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The Role of Federal Reserve Policy in Creating Wealth Inequality

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The Role of Federal Reserve Policy in Creating Wealth Inequality*

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Abstract

This paper studies the effects of expansionary monetary policy on wealth inequality in the United States context between 1976 and 2012. We use the novel local projections instrumental variable (LP-IV) approach in which we instrument changes in the policy rate using two different monetary policy shocks series previously developed in the literature. Our dependent variable is the distribution of real net wealth and the Gini coefficient obtained from two recently developed sources which provide high-frequency data on a quarterly basis: Realtime Inequality and the Federal Reserve's Distributional Financial Accounts. Contrary to prior studies, we find that conventional monetary policy does have persistent effects over the medium term, which we define as five years. Specifically, we find, on average, an expansionary monetary policy of 100 basis points cut in the policy rate increases the share of wealth for the top 10 and 1 percent and lowers the share for the bottom 50 and middle 40 percent of the distribution. Overall, wealth inequality, as measured by the Gini coefficient, increases by 0.005 on the Gini scale. The effect size varies over prior decades and with the business cycle but remains statistically significant and persistent during the decade of the Greenspan-Fed era. We find that expansionary policy appears more effective during economic expansions than contractions. Lastly, we conduct an exercise to estimate monetary policy's historical contribution to variation in the wealth distribution. The results of this exercise also confirm that monetary policy can account for significant variations in wealth distribution during some periods of recent U.S. history.

Keywords: Monetary policy, inequality, wealth effect

JEL codes: E52, D31

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1 Introduction

Rising inequality across advanced economies has become an increasing concern for 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 or 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 percent of households have roughly doubled their share of the nation's wealth since 1980. Today, the top 1 percent have more personal wealth than the bottom 90 percent. By some measures, there has been some reversal in this trend since the Global Financial Crisis (GFC). A commonly used metric of inequality is the Gini coefficient, an index which reflects differences at all parts of the distribution and theoretically bounded on a scale of zero (representing complete equality) and an upper bound of 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 of 0.84 in 2013 and has been gradually declining ever since; it stands at 0.83 as of their 2021 print. By other measures, however, wealth inequality has only increased since the GFC. Based on data of 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.

The widening wealth gap has multiple drivers, from changes in government policy to structural changes in the economy. The most critical may be tax policy, as wealth and capital gains in the United States have been regressively taxed less than income since the 1970s (Kaymak & Poschke, 2016; Hubmer et al., 2020). However, while government fiscal policy may be the most significant factor, Federal Reserve monetary policy has increasingly drawn scrutiny. In particular, critics single out more recent policies of ultra-low interest rates and Quantitative Easing or QE (large-scale purchases of debt securities) for pushing up asset prices for everything from stocks and bonds to real estate—and, perhaps, more purely speculative assets like cryptocurrencies—which exacerbate wealth inequalities between the rich and poor as the former own disproportionately a dipropionate share of those assets (for examples of this argument by the press, see Sloan & Podkul (2021), Petrou (2021), and Leonard (2022)).

Some empirical evidence lends credence to this assessment. Huston & Spencer (2016), for example, do find that monetary aggregates, M1, M2, and excess reserves, were positively correlated with equity prices. Some studies also find a positive correlation between unconventional policies like QE and increasing income and wealth inequality (Montecino & Epstein, 2015; Juan Francisco et al., 2018). However, there is no consensus in the literature on whether unconventional monetary policies significantly affect income or wealth inequality (Colciago et al., 2019).

[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

Among government policymakers, central bank officials have taken the defending their unconventional policies. Defending the Federal Reserve, former Fed chair Ben Bernanke has argued that the effects of Federal Reserve monetary policy on inequality are likely negligible and transitory.

> 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)

Yet, a partial basis of further QE policy in the immediate aftermath of the GFC was to induce a "wealth effect" in the hopes it would stimulate economic recovery (Huston & Spencer, 2016).

However, this focus on the stock market by Fed officials as a mechanism to influence 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 & 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 empirical assessment finds that mentions of stock market declines are "strongly predictive" of monetary easing; however, mentions of stock market highs are not predictive 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 for—at least—a decade before the financial crisis.

A basic question, then, 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 to this literature by assessing the effects of conventional monetary policy on wealth inequality in the United States context between 1976 and 2012. More specifically:

(i) We utilize wealth statistics from two recently developed datasets that provide high-frequency aggregate income and wealth distribution statistics: the Realtime Inequality database and the Fed's Distributional Financial Accounts.

