Federal Reserve Monetary Policy and Wealth Inequality: An instrumental-variable local projections approach*

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Abstract

A frequent refrain by the central bank community is that monetary policy has at worst minor and transitory effects on inequality. This paper assesses this claim using high-frequency aggregate data on real net wealth for the United States from two sources: Realtime Inequality (1976-2012) and the Federal Reserve's Distributional Financial Accounts (1989-2012). The impact of monetary policy shocks on wealth distribution is estimated using the instrumental-variable local projections (LP-IV) approach. The paper finds that expansionary monetary policy has positive and persistent effects on wealth inequality as measured by the Gini coefficient over the medium term, systematically increasing the share of wealth for the top 10% and 1% and shrinking the share for the bottom 50 and middle 40% of the distribution. The analysis also finds that the distributional effect of monetary policy has varied over time; the effects between 1976 and 1980 are modest in magnitude and transient relative to the 1990s and 2000s prior to the Great Financial Crisis. Expansionary policy increases inequality regardless of the business cycle; however, its effects are more substantial during economic expansions. The contribution of monetary policy to historical variation in wealth inequality is estimated, which suggests monetary policy accounts for as much as 15-16 percent of the increase in wealth inequality as measured by Realtime Inequality.

Keywords: Monetary policy, Monetary policy shocks, Wealth inequality, Wealth effect.

JEL codes: C36, D31, E52.

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1 Introduction

Rising inequality across advanced economies has become an increasing concern of the public and policymakers. High concentrations of income and wealth are associated with lower social mobility (Fisher et al., 2016; Yang & Zhou, 2022) and economic growth (Berg & Ostry, 2011; Ostry et al., 2014). These factors likely contribute to the political destabilization of democratic societies and the rise of populist movements in various countries (Pastor & Veronesi, 2020; Ingraham, 2020). As citizens increasingly perceive inequality, social preferences for redistributive correctives become intertwined with policy demands on the public sector (Roth & Wohlfart, 2018). Academics and policymakers, therefore, desire to understand the channels by which government policies may exacerbate or ameliorate inequality to better design policy and offset its disequalizing impact when the policy is socially desirable from the standpoint of other considerations. One such policy that has come to the fore of public debate in this respect is the contribution of monetary policy to income and wealth disparities. This paper takes up the wealth inequality issue in the context of the United States.

At this point, the contours of wealth inequality in the U.S. are well established. The top 0.1% of households have roughly doubled their share of the nation's wealth since 1980. Today, the top 10 percent have more personal wealth than the bottom 90%. By some measures, this trend has been reversing since the Great Financial Crisis (GFC). A commonly used metric of inequality is the Gini coefficient, an index that reflects differences at all parts of the distribution and is theoretically bounded on a scale of zero (representing complete equality) and one (complete inequality). According to data from the World Inequality Database, which tracks wealth on an annual basis, wealth inequality may have peaked at a Gini coefficient of 0.84 in 2013 and has been gradually declining ever since; it stands at 0.83 as of their 2021 release. By other measures, wealth inequality has only increased. Based on data from the most recent Survey of Consumer Finances (SCF) in 2019, conducted triennially by the Federal Reserve, the Gini coefficient of net wealth was 0.85, slightly down from 0.86 in 2016, but still very much up from 0.82 in 2007 (Alandangady & Forde, 2021).[1] In either case, the wealth gap remains large compared to before the neoliberal era of government policy.[2]

Among the various causes of this trend, central bank policy has drawn increasing scrutiny. Particularly since the GFC, critics have single out unconventional monetary policies such as ultra-low interest rates and Quantitative Easing or QE (i.e., large-scale purchases of debt securities) for pushing up asset prices on securities like bonds and stock market equity to real estate—and more

[1] Accessible version of Gini estimates from Figure 1 in Alandangady and Forde: https://www.federalreserve.gov/econres/notes/feds-notes/wealth-inequality-and-the-racial-wealth-gap-accessible-20211022.htm

[2] Emblematic policies include substantial tax cuts, particularly for affluent individuals and corporations, and a notable deregulation of sectors like finance, alongside a rollback of labor market protections in favor market flexibility, curtailing of social spending through welfare reform and austerity measures, privatization of public assets and services, coupled with a push towards globalization through free trade agreements like NAFTA which further weakened the bargaining power of labor.

purely speculative assets like cryptocurrencies—which exacerbate wealth inequalities between the rich and poor as the rich own a disproportionate share of those assets (Sloan & Podkul, 2021; Petrou, 2021; Leonard, 2022).

Some empirical evidence lends credence to this assessment. Huston and Spencer (2016), for example, do find that the dramatic increase of monetary aggregates such as M1, M2, and excess reserves from QE policy were positively correlated with equity prices. Some studies also find a positive correlation between QE and increasing income and wealth inequality in the U.S. (Montecino & Epstein, 2015; Juan-Francisco et al., 2018; Davtyan, 2023). Nevertheless, there is no consensus in the literature on whether conventional, let alone unconventional monetary policies, significantly affect income or wealth inequality in either direction (Colciago et al., 2019).

For their part in the debate, monetary technocrats, particularly central bankers, admit that while monetary policy has short-run effects on the distribution, "inequality is not a monetary phenomenon" (Carstens, 2021). Former Fed chair Ben Bernanke likewise attributes the increase in inequality to longer-term structural forces:

> The degree of inequality we see today is primarily the result of deep structural changes in our economy that have taken place over many years, including globalization, technological progress, demographic trends, and institutional change in the labor market and elsewhere. By comparison to the influence of these long-term factors, the effects of monetary policy on inequality are almost certainly modest and transient. (Bernanke, 2015)

While there is little controversy that structural factors have contributed to the growing wealth gap, monetary policy is nonetheless credited with the ability to influence the economy through the "wealth effect." Indeed, this was Bernanke's justification for subsequent rounds of QE in the hopes that it would stimulate the recovery after the GFC (Huston & Spencer, 2016).

Furthermore, taking advantage of monetary policy's influence on asset prices as a mechanism to stimulate economic activity is not new; it has been the modus operandi for the central bank at least since the mid-1990s under Fed chair Alan Greenspan. Cieslak and Vissing-Jorgensen (2017) analyze stock mentions within Federal Open Market Committee (FOMC) meeting minutes from 1996 to 2016. The authors find that 38 percent of stock market mentions are associated with the "wealth effect" view of stock market appreciation as a driver of consumption activity. Their investigation finds that mentions of stock market declines are "strongly predictive" of monetary easing; however, mentions of stock market highs are not predictive of contractionary policy. So, while the recent public debate has focused on unconventional monetary policy, the Fed has increasingly used its conventional policy tools in this manner to some extent for—at least—a decade before the financial crisis.

From this, a basic question arises: To what extent does the conventional monetary policy mechanism, i.e., adjustments to the interbank target rate, affect the wealth distribution? The extant empirical literature on this question is sparse, and results are mixed (Colciago et al., 2019). This paper contributes in the following ways:

(i) evaluating the distributive effects of monetary policy using two recently developed datasets that provide high-frequency aggregate wealth statistics: the Realtime Inequality database and the Fed's Distributional Financial Accounts;
(ii) using two measures of monetary policy shocks, each with a unique construction, in an instrumental variable setup estimated by local projections;
(iii) investigating the magnitude of these effects over time and at different points in the business cycle;
(iv) and estimating the historical contribution of monetary policy on wealth inequality.

Based on this analysis, conventional monetary policy has significant and persistent effects on the wealth distribution over the medium term, defined as five years. Expansionary monetary policy, on average, reduces the wealth share of the bottom 50 and middle 40 percent and increases the share for the top 10 and 1 percent. Overall, wealth inequality rises. The magnitude and transience of these effects vary over time. In the 1970s and 80s, monetary shocks dissipated after five years. After the 1980s, the shocks are three to six times as large in magnitude and remain significant. Over the business cycle, monetary policy shocks have a greater magnitude during economic expansions than contractions. It is also found that monetary policy accounts for significant variations in wealth distribution over recent U.S. history.

The rest of the paper is organized as follows: Section 2 reviews relevant literature on the intersection of monetary policy and wealth inequality. Section 3 discusses our sources of data and econometric approach. Section 4 presents the main results and robustness exercises, which dissect the Realtime data over time and the business cycle; the distributive effect is also estimated with DFA data. Section 5 estimates monetary policy's historical contribution to variation in the Gini coefficient. Section 6 will conclude with implications for policy and further research.

2 Related literature and conflicting findings

An extensive survey of the literature on central bank policy and income and wealth inequality is provided by Colciago et al. (2019). Wolff (2021) also provides an excellent broad review of the literature on measuring wealth inequality and the effects of conventional monetary policy (CMP) and unconventional monetary policy (UMP) on wealth distribution. This section will focus on more recent empirical work and how our paper fits into that literature as it specifically pertains to CMP.

A well-developed empirical literature has been preoccupied with analyzing the distributive effects of monetary policy (MP) on income. However, no consensus has emerged due to mixed results (Calciago et al., 2019). For example, both Davtyan (2017) and Coibion et al. (2017) examine the effects of CMP on measures of income inequality in the U.S. The former studies Gini index measures of disposable income and wage inequality from the OECD and Center for Economic and Policy Research (CEPR), respectively, in a structural vector autoregression (SVAR) model, which identifies monetary policy shocks in the Fed funds rate by the Choelesky decomposition method. Davtyan finds that contractionary policy reduces inequality over the medium term. Coibion et al., on the other hand, use income and labor earnings inequality measures constructed from the Consumer Expenditure Survey in a local projections approach with monetary policy shocks identified by the Romer and Romer (2004) narrative approach and finds contractionary monetary policy systematically increases multiple measures of inequality (Gini, 90-10 ratio, and standard deviation) of wage and total income as well household consumption and expenditure. Davtyan (2017) attributes the variation in findings to the choice of income measure. But the variation also likely lies in the differences in empirical methodology. There has long been skepticism that neither method appropriately identifies exogenous monetary policy shocks (Christiano et al., 1999).[3]

Discerning the precise effects of UMP is challenging to tease out as (1) no two central banks conduct such operations in quite the same way and do so in varying institutional and distributional contexts, and (2) such policies, like QE, for example, generally coincide with near-zero interest rate policy (Calciogo et al., 2019, p. 1209). Results are furthermore complicated by differing measures of the distribution as well as the econometric approach used to assess the effects of monetary policy. By comparison, the literature examining the intersection of central bank policy on wealth is still nascent. Most recent studies have mainly focused on UMP with mixed findings. The distributional effects of CMP on wealth have received less attention.

Colciago et al. (2019) classify three theoretical channels of monetary transmission to household wealth based on the existing literature. First, the *savings redistribution channel* arises from the influence policy rate changes have on the level of interest income received by savers and debt service paid by borrowers. While technically an income effect of MP, this channel plays an indirect role in the wealth accumulation process through the existing stock of debt and interest-bearing assets. As interest rates decrease, for example, debt service falls, making it easier for net debtors to save while net creditors lose interest income, and, therefore, this is likely to have an equalizing effect over time on wealth accumulation. Rising interest rates would result in the opposite effect. Second, MP has a direct wealth effect, which arises from asset price changes from bonds, equities, and real estate in response to interest rate policy changes. This channel is referred to as the *portfolio composition channel*. MP affects some asset prices more than others. Therefore, differences in the composition of household asset portfolios result in heterogeneous effects on the wealth distribution. MP may be more equalizing in economies with broad-based housing ownership, for example, as interest rate policy has a more direct relationship to housing demand. Lastly is the *unexpected inflation channel*. Unanticipated inflation affects the real value of both assets and liabilities of household balance sheets, generally increasing the net worth of net debtors and reducing the wealth of creditors.

