state that wage inequality declines after an immediate increase in response to an expansionary monetary policy shock, but not in Germany due to its rich re-distributional policies and labour market regulations. Since I analyse the effects on market wages before taxes and subsidies are considered, and I interpolate wages by sub-sample wages and not by macro indicators, I find significant equalising effects despite Germany's labour market regulations.

5.3 Unconventional Monetary Policy

Unconventional monetary policy measures have been implemented by the ECB to keep inflation at its target and to support the economic policy of the EU since the GFC. The tools were termed unconventional, because they were used for the first time and so the optimal implementation as well as the effects and side-effects were only known from theoretical considerations. Policy makers worried that quantitative easing (purchases of assets by a central bank) affects financial markets more directly and indirect effects only raise capital income, which benefits the wealthy. In addition, the declining effectiveness of QE over time (Kuttner, 2018) could result in weak labour market responses. As I will show, this is not the case. QE has a strong and persistent impact on lower wages and hence the ability to reduce wage inequality.

Figure 6 shows the impulse responses of the inequality measures and wage deciles to a one trillion Euro expansion of the ECB's balance sheet (spread over three consecutive quarters). This change represents a third of the cumulative balance sheet expansion realized between 2007 and 2018. The estimation is based on equation (6) by using balance sheet changes as policy variable instrumented by high frequency QE shocks and QE announcement dummies. The findings suggest significant wage increases at the bottom of the wage distribution over the three-year horizon. In line with dynamic equilibrium models that include indirect channels, it takes several quarters for the effects to become statistically significant. In the case of the 20th wage percentile it takes three quarters. The median wage does not only take slightly longer until it reacts to the monetary stimulus, the effect is only statistically significant after four quarters. Nevertheless, the unconventional measures support wage growth also at the middle of the distribution. In contrast, wages at the top of the wage distribution do not respond to QE in a meaningful way and hence, significantly different compared to lower wages (see Table A.9). This implies that QE has significant and robust equalising effects on the German wage inequality. A one trillion Euro balance sheet expansion leads to a persistent decline in the 80-20 percentile ratio. The decline in inequality stems mainly from the lower half of the distribution due to the stronger and quicker reaction of the 20th wage percentile in comparison to the median wage and the 80th wage percentile.

Figure 6: Responses to expansionary unconventional monetary policy



Note: The figure plots impulse responses as well as 68% and 95% confidence intervals (blue and grey shaded areas) of wage deciles (upper row) and inequality measures (lower row) to a 1 trillion Euro balance sheet expansion. Impulse responses are at the quarterly frequency using data from 1999-Q1 to 2019-Q4.

A comparison of the effects of policy rate changes and QE shows similarities as well as differences. First, both expansionary conventional and unconventional measures have equalising effects at the labour market. By increasing lower wages quicker and stronger than high wages, inequality declines at the bottom half of the distribution. Second, the transmission lag between the policy implementation and the adaption of wages is surprisingly similar for both measures. While the 20th wage percentile is already significantly higher after three quarters, the 80th wage percentile needs double the time. Therefore, both policy tools are not fundamentally different regarding their effects on wages and wage inequality, and QE can be considered a suitable complementary tool when hitting the zero lower bound. On the other hand, the policy measures seem to differ regarding the persistence of their effects. The reduction in inequality three years after a QE shock is only slightly above the lowest point after two years and statistically significant for most of the quarters, while the reduction in inequality has already halved and became statistically insignificant three years after a change in the policy rate. This is also true for other lags of the endogenous variables (P) in equation (6). Possible reasons are the longer implementation period of QE compared to an immediate change in the policy rate, and the particular effects of QE on long-term rates (see Table 2). Nevertheless, for long-run implications the length of the time-series is still too short to make concluding statements.

Regarding the magnitude of QE effects on inequality, I find an average decline of 4.1% in the 80-20 ratio two years after a one trillion Euro increase of the balance sheet. As the standard deviation of balance sheet changes is 0.3 trillion Euro, Figure 6 shows reasonable effects over the medium-run. The comparison of inequality responses after one year (2%) with the standard deviation of the annual inequality growth rate (1.5%) shows the economic relevance of QE shocks on the wage distribution. Interestingly, the relative effects of conventional and unconventional tools are pretty similar after two years. This implies that a one pp decline in the policy rate can be replaced by a one trillion Euro increase of the balance sheet to achieve similar wage inequality effects in case the effective lower bound is binding.

In contrast to changes in policy rates and the balance sheet, forward guidance is more difficult to quantify because central banks are not directly changing an observable variable. To approximate changes in interest rate expectations, OIS rates at different maturities are used (e.g. Lloyd, 2021). However, even the closest quarterly proxy variable, the quarterly change in the 2-year OIS rate, is not always strongly associated with the forward guidance shocks (first stage F-statistics between 7 and 11). Therefore, I do not focus on the effects of forward guidance in this paper, but refer the interested reader to the appendix (Figure A.9). While the effects are generally smaller and not statistically significant, they follow a similar pattern with positive wage effects and a slight equalising effect.

5.4 Robustness

The results presented so far depend on the interpolation of quarterly wage deciles, the identification of monetary policy shocks and the estimation of impulse responses. Hence, the following paragraphs show the robustness of my findings along these dimensions. Moreover, I will show in Section 6 that the quarterly results are consistent with findings from the annual specifications, however, with missing dynamic details.

First, I assess the sensitivity of my findings to other methods of temporal disaggregation. Using the Chow-Lin method (for stationary or cointegrated time-series) instead of the Litterman approach changes the quarterly inequality measure and the respective IRF only slightly. Similarly, it does not matter whether I use the seasonally adjusted wage deciles as indicator series or whether I use the unadjusted series and apply the adjustment algorithm after the interpolation on the estimated series. While I argue that the *average* wage deciles are observed directly from the SIAB data and hence are the most reliable low-frequency series, Hutter and Weber (2017) use the *first quarters* as benchmark. By applying the Litterman approach with a seasonally adjusted indicator series and using the Q1 values as benchmark for the other quarters, the estimated inequality series shifts towards the first quarter. As the within year dynamics remain similar, the monetary policy effects are weaker, but consistent. For a graphical representation of the similarities among those adjustments see Figure A.10.

Next, I consider the Gini coefficient for wages and the 90-10 percentile ratio as dependent variables in comparison to the 80-20 ratio. Due to the top-coded wage data in the SIAB, I have used the unaffected 80-20 ratio up to now. However, it is possible to impute the unobserved wages at the top and calculate alternative inequality measures.

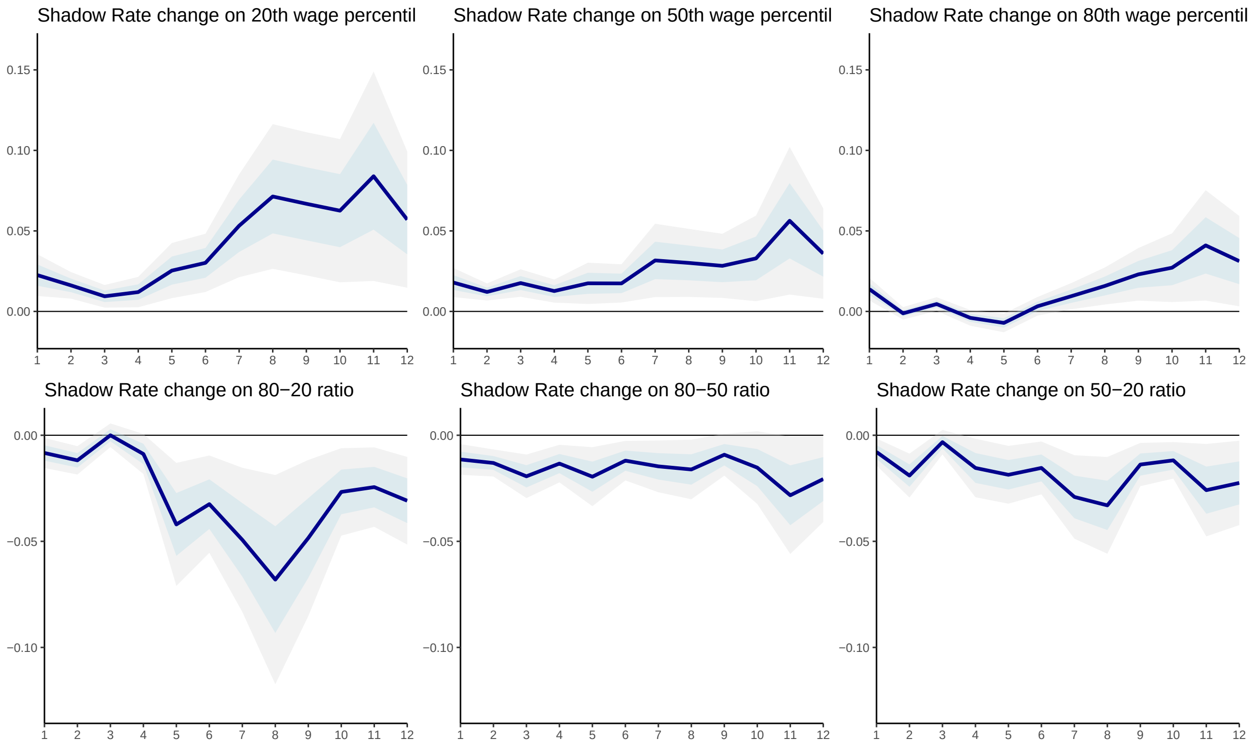
The effects on the 90-10 ratio are generally in line with the effects on the 80-20 ratio. The only difference is the slightly stronger decline in the 90-10 ratio after a policy rate change (see Figure A.11). Looking at the responses of the Gini coefficient, it is apparent again that policy rate changes affect wages more similarly across the wage distribution than balance sheet expansions. The effects on inequality measured by the Gini coefficient are volatile and only temporarily significant for a policy rate cut. In contrast, balance sheet changes lead to a significant and persistent decline in the Gini coefficient as depicted by Figure A.12 in the Appendix.

Third, I change the number of lags and add new controls to the LP framework. Changing the lags of the dependent variables from four to two or eight does not lead to relevant changes in the results. The same holds true for changing the lags of the control variables like the HICP or the instruments. Adding a dummy for recessions or a dummy that captures the introduction of the Hartz reform at the German labour market support my findings. Figure A.13 and A.14 present the results when the Hartz reform and recessions are considered, lagged balance sheet changes are included in the IR specification and the lagged HICP is added to the QE specification. It shows that the differences in the IR and QE specifications (see Section 5.1) do not cause the differences in the policy responses. The effects of policy rate changes become even smaller, while the effects of balance sheet changes remain economically and statistically significant.

Beside the high-frequency identification approach to identify monetary policy shocks, several authors follow the narrative approach by Romer and Romer (2004) (see Coibion et al., 2017; Holm et al., 2021). For the euro area, I find that this approach leads to (residual) shocks that correlate and are predictable by past GDP growth (using policy rate and balance sheet changes as dependent variables). Thus, these measures are not exogenous in the European case. Consequently, expansionary IR surprises lead to an increase in the 80-20 percentile ratio instead of a decline, as presented by Figure A.15. This shows that endogeneity is a critical source of bias in this setup. Otherwise, the effects with Romer shocks are broadly in line with my findings showing positive or non-significant wage growth and declining inequality after balance sheet expansions.

In addition, my results are robust to changes in high-frequency instruments. The responses of wage deciles and inequality measures are similar when I use shocks not adjusted by the poor man's sign restriction to control for information effects, although the instruments get weaker, or when I aggregate the shocks by simply summing over the monthly observations for each quarter without weighting. The results are also robust to simultaneously using all policy shocks as instruments to the change in the Shadow Rate by Krippner (2013) that capture the monetary policy stance more broadly, see Figure 7.

Figure 7: Responses to Shadow Rate changes



Note: The figure plots impulse responses as well as 68% and 95% confidence intervals (blue and grey shaded areas) of wage deciles (upper row) and inequality measures (lower row) to a 1 pp reduction in the Shadow Rate by Krippner (2013). Impulse responses are at the quarterly frequency using data from 1999-Q1 to 2019-Q4.

Finally, I also evaluate the role of the period under consideration. Especially, the responses to balance sheet changes could be affected, since QE was implemented first in 2008 and at a large scale since 2014. At the same time, QE shocks appear during the whole period due to the PCA approach. Hence, I re-estimate the QE LP for the period 2008-Q1 to 2019-Q4. The results are plotted in Figure A.17 in the Appendix. While the German wage inequality still declines significantly due to the reduction in wage differences, the responses of the wage deciles change slightly. The 80th wage percentile even decline a bit (instead of increasing) and the lower wages increase significantly only in the fourth quarter. Overall, the results are robust to changes in period, instruments, interpolation approach as well as variation in the included covariates.

6 Earnings Heterogeneity (Sub-)Channels

In the previous chapter, I have shown the relevance of the earnings heterogeneity channel for monetary policy. Interest rate changes and QE affect low wages quicker and stronger than high ones, but it is not clear why these heterogeneities across wage deciles arise. In addition, it is not obvious where the differences between conventional and unconventional policy measures come from. Therefore, I make use of the employment information in the SIAB data to decompose the earnings heterogeneity channel into four sub-channels and along relevant socio-economic groups.