(ii) We apply a novel econometric approach to identify the causal impact of unanticipated expansionary monetary policy using monetary policy shock measures in an instrumental variable set-up estimated by local projections. We use two measures of monetary policy shocks, each with its own novel construction, to obtain an estimated range.

(iii) The historical contribution of monetary policy is estimated.

The results indicate that conventional monetary policy does have positive and persistent effects on the wealth distribution over the medium term, which we define as five years. We find that, on average, an unanticipated 100 basis points cut in the policy rate, the Federal Funds Rate, increases the share of wealth for the top 10 and 1 percent, and, therefore, by identity, lowers the share for the bottom 50 and middle 40 percent of the distribution. Overall, wealth inequality, as measured by the Gini coefficient, increases by 0.005 on the Gini scale. The magnitude of these effects varies over different periods and under different economic conditions. We find that expansionary policy appears more effective during economic expansions than contractions. The results are also robust to various alternative specifications, including alternative constructions of wealth statistics. Lastly, we develop a prediction model to estimate monetary policy's historical contribution to wealth distributional dynamics. The result of this exercise also suggests that monetary policy can account for significant variations in wealth distribution over recent U.S. history.

The rest of the paper is organized as follows: Section 2 reviews some of the recent literature on the intersection of monetary policy and wealth inequality. Section 3 discusses our sources of data and econometric approach. Section 4 presents the results and robustness exercises. Finally, section 5 will conclude with a summary of our main findings and implications for policy.

2 Related Literature

An extensive survey of the extant literature on central bank policy and income and wealth inequality has been conducted by Colciago et al. (2019). Wolff (2021) also provides an excellent broad review of the literature related to measuring wealth inequality and the effects of monetary policy, both conventional and unconventional, on the wealth distribution. For our purposes, this section will focus on more recent empirical work and how our paper fits into that literature as it specifically pertains to conventional monetary policy.

A well-developed empirical literature has been preoccupied with analyzing the effects of conventional and unconventional monetary policy on the distribution of income. Yet, no consensus has entirely emerged on either front due to mixed results (ibid). Discerning the effects of unconventional policy is especially difficult as no two central banks conduct such operations in quite the same way and do so in varying institutional and distributional contexts. By comparison, the literature examining the intersection of central bank policy on wealth is still nascent. Most recent scholarship has mainly focused on unconventional monetary policy with mixed findings, while conventional policy has received relatively little attention.

The transmission of monetary policy (MP) to households theoretically occurs through three primary channels: First is the income effect: A change in interest rates influences the level of interest income received by savers and paid by borrowers. Essentially, changes in interest rates influence the net wealth accumulation rate through existing debt and interest-bearing assets; this is referred to as the savings redistribution channel. Second is the 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. Monetary policy affects some assets more than others. Therefore, differences in the composition of household asset portfolios result in heterogeneous effects on the distribution. MP may be more equalizing in economies with broad-based housing ownership as interest rate policy has a clearer relationship to housing demand. Lastly, there 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.

Based on the literature survey by Colciago et al. (2019), technically, only two studies attempt to estimate the impacts of conventional central bank policy on wealth inequality through the portfolio composition and savings redistribution channels.[2] Inui et al. (2017) studied expansionary MP by the Bank of Japan, estimated by local projections. They find the effects on the wealth distribution are insignificant. Hohberger et al. (2019) also study expansionary policy in the Euro Area estimated within an open-economy DSGE model and find that expansionary policy decreases wealth inequality. Neither study appears to account for inflation.

A recent 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, estimating the effect of expansionary monetary policy on various asset price indices, including equity stocks, bonds, housing prices, as well as the racial unemployment gap, over a five-year horizon. The authors use 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

[2] The couple other studies mentioned by Colciago et al. under the banner of conventional monetary policy study the effects of inflation, which is then used to infer the effects of one channel of monetary policy on the wealth distribution, the other conducts a microsimulation of an arbitrary interest rate change on the portfolios of households. While exercises are informative and useful, but they are of a different kin than direct estimates on wealth measures themselves.

Consumer Finances (SCF). To account for the inflation component, 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 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. However, given these sizable effects, one can may infer from their results that expansionary monetary policy would also affect the wealth distribution more broadly, though this is not the focus of their analysis.

