Working Papers

FEDERAL RESERVE BANK OF BOSTON

No. 25-1

Monetary Policy and the Distribution of Income: Evidence from U.S. Metropolitan Areas

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Abstract:
We use Zip code–level Statistics of Income data from the Internal Revenue Service to measure the distribution of income within U.S. metropolitan areas from 1998 through 2019. Exploiting geographic variation in income distribution over time, we study how unanticipated changes in the monetary policy stance shape the subsequent dynamics of income inequality. The results show that monetary policy persistently affects labor income inequality and that these distributional effects are amplified significantly in weak local labor markets.

JEL Classifications: E21, E52, E58

Keywords: Income inequality, distributional impact of monetary policy, high-frequency monetary policy surprises, local labor markets

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The authors thank Gregory Marchal for outstanding research assistance and Tyler Pike, Felix Galbis-Reig, Gerardo Sanz-Maldonado, and Sarah Siegel for their help with data collection. They also thank John Coglianese for helpful comments.

This version: January 2025 **https://doi.org/10.29412/res.wp.2025.01**

1 Introduction

The steady rise in income (and wealth) inequality over the past several decades, along with a growing lack of social mobility, has propelled the distributional footprint of monetary policy to the forefront of economic policymaking (see Bernanke, 2015; Draghi, 2016; BIS, 2021). From a theoretical perspective, understanding the redistributive channels through which monetary policy operates and transmits to the real economy should also enhance macroeconomic stability and improve prosperity for the economy as a whole (see Kaplan et al., 2018; Auclert, 2019).

Despite the importance of the nexus between monetary policy and income inequality, empirical analysis of that connection, especially for the United States, is scant.[1] The main empirical challenge is measuring income inequality in a way that suits such analysis. Longitudinal U.S. household income data that span many years are rarely available, while surveys of U.S. household income—which can be available at business cycle frequencies (for example, the Consumer Expenditure Survey)—may suffer from bias due to misreporting and missing responses. Moreover, comprehensive microdata underlying U.S. income distribution (for example, the Survey of Consumer Finances) are available only in infrequent waves, which are not suitable for studying how monetary policy affects the cyclical dynamics of income inequality.

In this paper, we provide new evidence showing how monetary policy may impact income inequality, using individual income tax returns filed with the U.S. Internal Revenue Service (IRS) and aggregated to the Zip code level. Exploiting the time series and spatial variation of these data over the past two decades—in combination with monetary policy surprises derived from high-frequency financial data—we document that contractionary (expansionary) monetary policy increases (decreases) income inequality by affecting the distribution of labor income. Furthermore, this effect appears to be more pronounced when local labor market conditions are already weak. Our findings imply that monetary policy has a disproportionate effect on workers who earn low wages and that local labor market conditions are key to explaining the heterogeneous response of income inequality to monetary policy over time and across space.

Our empirical approach consists of three steps. First, we use the IRS Statistics of Income (SOI) data on more than 14,000 Zip codes to compute a standard measure of income inequality—the ratio of income (per household) at the 90th percentile to income (per household) at the 10th percentile (the P90/P10 ratio)—*within* U.S. metropolitan statistical areas (MSAs) from 1998 through 2019. Underlying this step is the assumption that the SOI data at the Zip code level are a good proxy for individual income in a neighborhood and that income differences across Zip codes in the same MSA sufficiently capture income inequality within areas connected by a high degree of social and economic integration.

Second, we exploit variation in income inequality *across* MSAs to estimate the response of income inequality over time to unanticipated changes in the stance of monetary policy not correlated with cyclical economic factors that may exert their own effect on income inequality. Lastly, we ask

[1] While this topic has been the subject of a very active research agenda in recent years, the number of available empirical studies is surprisingly limited; see McKay and Wolf (2023) for a recent review.

whether the response of income inequality to monetary policy surprises depends on local labor market conditions.

Economic theory identifies two main mechanisms through which monetary policy can influence the distribution of income and wealth in the economy (see Kaplan et al., 2018; Auclert, 2019; Slacalek et al., 2020): a direct mechanism that affects individual financial income via policy-induced changes in interest rates and asset prices and an indirect mechanism that affects labor income through individuals' differential exposure to changes in aggregate demand—for example, low-skilled versus high-skilled workers, non-White versus White, high school-educated versus college-educated, and so on. While our data do not comprehensively cover individual financial income, they do provide a consistent breakdown over time of the share of total income attributed to salaries and wages (that is, labor income). We use this breakdown to gauge the importance of the indirect effects of monetary policy for the short-term dynamics of income inequality.

According to our baseline estimates, an unanticipated 25 basis point tightening of monetary policy during the course of year t induces a gradual and persistent increase in the P90/P10 ratio of *labor* income over the subsequent four years. Over the response horizon, the P90/P10 ratio of labor income is estimated to rise by about 0.75 percent per year, on average, with the statistically significant effects emerging in year $t+2$ and persisting through year $t+4$. The P90/P10 ratio for *total* income is also estimated to increase initially in response to a surprise tightening of monetary policy, with the peak response of about 1 percent in year $t+2$. Thereafter, however, the effect dissipates, becoming statistically insignificant by year $t+4$. The notably larger and more persistent response of earnings inequality relative to total income inequality indicates that monetary policy's indirect effects on labor income likely are the primary cause of its distributional impact.

The literature on the distribution of U.S. income finds that fluctuations in the aggregate unemployment rate disproportionately affect earnings at the bottom of the distribution relative to earnings at the top (see Heathcote et al., 2020). In addition, the literature documents that employment of low-skilled workers is more sensitive to monetary policy compared with employment of their higher-skilled counterparts (see Carpenter and Rodgers, 2004; Bergman et al., 2022). Motivated by this evidence, we analyze separately the responses of (real) income from salaries and wages accruing to the top decile and the bottom decile of the labor income distribution. The results indicate that an unanticipated tightening of monetary policy increases earnings inequality by depressing income from salaries and wages accruing to the bottom decile significantly more than labor income accruing to the top decile.

We then study how these effects vary with local labor market conditions, as empirical literature indicates that business cycle fluctuations have the largest effect on workers who are "marginally" attached to the labor market (see Hoynes et al., 2012; Aaronson et al., 2019; Patterson, 2023). Consistent with this evidence, our findings suggest that monetary policy has differential effects through the business cycle: A surprise tightening of monetary policy increases labor income inequality most profoundly when local labor market conditions are already weak.

Altogether, our empirical evidence suggests that the Federal Reserve's monetary policy actions, taken in pursuit of the mandated goals of maximum employment and price stability, have economically significant indirect effects on income inequality through the labor market and that these effects are uneven across the distribution of labor income. Certainly, the magnitude of our estimates cannot account for the rise in U.S. income inequality over the past two decades. Nonetheless, the results support the view that monetary policy can contribute meaningfully to cyclical fluctuations in income inequality, as policy-induced changes in aggregate demand differentially affect individual earnings.

In the context of the broader literature, our findings are related to those of Coibion et al. (2017), who also analyze the dynamic response of U.S. income inequality to unexpected changes in the monetary policy stance. Using self-reported income data from a rotating panel of households in the U.S. Consumption Expenditure Survey (CEX), Coibion et al. (2017) estimate—as we do—that an unanticipated tightening of monetary policy increases income inequality. However, they find larger effects on total income inequality than on earnings inequality in response to monetary policy surprises. Plausible explanations for the difference in results are that we use an MSA-level panel of income inequality data, monetary policy surprises identified from high-frequency financial data, and a different sample period that also includes unconventional monetary policy actions. The results may also differ due to measurement errors and the limited cross section of individual responses in the CEX relative to the comprehensive coverage of tax returns in the SOI data.