One potential source of the heterogeneity in monetary policy effects across wage percentiles is the compositional change of the work force over time. People shift the wage distribution by moving between non-employment, unemployment and employment. While there are several reasons why workers switch between non-employment and employment, like graduation, parental leave, migration or retirement, these transitions usually follow long-run trends and are mostly related to the institutional environment.[22] Regarding monetary policy, the transition between employment and unemployment of labour market participants is more relevant. As the latter is strongly related to business cycle movements, it is also affected by the stabilizing effects of monetary policy. In this respect, the "job creation channel" describes the effects of monetary policy on the wage distribution by firms creating and workers finding new jobs. As we do not know ex ante which types of jobs are created, if at all, we also do not know how wage inequality among employed is affected by this channel. For the overall population, this channel is, however, expected to have an equalising effect, because an accommodative monetary policy shock reduces unemployment and hence labour market participants with zero earnings (see Figure 4).

Beside the changing composition of the employed work force, also wage dynamics among employed can affect the wage distribution. Heathcote et al. (2010) show that

[22] The SIAB data do not allow to analyse compositional effects related to non-employment, since people outside the labour force, public servants and self-employed are not captured. However, I could not find significant effects of monetary policy changes on the share of migrants, young workers, old workers or employees on parental leave in Germany.

labour income at the top of the distribution is mainly affected by changes in hourly wages and labour income at the bottom is mainly affected by changes in hours worked and the unemployment rate. Related to these findings three further channels could explain the heterogeneities in my analysis. The "pure wage channel" describes the change in the hourly real wage while staying at the same job after a monetary policy shock. Increases in productivity or more negotiation power in a tighter labour market could lead to heterogenous wage changes across the distribution. The "working hours channel" explains a potential shift in the wage distribution due to changes in the hours worked after a monetary policy shock. When labour demand increases, existing capacities can be utilised more instead of creating new jobs. Thereby, only employed workers' earnings increase. Eventually, wages can also change after switching to a new job as described by the "job switching channel". While a promotion or voluntary change usually leads to wage rises, workers sometimes have to accept wage reductions after dismissals.[23]

As socio-economic characteristics are not equally distributed along the wage distribution, a distinction between gender, age and educational level could shed further light on the distributional consequences of monetary policy. Women are more likely to take on part-time jobs and hence they are over-represented in lower wage groups. The wages of young workers are on average lower than of those of old workers due to less work experience. Moreover, low-skilled workers are over-represented among unemployed and high-skilled workers usually receive higher wages and enjoy more stable work relationships. Hence, socio-economic groups are likely to be affected differently by monetary policy.

6.1 Data and Method

In order to decompose the earnings heterogeneity channel, I track the individual employment histories and worker characteristics in the SIAB data. Hence, I need to adjust the sample and frequency of the analysis. At the same time, I keep the specifications as similar as possible to make comparisons with the previous chapters.

[23]This analysis is complementary to Mitman et al. (2022) as they only analyse possible explanations via transition rates. However, a higher probability of changing jobs at the bottom of the distribution has not necessarily equalising effects, as workers could move to a job with the same or lower wages. That's why I look specifically at the wage gains from monetary policy.

First, I extend the current sample of employed workers subject to social security contributions (as defined in Section 2.2) by unemployed workers to capture the job creation channel directly.[24] While this channel is identified by the wage responses of unemployed workers to exogenous monetary policy changes, the identification of the other channels is built on data of employed workers who stay in the labour market. To describe the job switching channel, I select all workers who switch their full-time job within two years after a shock. The identification of the remaining two channels face the drawback that the SIAB does not contain data on hours worked but only daily wages. In order to capture the pure wage channel, I analyse the wage changes of all workers employed in the same job in the year before a policy shock and two years afterwards. To control for changes in working hours, I only consider full-time workers. Finally, the working hours channel is approximated by the changes in wages of workers who switch between part-time and full-time employment within two years after the shock.

Given the sample extension by unemployed workers and the need to distinguish between worker characteristics, it is not possible to apply temporal disaggregation anymore. The annual frequency is not ideal for monetary policy analysis, but allows me to compare the reasons and their relevance for the equalising effects of monetary policy. Furthermore, adding unemployed workers to the sample leads to a large number of people with no earnings. Thus, to better describe the consequences of unemployment across the wage distribution, I analyse the individual wage responses within permanent wage groups defined by the wage deciles. Each worker is assigned to a wage group according to his average (non-zero) wage over the last three years, given that he was employed at least once. Thereby, each of the groups contains unemployed workers as shown by Table 3. Due to the close relationship between wages and permanent earnings, the average wages increase over the ten groups. Moreover, workers in the top wage group are employed three times as long as in the first. In contrast, the number of unemployed workers is flat in the first three deciles, before it starts to decline. The number of part-time workers and women decline when moving to the top of the wage distribution. Note that the assignment to a wage decile group is fixed for all subsequent analyses, so that effects of a group can be compared across sub-samples.

[24]This includes workers without employment that receive some form of social benefits according to the German Social Code Book II or III and workers looking for a job while not being employed.

Table 3: Wage decile group - descriptive statistics

	1st dec	2nd dec	3rd dec	4th dec	5th dec	6th dec	7th dec	8th dec	9th dec	10th dec
average wage	30	43	54	65	76	88	101	118	148	250
unemployed	104,046	109,701	101,526	89,897	71,770	56,080	42,736	33,427	28,610	23,491
Employed										
all	777,779	846,133	875,891	900,291	930,629	957,453	978,855	993,568	1,001,627	1,009,675
full-time incumbent	89,877	164,708	245,497	329,266	415,578	492,824	550,966	584,394	602,444	591,804
full-time switcher	36,773	78,508	104,599	116,953	121,605	117,193	113,908	118,754	130,086	162,470
part-time/full-time	35,721	32,574	25,824	20,459	15,546	11,923	9,706	8,333	7,074	5,902
part-time	454,897	380,194	289,069	216,657	159,229	118,395	88,101	68,635	49,001	26,382
Women	677,295	664,765	575,925	504,925	453,315	405,006	366,932	331,819	275,487	168,730
Average tenure	1,953	2,105	2,214	2,361	2,651	3,055	3,516	3,793	3,955	3,657
Average age	42	41	40	40	40	41	42	43	44	46

Note: Descriptive statistics for the wage groups of the permanent earnings distribution for the period 1999-2019. Average wages are real gross daily average wages in Euro. Workers are counted as unemployed if they receive benefits related to their employment status or looking for a job while not being employed. Incumbents are workers who have not changed their job within three years (t-1 to t+2), while switchers did so in the same period. Average tenure counts the days since the last change in job.

Another necessary adjustment is the annual aggregation of monetary policy shocks. Since aggregating over twelve monthly shocks smooths out the effects and is only loosely related to the annual changes in policy measures, an IV approach does not work at annual frequency. Instead, I will conduct the "first-stage" at the monthly frequency and then, aggregate the predicted exogenous changes of the policy measures like Amberg et al. (2022). For this approach, I use the Target Rate shocks and QE shocks corrected for information effects together with the other covariates that I use in the analysis of sub-channels. More specifically, I estimate

$$policy_m^i = c + \phi X_m^i + \gamma Z_m^i + e_m, \quad i = IR, QE \tag{11}$$

where $policy_m^i$ is the monthly change in the ECB's policy rate or the nine months change in the ECB's balance sheet between $m+6$ and $m-3$ in line with the quarterly specification. In this regression the time subscript m represents months. The control variables X_m^i include lagged inflation over the last twelve months measured by the HICP, a lagged dummy for recessions and the change of the other policy tool. Z_m^i captures the instrumental variables of the endogenous policy tool. The current and lagged Target Rate shocks control for endogeneity in the change in the ECB's policy rate and the current and lagged QE shocks as well as the QE announcement dummy instrument the balance sheet changes.[25] Based on these regressions, I derive the predicted (exogenous) values of the policy changes

[25] Similarly to the quarterly setup, the heteroskedasticity robust first stage F-statistic is 7.9 for the policy rate changes and 12.9 for the balance sheet changes.

$\widehat{policy}_m^i$ at a monthly frequency. To harmonize the different frequencies of monetary policy and wage data, I apply the same weighted aggregation approach as in Section 4, which considers the timing of policy decisions, but over a whole year instead of quarters.

In order to exploit the panel structure of the SIAB data and to distinguish between the permanent earnings wage groups in a clean way, I apply a panel local projection framework that describes the effects of monetary policy on wages. The following regression is estimated by a fixed effects estimator:

$$\frac{y_{j,t+h} - y_{j,t-1}}{\overline{y_{d,t-1}}} = \alpha_j + \alpha_t + \sum_{d=1}^{10} D_{j,t} * [c_d^h + \beta_{1,d}^h \widehat{IR_t} + \beta_{2,d}^h \widehat{QE_t} + \phi_d^h X_t] + e_{j,t}^h, \quad (12)$$

where the dependent variable is the change in the real gross daily wage $y_{j,t}$ of individual j between year $t+h$ and $t-1$. This change is measured relative to the group-specific average wage of the previous year, because unemployed workers receive no wage and so it is not possible to apply the logarithm.[26] To simplify the following graphs, I will focus on the two-year horizon ($h = 2$) after the change in the monetary policy tool, as it takes several quarters to affect the labour market as shown in the quarterly analysis. α_j captures the individual fixed effects like gender or ability, while $e_{j,t}$ is the idiosyncratic error term. α_t represents year fixed effects to control for common shocks to all households. This also includes monetary policy shocks, but as I am interested in the differences across wage groups, this is no problem and has the advantage to control for potential other annual shocks that lead to cross-sectional correlation. To account for the differences across the permanent earnings distribution all control variables X_t, as well as the predicted change in the policy tools $\widehat{IR_t}$ and $\widehat{QE_t}$ are interacted with the categorical wage group variable $D_{j,t}$. X_t captures a recession dummy and the lagged normalized wage. In addition, I allow for different average wage growth rates across wage decile groups by c_d.

[26] The often used inverse hyperbolic sine transformation is no ideal solution due to its scale dependence (Chen and Roth, 2022). Using the inverse hyperbolic sine transformation or the arc-mean as done by Bloom et al. (2017) leads to the same qualitative conclusions but significantly larger effects.

6.2 Channel Decomposition

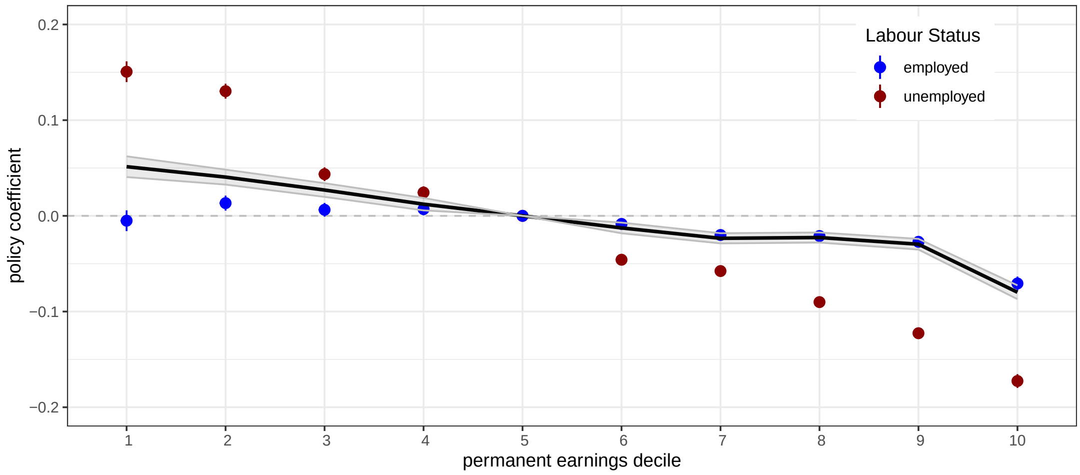
In this section, I estimate and compare the effects of monetary policy between employed and unemployed workers, before I estimate the parameters for sub-samples of employed workers to describe the remaining transmission channels. This provides a deeper insight into the interplay of monetary policy and wage inequality. The impulse responses at the annual frequency for the full sample can be found in the Appendix (Figures A.18 and A.19) and show the consistency with the quarterly results.

Figure 8 and 10 show the monetary policy effects on wages at the two year horizon for the overall sample and according to the employment status. It depicts the effects for each wage group in comparison to the fifth group (=baseline). The solid lines represent β^{IR} and β^{QE} of the overall sample. The grey band and the whiskers represent the 95% confidence intervals based on individual cluster-robust standard errors to account for within-individual serial correlation in the dependent variable.[27] While the effects are significantly positive at the bottom of the permanent wage distribution, they get smaller in the middle and negative in the upper half. The declining pattern clearly shows that both policy tools reduce wage inequality after two years if they are used in an expansionary manner, in line with the quarterly analysis.

Figure 8 decomposes the overall distributional effect of interest rate cuts into effects on employed and unemployed and thereby identifies the role of the job creation channel. The red dots show the coefficient estimates for the sample of unemployed workers. While policy rate cuts have strong and significant effects on unemployed at the bottom of the wage distribution, its impact declines significantly moving up the wage distribution. In contrast, the effects of conventional monetary policy on employed workers' wages are more similar across the wage distribution and decline only slightly at the top of the distribution (blue dots). Whereas the positive effects on employed workers account for a large share of the overall effects, the job creation channel clearly increases monetary policy effects at the bottom of the distribution. The creation of new jobs for low wage earners is an important mechanism for the overall equalising effects of IR cuts found in the data. The

[27] Following, Cameron and Miller (2015) I use year fixed effects to control for common shocks across all observations that might result in cross-sectional correlation and thereby avoid time clustering with only 20 year clusters.