More recently, an NBER working paper by Wolff (2021) estimates the historical contribution of Federal Reserve monetary policy on real net wealth using data from the SCF between 1983 and 2019. Net wealth here is defined as marketable assets, 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. Contrary to recent prior studies, Wolff finds that "Fed policy," defined rather broadly as face value changes in longer-term interest rates and inflation, 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" (2021, p. 39). Wolff also analyzes the racial wealth gap and finds from his results, counter to Bartscher et al. (2021), that Fed policy also reduced the racial wealth gap for the same reasons, Fed policy boosted house prices more than financial asset prices. Moreover, since homeownership is the largest component of average asset portfolios for black and white households, black households benefit from that appreciation.

Wolff's results are interesting and provocative, as well as entirely plausible for the reasons he states. 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 asset prices. The problem with this approach is that while adjustments in the policy rate exert significant influence over the path of long-term yields, such as the 10-year T-note, 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 co-movements in those variables. This is also likely to produce bias in his results.

Medlin and Epstein (2022) attempt to disentangle the effects of inflation and monetary policy on wealth in the U.S. context between 1970 and 2012. They apply a double instrumental variable approach, inspired by Bartscher et al., 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 distribution. They find that, on average, elevated inflation affects wealth at the top much than would be the case in the absence of contractionary monetary policy by the Fed to bring inflation back down to an acceptable rate. The authors simulate the inflation environment of 2021-2022 and the Fed's sharp tightening cycle in response. LPIV estimates indicate that the top 1 percent's wealth would contract in real terms by about 30 percent under a persistent inflation rate of 6 percent. By the Fed intervening with a 375-basis point increase in the federal funds rate, they estimate the Fed will have preserved 14 percent in real net wealth terms for the ultra-wealthy relative to the counterfactual—presuming the policy is successful in bringing inflation down to their declared target of 2 percent. Their findings lead to the conclusion that the Fed's contractionary policy serves as a wealth protection insurance against inflation for the top 1 percent during periods of accelerated inflation, which often comes at the expense of potential growth and unemployment for the rest of the economy.

Our approach in this paper similarly employs the LP-IV framework to identify the effects of conventional monetary policy, i.e., moderate changes in the policy rate, on the wealth distribution. Like

Bartscher et al., we employ two previously developed MP shock measures as instruments to obtain a range of estimates. As in by Inui et al. (2017) and Bartscher et al. (2021), we simulate expansionary monetary policy of a 100-basis point unanticipated cut to the policy rate.

The approach draws heavily on Bartscher et al. but differs in that we estimate the effect of expansionary policy directly on wealth distribution measures—wealth shares and the Gini coefficient of net wealth—as our dependent variable, as is similarly the case in Coibion et al. (2017), Furceri et al. (2017) and El Herradi et al. (2020) using various income measures.[3] Our wealth distributional statistics are defined in real net wealth terms, meaning all assets minus liabilities, adjusted for inflation. Our measure would thus account for the adjustments in household portfolios and the savings redistribution channel, the latter of which affects the accumulation of net wealth over the forecast horizon and accounts for changes in the price level.

As our results indicate a significant and persistent increase in wealth inequality from expansionary monetary policy, our findings add to the mix of results by Inui et al. (no significance effect) and Hohberger et al. (an equalizing effect). We also conduct an exercise inspired by Coibion et al. (2017) to estimate the historical contribution of conventional MP on the wealth distribution. The results of this exercise find that a significant portion of the variation in wealth inequality can be explained by MP, at times exacerbating wealth inequality and at other ameliorating it.

3 Data and Methodology

3.1 Data

Our analysis focuses on the change in the real net wealth distribution as the outcome of interest. We use two sources of wealth data: Realtime Inequality and the Federal Reserve's Distributional Financial Accounts (DFAs). Our observation period is constrained to the post-war era in the United States between 1976 and 2012—1976 due to the limitation of 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

Data on 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 tax data to produce consistent and timely statistics to track the evolution of income and wealth distribution. To the authors' knowledge, this is the highest frequency data currently available to date. 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.