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[3] Christiano et al. express skepticism about the ability of the Cholesky decomposition method to appropriately identify monetary policy shocks in the Fed funds rate because the method is sensitive to the ordering of the variables in the VAR and that it imposes restrictions that are not based on economic theory. The authors also discuss alternative identification strategies and evaluate their plausibility, including the Romer and Romer (2004) narrative method. They argue that the Romer and Romer method, which involves identifying monetary policy actions free from the influence of contemporaneous information about output and inflation, may not be as exogenous as presumed since the residuals may still be influenced by other information available to the Fed when making policy decisions, which is not accounted for. This could potentially bias the estimated effects of policy actions. Moreover, the authors emphasize that the narrative approach does not provide a complete picture of the systematic component of monetary policy, which may be crucial for understanding the economic effects of monetary policy.

Doepke and Schneider (2006) estimate the effects of the inflation channel using a microsimulation of a ten percent positive shock to the price level in the U.S. context between 1952 and 2004. They find that inflation reduces wealth inequality. Using a macro model and projecting forward from a 2005 survey of household portfolios, Meh et al. (2010) find a positive shock of 1 percent to the price level also reduces wealth inequality. Adam and Zhu (2016) perform a similar exercise to Doepke and Schneider for the Euro Area, projecting out from a 2010 survey, and find a 10 percent negative shock to the price level increases wealth inequality in the Euro Area on average—which implies that the positive shock would reduce wealth inequality. Only two studies attempt to estimate the impacts of CMP on wealth inequality through the portfolio composition and savings redistribution channels. Inui et al. (2017) studied expansionary CMP by the Bank of Japan, estimated by local projections. The authors find that the effects on the wealth distribution are insignificant. Hohberger et al. (2019) also studied expansionary policy in the Euro Area estimated within an open-economy dynamic-stochastic general equilibrium (DSGE) model and found that expansionary policy decreases wealth inequality. Neither Inui et al. nor Hohberger et al. appear to account for inflation or the price level.

More recent research also finds conflicting results. A working paper by Bartscher et al. (2021) analyzes the effects of expansionary monetary policy on the racial wealth and unemployment gaps. The authors take a two-step approach. First, they estimate the effect of expansionary monetary policy on various asset price indices, including equity stocks, bonds, house prices, as well as the racial unemployment gap, over a five-year horizon. The authors employ a relatively novel econometric identification strategy to estimate impulse responses to changes in monetary policy: the instrumental variable local projections (LP-IV) approach, in which monetary policy shock measures previously developed in literature are used as instrumental variables to identify exogenous variation from actual changes in the policy rate. The results are then used to simulate the effect on the wealth portfolio compositions of Black and White households from the 2019 Survey of Consumer Finances (SCF). To account for the inflation channel, they also estimate the effect of policy shocks on inflation to obtain a net effect through both the portfolio composition and inflation channel of monetary policy. Overall, they find that the effects of expansionary monetary policy on reducing the racial unemployment gap to be minor relative to the significant and persistent positive effects on financial assets and house prices, which exacerbates the racial wealth gap due to the relatively low share of ownership of these assets among Black households.

In contrast, Wolff (2021) estimates the historical contribution of Federal Reserve monetary policy on real net wealth using data from the SCF between 1983 and 2019. He defines net wealth as marketable assets (i.e., excluding non-financial assets like consumer durables) minus debts. To account for inflation, Wolff incorporates an inflation adjustment using the CPI-U-RS series from the Bureau of Labor Statistics. His methodology, however, is unique in that he feeds through changes in longer-term bond yields for various assets in standard present value models, with certain assumptions about modified duration, i.e., the sensitivity of asset price to changes in the interest rates, to estimate the changes in the approximate value of those assets in response to interest rate changes. Then, decomposes the average change in real net worth due to average asset price appreciation (depreciation). In contrast to other studies, Wolff finds expansionary monetary policy has, on net, reduced wealth inequality, as measured by mean net financial wealth, decreasing the Gini coefficient by 0.045 over the entire period.

> The reason is that Fed policy has boosted home prices a lot more in percentage terms than stocks, business, and bond values. It has also had a pronounced effect on reducing the real value of debt despite the moderate level of inflation. Both of these results benefit the middle class a lot more than the rich (Wolff, 2021, p. 39).

Wolff also analyzes the racial wealth gap and finds from his results that, counter to Bartscher et al. (2021), expansionary policy also reduced the racial wealth gap for the same reason. Moreover, since homeownership tends to be the most significant component of average asset portfolios for Black and White households, Black households benefit more from that appreciation.

Wolff's results are interesting and provocative. However, a couple of concerns arise from his methodology. First, Wolff uses changes in the yield on the longer-term treasuries as a proxy for the stance of monetary policy to estimate the changes in (average) asset prices. The problem with this approach is that while adjustments in the short-term policy rate exert significant influence over the path of long-term yields, such as the 10-year treasury note and 30-year treasury bond, average co-movements in those yields are not as tightly correlated and do not purely reflect the stance of monetary policy (Jordà, 2005a; Martin, 2017). Therefore, his estimates are likely to be subject to significant measurement error in estimating the 'true' effects of monetary policy on asset prices that may be related to other factors that affect bond market yields. A related concern is endogeneity. Wolff does not account for simultaneity bias in his method between asset prices and the central banks' reaction to volatility in those variables; this is also likely to produce bias in his results.

Medlin and Epstein (2022) investigate how inflation and monetary policy influence wealth in the U.S. context between 1970 and 2012. Drawing inspiration from Bartscher et al. (2021), the authors apply a double instrumental variable approach estimated by local projections to account for the effects of inflation and contractionary monetary policy on real net worth for the top 1, top 10, and bottom 50 percent of the wealth holders. Their findings suggest that an inflation shock significantly diminishes the real value of wealth for the top 1%. Fed intervention to reduce inflation with contractionary policy disproportionately benefits the top 1%. The authors simulate the inflation environment of 2021-2022 and the Fed's sharp tightening cycle in response. Their LP-IV estimates indicate that the top 1 percent's wealth would contract in real terms by about 30 percent under a persistent inflation shock of 6 percent, holding the policy rate constant. However, when the Fed intervenes with a 375 basis point (or 3.75 percentage points) increase in the federal funds rate, 14 percent in real net wealth terms is preserved for the ultra-wealthy relative to the counterfactual. In this respect, the authors conclude, the Fed's anti-inflation policy serves as a kind of wealth protection insurance against accelerating inflation for the top 1%, often at the expense of lower growth and higher unemployment for workers.

The approach of the current paper also draws heavily on Bartscher et al. with the LP-IV approach. Two MP shock measures were used as instruments to obtain a range of estimates. However, the distributive effects of monetary policy shocks are estimated with wealth distribution measures—the share and the Gini index of net wealth—as the dependent variable, complementary to Coibion et al. (2017), Devtyan (2017), Furceri et al. (2017) and El Herradi et al. (2020) who use various income measures.[4] The wealth distributional statistics are defined in real net terms (i.e., assets minus liabilities adjusted for inflation). As such, the approach captures wealth distributional dynamics through adjustments in household portfolios and the savings redistribution channel over time, which affects net wealth accumulation and also accounts for changes in the price level.

3 Applying the LP-IV approach to new wealth data

3.1 Data

The analysis of this paper focuses on the change in the real net wealth distribution as the outcome of interest. The difficulty of empirical analysis of wealth distribution is often the scarcity and consistency of wealth data. Given the interest in the topic by policymakers and the public since the GFC, researchers have made significant progress in producing more timely and consistent measures of wealth and income. Two new sources of wealth data have recently become available: Realtime Inequality and the Federal Reserve's Distributional Financial Accounts (DFAs).

The observation period is constrained to the post-war era in the United States between 1976 and 2012. We can only go back as far as 1976 due to the limitation of the available high-frequency wealth time series and 2012 due to the limitation of monetary policy shock measures used as instrumental variables in our econometric approach. All data obtained are at a quarterly frequency. This section describes the sources and characteristics of the data used in the analysis.

3.1.1 Net wealth distributional statistics: Realtime Inequality

Data on real net wealth shares for various groups identified by percentile of the distribution are obtained from Realtime Inequality. This database provides a high-frequency time series of the distribution of income and wealth for the United States constructed from the distributional national accounts methodology (DNA) (Blanchet, Saez, & Zucman, 2022). The basic idea of the DNA approach is to harmonize the system of national accounts with micro survey data, including the Survey of Consumer Finances (SCF) and IRS tax data, to produce consistent and timely statistics to track the evolution of income and wealth distribution. To the author's knowledge, this is the highest frequency data currently available. High-frequency data is particularly coveted for time series analysis of this kind to increase the available number of observations that can be used to estimate relationships at more granular intervals (Colciago et al., 2019, p. 1209). More granularity of time intervals also permits researchers to identify short-run versus longer-run effects in the case of certain estimation methods (Davtyan, 2017, p. 109).

The period of available observations is from 1976 through 2019. **Fig. 1** (a) plots these wealth shares directly from the data for five wealth groups. The distributional ranking is defined by the 1st percentile (P1) being the poorest group and the 99th percentile (P99) being the richest. And it is possible to further disaggregate P99 as Realtime conveniently does. I use the following

[4] Coibion et al. study the U.S. case, whereas the other two references conduct panel studies of multiple countries.

percentile groups: the bottom 50 percent (P50), the middle 40 percent (P50-P90), and the top 10 minus the top 1% (P90-P99), from the top 1% to the top 0.1% (P99-P99.1) and, finally, the top 0.1% (P99.1) of the distribution. The top 1% are split into two groups to define the distribution for more granularity at the top. I then use the information on net wealth and population share for each group to construct the Gini coefficient (see Appendix A.1 for methodology). **Fig. 1** (b) plots the resulting Gini coefficient, with the coefficient bounded between 0 and 1, with 0 being the most equal and 1 being the most unequal.

While well documented, the significant shift in total wealth illustrated in **Fig. 1** (a) remains striking. **Table 1** presents this more clearly by comparing 1980 and 2012. In 1980, the top 0.1% (P99.1) and the rest of the top 1% owned about 7.6 percent and 15.4 percent of all wealth, respectively. By the end of 2012, the top 0.1% had more than doubled their share to about 19 percent, while the rest of the top 1% gained only about 2.1 percentage points. By accounting identity, the share for the rest of the distribution naturally declined by the same amount. Over this same period, as illustrated in **Fig. 1** (b), we see a precipitous rise in the Gini coefficient from 0.73 to 0.81 during the same period.

3.1.2 Alternative financial wealth data: the Distributional Financial Accounts

It is worth emphasizing that measuring the distribution of income and wealth is a non-trivial task, of which statisticians and economists continue to develop and debate appropriate methods on both fronts (e.g., on income, see Rose (2018a); on wealth, see Wolff & Marley (1989) and Kuhn et al. (2019)). Different methodologies have implications for the computed income and wealth levels and their dynamics over time that could bias results (Rose, 2018b; Wolff, 2021). Therefore, it is important not to rely on any one measure where possible.

Fortunately, we have an alternative data source: the Federal Reserve's Distributional Financial Accounts (DFAs). The construction method is similar in many respects to the DNA approach; however, it is based on the Fed's Financial Accounts instead of the National Accounts. The DFAs use the distributional information provided in the SCF to allocate the Financial Accounts' aggregate measures of assets and liabilities to different sub-populations based on wealth, income, and other demographic characteristics (Batty et al., 2019). However, since the SCF is a triennial survey, the data must be interpolated to derive a consistent quarterly time series between surveys. The data is available from the third quarter of 1989 through 2022. Real values are computed using the GDP implicit price deflator to ensure compatibility with the Realtime data,

Fig. 2 presents the wealth share statistics constructed from DFA data for comparison. As before, panel (a) displays net wealth shares, and panel (b) the Gini coefficient. Panel (b) includes both the DFA and Realtime series. The first thing to notice is that Realtime starts from a higher level, indicating inequality is worse than measured by the DFA Gini coefficient. Nevertheless, the DFA Gini exhibits a similar long-term trend upward since the 1990s, but with some variation in dynamics during specific periods. The most evident being between the mid-1990s and early 2000s, wealth inequality appeared to plateau before declining over the early 2000s Dot-com stock market bubble collapse. Inequality continued to decline until the GFC. In contrast, the Realtime Gini indicates a steadier upward trend through the 1990s until the Dot-com bubble burst and then a plateauing until the GFC. The rise in inequality is also steeper after the GFC than the DFA Gini.