Figure 8: Decomposition of IR effects - employed vs unemployed workers



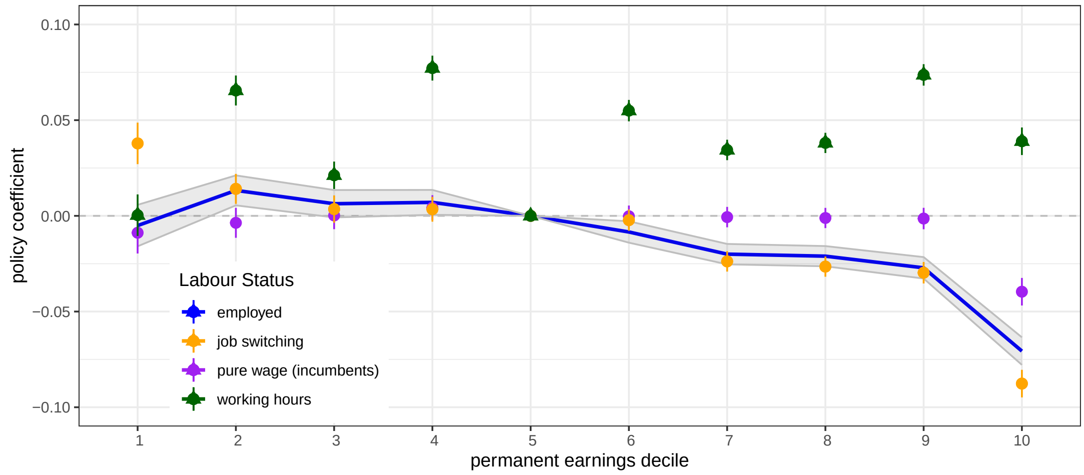
Note: The figure plots the effects of a 1 pp policy rate cut on wage growth for the permanent earnings wage groups (in comparison to the fifth bin) of the overall sample. It further decomposes these effects by depicting the respective coefficients for employed and unemployed workers. The grey band around the solid line and the whiskers represent 95% confidence intervals.

job creation channel is, however, not the only relevant sub-channel.

Figure 9 plots the effects of interest rate cuts of each wage decile group of employed workers and sub-samples thereof. The blue line and the grey band represent the blue dots and its (not visible) whiskers for all employed workers from Figure 8. The strongest wage effects stem from workers switching their jobs within two years after the policy change. This points to the relevance of a job switching channel. This effect is stronger at the bottom of the wage distribution than at the top and hence support the equalising effects of the job creation channel. While the effect sizes are similar or even larger for the working hours channel, there is no clear pattern across the distribution. Interest rate cuts also increase the wages of incumbent workers but the effect size is very similar across the distribution. This is also the reason for the limited equalising effects of interest rate cuts on the sample of employed worker.

Figure 10 and 11 present the decomposition of the earnings heterogeneity channel for QE. The effects of QE on wages of unemployed are significantly higher at the bottom of the distribution than the effects on the median wage group, but the differences are smaller then the effects of interest rate changes. The differences between the impact on employed workers' wages (blue dots) and the impact on unemployed workers' wages (red dots) are also smaller than before. While the job creation channel creates equalising

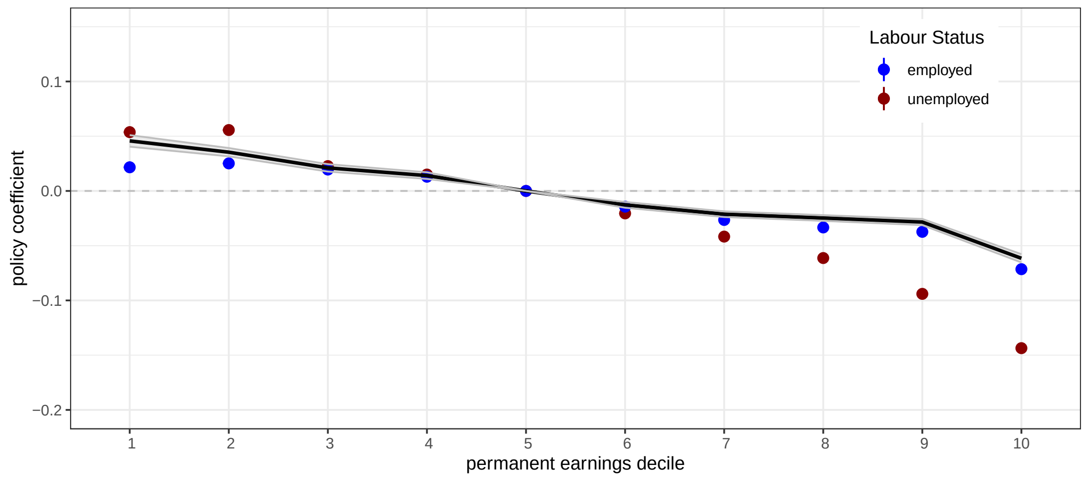
Figure 9: Decopositon of IR effects - sub-samples of employed workers



Note: The figure plots the effects of a 1 pp policy rate cut on wage growth for the permanent earnings wage groups (in comparison to the fifth bin) of the employed workers sample. It further decomposes these effects by depicting the respective coefficients for several sub-samples. The grey band around the solid lines represent 95% confidence intervals.

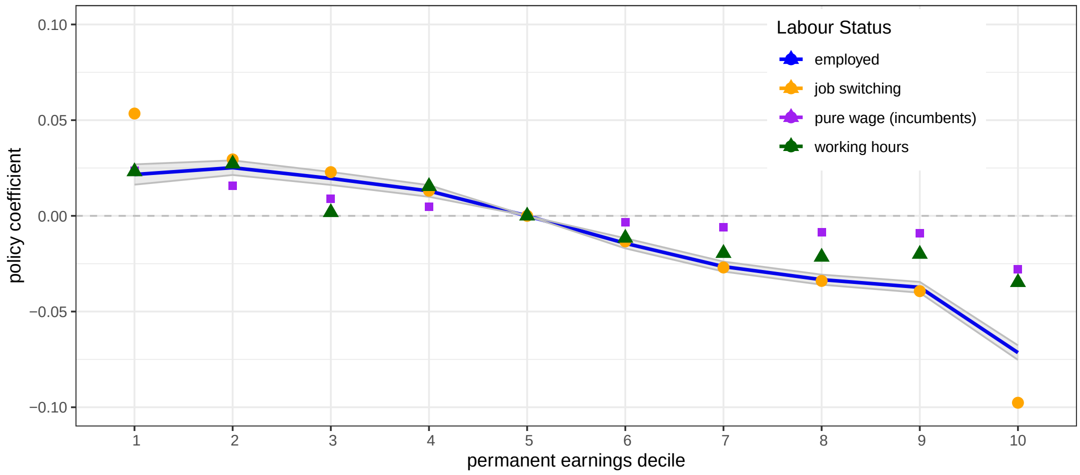
effects again, its relative importance that is observed for policy rate changes, cannot be confirmed for unconventional tools. The sub-channels related to the employed workers are equally important to describe the distributional consequences of QE. Figure 11 presents the respective decomposition, where the blue line represents the shock coefficients (β^{QE}) of the sample of all employed workers. The strongest equalising effects can be found again among job switchers moving from a full-time position to another. Comparatively

Figure 10: Decomposition of QE effects - employed vs unemployed workers



Note: The figure plots the effects of a one trillion Euro balance sheet expansion on wage growth for the permanent earnings groups of the overall sample. It further decomposes these effects by depicting the respective coefficients for employed and unemployed workers. The grey band around the solid line and the whiskers represent 95% confidence intervals.

Figure 11: Decomposition of QE effects - sub-samples of employed workers



Note: The figure plots the effects of a one trillion Euro balance sheet expansion on wage growth for the permanent earnings groups of the employed workers sample. It further decomposes these effects by depicting the respective coefficients for several sub-samples. The grey band around the solid line represent 95% confidence intervals.

smaller are the effects of QE on the wages of incumbent workers and workers changing the working hours, however, the effects are still significantly equalising, in contrast to the policy rate effects. Interestingly, the effects of QE are larger at the bottom of the distribution compared to the top for all identified sub-groups. Hence, the pure wage channel, the working hours channel and the job switching channel all work in the same direction and reduce wage inequality. This explains the stronger and more persistent effects of QE in the overall sample.

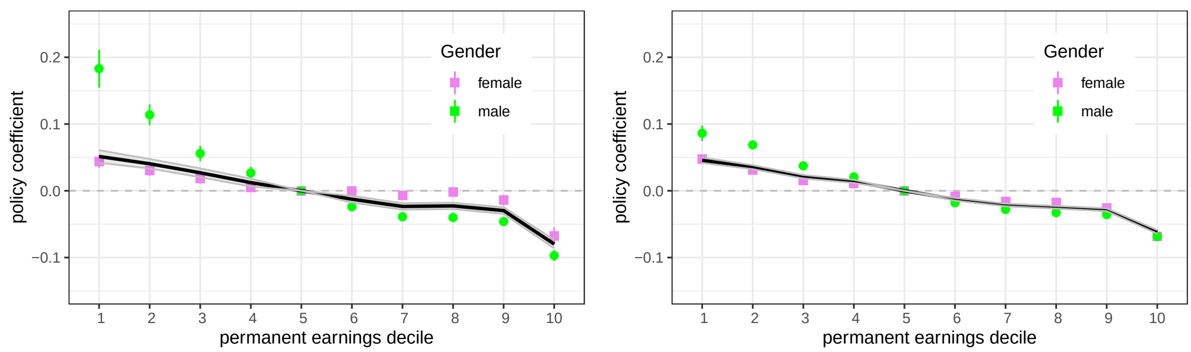
6.3 Socio-Economic Heterogeneity

In order to understand the distributional consequences of monetary policy and to describe who benefits from it and who does not, various socio-economic characteristics are relevant beside the employment status. By decomposing the overall sample along gender, age and educational level, I find additional sources of monetary policy heterogeneity.

Figures 12, 13 and 14 show the shock coefficients of expansionary conventional (β^{IR}) and unconventional (β^{QE}) monetary policy as defined in equation (12) for each wage group two years after a policy shock. Therefore, the differences between socio-economic characteristics can be easily compared to the graphs in the previous sub-section.

Figure 12 states the differences in the monetary policy effects between men and women. Policy rate and balance sheet changes affect male wages differently than female wages, especially in the lower half of the wage distribution. While QE is up to twice as effective in increasing male wages, IR cuts are nearly four times as effective in boosting male wages compared to female wages at the bottom of the distribution. These differences arise from the fact that men switch more often from unemployment or part-time to full-time employment and hence face larger wage increases. In addition, men were hit harder during the GFC, since they over-proportionally work in the industry and construction sector, which were affected most (Wall, 2023). Therefore, men benefited relatively more from countercyclical monetary policy measures in the period under consideration.

Figure 12: Gender decomposition

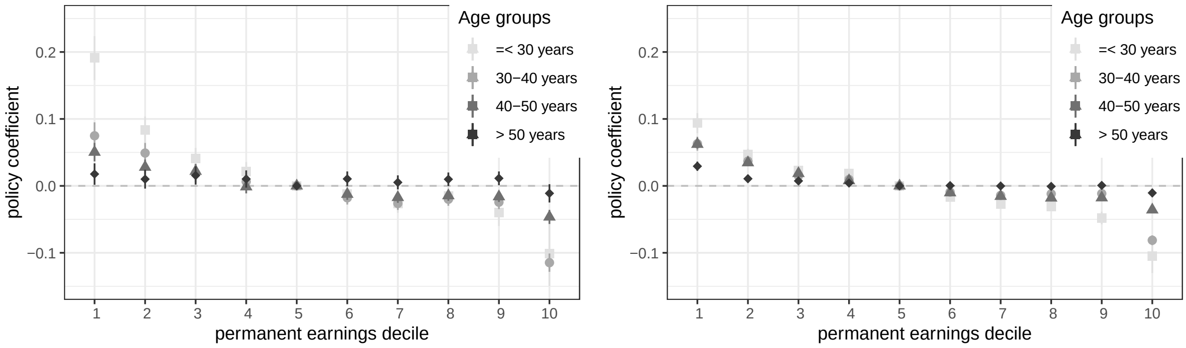


(a) IR shock (b) QE shock

Note: The figure plots the effects of a one pp point interest cut and a one trillion Euro balance sheet expansion on wage growth for the permanent earnings groups of the overall sample. It further decomposes these effects by gender. The grey band around the solid line and the whiskers represent 95% confidence intervals.

Figure 13 compares monetary policy effects between different age groups. While the pattern for each age group is similar to the overall sample, workers below 40 years benefit more from expansionary monetary policy at the bottom of the distribution. Especially at the ends of the distribution, the differences between younger and older workers are significant. Similarly to the gender decomposition, the differences in monetary policy effects are larger for interest rate cuts than for QE. However, also for QE we see significant differences across age groups. This points to the higher flexibility of young workers when looking for a new job. They are more willing to change job or location and hence are more likely to leave unemployment or find a better job. Regarding the equalising effects of monetary policy, we see only limited effects stem from the oldest group (>50 years).