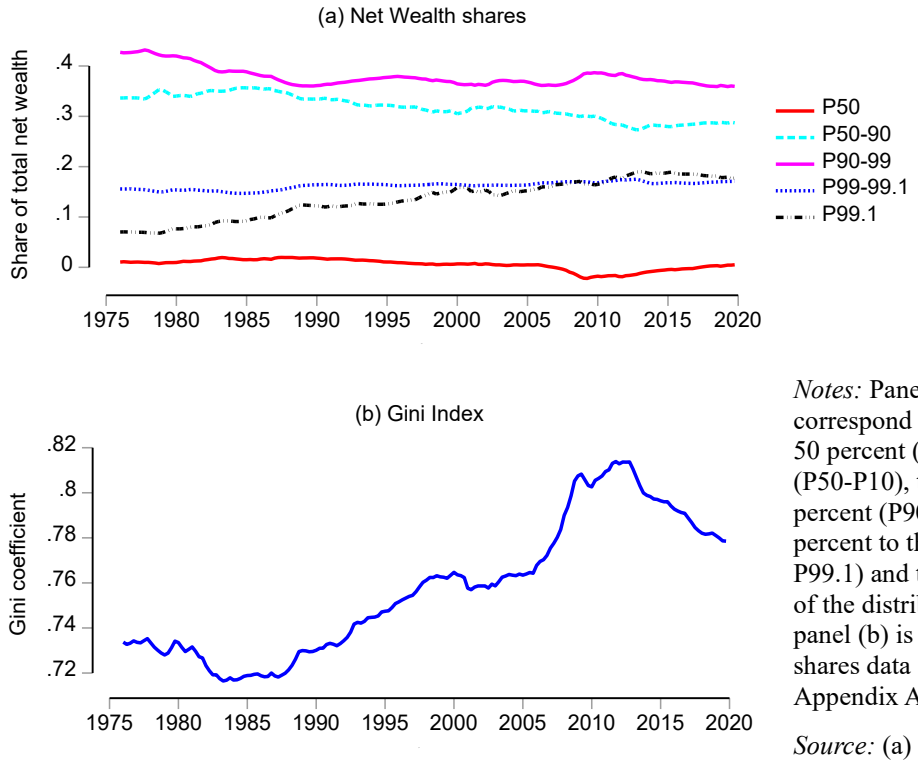
The period of available observations is from 1976 through 2019. Figure 1 (a) plots these wealth shares directly from the data for five wealth groups. The distributional ranking is defined by the 1st percentile being the poorest group and the 99th percentile being the richest. The groups include the following: the bottom 50 percent (P1-P50), the middle 40 percent (P50-P10), the top 10 minus the top 1 percent (P90-P99), from the top 1 percent to the top 0.1 percent (P99-P99.1) and, finally, the top 0.1 percent (P99.1) of the distribution. The top 1 percent are split into two groups to define the distribution more granularly at the top. We then use the information about these groups to construct the Gini

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

coefficient from the relative shares of their net wealth and populations (see Appendix A.1 for methodology). Figure 1 (b) plots the resulting Gini coefficient, with the coefficient bounded on the scale of 0 to 1, with 0 being the most equal and 1 being the most unequal.

While well documented, the significant shift in total wealth illustrated in Figure 1 (a) remains striking. Table 1 presents this more clearly. In 1980, the top 0.1% (P99.1) and the rest of the top 1 percent owned about 7.6 percent and 15.4 percent of all wealth, respectively. By the end of 2012, the top 0.1 percent had more than doubled their share to about 19%, while the rest of the top 1 percent 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 figure 1 (b), we see a rapid rise in the Gini coefficient from 0.73 to 0.81.

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



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 percent 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 figure 1 (a).

3.1.2 Alternative financial wealth data: the Distributional Financial Accounts

It is worth emphasizing that measuring the distribution of income and wealth is quite challenging, and 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 in one direction or another (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 but relies 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). The SCF is a triennial survey, so 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.

As in Wolff (2021), the wealth concept we are interested in for this analysis is marketable net wealth, defined as all financial assets and real estate minus liabilities. As financial and non-financial assets are delineated within the DFA, we can freely define this variable with the data given. Therefore, we construct the net wealth variable using Wolff's definition. We obtain the real net wealth from deflating the series by the CPI-U-RS.

Figure 2 presents the wealth share statistics constructed from DFA data for comparison to the Realtime statistics in Figure 1. As before, panel (a) displays net wealth shares and panel (b) the Gini coefficient corresponding to the evolution in wealth shares. In panel (b), we see the Gini coefficient exhibits a similar long-term trend upwards as in Figure 1 since the 1990s, but with some variation in dynamics during certain periods. The most evident being between the mid-1990s and early 2000s wealth inequality appears to plateau before declining over the early 2000s Dot-com stock market bubble collapse, whereas Figure 1 (b) indicates a steadier upward trend over the same period before the Dot-com burst.