At the same time, our results are consistent with the evidence from other countries. Using administrative individual income data for Scandinavian economies, Holm et al. (2021), Amberg et al. (2022) and Andersen et al. (2023) document economically and statistically significant effects of monetary policy on labor income inequality, as well as greater sensitivity to monetary policy at the bottom—compared with the top—of the labor income distribution.[2] While our analysis focuses on the distributional effects of monetary policy, it also contributes to the empirical literature documenting asymmetric effects of monetary policy over the course of a business cycle (Tenreyro and Thwaites, 2016; Angrist et al., 2018; Barnichon and Matthes, 2018; Aastveit and Anundsen, 2022). It also adds to the growing body of research that uses microdata across geographic areas to study the differential effects of monetary policy on local economic outcomes (Hazell et al., 2022; Herreño and Pedemonte, 2022).

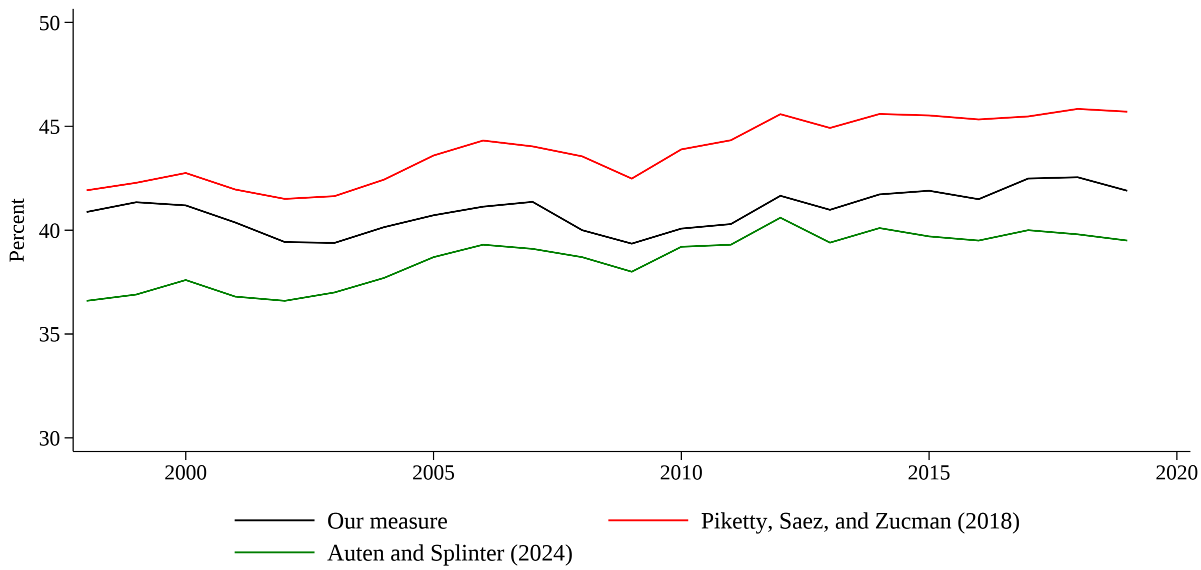
2 Data Sources and Methods

This section describes the data we use in our empirical analysis.

Income inequality data: Our measure of income inequality is derived from the IRS Statistics of Income (SOI), which tabulate individual income based on tax returns filed with the IRS. For each year, starting in 1998, the IRS aggregates selected income and tax items, including adjusted gross (pre-tax) income and salaries and wages, to the Zip code level. The SOI data also report

[2] Andersen et al. (2023) also find that the effects of monetary policy across the income distribution increase with time, a pattern consistent with monetary policy influencing income inequality primarily through indirect channels.

Figure 1: Top 10 Percent Income Share in the United States, 1998–2019



Note: The black line depicts the share of adjusted gross income earned by the top 10 percent of the 18,836 Zip codes computed from the SOI data (see Appendix A for details). The red and green lines are the shares of pre-tax national income earned by the top 10 percent of households using administrative tax returns, as computed by Piketty et al. (2018) and Auten and Splinter (2024), respectively (see `https://www.gabriel-zucman.eu/usdina/` and `https://www.davidsplinter.com/`).
Source: Authors' calculations using data from the IRS Statistics of Income.

limited information on financial income (interest income, dividends, and net capital gains), as well as business income and transfers. However, these additional sources of taxable income are not covered systematically over time. Therefore, our analysis uses only data on adjusted gross income and labor income, which are reported on a consistent basis from 1998 through 2019.[3] For each Zip code and year, we use these data and information on the number of annual tax returns filed to compute (real) adjusted gross income and labor income per tax unit (that is, per household). We use these data to measure income inequality within U.S. core-based statistical areas (CBSAs), which are home to roughly 90 percent of the country's population.[4]

To the extent that households within Zip codes are relatively homogeneous with respect to demographic characteristics, economic status, and living conditions, the SOI Zip code data offer the best alternative to administrative data on individual income, which are not publicly available. Figure 1 offers a glimpse at the suitability of our data for gauging trends in U.S. income inequality.

[3]The most recent year of available Zip code–level SOI data is 2021. We exclude 2020 and 2021 data from the analysis because the nature and composition of pre-tax income during that period was significantly affected by the COVID-19 recession and the associated unprecedented policy interventions.

[4]A core-based statistical area includes metropolitan and micropolitan statistical areas (MSAs and μSAs, respectively), that is, geographic entities with a high degree of social and economic integration. MSAs contain a core urban area with a population of 50,000 or more, and μSAs contain an urban core with a population of 10,000 to 49,999; for more information, see `https://www.census.gov/programs-surveys/metro-micro/about.html/`.

The black line shows the share of gross income that accrues to the top 10 percent of the 18,836 Zip codes that can be merged to the universe of 925 CBSAs.[5] For comparison, the red and green lines show the share of gross U.S. income going to the top 10 percent of households nationwide, as estimated by Piketty et al. (2018) and Auten and Splinter (2024), respectively, using administrative tax records. Despite some level differences, our series tracks closely with these two widely used measures of income inequality over the 1998–2019 period and exhibits similar higher frequency fluctuations.

Our data offer several advantages over the survey-based measures of personal income that previous research has used to study how monetary policy affects U.S. income inequality (see Coibion et al., 2017). One advantage is that measurement errors and misreporting are likely negligible, as labor income is reported to the taxpayers by their employers instead of being self-reported. Another advantage is that the risk of selection bias is minimal, given that individuals are required to report their income by law.[6] In addition, the Zip code–level nature of the data offers information on local income that can be used to measure income inequality within areas that have a high degree of social and economic interaction. The spatial variation in income inequality over time allows us to estimate the effects of monetary policy on income inequality, taking advantage of the heterogeneous distribution of income across metro areas. The time series and cross-sectional variation of our data help increase the power of our statistical analysis given that the SOI data are available only at an annual frequency and cover about two decades.

Panels A and B of Figure 2 illustrate the geographic dispersion of income inequality in our data—averaged over the 1998–2019 period—with inequality measured as the ratio of income per household in Zip codes that are in the 90th percentile (P90) relative to income per household in Zip codes that are in the 10th percentile (P10) of their respective CBSA distributions.[7] Panels C and D, on the other hand, show the distributions of total income and labor income at the beginning and end of the sample period.