Figure 13: Age decomposition



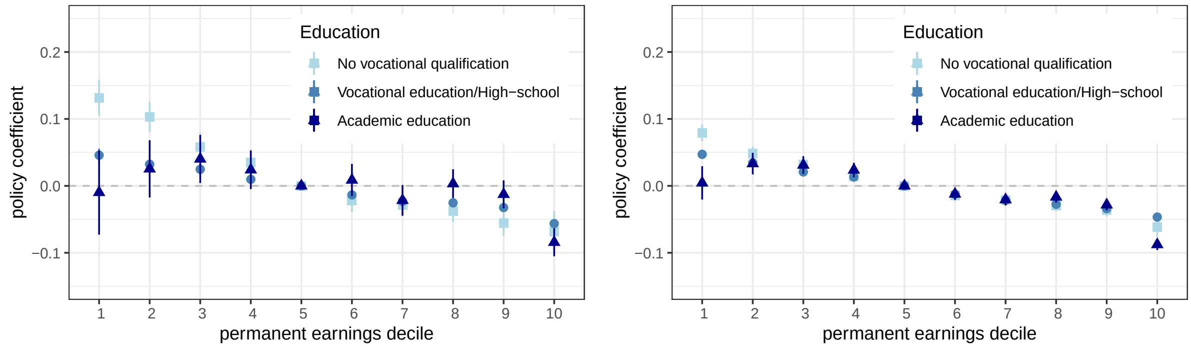
(a) IR shock (b) QE shock

Note: The figure plots the effects of a one pp point interest cut and a one trillion Euro balance sheet expansion on wage growth for the permanent earnings groups of the overall sample. It further decomposes these effects by age groups. The whiskers represent 95% confidence intervals.

Finally, Figure 14 decomposes the wage effects of monetary policy changes by educational level. Generally, I find that workers with a lower level of education (no vocational qualification) experience larger wage changes from expansionary monetary policy. This group is over-represented among unemployed workers and so they benefit relatively more from the positive stimulus of the labour market. However, for all three groups equalising effects are observed as the effects are slightly larger at the bottom of the distribution than at the top. The differences are generally larger for policy rate changes, but only get statistically significant for academics' wages after asset purchases. This points again to the strong role of the job switching channel in the transmission of unconventional monetary policy.

Overall, I find that the earnings of young workers, low-educated workers, and men increase most (at the bottom of the permanent wage distribution) in response to expansionary monetary policy shocks, independent of whether conventional or unconventional policies are analysed. While equalising tendencies along the wage distribution can be observed for all analyses as the effects are generally stronger at the bottom of the distribution than at the top, it also implies increases in (within wage group) inequality between these groups. In particular, older, higher educated, and female workers' wages show less responses as shown in the previous graphs. As female workers are usually more vulnerable with lower income and less labour market attachment (Grigoli et al., 2018), expansionary monetary policy might reduce wage inequality and the differences between low and high

Figure 14: Education decomposition



(a) IR shock (b) QE shock

Note: The figure plots the effects of a one pp point interest cut and a one trillion Euro balance sheet expansion on wage growth for the permanent earnings groups of the overall sample. It further decomposes these effects by education level. The whiskers represent 95% confidence intervals.

educated workers, but accelerate differences along the gender-dimension.

7 Conclusion

In this paper, I analyse the interplay between monetary policy and inequality. More specifically, I compare the effects of conventional and unconventional monetary policy on the German wage distribution. The two prerequisites for this analysis are the construction of quarterly wage deciles and the identification of exogenous monetary policy shocks. I derive quarterly wage and inequality measures using German administrative labour market data (SIAB). The observed within-year dynamics of a sub-sample of workers with reporting reasons unrelated to monetary policy serve as a benchmark for the overall population. Moreover, I identify and disentangle monetary policy shocks by the high-frequency approach. Financial market changes within a tight window around monetary policy announcements control for sources of endogeneity. A PCA combined with an orthogonal rotation allows me to distinguish the relevant factors and to interpret them as Target Rate and QE surprises. These exogenous shocks are used as instruments to estimate the effects of policy rate and balance sheet changes on the wage structure in an IV local projection framework.

My findings suggest that expansionary conventional and unconventional monetary policies have significant equalising effects that supported the recent decline in German wage inequality due to structural changes. Moreover, it compensates for the potential unequalising effects of unconventional monetary policy on wealth. While policy rate cuts raise wages across the whole wage distribution, quantitative easing has particularly strong effects at the bottom. Thus, unconventional measures have strong and robust distributional effects in the labour market. By comparison, the equalising effects of conventional monetary policy are a bit weaker and less significant. These responses highlight the importance of the earnings heterogeneity channel in explaining the redistributive effects of the ECB's policy actions. Not only the marginal propensity to consume declines with increasing income, also wage responses to monetary policy decline across the distribution. Hence, these insights are also of practical importance for monetary policy effectiveness. In line with the theory of this indirect channel, the effects of conventional and unconventional monetary policy take time to pass through the economy. Low wages tend to react after three quarters while the response of higher wages takes six quarters.

The rich data of the SIAB also allows me to identify individual wage responses and hence to distinguish between different sub-channels of the earnings heterogeneity channel. By including the unemployed, I find that especially the job creation channel and, among employed, the job switching channel explain the sizeable and equalising effects of monetary policy on wages. While the differences across the wage distribution decrease, expansionary monetary policy widens the wage differences between men and women as young, educated men benefit more from expansionary monetary policy.

The observed responses are economically relevant, but mainly to describe the contribution of monetary policy to the dynamics of inequality in the short and medium term. Given that the ECB's primary objective is price stability and that inflation has recently been above its target, contractionary policy measures must also be taken into account. Assuming symmetric effects, the equalising effects will be reversed when asset purchases are reduced and interest rates rise. However, by the results of Furceri et al. (2018), symmetry is not guaranteed and future research with more data on contractionary policy decisions is needed to identify long-run effects of QE. Similarly, longer time-series are needed to evaluate the differences between socio-economic groups, as monetary policy may affect people differently depending on which sectors are most affected during a recession.

Appendix

Table A.1: Overview: Macroeconomic variables

Variable	Description	Source
GDP EA	GDP at market prices, EA 19, chain linked volume (deflated), calender and seasonally adjusted	ECB SDW
Inv EA	Gross fixed capital formation (investment) at market prices, EA 19, chain linked volume (deflated), calender and seasonally adjusted	ECB SDW
HICP EA	Harmonized index of consumer prices, overall index, EA 19, seasonally and working day adjusted	ECB SDW
unemp EA	Unemployment rate >=25 years, EA 19, seasonally adjusted	ECB SDW
emp EA	Employment, EA 19, seasonally adjusted	ECB SDW
MRO rate	Main refinancing rate, ECB, variable and fixed tender	ECB SDW
ECB BS	Total assets/liabilities - Eurosystem, balance sheet	ECB SDW
2y OIS	2-year Overnight Index Swap rate, end of quarter	Refinitiv
mean wage	Daily real gross wages per worker, national accounts data (not seasonally adjsuted)	Destatis

Note: SDW=Statistical Data Warehouse

Figure A.1: Wage comparison: SIAB vs National accounts

Note: The figure compares the seasonally unadjusted mean wages of the main sample (red, dash-dotted), the sub-sample "employed changers" (blue, dashed) and the sub-sample "restricted employed changers" (green, dotted) to the mean wages of the German National Accounts data (orange). The dynamics of the sub-sample "employed changers" are most similar to the National Accounts data, although at a different level. The mean wages of the main sample ("all") confirm that important wage dynamics are unobserved in the SIAB data and a within-year interpolation is necessary.

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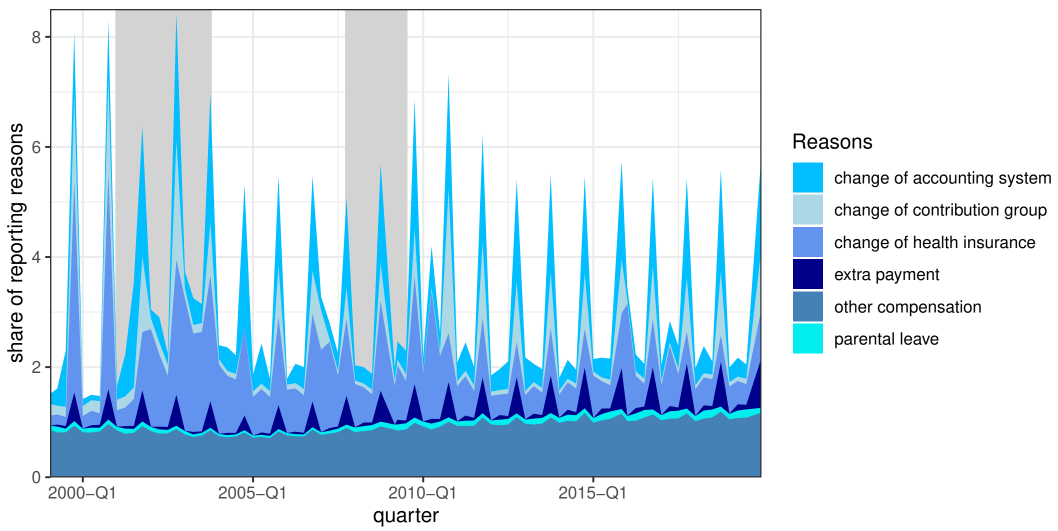
A Online Appendix

A.1 Data & Inequality

Spell data transformation

The transformation of the SIAB spell data into quarterly panel data follows the approach by Dauth and Eppelsheimer (2020). First, I split spells which cover more than one quarter and assign them respectively. Second, if a person has several wage sources, the longest employment duration (and the highest wage in case of equal duration) determines the main spell per person. I add the parallel spells to the main observation before I delete them, so that only one spell per person and period remains. Finally, I derive a quarterly panel structure by selecting one observation per person and quarter. This is accomplished by deleting spells with the same information within a quarter and by prioritizing reports other than the mandatory annual ones in case there are still several spells within one quarter.

Figure A.2: Reporting reasons - employed changers



Note: This figure plots the shares of the reporting reasons considered in the "employed changers" sample compared to the overall sample over time. The shaded grey areas depict recessionary phases in Germany.

Structural break adjustments

In 1978 and 1984 the procedure to report special payments changed. This led to a level shift in average wages for which I control in the time-series. I use a simple regression (for

Table A.2: Summary Statistics - SIAB sample (1975-2019 vs 1999-2019)

	Mean	Std Dev	10th perc	Median	90th perc
Age	39.95	10.79	25	40	55
Tenure	2,397.80	2,400.95	204	1,583	5,844
Education	1.99	0.50	1	2	3
Real gross daily wage	98.66	61.93	42	88	161
Observations per quarter	453,300	62,119	359,108	472,776	525,717
Changers per quarter	66,615	28,607	41,041	63,919	85,226
Employed changers per quarter	15,080	17,127	5,559	11,076	31,618
Age	41.30	10.47	27	42	55
Tenure	2,834.72	2,773.11	235	1,904	6,990
Education	2.09	0.49	2	2	3
Real gross daily wage	103.92	71.02	42	90	175
Observations per quarter	487,113	29,184	452,475	486,015	534,133
Changers per quarter	73,331	22,326	57,356	69,161	88,299
Employed changers per quarter	20,250	22,024	10,272	13,076	34,685

Note: The table contains summary statistics of the main sample in the period 1975-Q1 to 2019-Q4 (upper half) and the period 1999-Q1 to 2019-Q4 (lower half). Wages are in Euro, 2015 prices. Tenure counts the days since the start of the current job. Education takes a value of 1 for individuals without a degree, 2 for vocational training, 3 for high school, 4 for high school and vocational training, 5 for graduates of technical colleges and 6 for university graduates.

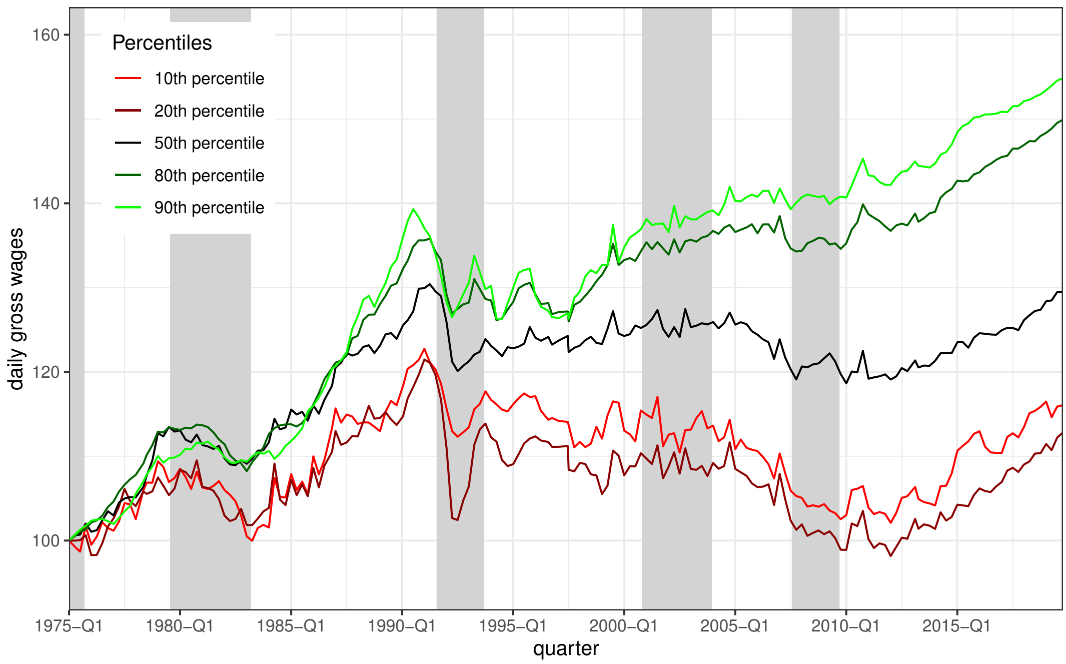
the period before the Reunification) with a trend and a shift parameter to increase the wages to the path after 1978 and 1984, respectively. In addition, the data show significant outliers in 1988-Q4 and 1997-Q1. In these quarters the number of reported (intra-year) changes jumped due to institutional and reporting changes and led to misleading values in the sub-samples. I correct these values by a simple moving average approach considering the seasonality in the data. I use the average value of the quarters one year before and one year ahead to capture the seasonality and trend in the wage percentiles for the respective sub-samples. As the analysis of monetary policy will be for the period 1999-2019, the interpolation is of little relevance for the main results.