3.1.4 Monetary policy shocks as instruments

The next data component is monetary policy shock measures. Macroeconomic conditions influence both the level of wealth and monetary policy decisions. To address this endogeneity bias, researchers often construct exogenous monetary shocks to help identify the causal effects of unanticipated changes in monetary policy on an outcome variable of interest.

The most widely used of these shock measures in the literature is by Romer and Romer (2004). Romer and Romer attempt to address the endogeneity problem by regressing Fed officials' intended policy rate changes, identified from primary documents such as Federal Open Market Committee (FOMC) meeting transcripts and FOMC member public speeches, the so-called "narrative" approach, on the Fed's internal projections of inflation, GDP, and unemployment. The next step is to extract the residuals from those regressions. These residuals, or "innovations" in econometric parlance, represent the "exogenous" component of policy rate changes.

An alternative construction is provided by Gertler and Karadi (2015), who construct monetary policy shocks using high-frequency data to identify surprise changes in Fed Funds futures contracts around 30-minute policy announcement windows by the FOMC. The basic idea of their approach is to identify periods in which there is significant variation in interest rates that macroeconomic conditions or financial markets cannot explain. To do this, they estimate a set of vector autoregression (VAR) models that capture the joint dynamics of interest rates, credit spreads, and other macroeconomic variables. The residuals are likewise extracted from these regressions to serve as policy innovations.

Using these monetary shock measures directly in structural VAR or local projection methods is standard practice. The issue with this approach is that these various shock measures may contain measurement error, leading to biased results when treated as the 'true' shock in standard specifications (Stock & Watson, 2018). However, to the extent such measures are exogenous by construction, meaning they are uncorrelated with the other shocks hitting the economy, they can still be helpful instruments in identifying the exogenous variation in the actual policy rate (p. 923). Therefore, using these measures as proxies for structural shocks in an instrumental variable setup produces an (arguably more) credible quasi-experimental design to identify the cause-and-effect relationship relative to standard LP or structural VAR approaches.

Following Bartscher et al. (2021), both monetary policy shock measures described above are used in the econometric analysis in a two-stage instrument variable setup estimated by local projections. Further details on this methodology are discussed in section 3.2. The original shock series Romer and Romer (RR) developed extended from 1969-Q1 through 1996-Q4. Updated shocks through 2012-Q4 are obtained from Breitenlechner (2018). Gertler-Karadi (GK) shocks' data extends from 1979-Q3 to 2012-Q2 (Gertler & Karadi, 2015). **Fig. 3** plots the two measures for comparison.

It should be noted that Breitenlechner innovated on the original RR shock measure. To account for policy at the zero lower bound after 2008, Breitenlechner approximates the policy rate with the "shadow short rate" recommended by Krippner (2015). The shadow rate is an estimated short-term rate based on longer-maturity interest rates. In terms of results, RR and GK shock measures generally produced similar findings pre-2008, before the advent of unconventional policies like Quantitative Easing and longer-term forward guidance. When the post-2008 period is included, the two measures produce only slightly more variation of responses in distributional wealth measures.

3.1.5 Macroeconomic variables

Several macro variables are also used as controls, including the U.S. unemployment rate, real GDP growth, the inflation rate, and the ten-year treasury yields. These variables were obtained through the Federal Reserve Economic Database (FRED). How these control variables fit into our methodology is further elaborated on in section 3.2, which describes the econometric approach. **Table B1** in Appendix B provides a variable description and the data sources. **Table B2** in Appendix B provides descriptive statistics of all the variables used in the analysis, including each percentile group share for Realtime and DFA wealth measures.

3.2 Econometric approach: Instrumental variable local projections

The local projection (LP) method developed by Jordà (2005b) is an increasingly popular alternative to system-based VAR methods to compute impulse response functions (IRFs), which estimate the dynamic relationship between variables over time. LP estimates impulse responses directly by conducting separate regressions for each horizon of interest, which inherently provides a model structure that doesn't require a comprehensive understanding of the underlying data-generating process.

The LP method offers some advantages. VAR models can be more complex and require more decisions regarding specification (e.g., lag length, identification restrictions) and data to be stationary, which may involve variable transformation by difference. LP, on the other hand, is more straightforward and more robust to model misspecification and non-stationary time series (Montiel Olea & Plagborg-Møller, 2021). The trade-off is that VAR, in some cases, may be more efficient (i.e., have smaller standard errors) as it utilizes more information, but only when the model is correctly specified. However, when the true model is unknown or as complex as the macro distributional determination of wealth, LP can provide more consistent estimates without imposing strong assumptions.

The LP method has been used in multiple studies of monetary policy and income inequality, e.g., Coibion et al. (2017), Inui et al. (2017), Furceri et al. (2018), Aye et al. (2019), and wealth inequality by Inui et al. (2017). It is common in all these studies to use monetary policy shock measures directly as a regressor. Bartscher et al. (2021) are the exception as they use the local projections instrumental variable (LP-IV) approach formalized in Stock and Watson (2018). We apply this same approach to better address the endogeneity concerns raised in section 3.1.4, including the measurement error inherent in such monetary policy shock measures.

Following Bartscher et al. (2021), actual changes in the Federal funds rate (FFR), the Federal Reserve's primary policy tool, are instrumented using RR and GK monetary shock measures in a two-stage instrumental variable setup estimated by general methods of moments (GMM), as per Jordà (2023), to better accommodate IV estimation.

The first stage of the specification takes the following form:

$$\Delta r_t = b\Delta z_t + \delta x_t + \varepsilon_t \tag{1}$$

Where Δr_t denotes quarterly changes in the FFR at time *t* and Δz_t is the change in the monetary policy shock measure—from Romer-Romer or Gertler-Karadi—that proxy for structural policy shocks to help identify the exogenous variation in the policy rate. The term x_t denotes a vector of contemporaneous controls of macro variables, including the unemployment rate, inflation rate, growth rate, and 10-year treasury yield, to ensure both the exogeneity condition is satisfied and reduce the sampling variance of the estimator by reducing the variance of the error term (Stock & Watson, 2018, p. 925).

The resulting first-stage estimates of changes in the FFR, $\widehat{\Delta r_t}$, are then carried over into the second stage, which estimates IRFs directly from local projections. Specifically, for each future period h, equation (2) is estimated:

$$y_{t+h} - y_t = \alpha_h + \beta_h \widehat{\Delta r_t} + \gamma_h X_t + v_{t+h}; \qquad \text{for } h = 0, 1, \dots, H. \tag{2}$$

Where y_t denotes a vector of dependent variables of interest, including the shares of net wealth for defined percentile groups discussed in section 3.1.1 and the Gini coefficient. The term X_t denotes a vector of lag control variables, including four lags of the outcome and explanatory variable and the same macro variables used in the first stage.

An advantage of the LP approach is that it is easy to scale the size of impulses to explanatory variables. While typical IRF analysis would estimate a positive one standard deviation shock, as is often the case in VAR approaches, the LP method normalizes coefficient estimates to the unit of the impulse variable. As our analysis is interested in the effects of expansionary monetary policy, we scale our policy rate impulses to a 100 basis points (or one percentage point) drop in the FFR, as is commonly done in the literature.

4 The distributional effects of monetary policy on wealth

In this section, I discuss the results of the LP-IV impulse response estimates in two parts: First, the estimated responses of wealth shares and the Gini coefficient to the expansionary monetary policy of 100 basis points (bp) decline in the policy rate, the Federal Funds Rate, using data from the Realtime Inequality as the baseline result. Then, various robustness checks are performed by looking at different periods of U.S. history and how effects may differ at different points in the business cycle. Second, the same LP-IV approach is applied to wealth share data from the DFA.

4.1 Baseline results

The main results are presented in **Fig. 4** and **Table 2**. Beginning with **Fig. 4**, panels (a) through (e) plot the estimated cumulative impulse responses of real net wealth shares, in levels, by percentile group to a 100 bp surprise expansionary shock to the policy rate. The last panel, (f), is the estimated response of the Gini coefficient estimated by LP-IV directly. Two estimates are provided in the figures, those estimated from Romer-Romer (RR) monetary policy shock measures (solid red line) over 1976Q1-2012Q4, and Gertler-Karadi (GK) shock measures (dashed blue line) over 1979Q3-2012Q2. Confidence intervals are computed with Newey-West standards for each shock at the 10 percent level. **Table 2** presents the same cumulative point estimates in **Fig. 4** truncated by horizon year, corresponding to the fourth quarter cumulative change in that year since the shock. The top panel of the table provides estimates from RR shocks; in the lower panel, GK shocks.

The results of each panel are as follows. Expansionary monetary policy, on average, is correlated with a decline in the share of the bottom 50 percent of the distribution by about 0.002 or 0.2 percentage points (pp) after 20 quarters (or five years) and about 0.1 pp under GK shocks. For the middle 40 percent, by about 0.6 (GK) to 0.7 (RR) pp. The top 10% minus the top 1% decreased by 0.2 pp. On average, the top 1% gain. Between the top 1% and 0.1%, the share level increases by about 0.2 pp, and between 0.1 (RR) and 0.2 (GK) pp for the top 0.1%. The Gini coefficient in panel (f) indicates wealth inequality rises between 0.004 and 0.005. According to **Table 2**, all effects are statistically significant at the 1 percent level after five years except for the top 0.1% under RR shocks.

Note that while the cumulative effect on the Gini coefficient may appear small in magnitude, about half a basis point increase or 0.005. But that is in the context of an increase in the actual Gini coefficient between 1980 and 2012 of about 0.08. That would imply that a modest expansionary shock of 100 basis points can account for 6 percent of the total increase in overall wealth inequality. That is non-trivial, considering that adjustments in the policy rate follow multiple adjustments of several hundred basis points. Furthermore, the effect is sustained, meaning that the result indicates that monetary policy has a lasting effect over the medium term. Of course, this assumes a one-time policy rate change, holding all else constant.

These results are also quite robust, including to different lag choices—I run separate estimates with two- and six-year lags, instead of four as in this result—and alternative combinations of second-stage lag control variables, e.g., removing inflation or the treasury note yield, or including asset price variables such as the S&P 500 and the Case-Shiller national home price index. The results do not qualitatively change, though the magnitude of the effects vary.

To ensure the changes in wealth shares estimates are consistent with the results of the Gini coefficient in panel (f) of **Fig. 4**, we do a cross-check analysis by constructing the Gini coefficient from the response estimates of wealth shares in panels (a) through (e) to confirm the Gini coefficient is moving in the same direction and by approximately the same magnitude. See Appendix A.2 for a walk-through of the methodology. The results of this exercise are provided in **Fig. 5**, which indicates the Gini coefficient does rise by a similar magnitude, between 0.004 to 0.005 on the Gini index, and indicates a sustained and statistically significant effect over the medium term. Therefore, the effects of the monetary policy do not appear to be transitory, as suggested by Bernanke (2015), at least as colloquially understood. Instead, the effects will persist until the central bank alters policy to a contractionary stance.

4.2 Robustness checks

Some robustness checks have already been included in the main results presented. For one, we do not rely on a single MP shock measure as an instrument; we use two to obtain a range of estimates. Second, in addition to estimating the response of the pre-constructed Gini coefficient directly, I also doublecheck the result is consistent with the response of wealth shares themselves (estimated separately) using a post-constructed Gini coefficient as in **Fig. 5**.

However, while our main results suggest that, on average, expansionary monetary policy does increase wealth inequality, the estimated effects may vary over different periods of U.S. history or at different points during the business cycle. Furthermore, alternative measures of wealth constructed from alternative methodological approaches are important to confirm that results are not a statistical artifact of the Realtime DNA methodology. Therefore, I conduct robustness exercises that address each of these considerations.

4.2.1 Effects of expansionary monetary policy during different periods

An advantage of high-frequency data, such as quarterly time series, is that more observations are available to estimate relationships between variables with more granularity and degrees of freedom. As such, delineating between historical periods of study carries less risk of overfitting. In this instance, we split the observations into two main periods of interest: (1) the two decades before the Greenspan era Fed and (2) during Greenspan's tenure in which asset prices, particularly the stock market, were an implicit target of monetary policy per Cieslak & Vissing-Jorgensen (2017). How do these two eras compare?