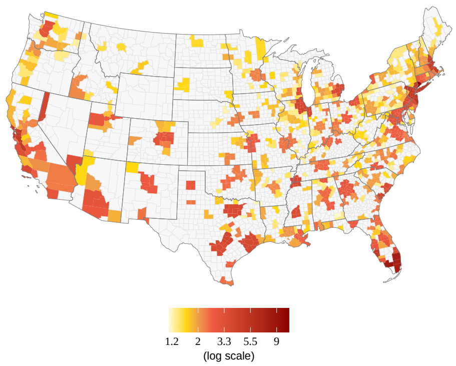
Three salient observations emerge from the figure. First, as shown in Panels A and B, both total and labor income are unevenly distributed across metro areas, with noticeably greater inequality observed in coastal areas. Second, some metro areas that are unequal with respect to the distribution of total income are also unequal in terms of labor income (the cross-sectional correlation of the logarithm of the P90/P10 ratio of total income and salaries and wages is 0.88). This suggests that in these metro areas, salaries and wages account for a large share of total income in Zip codes that are at the top of the income distribution and Zip codes that are at the bottom of the income distribution. Third, as shown in Panels C and D, the uneven distribution of income across metro areas varies over time, as some areas became more unequal and other less unequal with the passage of time. Overall, however, inequality increased significantly for both measures of income over the

[5] See Appendix A for details.

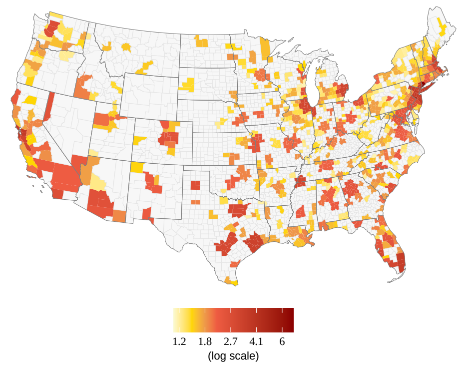
[6] It should be noted, however, that not everyone is required to file tax returns, and that those not required likely have limited income. As a result, tax data may not provide comprehensive coverage of very low-income households.

[7] To compute the P90/P10 measure of income inequality, we require that CBSAs have at least 10 Zip codes. This restriction reduces our sample to 16,488 distinct Zip codes in 517 CBSAs.

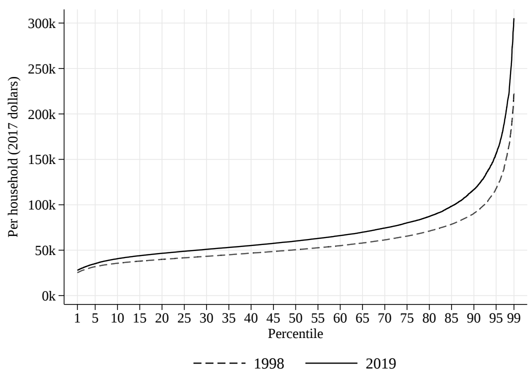
Figure 2: Income Inequality across U.S. Metro Areas and Time



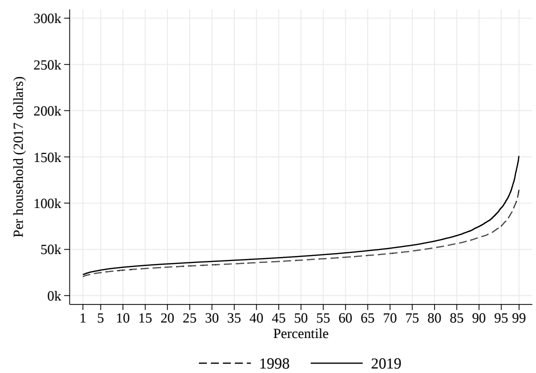
A. Avg. P90/P10 ratio: Adjusted gross income



B. Avg. P90/P10 ratio: Salaries & wages



C. Adjusted gross income across metro areas



D. Salaries & wages across metro areas

Note: Panels A and B depict the distributions of the CBSA-specific time-series averages of the P90/P10 ratio of total income and the CBSA-specific time-series averages of the P90/P10 ratio of labor income, respectively, for an unbalanced panel of 517 CBSAs from 1998 through 2019. Panels C and D depict the 1998 (dashed line) and 2019 (solid line) distributions of (real) total income per household and (real) labor income per household, respectively, for 16,488 Zip codes in the same 517 CBSAs (see Appendix A for details).
Source: Authors' calculations using data from the IRS Statistics of Income.

sample period; both distributions became notably more skewed toward higher income levels as income in Zip codes at the top of the income distribution rose more rapidly from 1998 to 2019 than income in Zip codes at the bottom or in the middle of the distribution.

Monetary policy surprises and other controls: We identify changes in the monetary policy stance that are orthogonal to the state of the economy by following a well-established literature that uses changes in interest rates or interest rate futures in narrow windows bracketing Federal Open Market Committee (FOMC) announcements to isolate monetary policy surprises.[8] By using

[8] See, for example, Kuttner (2001), Gürkaynak et al. (2005), Jarociński and Karadi (2020), Swanson (2021), and Miranda-Agrippino and Ricco (2021).

monetary policy surprises identified from high-frequency financial data, we ensure that the dynamic response of income inequality that we estimate reflects unanticipated changes in the monetary policy stance and not other economic or financial developments to which policymakers may be responding.

In our baseline analysis, we include monetary policy surprises identified using the methodology developed by Miranda-Agrippino and Ricco (2021). These surprises represent unanticipated shifts to either the target range or the expected path of the federal funds rate—that is, unanticipated shifts in the overall monetary policy stance—that are orthogonal to the state of the economy. Given that our income inequality data are available at only an annual frequency, we compute annual monetary policy surprises by summing the FOMC meeting–specific policy surprises for each calendar year in the 1998–2019 sample period. As a robustness check, we redid the analysis using policy surprises as estimated by Jarociński and Karadi (2020) and found quantitatively and qualitatively similar results (see Appendix B).

Because U.S. metro areas differ significantly with respect to labor market conditions, industry structure, population dynamics, and sociodemographic characteristics, we use the available CBSA-level data from multiple sources to account for various confounding local factors. Specifically, we rely on data from the U.S. Bureau of Labor Statistics Local Area Unemployment Statistics (LAUS) to compute CBSA-level unemployment rates, on data from the U.S. Bureau of Economic Analysis to compute local growth rates of real personal income, and on data from the U.S. Census Bureau for local population growth data. We also use the Quarterly Census of Employment and Wages (QCEW) to compute annual CBSA-level shares of employment in the construction, tradable goods, and non-tradable goods sectors, thus ensuring that our analysis takes into account differences in industrial structure and the resulting differences in cyclical sensitivity across U.S. metro areas.[9]

To account for sociodemographic differences across metro areas, we use Quarterly Workforce Indicators (QWI) to compute annual CBSA-level employment shares of White, Black, and Hispanic workers, as well as the share of higher-educated workers, that is, workers with at least some college or equivalent degree. These local sociodemographic characteristics are important controls in our analysis, as previous research shows that labor market experiences of different categories of workers are key drivers of local income inequality and may also explain, at least in part, its sensitivity to monetary policy (Carpenter and Rodgers, 2004; Bergman et al., 2022) and cyclical economic fluctuations (Hoynes et al., 2012). After imposing the necessary filters and merging our CBSA-level income inequality data with data sources on local economic conditions, we are left with a slightly unbalanced panel of 317 CBSAs—all of which are MSAs—over the 1998–2019 period (see Appendix A for details).

One noteworthy feature of the MSA-panel nature of our data is that in addition to including the local factors, it allows us to control for aggregate economic conditions that affect the entire cross section of MSAs, such as inflation, output growth, state of the national labor market, and broad financial conditions. In combination with our use of "cleanly" identified monetary policy surprises, the inclusion of these aggregate variables as additional conditioning covariates further

[9] Our definitions of these sectors follows Mian and Sufi (2014).

assuages concerns that local income inequality dynamics do not reflect developments in the national economy to which monetary policy may be responding.

3 Dynamic Effects of Monetary Policy on Income Inequality

This section discusses our findings on how changes in the monetary policy stance affect income inequality over time. First, it describes our econometric framework. Then it presents the main results and other results documenting heterogeneity in the response of income inequality to monetary policy across local business cycles.