Table A.3: Interpolation Regression BIC values

	p10	p20	p30	p40	p50	p60	p70	p80	p90
Int+unadj	-2.80	-1.24	-0.75	-1.12	-1.87	-1.85	-1.31	-1.39	-0.19
unadj	-1.34	-0.48	0.29	-0.14	0.33	0.89	1.30	1.55	2.68
Intercept	-2.36	-1.05	-0.70	-0.71	-1.65	-1.56	-1.12	-0.89	0.04
Int+trend	-2.27	-0.97	-0.62	-0.63	-1.57	-1.48	-1.03	-0.82	0.11
Int+adjusted	-2.81	-1.25	-0.76	-1.15	-1.89	-1.86	-1.34	-1.39	-0.19
Restricted	-2.57	-1.01	-0.79	-1.27	-1.95	-1.72	-1.12	-0.87	0.12

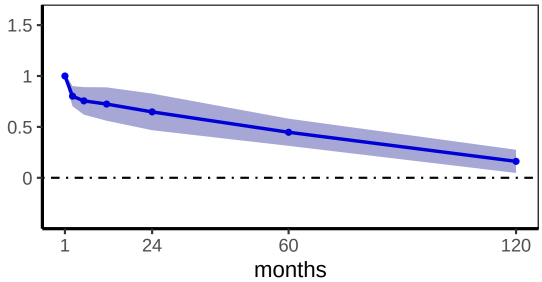
Note: This table shows the BIC values for different interpolation regression specifications (rows) and for different wage percentiles (columns). Each GLS regression is based on the Litterman approach and wage percentiles are from the "employed changers" sample, but with different indicator series: 1) intercept and unadjusted wage percentile, 2) unadjusted wage percentile, 3) intercept, 4) intercept and trend, 5) intercept and seasonally adjusted wage percentile, 6) intercept and seasonally adj. wage percentiles from the "restricted employed changers" sample. Lower BIC values point towards higher explanatory power.

Figure A.3: Quarterly wage percentiles

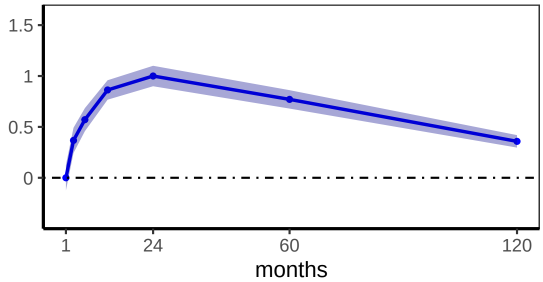


Note: This figure plots the development of the 10th/20th/50th/80th/90th wage percentile of the main sample over the period 1975-Q1 - 2019-Q4, normalized to 1975-Q1. The percentiles are temporally disaggregated by the Litterman approach, using the seasonally adjusted quarterly wage percentiles of the "employed changers" sub-sample as indicator series. The 90th wage percentile contains imputed wages due to right-censoring of the wages in the SIAB. The shaded grey areas depict recessionary phases in Germany.

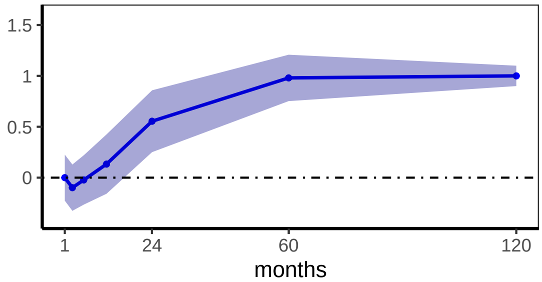
A.2 Monetary Policy shocks



(a) Factor loadings - Target Rate



(b) Factor loadings - Forward Guidance



(c) Factor loadings - QE

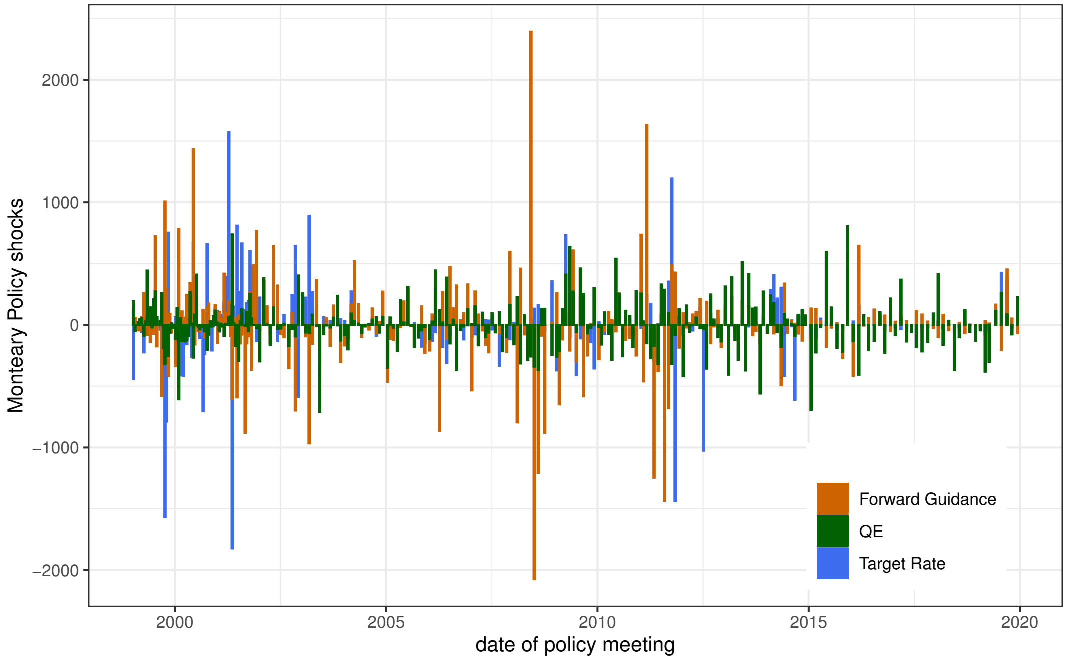
Note: The plots represent the factor loadings of the first three factors of the PCA over different maturities (1 month to 10 years), rotated and scaled to the one-month OIS rate (Target Rate), two-year OIS rate (Forward Guidance) and ten-year OIS rate (QE). The shaded areas represent 95% confidence intervals. The lines in these figures are defined by the factor loadings and the patterns are not assumed but estimated. Source: own calculations based on the EA-MPD

Table A.4: First Stage - IR

	Shock coef	SE	F-Stat	p-value
80-20 percentile ratio	-0.05	0.02	15.4	0.000
80-50 percentile ratio	-0.04	0.02	11.1	0.003
50-20 percentile ratio	-0.04	0.01	9.2	0.008
20th wage percentile	-0.04	0.01	14.5	0.000
50th wage percentile	-0.03	0.01	15.4	0.000
80th wage percentile	-0.04	0.01	22.5	0.000

Note: First stage regressions of policy rate changes instrumented by Target Rate shocks for the six main dependent variables. The columns show the shock coefficient (1), the Newey West standard error (2), the HAC F-Statistic (3), the p-value of the weak instrument test (4)

Figure A.5: Detailed monetary policy shocks



Note: Monetary policy shocks decomposed into Target Rate, Forward Guidance and QE shocks for each Governing Council meeting. The shocks are rotated and scaled but not corrected for information effects. Based on the data of the EA-MPD by Altavilla et al. (2019).

Table A.5: First Stage - QE

	Shock coef	SE	F-Stat	p-value
80-20 percentile ratio	0.02	0.02	3.1	0.083
80-50 percentile ratio	0.04	0.02	4.4	0.040
50-20 percentile ratio	0.02	0.02	3.1	0.082
20th wage percentile	0.04	0.02	9.6	0.003
50th wage percentile	0.04	0.02	9.5	0.003
80th wage percentile	0.04	0.02	4.6	0.035

Note: First stage regressions of balance sheet changes instrumented by QE shocks for the six main dependent variables. The columns show the shock coefficient (1), the Newey West standard error (2), the HAC F-Statistic (3), the p-value of the weak instrument test (4)

Table A.6: First Stage - QE (+ announcement)

	Shock coef	SE	An. coef	SE	F-Stat	p-value
80-20 percentile ratio	0.03	0.02	0.44	0.12	15.3	0.000
80-50 percentile ratio	0.04	0.02	0.43	0.12	7.3	0.002
50-20 percentile ratio	0.03	0.02	0.48	0.11	19.4	0.000
20th wage percentile	0.04	0.02	0.50	0.11	21.8	0.000
50th wage percentile	0.04	0.02	0.50	0.11	15.9	0.000
80th wage percentile	0.04	0.02	0.28	0.12	4.8	0.012

Note: First stage regressions of balance sheet changes instrumented by QE shocks and QE announcement dummy for the six main dependent variables. The columns show the shock coefficient (1), the Newey West standard error (2), the announcement dummy coefficient (3), the Newey West standard error (4), the HAC F-Statistic (5), the p-value of the weak instrument test (6)

Table A.7: Test for lag-exogeneity

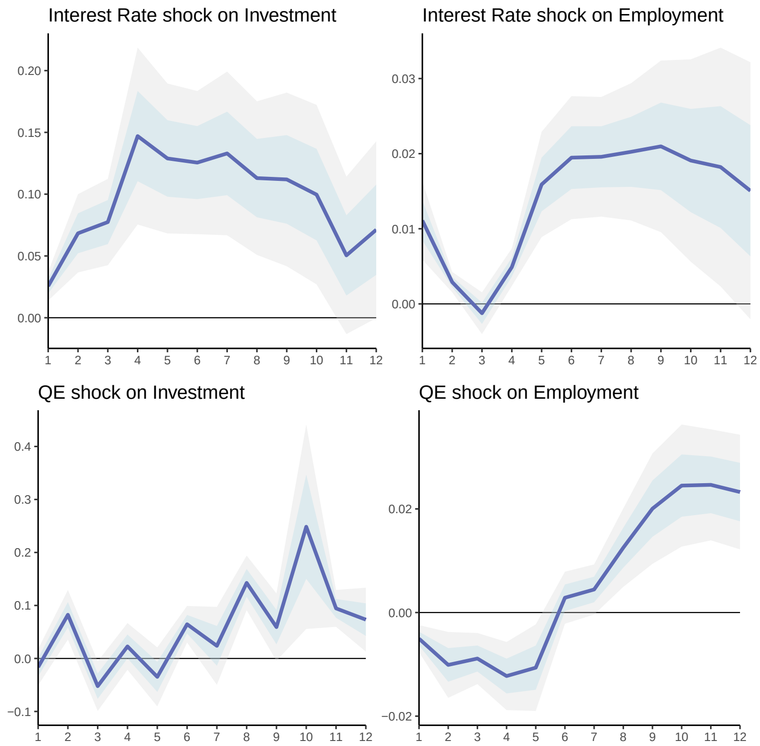
	Dependent variable:											
	Target shock				QE shock				QE announcement			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
80-20 ratio, lag 1	13.523				11.455				0.753			
	(13.720)				(9.770)				(1.666)			
80-20 ratio, lag 2	−17.729				−5.149				1.738			
	(15.137)				(10.779)				(1.839)			
80-20 ratio,lag 3	−3.611				6.905				−0.453			
	(15.205)				(10.828)				(1.847)			
80-20 ratio, lag 4	9.602				−12.438				−0.685			
	(13.306)				(9.475)				(1.616)			
80th wage perc, lag 1		−0.438				−0.487				0.017		
		(0.395)				(0.281)				(0.049)		
80th wage perc, lag 2		0.175				0.217				0.0001		
		(0.462)				(0.329)				(0.057)		
80th wage perc, lag 3		0.858				0.546				0.044		
		(0.464)				(0.331)				(0.058)		
80th wage perc, lag 4		−0.586				−0.284				−0.031		
		(0.375)				(0.267)				(0.047)		
Median wage, lag 1			−0.952*				−0.365				0.074	
			(0.396)				(0.302)				(0.055)	
Median wage, lag 2			−0.144				0.302				−0.053	
			(0.458)				(0.349)				(0.063)	
Median wage, lag 3			1.451**				0.139				−0.018	
			(0.463)				(0.353)				(0.064)	
Median wage, lag 4			−0.424				−0.195				−0.023	
			(0.388)				(0.296)				(0.054)	
20th wage perc, lag 1				−0.555				−0.486				0.029
				(0.441)				(0.318)				(0.058)
20th wage perc, lag 2				0.516				0.250				−0.039
				(0.488)				(0.352)				(0.064)
20th wage perc, lag 3				0.481				0.063				0.016
				(0.489)				(0.353)				(0.064)
20th wage perc, lag 4				−0.558				0.111				−0.034
				(0.422)				(0.305)				(0.055)
Constant	−4.452	−1.303	6.163	6.446	−1.807	1.182	11.004	3.633	−3.156**	−4.045**	1.967	1.735
	(7.693)	(10.992)	(15.323)	(9.078)	(5.478)	(7.833)	(11.675)	(6.544)	(0.934)	(1.366)	(2.121)	(1.192)
Observations	80	80	80	80	80	80	80	80	80	80	80	80
R^2	0.018	0.036	0.086	0.059	0.003	0.028	0.032	0.008	0.165	0.144	0.036	0.026

Note: Test for lag-exogeneity of the instruments in the IV local projection framework as suggested by Stock and Watson (2018). The lagged dependent variables (80-20 ratio, 20th wage percentile, 50th wage percentile, 80th wage percentile) are tested for their ability to explain the monetary policy shocks and the QE announcements.