Fig. 6 plots the wealth share responses to 100 bp expansionary monetary policy estimated between 1976Q1 and 1980Q4. For the sake of space, the figure only reports responses for the bottom 50 (P50) and top 10 percent of the distribution, with the latter disaggregated into three groups (P90-99, P99-99.1, and P99.1), the same as in **Fig. 4**. Only instrumental RR shocks are presented because GK shocks are unavailable for the 1970s.

The results indicate that the effects of expansionary policy were more moderate and transitory over the medium term during this period. The bottom 50% wealth share declines by less than 0.001 while the top 10% gain as a group between the top 10% and top 1% (P90-99) and the group between the top 1 and 0.1 percent as shown in panels (b) and (c), with the effect in panel (c) remaining significant and persistent relative to other groups. Overall wealth inequality, as measured by the Gini coefficient in panels (e) and (f), indicates a modest rise between 0.0015 and 0.002 after ten quarters, or two and half years, but eventually subsides after five years to a negligible change.

Fig. 7 reports response estimates between 1990Q1 and 2006Q4 using RR and GK policy shock instruments. This era coincides with Alan Greenspan's tenure as Fed chair. Interestingly, the results indicate a greater magnitude of changes in relative wealth shares and the Gini coefficient compared to the baseline results in **Fig. 4**. On average, net wealth shares for the bottom 50 percent fall by 0.015 after five years while rising for the top 1% overall and with much of the accrual going to the top 0.1%. Per panel (e) of **Fig. 7**, the Gini coefficient rises significantly by 0.03 points on the Gini index. However, the cross-check of the Gini in panel (f) suggests the effect may be overstated, increasing to around only 0.015. Recall the cross-check is the estimated change reconstructed from the changes in individually estimated effects across the distribution. Therefore, this implies a greater statistical discrepancy in the response of wealth shares during this period relative to direct estimates. In either case, the effect registers more than double the Gini increase of 0.005 found in **Fig. 4** baseline results.

4.2.2 Accounting for the business cycle

Fed officials set monetary policy in response to the business cycle, increasing the policy rate when economic expansions are perceived to carry the risk of inflation and cutting the rate at signs of a recession—in many cases, the recession is the result of Fed tightening itself. Previous empirical evidence suggests there are asymmetric effects of monetary policy on income inequality (Furceri et al., 2017). I test whether this is the case for wealth inequality as well.

Fig. 8 and **Fig. 9** present our results of expansionary MP shock on the wealth shares and the Gini coefficient during economic recessions and expansions, respectively. To obtain the estimates of both figures, we modify the specification of lag control variables in equation (2), substituting the vector of macro variables of the unemployment rate, output growth, inflation, and 10-year T-note yield with four lags of the NBER dummy indicator of recessions, which takes the value of 1 when the economy is in an official recession. The macro variables must be substituted because they are also coincident indicators used by the NBER for determining official recession periods and, thus, are highly collinear with the recession dummy. In **Fig. 8**, to determine the effects during recessions, we constrain observations between 1980Q1 and 2012Q4 to those in which the recession indicator is equal to 1 in the present quarter or the past two quarters, i.e., up to 6 months after a recession. This specification is a reasonable (and even conservative) constraint formulation given that recessions have long-lasting effects—well beyond six months—likely to influence household wealth dynamics. For **Fig. 9**, we constrain the indicator to only observations in which the dummy equals zero.

The results shown in **Fig. 8** and **Fig. 9** suggest that expansionary shocks have larger effects on wealth inequality during economic expansions than contractions. The patterns are similar in both cases, but the magnitudes vary in terms of the change in the distribution. The bottom 50% (panel (a)) share declines, as does the next 9% (panel (b)), while the top 1% generally gain (panels (c) and (d)). The Gini coefficient (panel (e)) still rises by between 0.004 to 0.005, which is close to the outcome effect in our baseline results in **Fig. 4**. This suggests economic recessions have larger countervailing effects that push in the other directions and are more influential on wealth dynamics, particularly for upper echelon—exemplified by the volatile response in the top 0.1% share. **Fig. 9**, conversely, indicates expansionary policy shocks are more potent on the wealth distribution. The Gini coefficient increases by around 0.02. The cross-check Gini in panel (f) of

Fig. 9 also indicates approximately the same magnitude by RR shock estimates but a little less by GK shock estimates.

4.2.3 DFA wealth data

Variations in the methodology used to construct the wealth distribution result in variation in levels between measures and, therefore, in the dynamics in one period versus another. These dynamics have implications for the statistical relationships we are attempting to identify. Therefore, it is worth comparing results using alternative wealth measures to inform scholarship on whether the relational direction and or magnitudes of correlation are possibly a statistical artifact of the methodological idiosyncrasies between measures.

To this end, we estimate DFA wealth share impulse responses using as the dependent variable. The results are reported in **Fig. 10** for four mutually exclusive percentile groups: the bottom 50% (P50), the middle 40% (P50-90), the next 9% (P90-99), i.e., the top 10% minus the top 1%, and the top 1% (P99). As before, we also estimate the impulse response of the Gini coefficient in panel (e), and we conduct a cross-check analysis to ensure that the responses of wealth shares are consistent with the direction and magnitude of the response of the Gini coefficient in panel (e), which is reported in panel (f). The observation period is also shorter, extending from 1989-Q3 to 2012-Q4.

The results from **Fig. 10** also indicate expansionary monetary policy has a statistically significant and sustained effect on the wealth distribution. The bottom 50 initially experience a larger shock, dissipating after ten quarters. The middle 40 experience a more substantial fall in their share of wealth. The next 9% and top 1% increase. Panel (e) indicates the overall distribution becomes more unequal; the Gini index rises 0.01 gradually over ten quarters and remains positive and statistically significant after five years. The Gini cross-check in panel (f) agrees, though it settles slightly lower. Overall, the results confirm the same relationship to expansionary monetary policy as in **Fig. 4** despite the data being from an alternative construction of the wealth distribution by the Federal Reserve.

5 Estimating the historical contribution of monetary policy

In this section, the contribution of monetary policy is estimated on historical changes in net wealth distribution as measured by Realtime inequality and DFA data.

The focus of the previous sections has been on assessing whether expansionary monetary policy affects the wealth distribution. Our results so far indicate it does. The effects are both statistically significant and persistent over the medium term. However, the impulse response exercise assumes all else is constant over the estimated horizon. This assumption is, of course, unrealistic. The economy is a dynamic system with constantly changing variables, both in terms of the policy rate and other macro variables in response, all of which have heterogeneous effects on agents' behavior in the economy. Therefore, how can we quantify the contribution of MP shocks to historical changes in the wealth distribution while accounting for these other factors impacting the distribution?

Coibion et al. (2017) present a procedure that attempts to do this. In Figure 5 of their article (p. 82), the authors attempt to quantify the historical contribution of MP shocks to variation in income, earnings, expenditure, and consumption inequality. The procedure is quite straightforward.

Actual changes of the dependent variable, Δy_t, are regressed on the right-hand side of equation (2) to fit a prediction model of parameter estimates.[5] This model is then used to forecast the change in the dependent variable, feeding through the actual values of the predictors. The model is then estimated again with the explanatory variable of interest, the federal funds rate, set to zero. Estimates from the second model are then subtracted from the first to extract the predicted changes in the dependent variable related to monetary policy.

The results of this exercise are shown in **Fig. 11** for Realtime Inequality wealth data. Both actual and predicted variables are presented as a moving average over the previous and subsequent quarter values to smooth out high-frequency volatility; incidentally, this also smooths out much of the variance between RR and GK estimates.

Fig. 11 indicates that, at times, MP shocks account for a substantial portion of the co-movements in the wealth distribution by as much as half or more in some periods. In some instances, MP shocks also appear to be pushing in the opposite direction as the Fed alters the stance of monetary policy between expansion and contraction, sometimes exacerbating inequality while at others reducing it.

The actual and predicted changes in the Gini coefficient in **Fig. 11** are delineated in **Table 3** by decade until the GFC for a cursory comparison. The results in Table 3 indicate that monetary policy increased inequality during the 1980s and 1990s and had a relatively neutral effect during the 2000s leading up to the GFC, with wealth inequality rising in the early 2000s before declining. During the GFC and subsequent recession, which officially started in 2008 and ended in the second quarter of 2009, inequality fell before rising again, coinciding with the first round of QE between November 2008 and March 2010. Per the S&P 500 index, the stock market recovery was also well underway by the end period. The U.S. housing market was still tumbling, only reaching its trough in 2011 before recovering, according to the S&P Case-Shiller Home Price Index. Subsequent rounds of QE also appear to have had little effect on inequality by this estimate. However, this paper primarily focuses on conventional policy effects through the Federal Funds Rate, not on large-scale securities purchases.

[5] It should be noted that this is a substantively different procedure than estimation by local projections. In Coibion et al. (2017), it is implied their version of this exercise uses estimates obtained by local projections from equation (2) of their paper. However, a review of their replication code indicates this is not the case. They simply estimate a prediction model by regressing 20 lags of Romer-Romer MP shocks, the same as their LP forecast horizon, on changes in their dependent variables by OLS. The difference in LP procedure lies in the construction of cumulative forward and backward changes in the dependent variable for each horizon of interest, which is then regressed on the explanatory variable by OLS. In our case, we stick with the two-step GMM estimator, maintaining the first-step instrumental variable procedure, but we are likewise just estimating a prediction model on first order changes in the dependent variable.

Clearly, monetary policy does not account for *all* the variation in the wealth distribution since 1980. However, these results suggest monetary policy can and does account for some of it and, in certain periods, a substantive component.

Lastly, I conducted the same analysis using the DFA wealth data as a robustness check. The results are presented in Appendix B; see **Fig. B1** and **Table B3**. Interestingly, these results conflict with those obtained from the Realtime data. In this instance, there is a significantly higher correlation between predicted changes in the Gini coefficient and MP. **Table B2** shows that while the Gini index rose by 0.075 between 1990 and 2012, MP acted in a counterbalancing manner, i.e., MP was equalizing. According to the estimates in Table B3, without the influence of the Fed's monetary policy, inequality would have been 38.7 percent worse. This result starkly contrasts the findings from the Realtime data presented in **Table 3**. Given that the same methodology was applied, the discrepancy in results can be attributed to differing methodological constructions of wealth shares between Realtime and the DFA—this highlights the need for greater study using multiple measures and, perhaps, explains differences in results in the literature.

6 Conclusion

The role of monetary policy in exacerbating income and wealth inequality is still a hotly contested question. The public debate and empirical literature are focused mostly on unconventional monetary policy. This paper studies the distributional effects of conventional monetary policy on wealth. The findings add to the varied results in the literature so far.

Estimating over the 1976-2012 period, I find that, on average, expansionary monetary policy shocks of 100 basis points (one percentage point) increase the share of the wealth of the top 10% and lower it for the bottom 50% and middle 40% of the distribution as measured by Realtime Inequality wealth statistical measures. We also estimate the effect on the Gini index of net wealth, the most well-known inequality metric, and find that the Gini coefficient increases by 0.005 points, or half a basis point, on the Gini scale bounded between 0 and 1. These effects are statistically significant and persistent over the medium term, defined as five years.

As an additional robustness exercise, I also estimate the effect using data from the Federal Reserve's Distributional Financial Accounts. Over the 1989-2012 period, I found a significantly positive and persistent effect between conventional expansionary policy and wealth inequality over the medium term. Specifically, a 100 basis point expansionary monetary policy shock is correlated with an increase in the Gini coefficient of around 0.01. These findings add to the mix of results by Inui et al. (2017) (no significance effect) as well as Hohberger et al. (2019) and Wolff (2021) (an equalizing effect).