Baseline effects: We estimate the dynamic response of income inequality to monetary policy surprises using a panel version of the local projections framework proposed by Jordà (2005). Specifically, letting $i = 1, \dots, N$ index MSAs and $t = 1, \dots, T$ index time (in years), we use our panel to estimate:

$$y_{i,t+h} = \alpha^{(h)} y_{i,t} + \beta^{(h)} MPS_t + \mathbf{x}_{i,t}^{\top} \boldsymbol{\gamma}^{(h)} + \mathbf{z}_t^{\top} \boldsymbol{\theta}^{(h)} + \eta_i^{(h)} + \epsilon_{i,t+h}^{(h)}; \quad h = 1, \dots, H, \tag{1}$$

where $y_{i,t+h}$ denotes the logarithm of our measure of income inequality for MSA i in year $t+h$, MPS_t is the sum of monetary policy surprises in year t, and $\mathbf{x}_{i,t}$ and $\mathbf{z}_t$ denote vectors of MSA-specific and aggregate controls, respectively.

For each MSA, the vector of local controls $\mathbf{x}_{i,t}$ comprises the log-difference (from year $t-1$ to year t) of real personal income, the change (from year $t-2$ to year t) in the local unemployment rate, the log-difference (from year $t-1$ to year t) of population, employment shares (as of year t) of Black, Hispanic, and higher-educated workers, and employment shares (as of year t) in the construction, tradable goods, and non-tradable goods sectors.[10] In addition to the current level of income inequality $y_{i,t}$, which controls for the persistence of income inequality over time, specification (1) includes MSA fixed effects $\eta_i^{(h)}$, $i = 1, \dots, N$, which capture unobservable (time-invariant) differences in local labor market characteristics or any other MSA-specific factors—provided that they do not vary over time—that may influence the dynamics of income inequality.

The vector of aggregate controls $\mathbf{z}_t$ comprises the log-difference (from year $t-1$ to year t) of real GDP, the two-year change (from year $t-2$ to year t) in the national unemployment rate, the log-difference (from year $t-1$ to year t) of core PCE price index, the average levels (as of year t) of the 3-month and 10-year (nominal) Treasury yields, the average level (as of year t) of the Gilchrist and Zakrajšek (2012) excess bond premium, and the log-difference (from year $t-1$ to year t) of the S&P 500 stock price index.

The coefficient of interest in this specification is $\beta^{(h)}$, a semi-elasticity measuring the impact of an unexpected policy tightening/easing of 100 basis points during year t on income inequality (in

[10] As shown by Hamilton (2018), the two-year change (from year $t-2$ to year t) in the unemployment rate is equivalent to the year-t deviation of the unemployment rate from its "Hamilton" trend. We drop the employment shares of White and less-educated workers, along with the share of employment in "other" sectors, from $\mathbf{x}_{i,t}$ due to multicollinearity.

percent) in year $t+h$. Note that the linearity of our baseline regression specification implies that an unanticipated monetary policy easing has a symmetric and opposite effect on the dynamic response of income inequality compared with a tightening surprise. For $h = 1, \ldots, 4$ years, we estimate specification (1) by OLS. All statistical inference is based on the asymptotic covariance matrix clustered at the MSA (i) and year (t) level and is robust to arbitrary cross-sectional dependence and serial correlation in the error term $\epsilon_{i,t}^{(h)}$ (see Cameron et al., 2011).

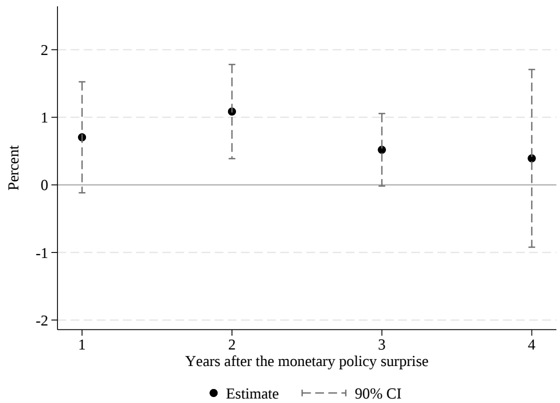
Figure 3 shows the impulse responses of within-MSA income inequality to an unanticipated tightening of monetary policy. Panels A and C focus on total income inequality and labor income inequality, respectively, where inequality is measured as the logarithm of the P90/P10 ratio of the specified income variable. Panels B and D decompose the dynamic effects of monetary policy surprises on total income inequality and labor income inequality into separate responses at the top and bottom of the income distribution—that is, the 90th (P90) percentile and the 10th (P10) percentile of the logarithm of (real) total income and the logarithm of (real) salaries and wages, respectively.

According to Panel A, following an unexpected 25 basis point tightening of monetary policy in year t, total income inequality is estimated to increase gradually over the subsequent two years, with the peak—and statistically significant—response of slightly more than 1 percent in year $t+2$. Thereafter, the effect of a policy tightening starts to weaken and by year $t{+}4$ is no longer statistically different from zero. It is worth noting that the size and shape of this response are not obvious a priori, as various sources of income—including labor, financial, and business income—may respond differently to an unanticipated change in the monetary policy stance. In addition, the composition of income varies at the bottom and the top of the income distribution, with salaries and wages representing a major source of income for workers at the bottom of the income distribution (see Piketty et al., 2018). An unexpected tightening of monetary policy may therefore increase, decrease, or leave unchanged our measure of total income inequality, depending on which component of total income responds more and which part of the income distribution is more sensitive to changes in the policy stance.

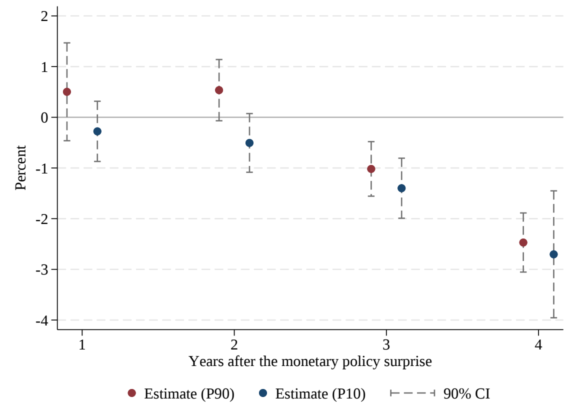
Panel B shows that the increase in the P90/P10 ratio of total income in the first two years following a shift to tight policy reflects the confluence of two opposite effects: a rise in (real) income at the top decile (P90) of the income distribution and a decline in (real) income at the bottom decile (P10) of the income distribution. Thereafter, total income at the top and the bottom of the distribution both decline significantly and by roughly an equal amount, implying essentially no impact on the corresponding P90/P10 ratio. Although movements in non-labor income may explain these differential responses, the absence of consistent reporting of financial and business income in our data prevents us from estimating the effects of monetary policy on each component of total income separately.[11] Accordingly, the rest of our analysis relies on the comprehensive coverage of salaries and wages to analyze whether the distributional effects of monetary policy operate mostly

[11] Absent granular data, it is difficult to estimate the response of non-labor income, as monetary policy may have non-monotonic effects on financial (that is, dividend, interest, and capital gains) and business income.