*p<0.05; **p<0.01; ***p<0.001

A.3 Monetary Policy effects

Figure A.6: Macro responses to monetary policy changes II



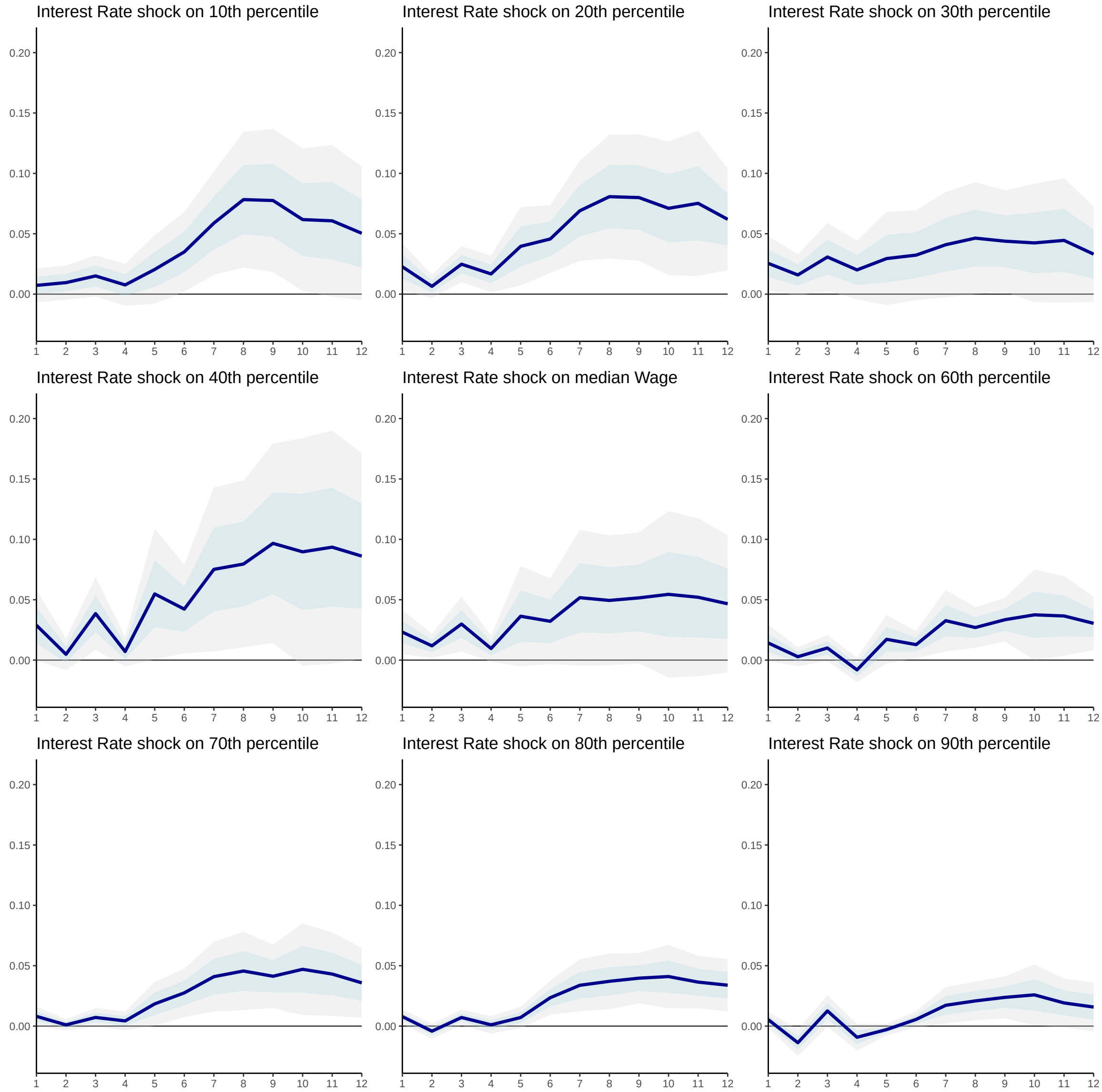
Note: The figure presents impulse responses of investment and employment to a 1 pp expansionary policy rate change (upper row) and a 1 trillion Euro expansionary balance sheet change (lower row) instrumented by Target Rate shocks and QE shocks/QE announcements, respectively. Time is in quarters. The blue and grey shaded areas indicate 68% and 95% confidence intervals, respectively.

Table A.8: IR Effect Differences - Z-Tests

Q	β 20p	β 50p	β 80p	z-test 80vs20	z-test 80vs50	z-test 50vs20
1	0.023***	0.023***	0.008*	1.431*	1.560*	-0.040
2	0.006*	0.012***	-0.004	1.824**	2.684***	-0.757
3	0.025***	0.030***	0.007*	2.126***	1.887**	-0.369
4	0.017***	0.010	0.001	1.835**	1.287*	0.753
5	0.040***	0.036*	0.007*	1.893**	1.350*	0.120
6	0.046***	0.032**	0.023***	1.384*	0.444	0.586
7	0.069***	0.052**	0.034***	1.477*	0.583	0.486
8	0.081***	0.049**	0.037***	1.521*	0.414	0.825
9	0.080***	0.052**	0.040***	1.403*	0.400	0.740
10	0.071***	0.054*	0.041***	0.962	0.357	0.368
11	0.075***	0.052*	0.036***	1.188*	0.444	0.510
12	0.062***	0.047*	0.034***	1.163*	0.413	0.423

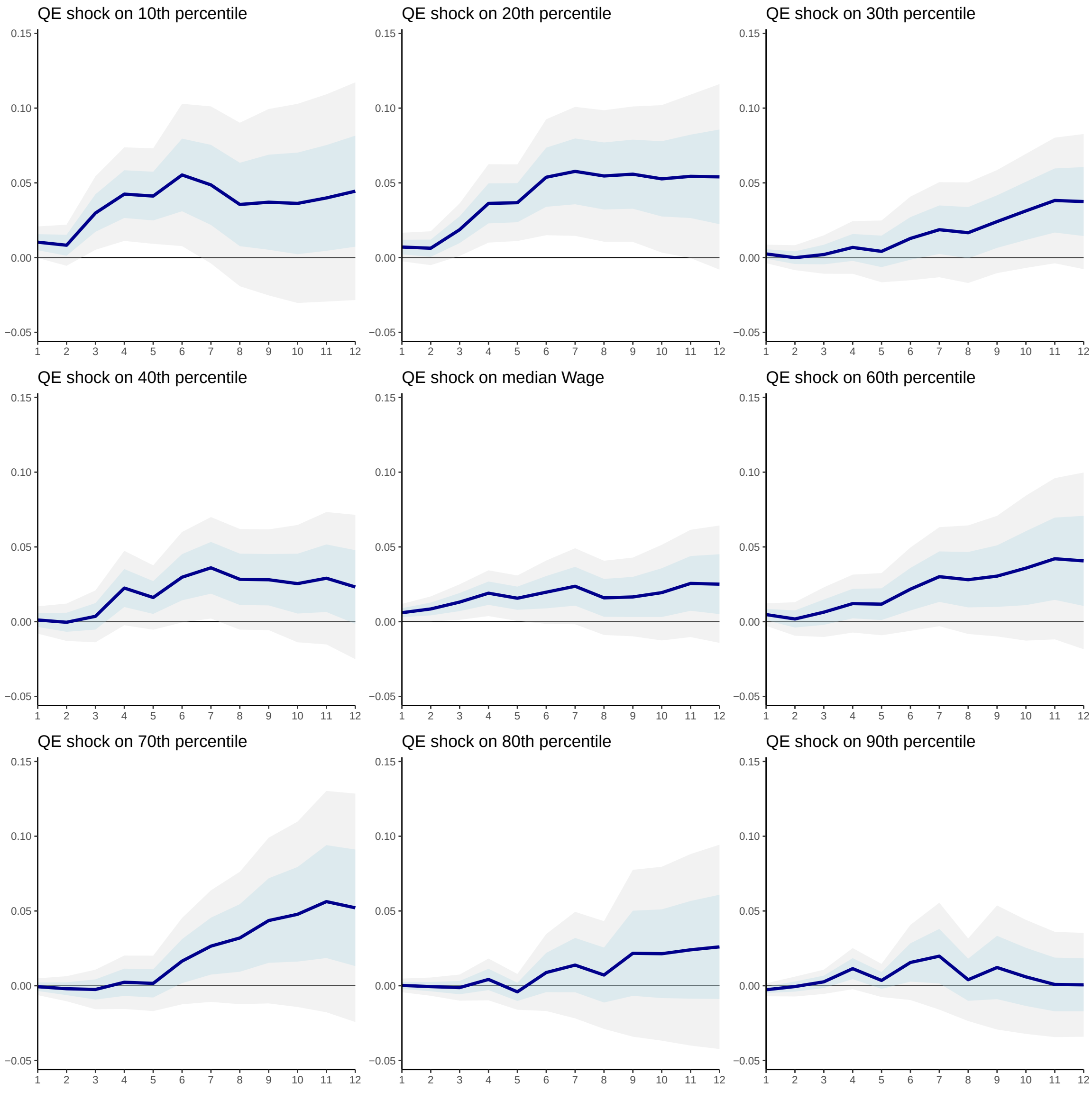
*Note: Policy rate cut coefficients for the 20th, 50th and 80th wage percentile and the respective z-tests (Clogg et al., 1995) to check the (statistically significant) difference between wage decile coefficients. * p<0.32, ** p<0.1, *** p< 0.05*

Figure A.7: Wage percentile responses to IR shocks



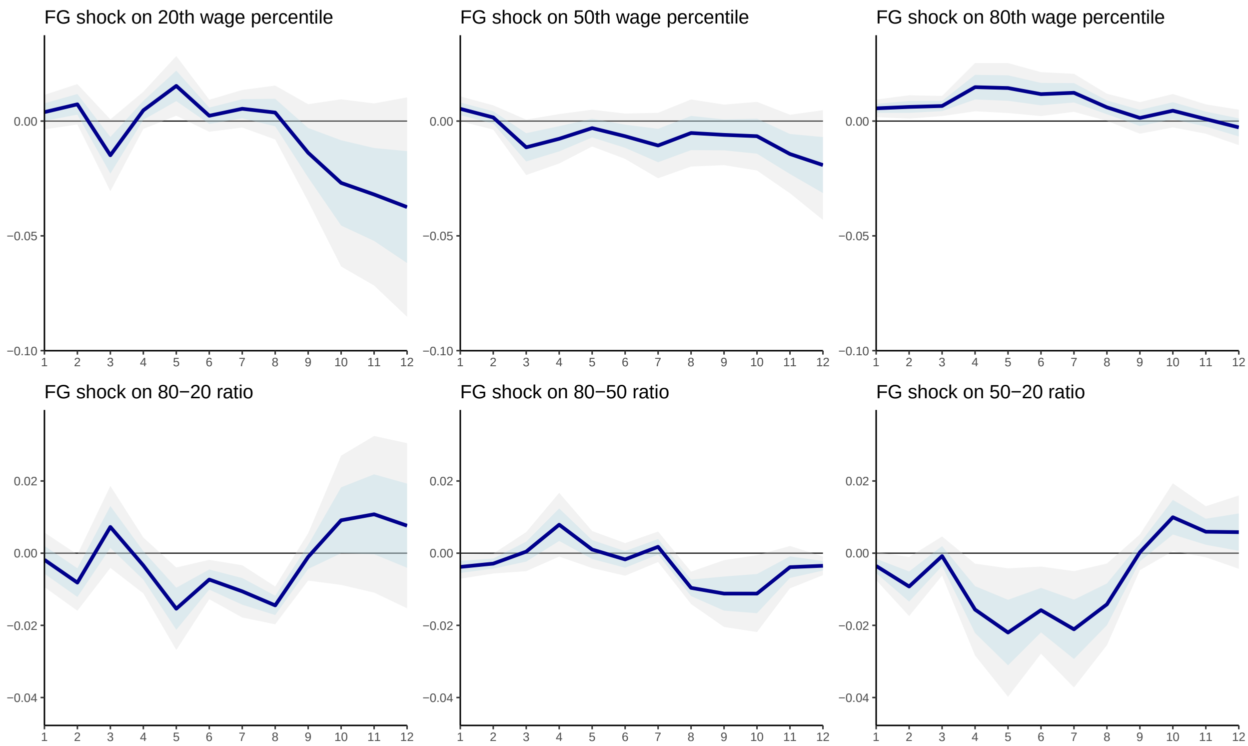
Note: The figure plots impulse responses as well as 68% and 95% confidence intervals (blue and grey shaded areas) of all wage deciles to a 1 pp policy rate cut. Impulse responses are at the quarterly frequency using data from 1999-Q1 to 2019-Q4.

Figure A.8: Wage percentile responses to QE shocks



Note: The figure plots impulse responses as well as 68% and 95% confidence intervals (blue and grey shaded areas) of all wage deciles to a 1 trillion Euro balance sheet expansion. Impulse responses are at the quarterly frequency using data from 1999-Q1 to 2019-Q4.