Analyzing from the mid-1970s through the 1980s, we also find that the effects of expansionary conventional monetary policy on the wealth distribution were weaker and transient, as argued by former Fed chair Ben Bernanke. However, the effects of expansionary policy appear to have increased in importance over the 1990s and early 2000s as we estimate the effect size on overall wealth inequality to be larger and persistent. During Greenspan's tenure as Fed chair, expansionary monetary policy increased the Gini coefficient, on average, by around 0.015. This period coincides with more frequent discussions by the FOMC of the “wealth effect” channel of monetary policy. We also find that the magnitude of the effect is greater during economic expansions versus contractions.

Since the 1980s, monetary policy appears to have grown in importance. That is likely because of structural policy changes to the tax code; as the capital gains tax has become more regressive, it allows rich households to lock in asset price appreciation. Since benefits of expansionary monetary policy disproportionately accrue to those already holding wealth (e.g., through asset price inflation), it can lead to further concentration of wealth. This concentration can give these households more significant capital to reinvest and generate even more wealth, exacerbating wealth inequality. Or utilize the gains to gather more significant influence politically, further entrenching their ability to shape policy in their favor.

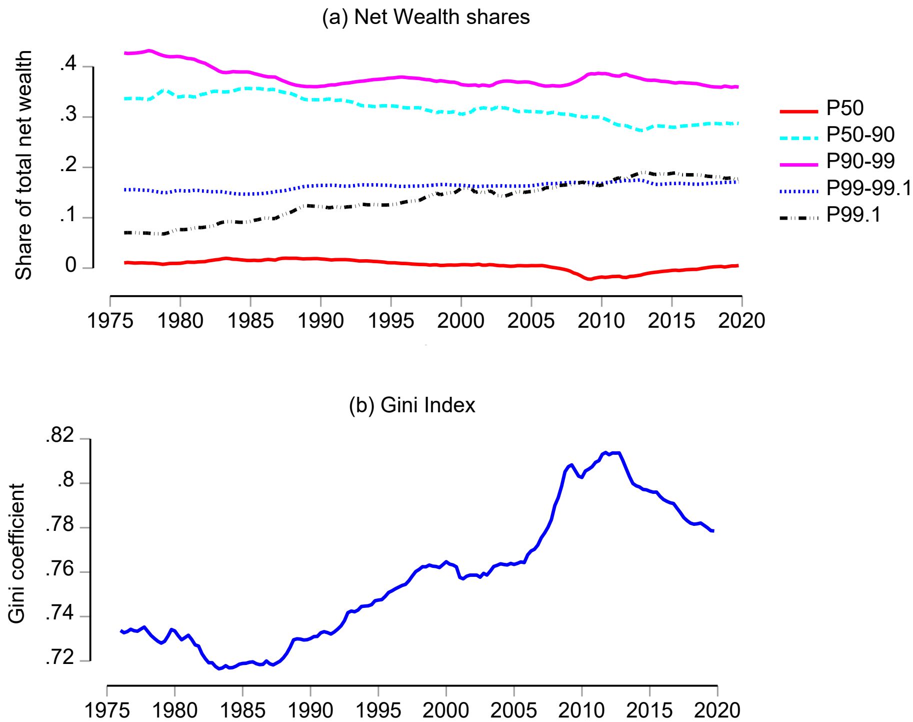
Moreover, as shown by Medlin and Epstein (2022), the Fed’s anti-inflation bias has tended to benefit the top 1% by preserving their wealth in real terms. How much we can precisely attribute the low inflation environment in the post-1980s “Great Moderation” to “good” Fed policy is still a matter of considerable debate (Davis & Kahn, 2008; Ćorić, 2011). But we do know that the environment of low inflation is another structural factor that advantages wealth at the top.

The implications for monetary policy are that Fed officials must consider when their policies are most potent on the wealth distribution. As downturns have multiple adverse and long-lasting effects on the economy, increasing wealth inequality might be an acceptable trade-off of expansionary policy. However, if monetary policy remains overly accommodative during economic expansions, the results above indicate it could disproportionately amplify wealth disparities.

Finally, the last exercise estimates the historical contribution of U.S. central bank policy to changes in the wealth distribution. The results indicate that monetary policy can account for significant co-movements in the Gini index. Furthermore, the correlation appears larger when estimated on wealth statistics constructed from the Federal Reserve’s DFAs. Whether monetary policy has contributed to inequality depends on the period of scrutiny and the choice of wealth data. Based on these estimates, monetary policy may account for as much as 15 to 16 percent of the actual increase in the Gini index of wealth between 1980 and 2012. This finding contrasts with Wolff (2021), who finds that Fed policy has decreased wealth inequality between 1983 and 2019 by 0.045 in the Gini index, implying that inequality would be nearly 50 percent worse if not for Fed policy. However, when the same exercise is run with DFA data, it appears monetary policy has reduced wealth inequality by 38.7 percent, consistent with Wolff’s findings.

In either case, monetary policy does not appear neutral or de minimis in its distributional effects, as some argue. Though, certainly, more research is required to better understand the differences between wealth statistics that often lead to differences in results in the literature, under what conditions or characteristics of household portfolios does monetary policy exacerbate wealth inequality, and what (re)distributional policy offsets might be necessary under a monetary governance regime reliant on interest rate policy to manage economic activity when that policy does have significant distributional consequences.

Fig. 1: Net wealth distributional statistics: Realtime Inequality, 1976Q1-2019Q4



Notes: Panel (a) percentile groups correspond to the following: the bottom 50 percent (<P50), the middle 40 percent (P50-P10), the top 10 minus the top 1 percent (P90-P99), from the top 1 per-cent to the top 0.1 percent (P99-P99.1) and the top 0.1 percent (>P99.1) of the distribution. The Gini index in panel (b) is constructed from the wealth shares data shown in panel (a). See Appendix A.1 for methodology.

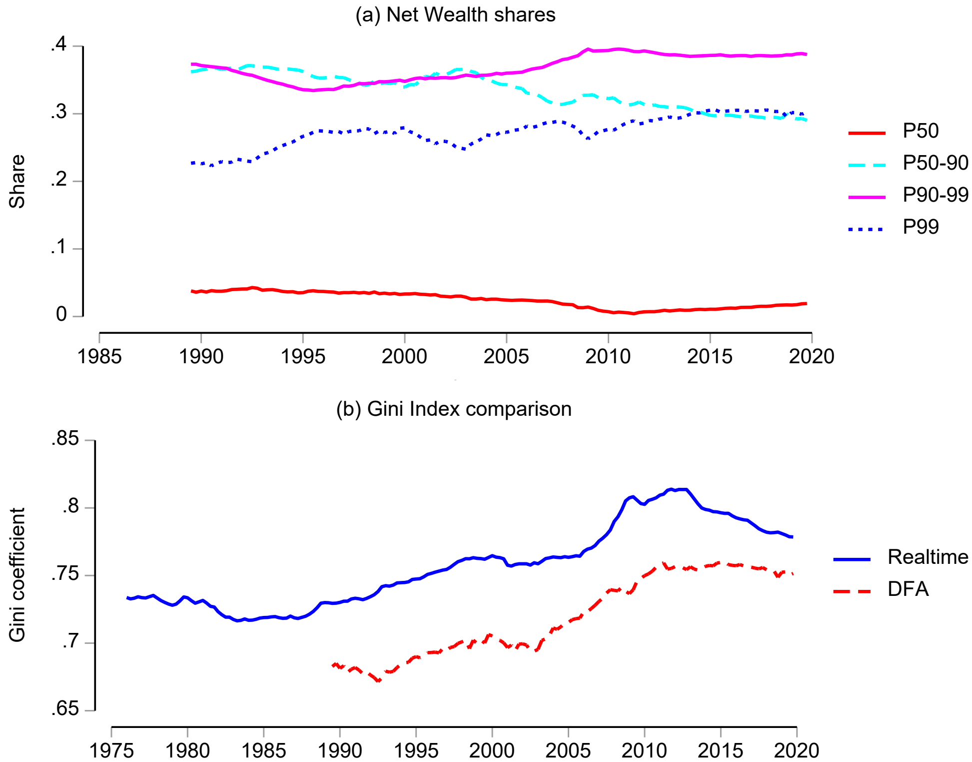
Source: (a) Realtime inequality; (b) authors' calculation.

Table 1. Change in wealth shares and population by percentile group overtime.

	1980-Q1	1980-Q1	2012-Q4	2012-Q4	Change	Change
Group	Wealth share	Population	Wealth share	Population	Wealth share	Population
P99.1	7.60%	153.8K	18.90%	233.2K	11.30%	79.4K
P99-P99.1	15.40%	1.4M	17.50%	2.1M	2.10%	0.7M
P90-P99	42%	13.9M	37.70%	21M	-4.30%	7.1M
P50-P90	34%	61.9M	27.30%	93.3M	-6.70%	31.4M
P50	1%	77.4M	-1.40%	116.6M	-2.40%	39.2M

Notes: Values in the table correspond to the wealth dynamics illustrated in Fig. 1 (a).

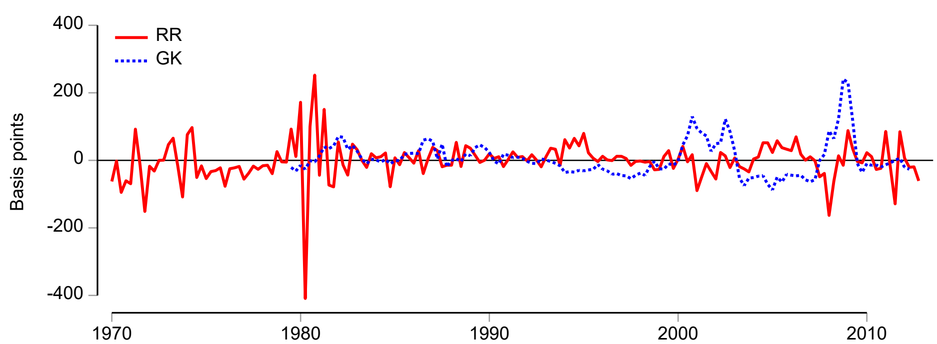
Fig. 2: Net wealth distributional statistics: Distributional Financial Accounts, 1989Q3-2019Q4



Notes: The Gini index in panel (b) is constructed from the wealth shares data shown in panel (a). See Appendix A for the methodology.

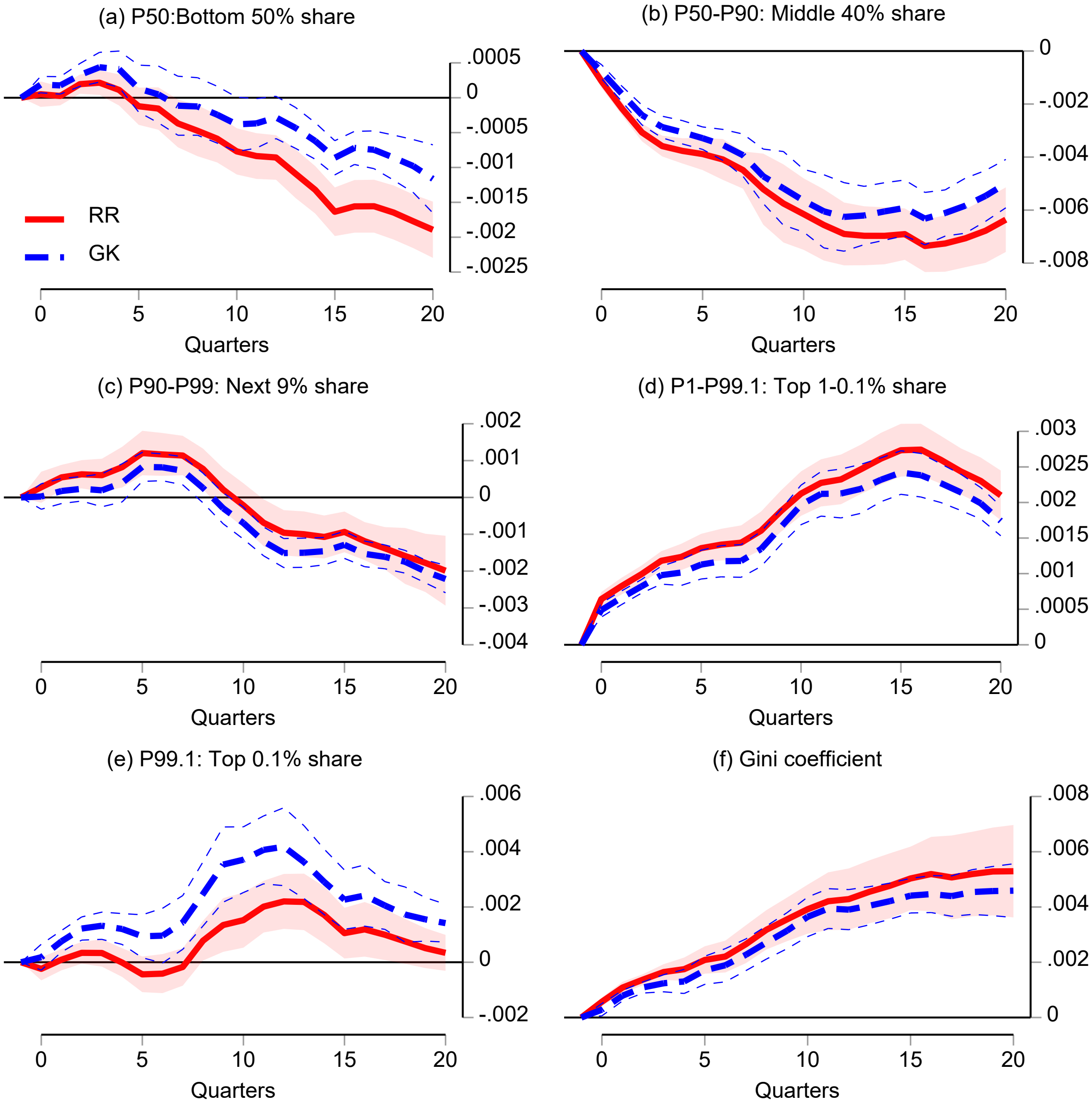
Sources: Board of Governors of the Federal Reserve System, authors' calculation.