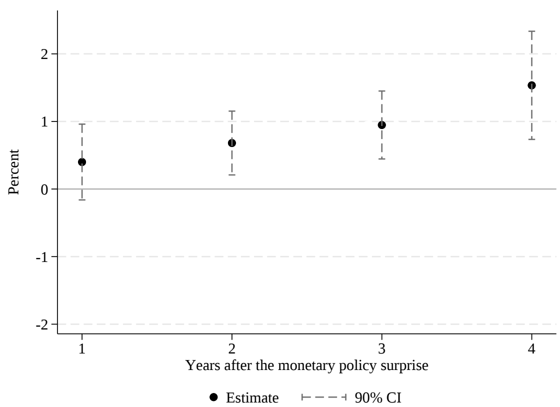
Figure 3: Response of Income Inequality to a Monetary Policy Tightening



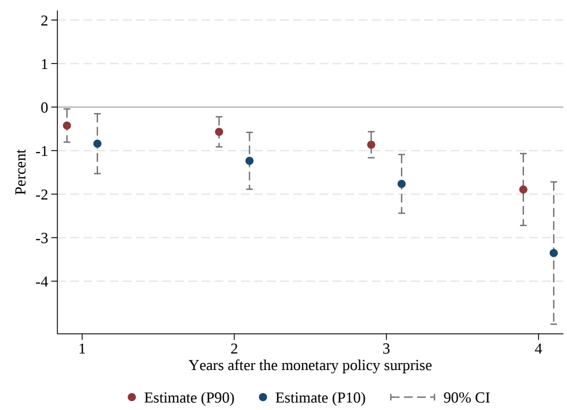
A. P90/P10 ratio: Adjusted gross income



B. P90 and P10: Adjusted gross income



C. P90/P10 ratio: Salaries & wages



D. P90 and P10: Salaries & wages

Note: Sample: an unbalanced panel of 317 MSAs from 1998 through 2019 ($\bar{T} = 21.9$ (years); Obs. = 6,855). The dependent variable in Panels A and C is $100 \times \ln[\text{P90/P10}]_{i,t+h}$; the dependent variables in Panels B and D are $100 \times \ln \text{P90}_{i,t+h}$ and $100 \times \ln \text{P10}_{i,t+h}$, where $\text{P90}_{i,t+h}$ denotes the 90th percentile and $\text{P10}_{i,t+h}$ denotes the 10th percentile of the specified (real) income variable (that is, adjusted gross income or salaries and wages, both per household) in MSA i in year $t+h$ computed from the Zip code–level data. The dots depict the estimated impact of an unexpected monetary policy tightening of 25 basis points during year t on the specified measure of income inequality in year $t+h$, that is, $0.25 \times \hat{\beta}^{(h)}$, where $\hat{\beta}^{(h)}$ denotes the OLS estimate of coefficient $\beta^{(h)}$, $h = 1, \ldots, 4$, from specification (1). The associated whiskers represent the 90 percent confidence intervals (CIs), computed using an asymptotic covariance matrix clustered at the MSA (i) and year (t) level.

though changes in the distribution of labor income.

Panel C provides strong evidence supporting the view that the labor market plays a key role in shaping the distributional footprint of monetary policy. Our estimates indicate that an unanticipated tightening of monetary policy in year t induces a gradual increase—about 0.75 percent per year, on average—in the P90/P10 ratio of labor income in years $t+1$ through $t+4$. Put differently, an unexpected 25 basis point cumulative tightening of monetary policy in year t (roughly

1.5 standard deviations) leads to a cumulative rise in the average P90/P10 ratio of salaries and wages of about 3 percent—from 1.8 to 1.85 or about one within-MSA standard deviation—over the subsequent four years. This economically sizable effect is consistent with the view presented in the theoretical literature arguing that monetary policy primarily affects the dynamics of income inequality indirectly, namely through the heterogeneous exposure of labor income to changes in aggregate demand (see Kaplan et al., 2018; Auclert, 2019; Slacalek et al., 2020).

Given that labor income inequality appears to be relatively more sensitive to changes in the monetary policy stance, a natural follow-up question is whether the distribution of wages and salaries widens because the lower part of the distribution responds to monetary policy more than the upper part. This question is also motivated by a finding that earnings of low-income workers fluctuate sharply with business cycles (see Heathcote et al., 2020; Bergman et al., 2022).

Panel D offers an answer to this question by decomposing the response of the P90/P10 ratio of labor income to a surprise tightening of monetary policy in year t into separate responses at the top and bottom of the distribution. According to our estimates, the policy-induced movements in the bottom part of the distribution—especially during the latter part of the response horizon—account for the bulk of the response of labor income inequality to a monetary policy surprise: Starting in year $t+2$, the estimated declines in (real) income accruing to the 10th percentile of the labor income distribution become, in absolute terms, notably greater than the corresponding declines in (real) income accruing to the 90th percentile. This divergence is consistent with the monotonically increasing impact of monetary policy on the P90/P10 ratio of labor income over the response horizon shown in Panel C.

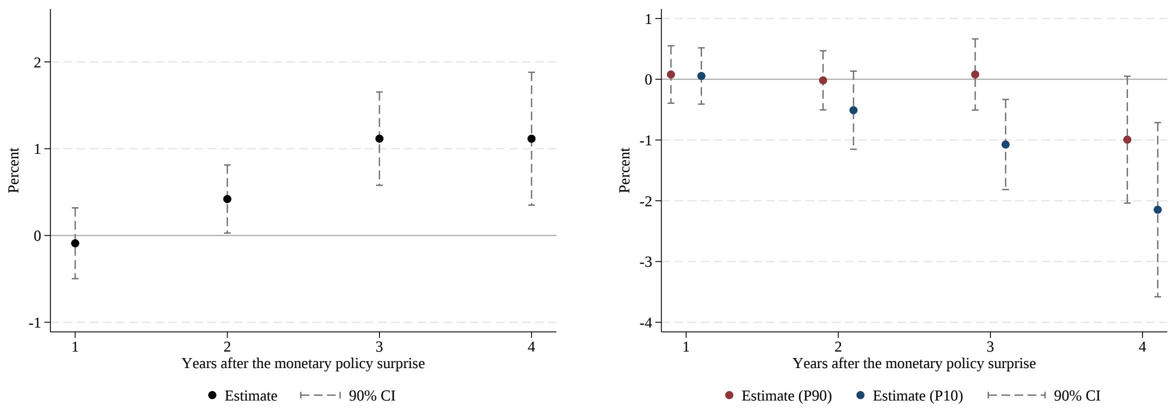
The role of local labor markets: One possible explanation for the significantly more pronounced reaction of the bottom part of the labor income distribution to changes in the monetary policy stance is that the labor market outcomes of low-income workers are cyclically more sensitive to such changes compared with the outcomes of higher-income workers (see Aaronson et al., 2019; Patterson, 2023). This explanation would be consistent with the fact that labor income inequality tends to increase significantly in recessions but remains relatively stable in expansions (see Heathcote et al., 2020).

To evaluate the strength of this explanation and estimate the potential state-dependent effects of monetary policy on labor income inequality, we modify the baseline specification (1) as follows:

$$\begin{aligned} y_{i,t+h} = {} & \alpha^{(h)} y_{i,t} + \beta^{(h)} MPS_t + \mathbf{x}_{i,t}^{\top}\boldsymbol{\gamma}^{(h)} + \mathbf{z}_t^{\top}\boldsymbol{\theta}^{(h)} \\ & + \mathbb{1}\big[u_{i,t} - u_{i,t-2} > 0 \ \&\ u_{i,t} > u_t^N\big] \times \big[\alpha_w^{(h)} y_{i,t} + \beta_w^{(h)} MPS_t + \mathbf{x}_{i,t}^{\top}\boldsymbol{\gamma}_w^{(h)} + \mathbf{z}_t^{\top}\boldsymbol{\theta}_w^{(h)}\big] \\ & + \mathbb{1}\big[u_{i,t} - u_{i,t-2} > 0 \ \&\ u_{i,t} > u_t^N\big] + \eta_i^{(h)} + \epsilon_{i,t+h}^{(h)}; \quad h = 1, \dots, H, \end{aligned} \tag{2}$$

where $\mathbb{1}[\cdot]$ is a 0/1-indicator function that equals 1 if its argument is true and 0 otherwise. The state-dependence in specification (2) captures local labor market conditions as measured by the change in the MSA-level unemployment rate $u_{i,t}$ from year $t-2$ to year t and where the local unemployment rate is in relation to the national unemployment rate u_t^N. In this case, the coefficient $\beta_w^{(h)}$ measures