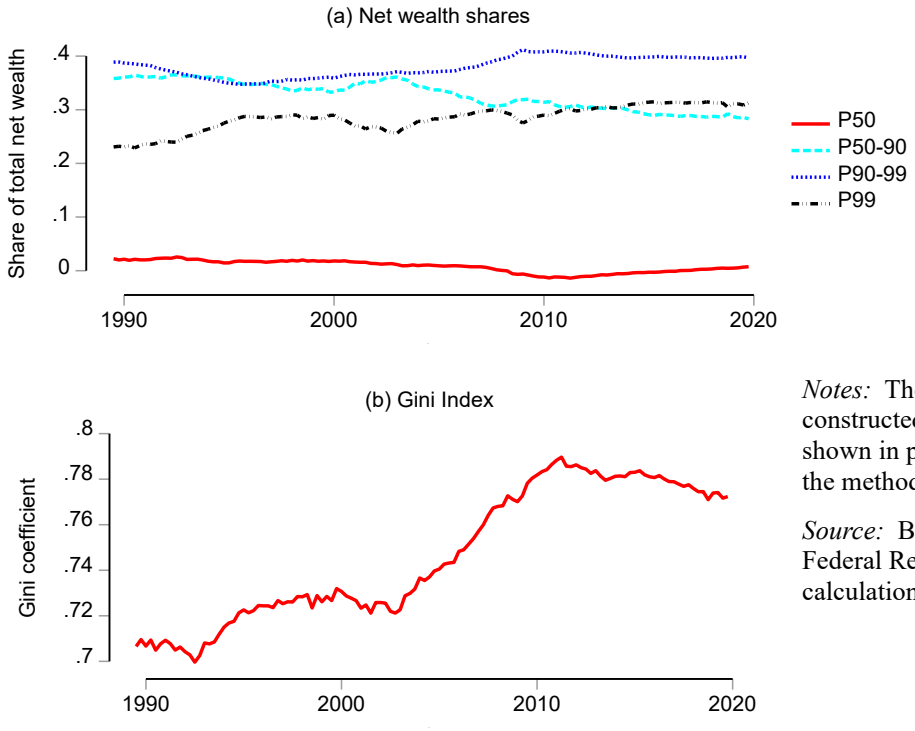
3.1.4 Monetary policy shock measures

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

One of the most widely cited of these shock measures in the literature is from 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 are large movements 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. They then extract the residuals from these models.

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



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

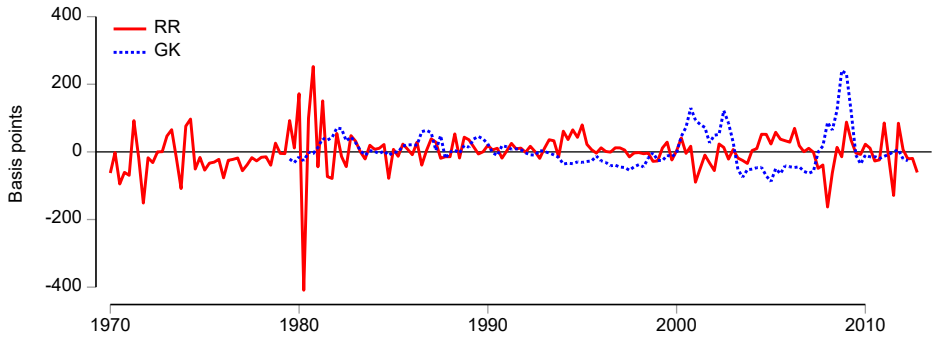
Source: Board of Governors of the Federal Reserve System, authors' calculation.

Using these monetary shock measures directly in structural VAR or local projection methods is standard practice. An 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 useful as an instrument to identify the exogenous variation in the actual policy rate (ibid., p. 923). Therefore, using these measures as proxies for structural shocks in an instrumental variable set-up 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), we use both monetary policy shock measures described above in our econometric analysis in a two-stage instrument variable set up estimated by local projections. Further details on this methodology are discussed in section 3.2. The original shock series developed by Romer and Romer (RR) extended from 1969-Q1 through 1996-Q4. We obtained an updated series through 2012-Q4 from Breitenlechner (2018). Data for Gertler-Karadi (GK) shocks extend from 1979-Q3 to 2012-Q2. Figure 2 plots the two measures for comparison.