Fig. 3: Comparing monetary policy shock series: Romer-Romer vs. Gertler-Karadi.



Notes: This figure compares the two monetary policy shock series used in the analysis: Romer-Romer (RR) and Gertler-Karadi (GK) shocks. The available data for RR shocks extends from 1970-Q1 to 2012-Q4 and GK shocks from 1979-Q3 to 2012-Q2.

Fig. 4: LP-IV impulse response of wealth statistics to expansionary policy (baseline).



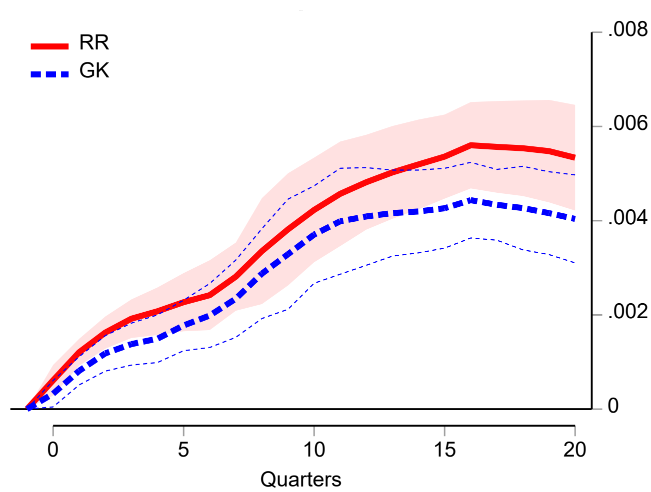
Notes: This figure shows the cumulative impulse response estimates of wealth shares for various percentile segments of the wealth distribution and the Gini coefficient to an unanticipated expansionary shock of 100 basis points to the policy rate. The shares are measured in decimals. The results of two instrument variables are presented. The solid-red line indicates Romer-Romer (RR) shock measures. The light red shaded region corresponds to the 90-percent confidence interval obtained from Newey-West robust standard errors. The thick dashed blue line indicates Gertler-Karadi (G.K.); the thin dashed blue lines correspond to the 90-percent confidence interval for these estimates. The response estimates represent the average effect between 1976-Q1 (144 observations) and 2012-Q4 for RR shocks and from 1979-Q3 to 2012-Q2 for GK shocks (131 observations).

Table 2. Baseline LP-IV response point estimates.

Shock series	Group share	Horizon				
		Year 1	Year 2	Year 3	Year 4	Year 5
RR	P50	-0.0002**	0.0004*	0.0008***	0.0016***	0.0018***
	P50-90	0.0036***	0.0045***	0.0066***	0.0069***	0.0068***
	P90-99	-0.0006**	-0.0011***	0.0007*	0.0009***	0.0018***
	P99-99.1	-0.0012***	-0.0014***	-0.0023***	-0.0027***	-0.0023***
	P99.1	-0.0003	0.0002	-0.0020***	-0.0011*	-0.0005
	Gini	-0.0016***	-0.0027***	-0.0042***	-0.0050***	-0.0053***
GK	P50	-0.0004***	0.0001	0.0004*	0.0009***	0.0010***
	P50-90	0.0029***	0.0039***	0.0060***	0.0059***	0.0055***
	P90-99	-0.0002	-0.0007***	0.0012***	0.0013***	0.0020***
	P99-99.1	-0.0010***	-0.0012***	-0.0021***	-0.0024***	-0.0020***
	P99.1	-0.0013***	-0.0014**	-0.0041***	-0.0023***	-0.0016***
	Gini	-0.0012***	-0.0023***	-0.0039***	-0.0044***	-0.0046***

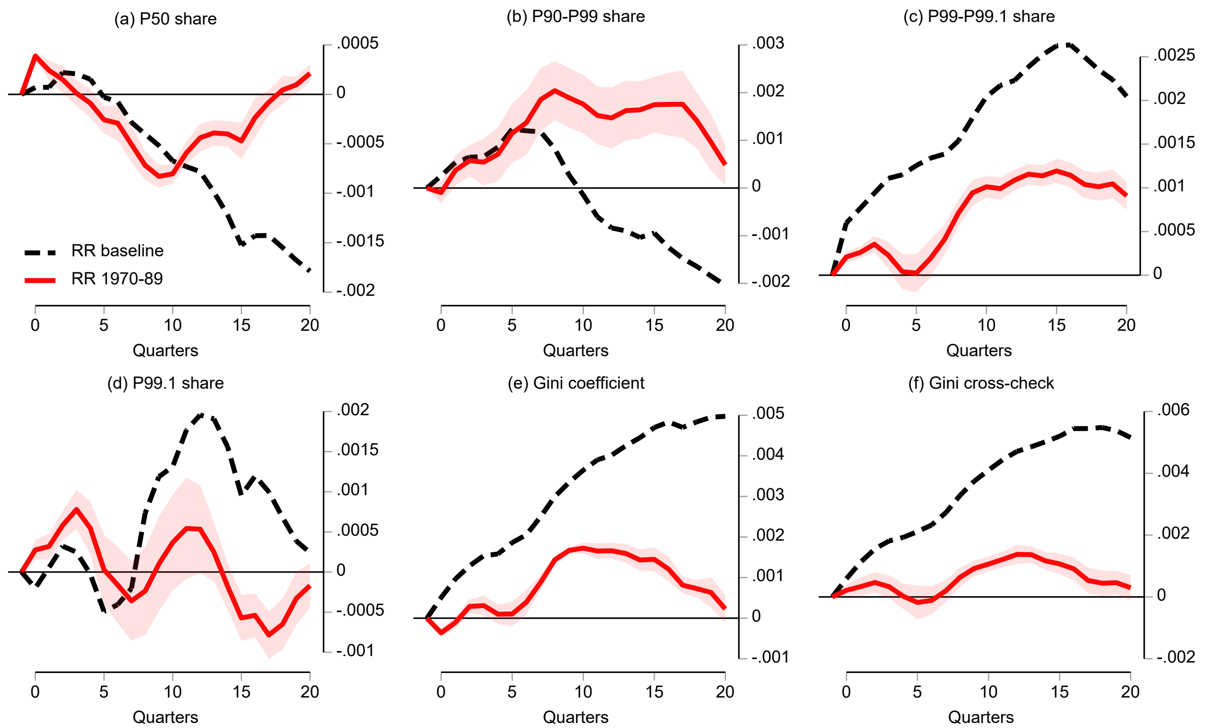
Notes: The table shows LP-IV response estimates corresponding to Figure 4. In the upper panel, Romer-Romer (RR) shocks; in the lower panel, Gertler-Karadi (GK). *, **, and *** denote statistical significance at the 10, 5, and 1 percent levels, respectively. The response estimates represent the average effects between 1976-Q1 and 2012-Q4 for RR shocks (144 observations) and from 1979-Q3 to 2012-Q2 for GK shocks (131 observations).

Fig. 5: Cross-check of the Gini coefficient from response estimates of wealth shares.



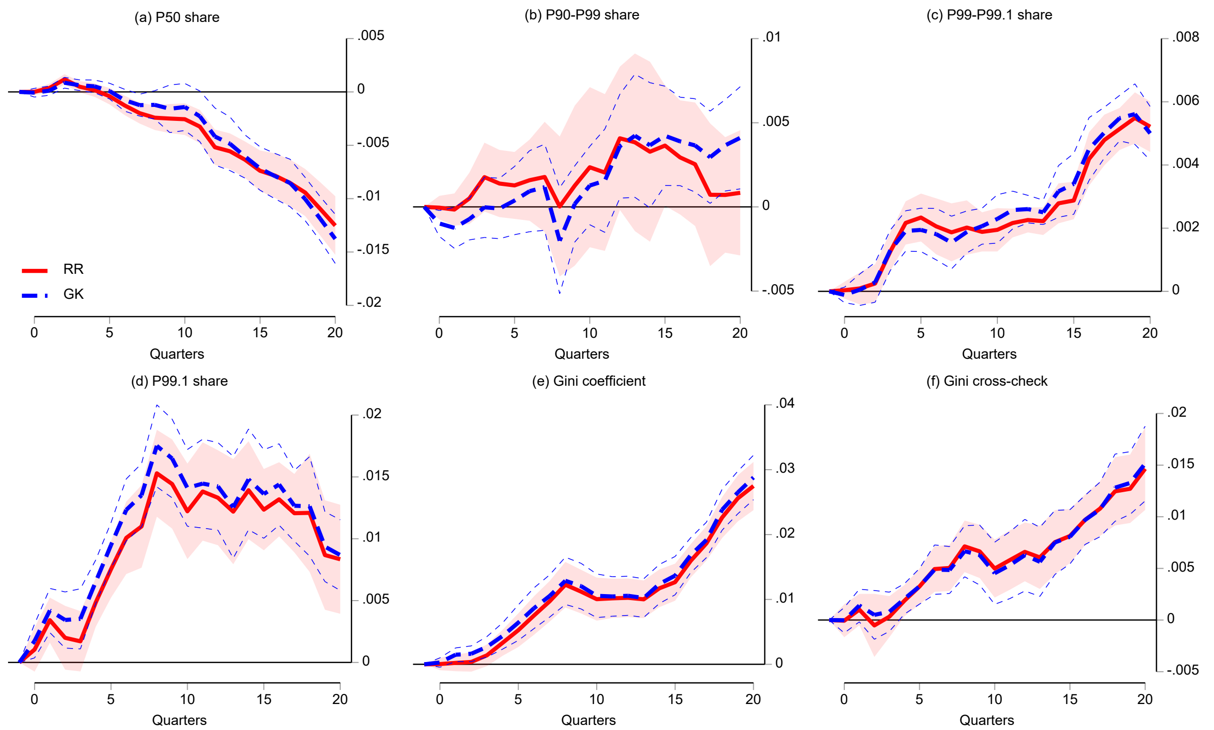
Notes: This figure provides a robustness check to the estimated response of the Gini coefficient in Figure 4 (f), which regresses directly on the Gini coefficient constructed from the data. However, this estimated response of the change in the Gini coefficient is directly constructed from the response estimates of wealth shares, i.e., Figure 4 (a) through (e). The confidence intervals are constructed from the same process. See Appendix A for the methodology.