FIGURE 4: Response of Labor Income Inequality to a Monetary Policy Tightening
(In Weak Local Labor Markets)



A. P90/P10 ratio: Salaries & wages

B. P90 and P10: Salaries & wages

NOTE: Sample: an unbalanced panel of 317 MSAs from 1998 through 2019 ($\bar{T}$ = 21.9 (years); Obs. = 6,855). The dependent variable in Panel A is $100 \times \ln[\text{P90}/\text{P10}]_{i,t+h}$, where $\text{P90}_{i,t+h}$ denotes the 90th percentile and $\text{P10}_{i,t+h}$ denotes the 10th percentile of (real) salaries and wages (per household) in MSA i in year $t+h$ computed from Zip code–level data; the dependent variables in Panels B are $100 \times \ln \text{P90}_{i,t+h}$ and $100 \times \ln \text{P10}_{i,t+h}$. The dots depict the estimated additional impact of an unexpected monetary policy tightening of 25 basis points during year t on the specified measure of income inequality in year $t+h$ when local labor markets are already weak—that is, $0.25 \times \hat{\beta}_w^{(h)}$, where $\hat{\beta}_w^{(h)}$ denotes the OLS estimate of coefficient $\beta_w^{(h)}$, $h = 1, \ldots, 4$, from specification (2). The associated whiskers represent the 90 percent confidence intervals (CIs), computed using an asymptotic covariance matrix clustered at the MSA (i) and year (t) level.

the "excess" sensitivity of labor income inequality to unanticipated changes in the monetary policy stance when local labor market conditions are already weak: The local unemployment "gap" in year t is positive (that is, $u_{i,t} - u_{i,t-2} > 0$), and the local unemployment rate exceeds the national average. It is worth noting that in specification (2), the transmission of monetary policy surprises as well as that of any other factor included in the vectors of the MSA-specific and aggregate controls are all allowed to influence income inequality nonlinearly, depending on the strength or weakness of local labor market conditions.

Figure 4 illustrates how the response of earnings inequality to an unexpected tightening of monetary policy is exacerbated in those circumstances. As shown in Panel A, when local labor market conditions are already weak, a 25 basis point unanticipated tightening of monetary policy in year t has no additional effect on labor income inequality in year $t+1$. Beyond the immediate horizon, however, weak local labor market conditions significantly amplify the policy-induced increase in earnings inequality. According to our estimates, the P90/P10 ratio of salaries and wages increases by an additional 0.5 percentage point in year $t+2$ and by another full percentage point in both years $t+3$ and $t+4$, relative to the baseline effect shown in Panel C of Figure 3; note that these effects, in addition to being economically large, are statistically different from zero at the 10 percent significance level.

Furthermore, as shown in Panel B, the excess sensitivity of the response of earnings inequality in weak local labor markets is driven entirely by the movement at the bottom of the labor income distribution: An unanticipated shift to tight policy leads to an additional economically sizable and durable decline in (real) salaries and wages accruing to the bottom decile of the distribution, while wages and salaries accruing to the top decile show no such excess sensitivity for most of the response horizon.

This evidence points to a pronounced heterogeneity in the response of income inequality to monetary policy across MSAs experiencing different labor market conditions. It also confirms that, for the most part, the distributional impact of monetary policy works through labor market outcomes of workers at the bottom of the income distribution, consistent with the view that economic downturns disproportionately hurt workers at the bottom rungs of the productivity/income ladder, and especially so when local labor markets are already weak. As a result, a shift to contractionary monetary policy has significantly more severe consequences at the bottom of the income distribution than at the top when local labor markets are already weak. These findings are consistent with previous research showing that unemployment rates, participation rates, and earnings of workers at the bottom of the income distribution are relatively more sensitive to aggregate demand and labor market cycles (see Aaronson et al., 2019).

4 Conclusion

Using publicly available IRS income data aggregated to the Zip code level, this paper examines how monetary policy affects income inequality across U.S. metropolitan statistical areas (MSAs). Our main finding indicates that contractionary monetary policy surprises increase income inequality and that most of this effect is due to the response of labor income. Specifically, we estimate that labor income inequality (the ratio of labor income at the top decile of the income distribution to labor income at the bottom decile of the distribution within each MSA) increases about 0.75 percent per year, on average, over a four-year horizon in response to an unanticipated 25 basis point tightening of monetary policy. Furthermore, our findings suggest that the bulk of this increase is due to the decline of earnings at the bottom of the labor income distribution. We also find that this effect appears to be notably more pronounced when local labor market conditions are already fragile—that is, the local unemployment gap is positive and the local unemployment rate is above the national average.

These results suggest that monetary policy has important distributional consequences via the earnings dynamics of lower-income workers and that differences in local labor market conditions are key to explaining the heterogeneous response of income inequality to monetary policy at business cycle frequencies. Our findings contribute to the theoretical and empirical debate on the redistributive channels of monetary policy and the way in which monetary policy transmits to the real economy. They also add to the debate on the welfare effects of monetary policy. In particular, by preventing episodes of high inflation—which disproportionately erode income of households at the bottom of the distribution—and economic downturns—which particularly hurt low-wage workers through unemployment spells—monetary policy can foster a more equitable society.

By design, our analysis focuses on the indirect effect—through the labor market—of monetary policy on income inequality. As a result, our estimates do not consider the general-equilibrium effects that monetary policy has on the distribution of income through other channels. For example, monetary policy directly affects asset prices and by implication, financial and business income. While data limitations prevent us from studying the full effects of monetary policy through multiple channels, the key finding of this paper is that the distributional footprint of monetary policy in the United States primarily reflects the uneven adjustment of labor income across different income groups and locations.

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Supplementary Material

— For Online Publications Only —

The supplementary material is divided into two appendices (A and B). Appendix A provides details on the sources and construction of the key variables used in the analysis, along with their summary statistics. Appendix B contains a robustness check of our main results that uses an alternative version of high-frequency monetary policy surprises.

A Variable Construction and Summary Statistics

Income inequality: As noted in the main text, we construct an annual measure of income inequality at the metropolitan statistical area (MSA) level using the Statistics of Income (SOI) from the Internal Revenue Service (IRS). The SOI data tabulate individual income based on tax returns filed with the IRS, and starting in 1998, the IRS provides selected income and tax items, including adjusted gross (pre-tax) income and salaries and wages, aggregated to the Zip code level.[12] (The data are available at https://www.irs.gov/statistics/soi-tax-stats-individual-income-tax-statistics-zip-code-data-soi.)

The construction of the data set used in our analysis involves several steps. We start with the universe of 41,021 distinct U.S. Zip codes in the SOI data. After dropping invalid Zip codes (for example, "00000," "99999," and so on) and imposing the restriction that a Zip code must have income data available over the entire 1998–2019 sample period (that is, 22 years), we are left with 24,757 Zip codes.[13] Keeping only Zip codes that can be matched to the universe of 925 core-based statistical areas (CBSAs) leaves us with a balanced panel of 18,836 Zip codes from 1998 through 2019. For each Zip code and year from 1998 through 2019, we use these data and information on the number of annual tax returns filed to compute real adjusted gross income (AGI) and real salaries and wages per tax unit (that is, per household).[14] These are the data used to compute the top 10 percent income share that is shown in Figure 1 in the main text.