It should be noted that Breitenlechner innovates on the original RR shock measure. To account for unconventional monetary policy at the zero lower bound, 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 produce similar findings pre-2008 before the advent of unconventional policies like Quantitative Easing and more aggressive forward guidance. When the post-2008 period is included, the two measures produce more variation of responses in distributional wealth measures.

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 extend from 1970-Q1 to 2012-Q4; GK shocks from 1979-Q3 to 2012-Q2.

3.1.5 Macroeconomic variables

Several macro variables are also used as controls in regressions, including the U.S. unemployment rate, nominal GDP, and headline CPI. 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 our econometric approach.

3.2 Econometric approach: Instrumental variable local projections

The local projection (LP) method developed by Jordà (2005b) is an increasingly popular alternative to structural VAR methods to compute impulse response functions (IRFs) which estimate the dynamic relationship between variables over time. This method has been used previously in 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 on 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. are the exception as they use the local projections instrumental variable (LP-IV) approach formalized econometrically by 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., we instrument actual changes in the Federal Funds Rate (FFR), the Federal Reserve's primary policy tool, using RR and GK monetary shock measures in a two-stage instrumental variable set-up estimated by General Methods of Moments (GMM). 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 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:

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

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 (bp) drop in the FFR, as is commonly done in the literature.

4 Results

In this section, we 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. We then apply the same LP-IV approach using wealth share data from the Distributional Financial Accounts. We also perform various robustness checks by looking at different periods of U.S. history and how effects may differ at different points in the business cycle.

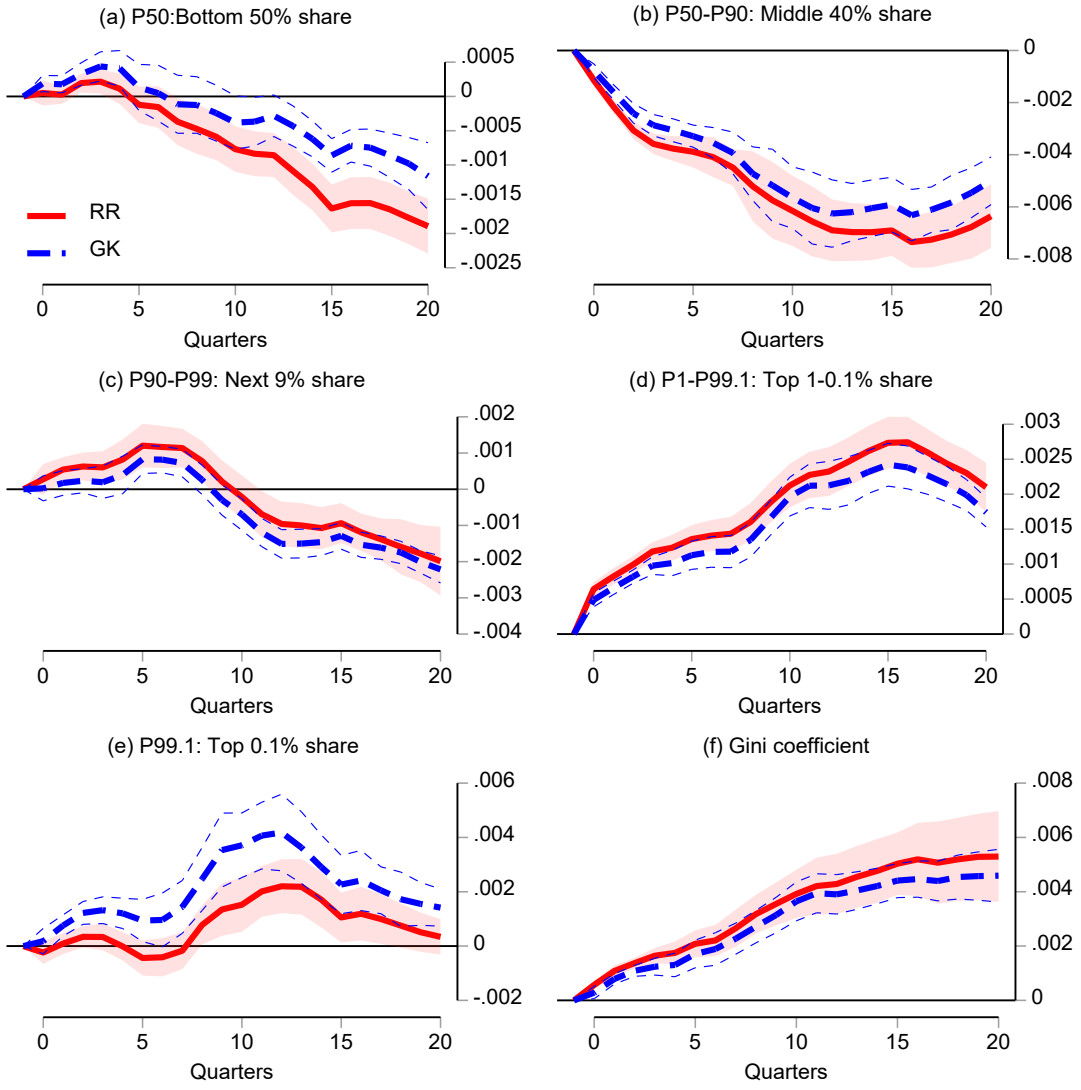
In the second part, we take a different approach. The last part of the analysis estimates the contribution of monetary policy on historical changes in net wealth distribution as measured by Realtime inequality and DFA data. The exercise is inspired by Coibion et al. (2017), who conducted a similar exercise on various income-related inequality measures.