Fig. 6: The effect of monetary policy from 1976 through the 1980s.



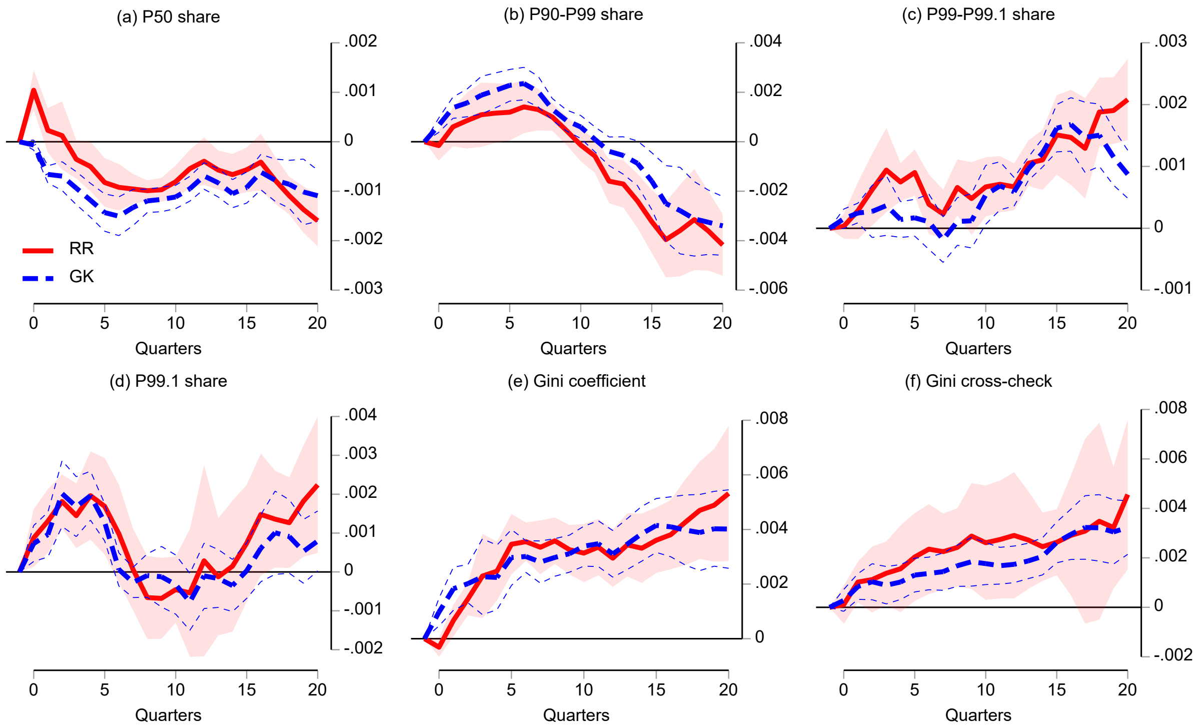
Notes: This figure shows response estimates to a 100 basis point policy using RR shocks only for the instrument; it is the only available measure going back to the mid-1970s. The result is the average response estimated from 1976-Q1 to 1989-Q4. Light-red shaded region denotes 90-percent confidence intervals obtained from Newey-West robust standard errors. The baseline RR response is also presented for comparison, denoted by the dashed line. Panel (e) represents the estimated response directly on the Gini coefficient as pre-constructed from wealth shares. See Appendix A.1 for the methodology. Panel (f) is the cross-check method constructed from the response estimates of wealth shares, panels (a)-(d); see Appendix A.2 for the methodology.

Fig. 7: Effect of monetary policy between 1990 and 2006.



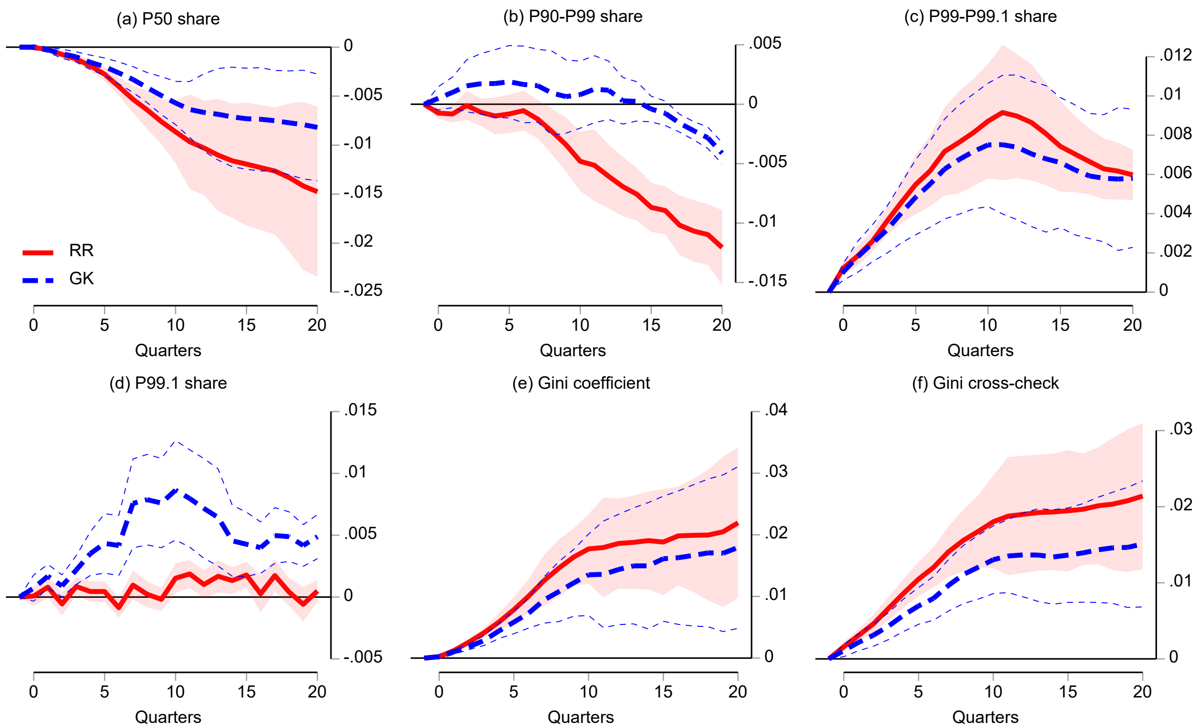
Notes: The figure plots cumulative response estimates to 100 basis point expansionary monetary policy shock—average response estimates for the 1990Q1-2006Q4 period. The light red shaded region corresponds to the 90-percent confidence interval estimated from RR shocks obtained from Newey-West robust standard errors; the thin dashed blue lines indicate the confidence interval from GK shocks.

Fig. 8: Expansionary monetary policy shocks during economic recessions.



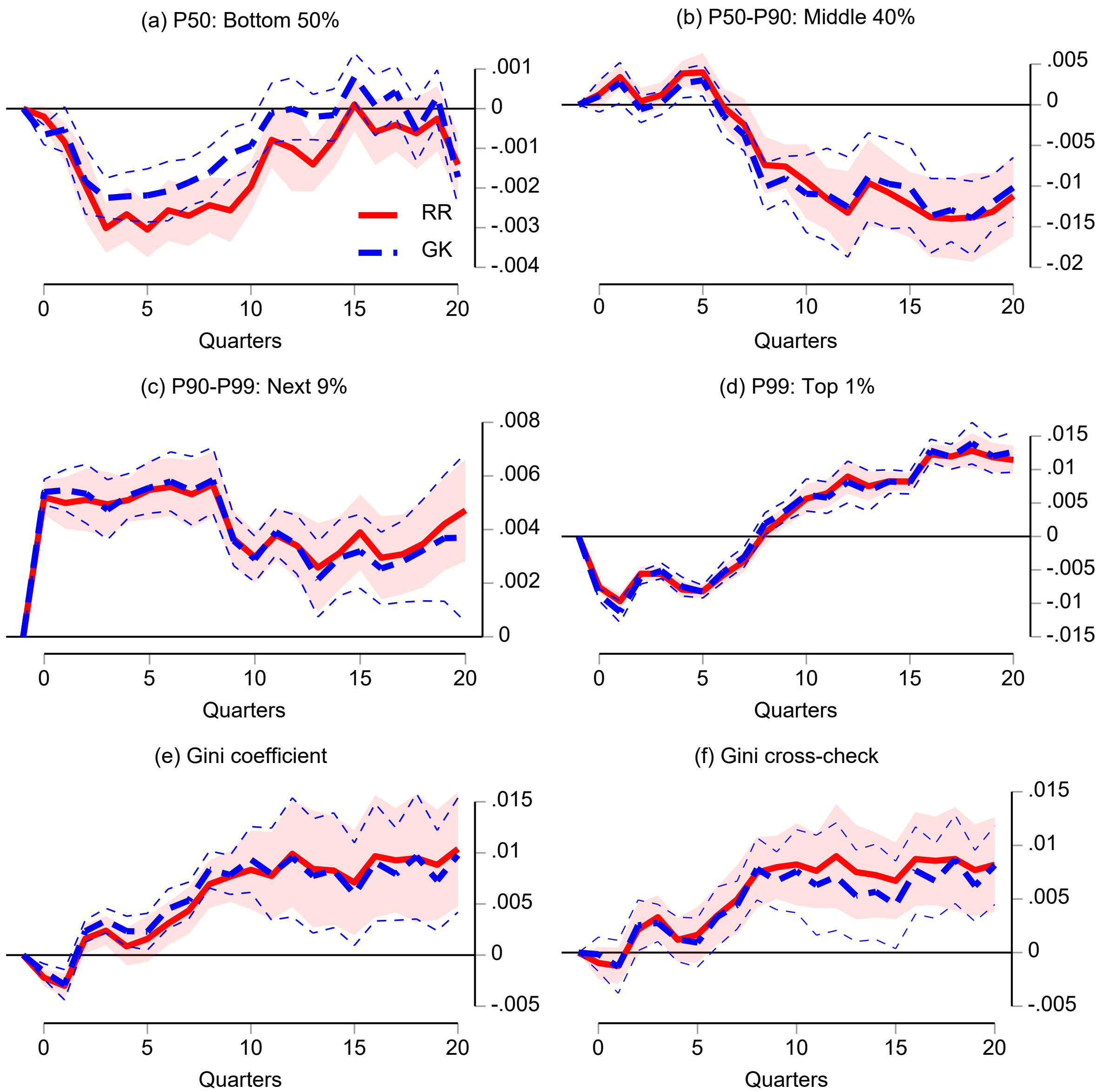
Notes: Response estimates to a 100bp expansionary surprise cut to the policy rate. Observations are constrained to periods in which a recession occurred in the two quarters, as indicated by the NBER business cycle indicator.

Fig. 9: Expansionary monetary policy shocks during economic expansions.



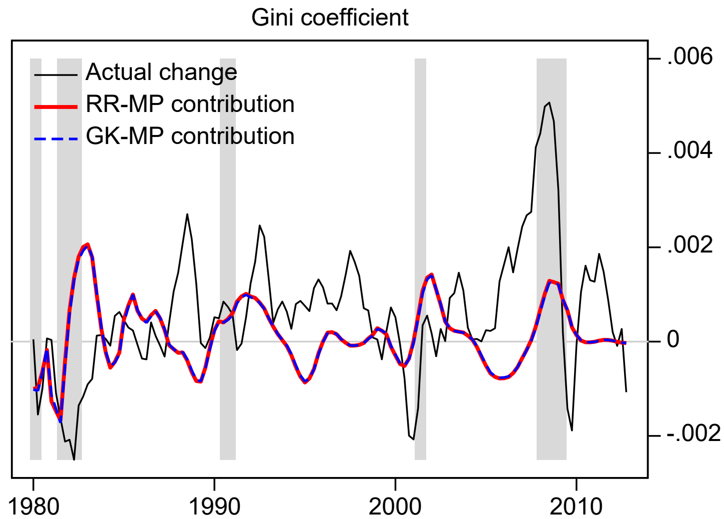
Notes: Response estimates to 100 basis point expansionary cut to the policy rate. Observations are constrained to periods with an economic expansion, as indicated by the NBER business cycle indicator.