To compute the P90/P10 income ratios—our measure of income inequality—we require that a CBSA has at least 10 Zip codes per year. This filter reduces the number of Zip codes to 16,488 in 517 CBSAs. The average number of Zip codes per CBSA in this sample is 35, and the range is 10 to 250. Using Zip code–level income variation within each CBSA, we compute $[\text{P90/P10}]_{i,t}$—the ratio of (real) income per household in Zip codes (in CBSA i) that are in the 90th percentile (P90) relative to the (real) income per household in Zip codes that are in the 10th percentile (P10) of their within-CBSA income distribution in year t. These are the data underlying Panels A through D of Figure 2 in the main text.

[12] Adjusted gross income corresponds to gross income less deductions, or "adjustments" to income, that a tax filer is allowed to take. Gross income comprises wages, dividends, capital gains, and business and retirement income, as well as all other forms of income (for example, tips, rents, interest). Examples of adjustments to gross income include half of the self-employment taxes that a tax filer may have paid, self-employed health insurance premiums, contributions to certain qualified retirement accounts, interest paid on student loans, education expenses, and so on.

[13] SOI Zip code–level data for adjusted gross income and salary and wages are not available for the years 1999, 2000, and 2003. To address this data gap, we interpolate the missing data using SOI county-level data for gross income and salary and wages, which are available for those three years. Specifically, we assume that in each of those years, a Zip code's income grew at the same rate as its corresponding county's income. To account for heterogeneity across Zip codes within a county, we weigh the county's growth rate by the Zip code's previous year's share of the total county income. This approach allows us to estimate the missing data, controlling for the heterogeneity in county- and Zip code–level income trends.

[14] The reported nominal income variables are deflated using the (chain-weighted) Personal Consumption Expenditure (PCE) price index (2017 = 100).

Merging this sample of 517 CBSAs with data sources on local economic conditions and sociodemographic characteristics produces a (slightly) unbalanced panel of 14,621 Zip codes in 317 CBSAs, all of which are MSAs; this is a sample used to estimate the impulse response functions in Figure 3 and Figure 4 in the main text.

Local-level controls: We control for (time-varying) heterogeneity across MSAs in several key dimensions:

- *Economic conditions*: To control for differences in local economic conditions, we use data from the U.S. Bureau of Labor Statistics Local Area Unemployment Statistics (LAUS) to compute annual MSA-level unemployment rates, and we use data from the U.S. Bureau of Economic Analysis to compute annual growth rates (log-differences) of real personal income for each MSA. To control for the significant population shifts across MSAs during our sample period, we compute annual MSA-level population growth rates (log-differences) using data from the U.S. Census Bureau. To minimize the effects of extreme observations on our estimation results, we (symmetrically) winsorize the MSA-level growth rates of real personal income and population at the 0.5th and 99.5th percentiles, and we winsorize the MSA-level unemployment rates at the 99.5th percentile.

- *Industrial structure*: We capture differences in industrial composition—and the resulting differences in cyclical sensitivity—across MSAs by using data from the Quarterly Census of Employment and Wages (QCEW). Specifically, we compute annual MSA-level shares of employment in the construction, tradable goods, and non-tradable goods sectors (see Mian and Sufi, 2014).

- *Sociodemographic characteristics*: We control for differences in race across MSAs by using data from the Quarterly Workforce Indicators (QWI) to calculate annual MSA-level shares of employment accounted for by Black and Hispanic workers. Using the QWI data, we also calculate the annual MSA-level shares of employment accounted for by workers with higher education, that is, those with at least some college education.

Aggregate controls: We control for standard macroeconomic cyclical and financial indicators:

- *State of the macroeconomy*:
  - Economic growth: computed as (Q4/Q4) log-difference of (quarterly) real GDP from year $t-1$ to year t.
    Source: Federal Reserve Economic Data.
  - Labor market: computed as an average of monthly national civilian unemployment rates in year t.
    Source: Federal Reserve Economic Data.
  - Inflation: computed as (Dec/Dec) log-difference in (monthly) core PCE price index from year $t-1$ to year t.
    Source: Federal Reserve Economic Data.

- *Financial conditions*:
  - Short-term interest rates: computed as an average of daily yields on three-month Treasury bills in year t.
    Source: Federal Reserve Economic Data.

- Long-term interest rates: computed as an average of daily yields on nominal 10-year Treasury coupon securities in year t.
  Source: Federal Reserve Economic Data.
- Sentiment in credit markets: computed as an average of monthly excess bond premium (EBP) estimates in year t.
  Source: Favara et al. (2016).
- Stock market performance: computed as a (EOP/EOP) log-difference of the daily S&P 500 stock price index from year $t-1$ to year t.
  Source: S&P Global Ratings.

Monetary policy surprises: The results reported in the main text are based on the version of high-frequency monetary policy surprises computed by Miranda-Agrippino and Ricco (2021) (MAR (2021)). We construct an annual time series of monetary policy surprises by summing up the surprises specific to Federal Open Market Committee (FOMC) meetings for each calendar year of the 1998–2019 sample period.

Table A-1 contains the selected summary statistics for all the variables used in the analysis.

TABLE A-1: Summary Statistics

Variable	Mean	SD	P5	P50	P95
A. MSA-level income inequality[a]					
P90/P10 ratio: adjusted gross income	2.07	0.93	1.32	1.86	3.30
– P90 (2017$ per household)	80,387	37,166	52,004	72,587	125,352
– P10 (2017$ per household)	39,482	6,783	29,134	38,992	51,176
P90/P10 ratio: salaries & wages	1.79	0.53	1.27	1.68	2.60
– P90 (2017$ per household)	53,028	17,707	37,050	49,583	78,190
– P10 (2017$ per household)	29,848	4,742	22,626	29,606	38,229
B. MSA-level controls[a]					
Real disposable income growth (%)	2.48	2.77	−2.16	2.51	6.97
Unemployment rate (%)	5.84	2.37	2.92	5.32	10.53
Population growth (%)	1.03	5.35	−6.67	0.49	10.75
Construction employment share	0.05	0.02	0.03	0.05	0.09
Tradable goods employment share	0.21	0.05	0.15	0.20	0.29
Non-tradable goods employment share	0.14	0.07	0.04	0.14	0.27
Black employment share	0.10	0.09	0.01	0.06	0.31
Hispanic employment share	0.10	0.13	0.01	0.05	0.38
Higher-educated employment share	0.49	0.05	0.42	0.48	0.56
C. Aggregate controls[b]					
Real GDP growth (%)	2.33	1.60	0.11	2.63	4.71
Unemployment rate (%)	5.74	1.79	3.89	5.18	9.28
Core PCE inflation (%)	1.68	0.37	1.13	1.65	2.29
3-month Treasury yield (%)	1.96	1.97	0.05	1.40	4.91
10-year Treasury yield (%)	3.62	1.31	1.84	3.46	5.65
Excess bond premium (pps.)	0.13	0.57	−0.49	−0.10	1.12
S&P 500 return (%)	5.47	18.29	−26.61	9.95	25.37
D. Monetary policy surprises[b]					
MAR (2021) (pps.)	0.01	0.16	−0.22	0.05	0.14
JK (2020) (pps.)	−0.08	0.23	−0.33	−0.04	0.14

NOTE: Entries in the table report selected summary statistics for the variables used in the analysis: MSA-level measures of income inequality (Panel A), MSA-level controls (Panel B), aggregate controls (Panel C), and monetary policy surprises (Panel D).

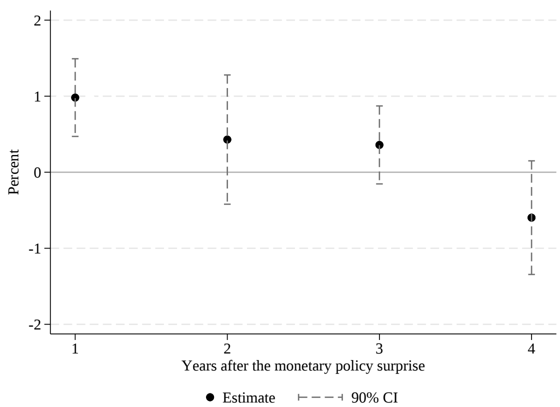
[a] Unbalanced panel of 317 MSAs from 1998 through 2019 ($\bar{T} = 21.9$ (years); Obs. = 6,855).