Figure A.9: Responses to expansionary forward guidance



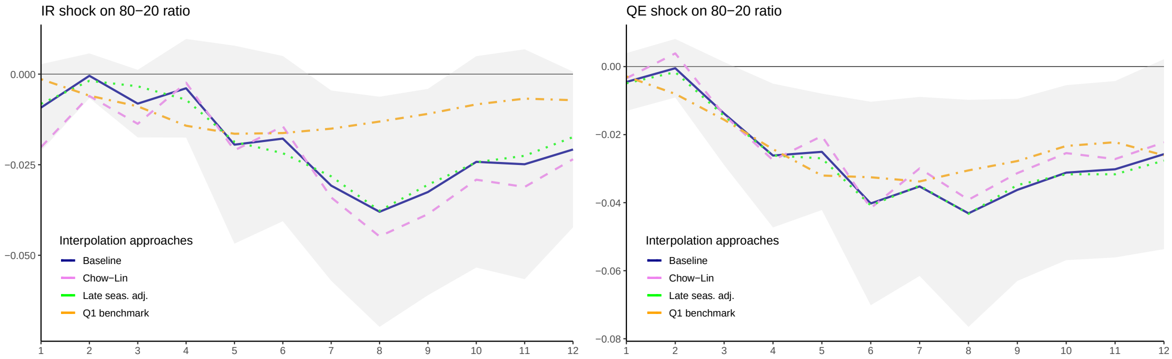
Note: The figure plots impulse responses as well as 68% and 95% confidence intervals (blue and grey shaded areas) of wage deciles (upper row) and inequality measures (lower row) to a 1 pp reduction in the 2y OIS rate. Impulse responses are at the quarterly frequency using data from 1999-Q1 to 2019-Q4.

Table A.9: QE Effect Differences - Z-Tests

Q	β 20p	β 50p	β 80p	z-test 80vs20	z-test 80vs50	z-test 50vs20
1	0.006*	0.012*	0.005	0.059	0.995	-0.636
2	0.006	0.013*	-0.006	1.192*	2.443***	-0.620
3	0.024*	0.017**	-0.001	1.893**	1.830**	0.483
4	0.034***	0.018***	0.000	2.429***	1.955**	1.064*
5	0.035***	0.024**	-0.002	1.965***	1.908**	0.538
6	0.057***	0.025**	0.005	1.821**	1.061*	1.120*
7	0.061***	0.026**	0.008	1.694**	0.832	1.138*
8	0.051***	0.016*	0.000	1.815**	0.811	1.296*
9	0.053***	0.024*	0.024	0.702	0.018	0.840
10	0.048***	0.024*	0.014	0.782	0.283	0.634
11	0.056**	0.029*	0.020	0.769	0.232	0.679
12	0.048**	0.023*	0.021	0.620	0.078	0.661

*Note: Balance sheet expansion coefficients for the 20th, 50th and 80th wage percentile and the respective z-tests (Clogg et al., 1995) to check the (statistically significant) difference between wage decile coefficients. * p<0.32, ** p<0.1, *** p< 0.05*

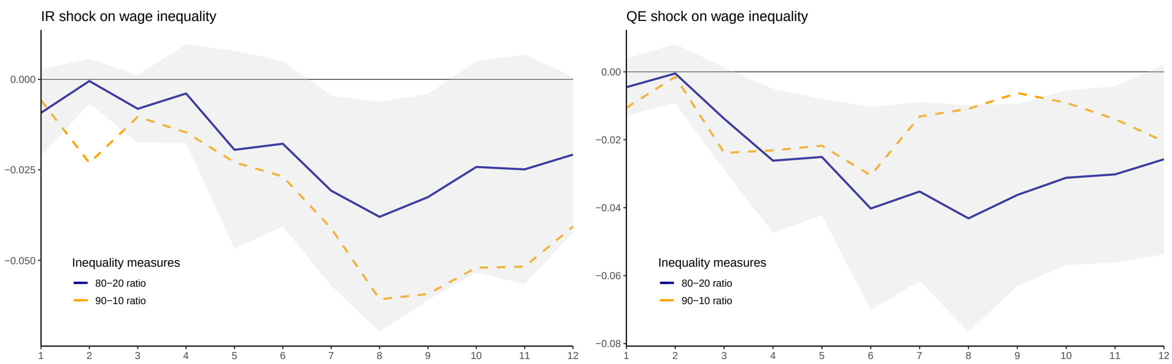
Figure A.10: Alternative interpolation methods



(a) IR shock (b) QE shock

Note: The figure plots impulse responses as well as 95% confidence intervals (grey shaded areas) of the baseline 80-20 percentile ratio to a) a 1 pp policy rate cut and to b) a 1 trillion Euro balance sheet expansion. In addition, impulse responses of 80-20 ratios based on different interpolation approaches are shown: Chow-Lin interpolation (pink, dashed), seasonal adjustment after the interpolation (green, dotted), first quarters as benchmark for interpolation (orange, dash-dotted). Impulse responses are at the quarterly frequency using data from 1999-Q1 to 2019-Q4.

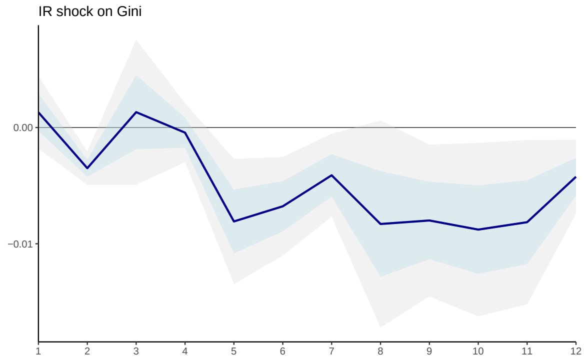
Figure A.11: Responses of the 90-10 percentile ratio



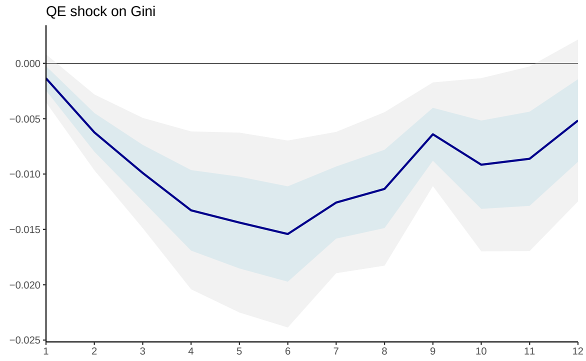
(a) IR shock (b) QE shock

Note: The figure plots impulse responses as well as 95% confidence intervals (grey shaded areas) of the baseline 80-20 percentile ratio to a) a 1 pp policy rate cut and to b) a 1 trillion Euro balance sheet expansion. In addition, the impulse responses of the 90-10 percentile ratio are shown for comparison.

Figure A.12: Responses of the Gini coefficient



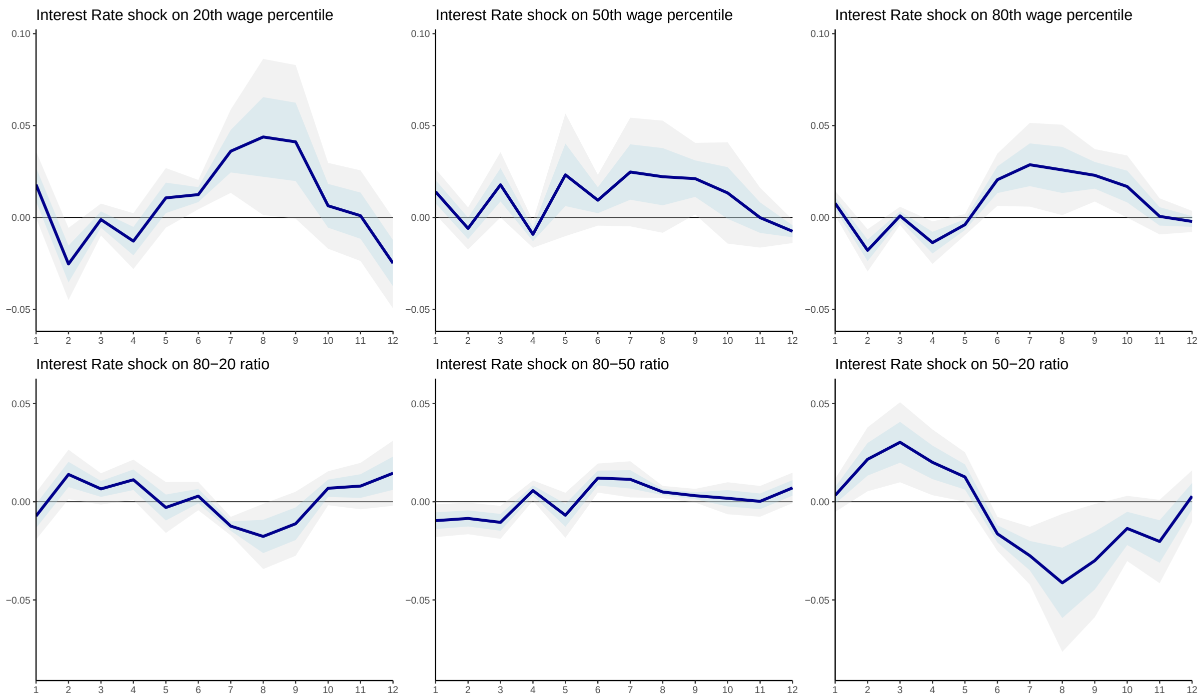
(a) IR shock



(b) QE shock

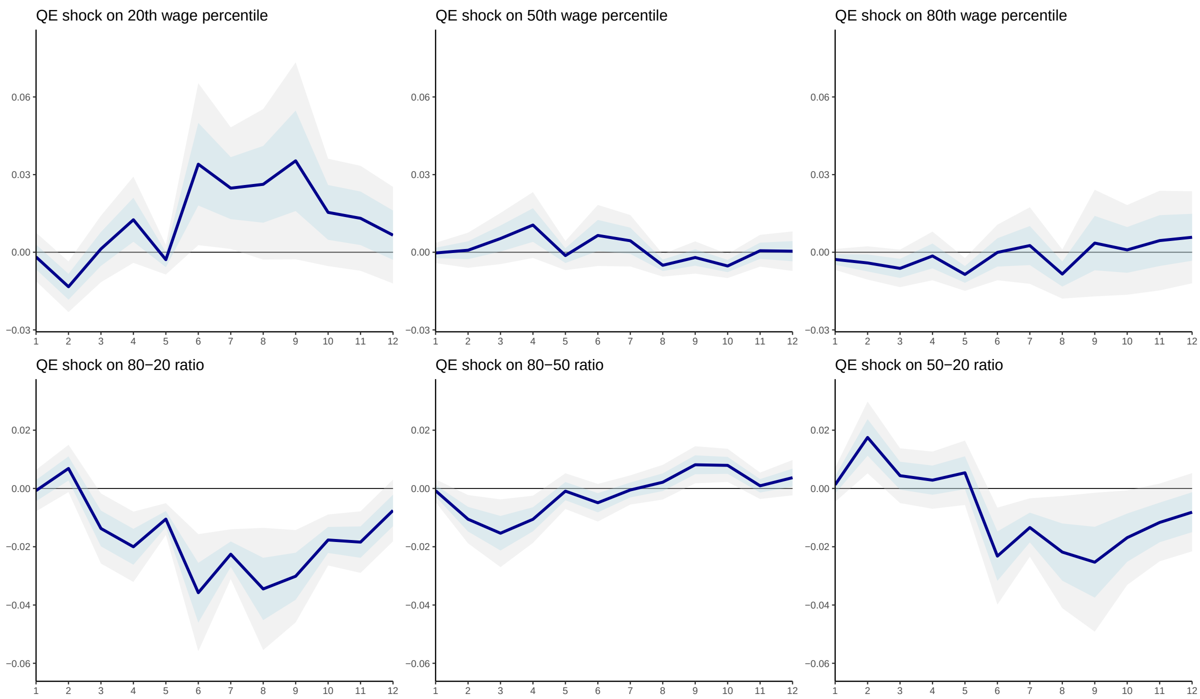
Note: The figure plots impulse responses as well as 68% and 95% confidence intervals (blue and grey shaded areas) of the wage Gini coefficient to a) a 1 pp policy rate cut and to b) a 1 trillion Euro balance sheet expansion.