Fig. 10: Response of DFA wealth statistics to expansionary policy rate shock**.**



Notes: This figure shows response estimates of the wealth shares to surprise 100 basis point expansionary shock to the policy rate. The measure is real net wealth shares by percentile group computed from the DFAs between 1990Q1 and 2012Q4. As before, RR and GK monetary policy shock measures are used as instruments. 90-percent confidence intervals correspond to the lightly-red shaded region for RR shocks, and the thin-blue dashed lines denote the interval for GK shocks.

Fig. 11: The contribution of monetary policy to historical variation in wealth inequality.



Notes: Observation period: 1980Q1-2012Q4. This figure plots the predicted changes in Realtime Inequality wealth shares by percentile group and the Gini coefficient due only to monetary policy shocks estimated using RR shock instruments (red line) and GK shock instruments (blue line) against actual changes in the dependent variable (thin black line). All plotted series are centered on three-quarter moving averages. The gray-shaded regions are U.S. recessions, according to NBER.

Table 3. MP contribution to net change in Gini coefficient delineated by period, 1980-2012.

	Volcker - Greenspan [a]	***Greenspan*** [a]	***Greenspan - Bernanke*** [a]	***QE - GFC & recession*** [b]	***QE – Recovery*** [b]	***Whole period*** [c]
	1980-1989	1990-1999	2000-2007	2008-2010Q1	2010Q2-2012Q4	1980-2012
Change in actual Gini	-0.003	0.034	0.021	0.019	0.009	0.080
RR-MP contribution (%)	0.003 (-100%)	0.005 (14.7%)	0.000 (0%)	0.006 (31.6%)	0.000 (0%)	0.013 (16.3%)
GK-MP contribution (%)	0.002 (-67%)	0.004 (11.8%)	0.000 (0%)	0.005 (26.3%)	0.000 (0%)	0.012 (15%)

Notes: Years include all quarters unless otherwise specified. [a] Fed chair tenures: Paul Volcker, 1979-1989; Alan Greenspan, 1987-2006; Ben Bernanke, 2006-2014. [b] Quantitative easing (QE) periods: QE-1, Nov. 2008 - Mar. 2010; QE-2, Nov. 2010 - Jun. 2012; QE-3, Sep. 2012 - Oct. 2014. [c] Dates displayed correspond to RR estimates. GK estimates stop at 2012Q2.

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Appendix A

Appendix A expounds on the methodology used to derive the Gini index from Realtime Inequality and the Fed's Distributional Financial Statistics (DFAs) wealth statistics, as well as the Gini cross-check method.

A.1 Constructing the Gini coefficient from wealth share and population count data

The Gini coefficient is defined simply as the area between the line of perfect equality, the 45-degree line, and the observed Lorenz curve as a percentage of the area between the 45-degree line and the line of perfect inequality. Given the available data provided on wealth shares and population shares from the Realtime and DFA data, we have everything we need to compute the Gini measure of wealth inequality without direct reference to the Lorenz curve; note, however, that this is a rough estimation since we have a small number of predefined groupings.

For example, recall, the wealth percentile groups used in our analysis from Realtime include the following: P50, P50-90, P90-P99, P99-P99.1, and P99.1. These groups are mutually exclusive, meaning there is no overlap of wealth between them. This is a required condition to appropriately approximate the Gini coefficient.

We use the following formula to calculate G:

$$G_t = 1 - \sum_{p=1}^{j} S_{p,t} \tag{A1}$$

$$S_{p,t} = \left(\frac{\omega_{p,t}}{W_t}\right)\left(\frac{n_{p,t} + 2\sum_{p+i}^{j} n_{p+i,t}}{N_t}\right) \tag{A2}$$

The term $S_{p,t}$ defines the area under the Lorenz curve, which represents the distribution of wealth with respect to percentile group p at time t. The term $\omega_{p,t}$ (omega) is the total value of net wealth held by each predefined percentile group p at time t, and W is the total net wealth of the whole population. The term $\left(\frac{\omega_{p,t}}{W_t}\right)$, then, represents the share of wealth held by the percentile group. n_p denotes the population count of the percentile group p, which shares the common denominator N representing the total population; the quotient of these two terms is the share of the population percentile group p. The term $\sum_{p+\mathrm{i}}^{j} n_{p+\mathrm{i},t}$ represents the cumulative population that is richer by summing the population counts of each group holding more wealth $(p+1, p+2, \dots, p+j)$ than group p and dividing by N. The Gini, then, can be computed as the 1 minus the sum of S-values of all predefined percentile groups $(p, p+1, \dots, p+j)$.

A.2 Computing the change in the Gini coefficient from response estimates of wealth shares

In our empirical results, we cross-check that the response of the Gini coefficient is consistent with the estimated cumulative change of wealth shares by percentile groups. The calculation is straightforward and merely involves multiplying the change in wealth share for each percentile group by the term that represents the population distribution. For this, we assume that the population shares do not change over the horizon period. This is a reasonable assumption when we look at the respective shares of the population for each percentile group over time: Even while wealth shares are changing and the population itself is growing, the relative population shares stay the same.

However, we still require a reference population. Therefore, we take the mean value of population shares over the observation period, $\left(\frac{n_{p,t}+2\widehat{\sum_{p+\iota}^{J}}n_{p+\iota,t}}{N_t}\right)$. We then sum up the change in wealth shares by each percentile grouping p at time horizon $t+h$ represented by the term $\left(\Delta\frac{\omega_{p,t+h}}{W_{t+h}}\right)$ in equation A3:

$$\Delta S_{p,t+h} = \left(\Delta\frac{\omega_{p,t+h}}{W_{t+h}}\right)\left(\frac{n_{p,t}+2\widehat{\sum_{p+\iota}^{J}}n_{p+\iota,t}}{N_t}\right) \tag{A3}$$

We then compute the change in the Gini coefficient for each time horizon *h* quarters as the change in the sum of S-scores. Thus, the cross-check Gini estimate indicates how much inequality would increase (or decrease) while holding population shares constant.

$$\Delta G_{t+h} = -1\left(\sum_{p=1}^{j}\Delta S_{p,t+h}\right) \tag{A4}$$

Note this is a rough estimate as there is likely to be a statistical discrepancy given that wealth shares are estimated separately. By accounting identity, a change in the wealth share of one percentile group should be exactly equal to the change in another or the sum of changes of the other groups. However, in some cases, there will be a small discrepancy as the sum of all cumulative wealth share changes does not always add up to exactly zero but comes very close.

The main point of the cross-check analysis is to ensure that the estimates in wealth shares are consistent with direct estimates on the Gini coefficient as a dependent variable of the LP-IV approach and to detect any major statistical artifacts or anomalies that might lead us to make inaccurate conclusions.

Appendix B

Appendix B provides additional tables and figures that were left out of the main body of the paper for the sake of space.

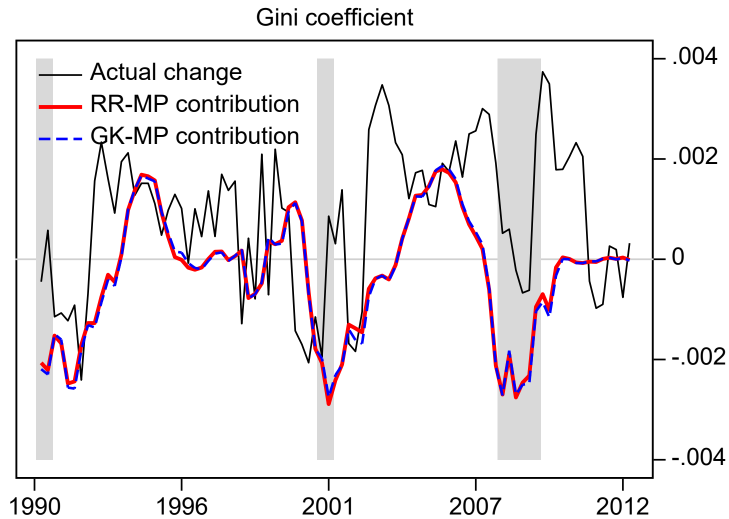
Table B1. Financial market indices and macroeconomic variables and their sources.

Variable	*Description*	*Time period*	*Source*
FFR	Effective Federal Funds Rate	1970q1 - 2022q4	FRED
T-note yield	10-yr constant maturity Treasury note yield	1970q1 - 2022q4	FRED
Unemployment rate	U-3 unemployment rate, seasonally adjusted	1970q1 - 2022q4	FRED
GDP	Nominal GDP	1970q1 - 2022q4	FRED
CPI	Headline CPI, all urban consumers	1970q1 - 2022q4	FRED
GDP deflator	GDP implicit price deflator	1977q4 - 2022q4	FRED

Table B2. Descriptive statistics.

Variable	*Obs.*	*Mean*	*Std. dev.*	*Min.*	*Max.*
FFR (effective rate, %)	172	5.863	3.741	0.070	17.790
ΔFFR (pp)	171	-0.049	1.019	-4.000	6.030
Unemployment rate (%)	172	6.382	1.570	3.900	10.700
CPI	172	0.512	0.225	0.148	0.898
CPI inflation (annualized)	168	-0.005	1.585	-5.879	9.557
T-Note yield (%)	172	6.977	2.782	1.640	14.840
RGDP (billions of dollars)	172	11,436.070	4,112.322	5,579.005	18,413.070
RGDP growth (%, annualized)	168	0.018	3.047	-11.672	9.386
Realtime wealth data					
P50 share (decimal)	148	0.007	0.011	-0.022	0.020
P50-90 share	148	0.324	0.020	0.273	0.357
P90-99 share	148	0.381	0.020	0.360	0.432
P99-99.1 share	148	0.161	0.007	0.147	0.175
P99.1 share	148	0.126	0.034	0.068	0.189
Gini coefficient	148	0.751	0.028	0.716	0.814
DFA wealth data					
P50 share (decimal)	94	0.028	0.011	0.004	0.0043
P50-90 share	94	0.345	0.019	0.310	0.371
P90-99 share	94	0.362	0.019	0.334	0.396
P99 share	94	0.265	0.019	0.223	0.293
Gini coefficient	94	0.709	0.026	0.672	0.759

Fig. B1: Historical contribution of MP on the wealth distribution: DFA data, 1990Q1-2012Q4.



Notes: This figure plots the predicted changes in DFA wealth share levels by percentile group and the Gini coefficient between 1990Q4 and 2012Q4 from monetary policy shocks estimated using RR shock instruments (red line) and from 1990Q1 to 2012Q2 using GK shocks instruments (blue line) against actual changes in the dependent variable (thin black line). All plotted series are centered on three-quarter moving averages. The gray-shaded areas are U.S. recessions, according to NBER.

Table B3. Historical MP contribution to changes in Gini coefficient, DFA data, 1990-2012.

	Greenspan [a]	***Greenspan - Bernanke*** [a]	***QE1 - GFC & recession*** [b]	***QE - Recovery*** [b]	***Whole period*** [c]
	1990Q4-1999Q4	2000Q1-2007Q4	2008Q1-2010Q1	2010Q2-2012Q2	1991Q4-2012Q2
Change in actual Gini	0.023	0.035	0.011	0.006	0.075
RR-MP contribution	-0.010	-0.003	-0.015	0.000	-0.029
(%)	(-43.5%)	(-8.6%)	(-136%)	(0%)	(-38.7%)
GK-MP contribution	-0.011	-0.003	-0.016	0.000	-0.030
(%)	(-47.8%)	(-8.6%)	(-145%)	(0%)	(-40%)

Notes: Estimates derived from the prediction model. Dates include all quarters unless otherwise specified. [a] Fed chair tenures: Alan Greenspan, 1987-2006; Ben Bernanke, 2006-2014. [b] Quantitative easing (QE) periods: QE-1, Nov. 2008 - Mar. 2010; QE-2, Nov. 2010 - Jun. 2012; QE-3, Sep. 2012 - Oct. 2014. [c] Dates displayed correspond to RR estimates. GK estimates stop at 2012Q2.