[b] Annual data from 1998 through 2019 (Obs. = 22).

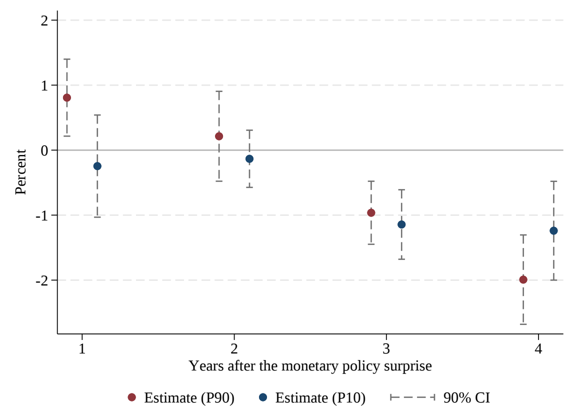
B Sensitivity Analysis

This appendix uses the Jarociński and Karadi (2020) (JK (2020)) version of monetary policy surprises to study the impact of monetary policy on income inequality. As shown in Figures B-1 and B-2 below, the results are quantitatively and qualitatively similar to those reported in Figures 3 and 4 in the main text.

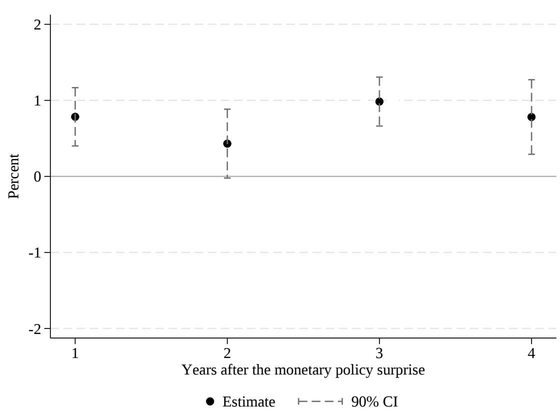
FIGURE B-1: Response of Income Inequality to a Monetary Policy Tightening



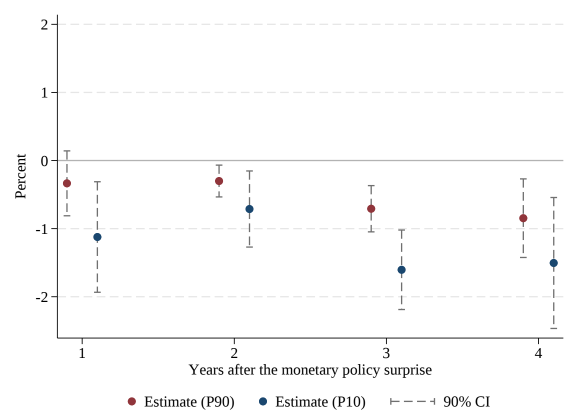
A. P90/P10 ratio: Adjusted gross income



B. P90 and P10: Adjusted gross income



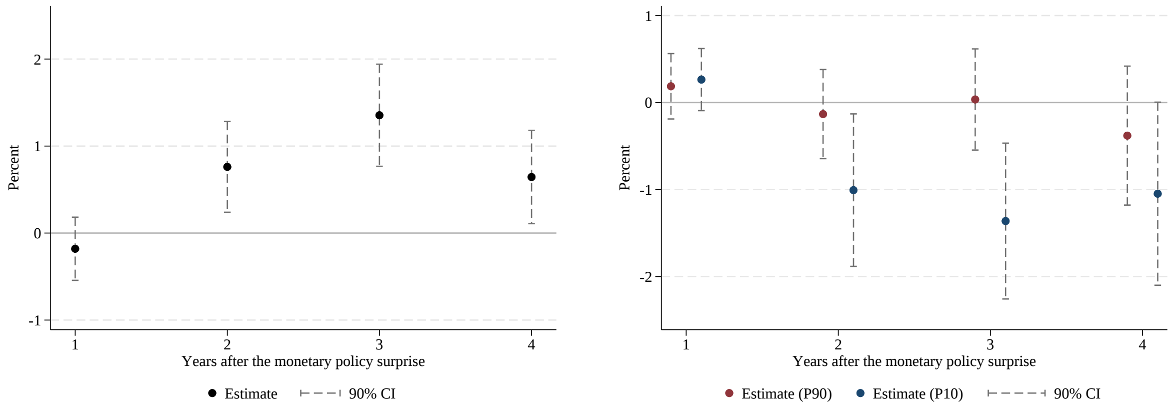
C. P90/P10 ratio: Salaries & wages



D. P90 and P10: Salaries & wages

NOTE: Sample: an unbalanced panel of 317 MSAs from 1998 through 2019 ($\bar{T}$ = 21.9 (years); Obs. = 6,855). The dependent variable in Panels A and C is $100 \times \ln[\text{P90}/\text{P10}]_{i,t+h}$; the dependent variables in Panels B and D are $100 \times \ln \text{P90}_{i,t+h}$ and $100 \times \ln \text{P10}_{i,t+h}$, where $\text{P90}_{i,t+h}$ denotes the 90th percentile and $\text{P10}_{i,t+h}$ denotes the 10th percentile of the specified (real) income variable (that is, adjusted gross income or salaries and wages, both per household) in MSA i in year $t+h$ computed from the Zip code–level data. The dots depict the estimated impact of an unexpected monetary policy tightening of 25 basis points (JK (2020) version) during year t on the specified measure of income inequality in year $t+h$, that is, $0.25 \times \hat{\beta}^{(h)}$, where $\hat{\beta}^{(h)}$ denotes the OLS estimate of coefficient $\beta^{(h)}$, $h = 1, \ldots, 4$, from specification (1) in the main text. The associated whiskers represent the 90 percent confidence intervals (CIs), computed using an asymptotic covariance matrix clustered at the MSA (i) and year (t) level.

Figure B-2: Response of Labor Income Inequality to a Monetary Policy Tightening
(In Weak Local Labor Markets)



A. P90/P10 ratio: Salaries & wages

B. P90 and P10: Salaries & wages

Note: Sample: an unbalanced panel of 317 MSAs from 1998 through 2019 ($\bar{T} = 21.9$ (years); Obs. = 6,855). The dependent variable in Panel A is $100 \times \ln[\mathrm{P90}/\mathrm{P10}]_{i,t+h}$, where $\mathrm{P90}_{i,t+h}$ denotes the 90th percentile and $\mathrm{P10}_{i,t+h}$ denotes the 10th percentile of (real) salaries and wages (per household) in MSA i in year $t+h$ computed from Zip code–level data; the dependent variables in Panels B are $100 \times \ln \mathrm{P90}_{i,t+h}$ and $100 \times \ln \mathrm{P10}_{i,t+h}$. The dots depict the estimated additional impact of an unexpected monetary policy tightening of 25 basis points (JK (2020) version) during year t on the specified measure of income inequality in year $t+h$ when local labor markets are already weak—that is, $0.25 \times \hat{\beta}_w^{(h)}$, where $\hat{\beta}_w^{(h)}$ denotes the OLS estimate of coefficient $\beta_w^{(h)}$, $h = 1, \ldots, 4$, from specification (2) in the main text. The associated whiskers represent the 90 percent confidence intervals (CIs), computed using an asymptotic covariance matrix clustered at the MSA (i) and year (t) level.