Figure A.13: Robust conventional policy effects



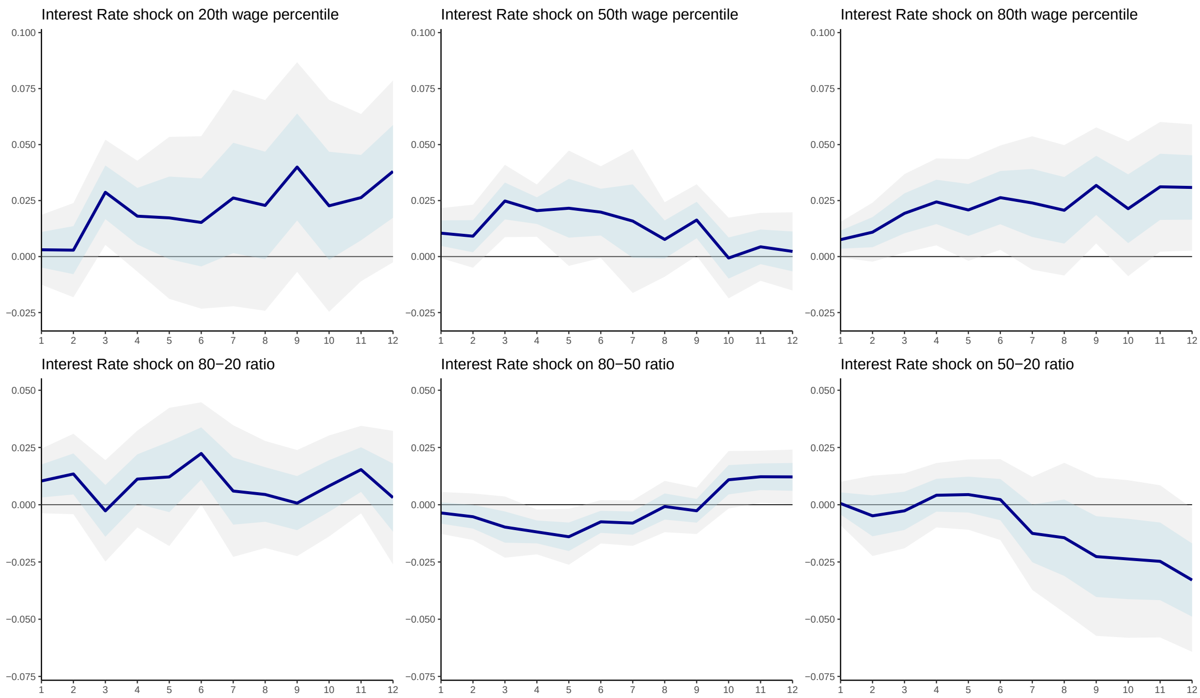
Note: The figure plots impulse responses as well as 68% and 95% confidence intervals (blue and grey shaded areas) of wage deciles (upper row) and inequality measures (lower row) to a 1 pp policy rate cut. Impulse responses are at the quarterly frequency using data from 1999-Q1 to 2019-Q4. In comparison to the baseline specification, a recession dummy, a HartzIV dummy and lagged balance sheet changes are added as controls.

Figure A.14: Robust unconventional policy effects



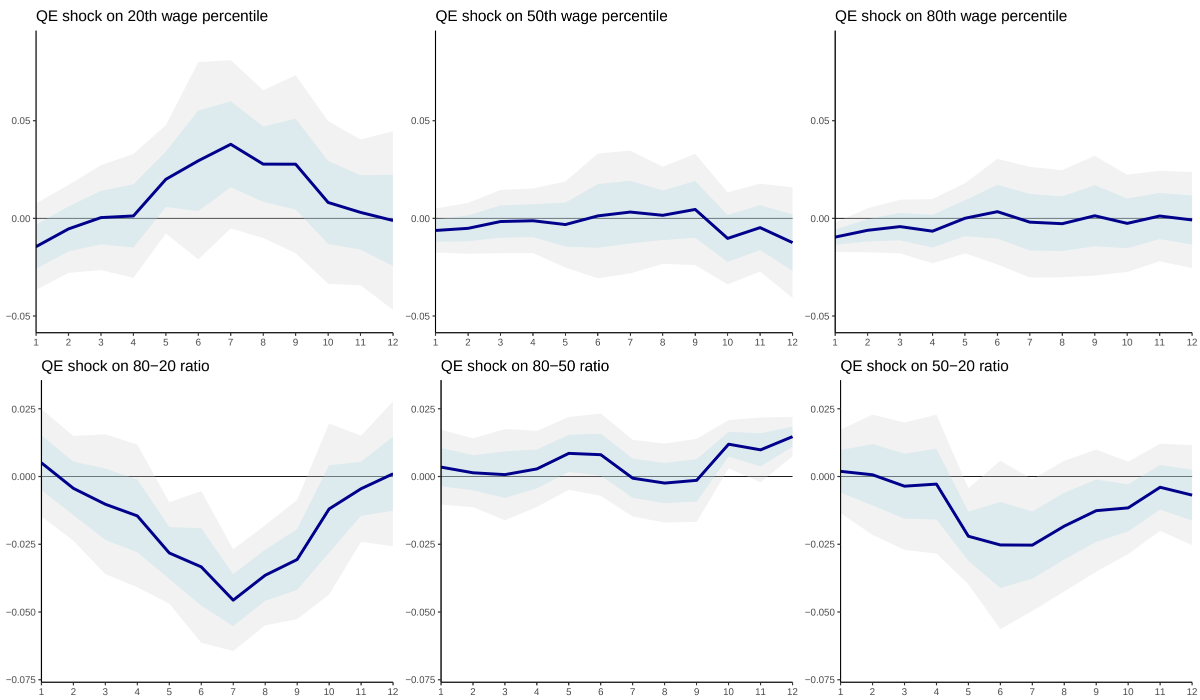
Note: The figure plots impulse responses as well as 68% and 95% confidence intervals (blue and grey shaded areas) of wage deciles (upper row) and inequality measures (lower row) to a 1 trillion Euro balance sheet expansion. Impulse responses are at the quarterly frequency using data from 1999-Q1 to 2019-Q4. In comparison to the baseline specification, a recession dummy, a HartzIV dummy, current and lagged HICP are added as controls and the number of lagged endogenous variables is increased to 8.

Figure A.15: IR Romer shock effects



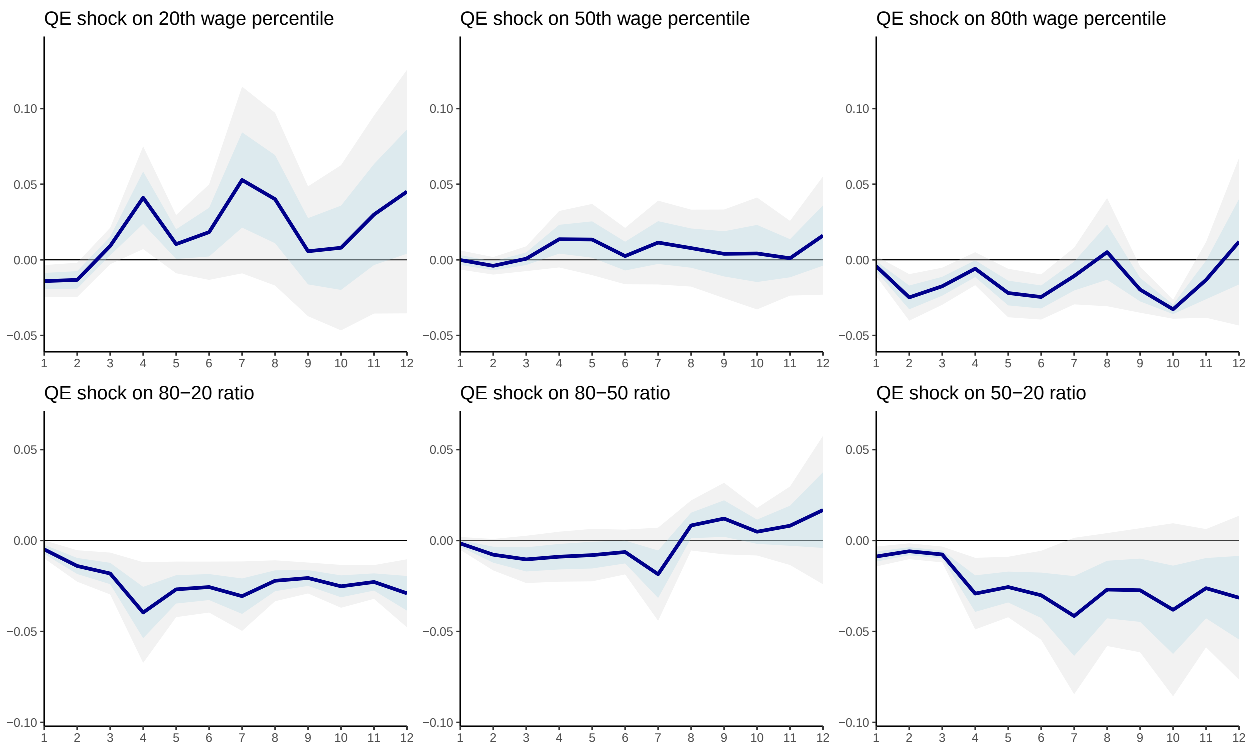
Note: The figure plots impulse responses as well as 68% and 95% confidence intervals (blue and grey shaded areas) of wage percentiles (upper row) and inequality measures (lower row) to a policy rate Romer shock. Note that no instrumental variables are used in this setup, as Romer shocks are assumed to be exogenous. Impulse responses are at the quarterly frequency using data from 1999-Q1 to 2019-Q4.

Figure A.16: QE Romer shock effects



Note: The figure plots impulse responses as well as 68% and 95% confidence intervals (blue and grey shaded areas) of wage percentiles (upper row) and inequality measures (lower row) to a QE Romer shock. Note that no instrumental variables are used in this setup, as Romer shocks are assumed to be exogenous. Impulse responses are at the quarterly frequency using data from 1999-Q1 to 2019-Q4.

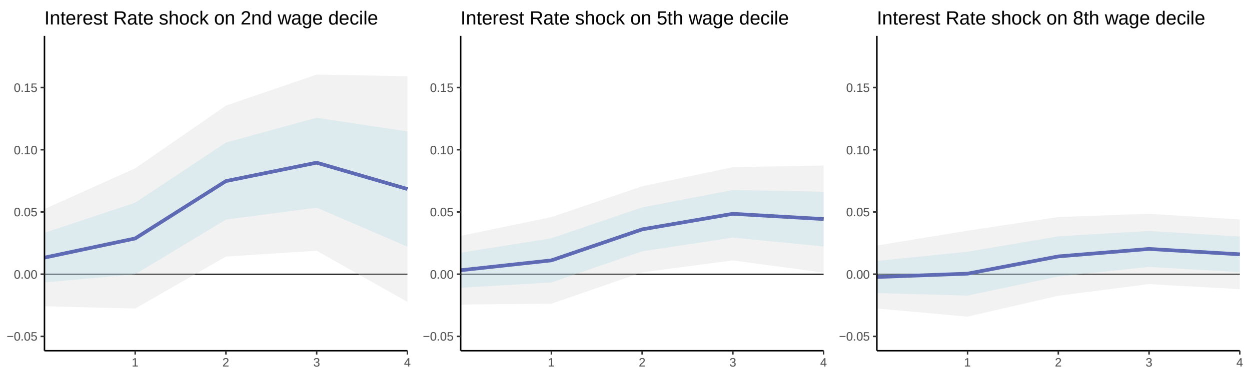
Figure A.17: QE shock effects 2008-2019



Note: The figure plots impulse responses as well as 68% and 95% confidence intervals (blue and grey shaded areas) of wage deciles (upper row) and inequality measures (lower row) to a 1 trillion Euro balance sheet expansion. Impulse responses are at the quarterly frequency using data from 2008-Q1 - 2019-Q4 (the pre-QE period is excluded).

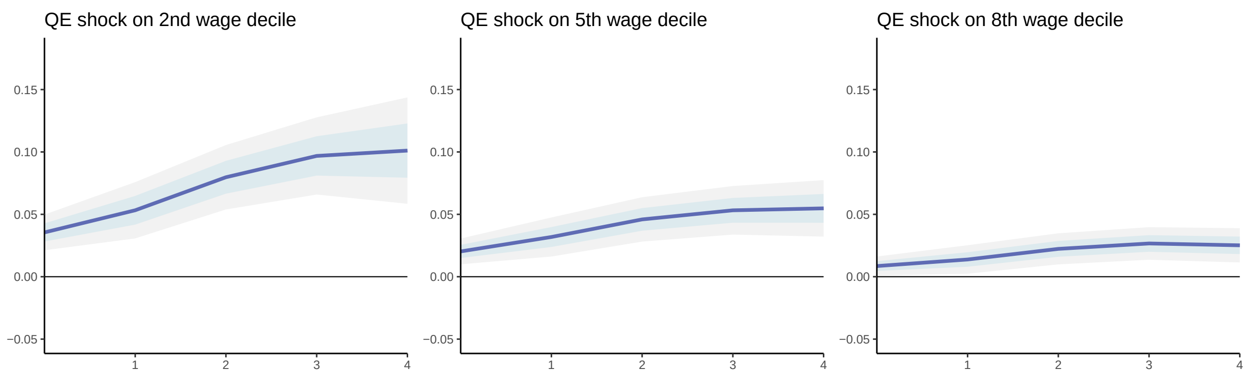
A.4 Transmission Channels

Figure A.18: Annual effects of conventional monetary policy



Note: The figure plots impulse responses as well as 68% and 95% confidence intervals (blue and grey shaded areas) of individuals within the respective permanent wage decile to a 1 pp policy rate cut. Impulse responses are at the annual frequency using data from 1999 to 2019.

Figure A.19: Annual effects of unconventional monetary policy



Note: The figure plots impulse responses as well as 68% and 95% confidence intervals (blue and grey shaded areas) of individuals within the respective permanent wage groups to a 1 trillion Euro balance sheet expansion. Impulse responses are at the annual frequency using data from 1999 to 2019.

Figure A.18 and A.19 show the average individual wage responses in the ten wage decile groups to expansionary monetary policy changes based on equation (12). The time fixed effects are excluded to make the IRFs comparable to the quarterly results in Section 5, which are in line with the annual responses. Expansionary conventional and unconventional monetary policy have significantly positive effects on wages that are largest at the bottom of the wage distribution. The effects are even larger than in the quarterly analysis and significantly different between the middle and the top of the distribution, since unemployed worker are now also included in the sample and their number is declining over the wage groups. Again, the policies take some time to have their maximum effect, and a one trillion expansion of the balance sheet has more persistent and slightly larger effects than a one pp cut in the policy rate. The grey bands depict the 95% confidence intervals based on individual and time cluster-robust standard errors, which take into account heteroscedasticity and autocorrelation.