4.1 The effect of expansionary monetary policy on wealth shares and the Gini coefficient

The main results are presented in Figure 4. Panel (a) through (e) plot the estimated cumulative impulse responses of real net wealth shares, in levels, by percentile group to a 100bp 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 monetary policy shock measures (solid red line), over 1976.Q1-2012.Q4, and Gertler-Karadi shock measures (dashed blue line) over 1979.Q3-2012.Q2.

The results of each panel are as follows: Expansionary monetary policy, on average, appears to modestly reduce the share of the bottom 50 percentile 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 G.K. shocks. For the middle 40 percentile, by about 0.5 to 0.6 percentage points. The top 10 percentile minus the top 1 decreased by 0.2 percentage points. On average, the top 1 percent gain. Between the top 1 and 0.1 percent, the share level increases by about 0.2 pp, and between 0 and 0.1 pp for the 0.1 percentile. The Gini coefficient in panel (f) indicates wealth inequality rises between 0.004 and 0.005 on a scale between 0 and 1, with one being the most unequal. All effects are statistically significant based on a 90 percent confidence interval computed using Newey-West standard errors. The effects may appear small in magnitude, but we are talking about only a modest reduction of 100 bp change in the policy rate. Therefore, more significant movements, which are not uncommon, will have larger effects. 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.

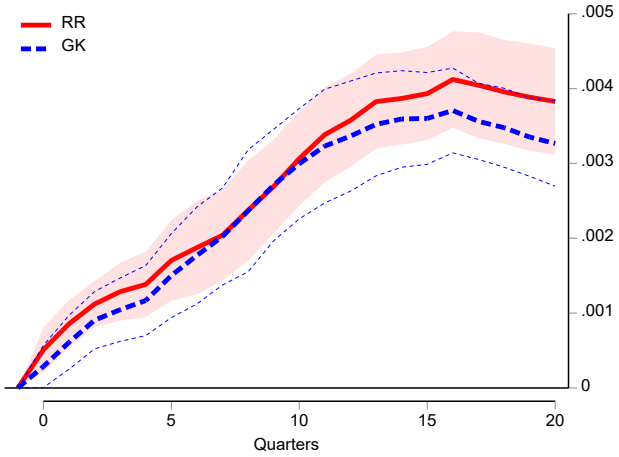
Fig. 4: LP-IV impulse response estimates of wealth statistics to a 100bp expansionary policy.



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 and 2012-Q4 for RR shocks and from 1979-Q3 to 2012-Q2 for GK shocks.

These results are quite robust, including to different lag choices—we 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 materially change, though magnitudes vary.

Fig. 5: Cross-checking the response 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.

To ensure the changes in wealth shares estimates are consistent with the results of the Gini coefficient in panel (f) of Figure 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 Figure 5, which does indicate the Gini coefficient does rise by a similar magnitude, between 0.003 to 0.004 on the Gini scale, 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, at least as colloquially understood. Instead, the effects are likely to persist for some time until the central bank alters policy to a contractionary stance.

4.2 Robustness checks

A couple of robustness checks are already built into the results presented so far. 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, while we estimate the response of the Gini coefficient directly, we also double check the result is consistent with the response of wealth shares themselves for the different wealth groups, as in Figure 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. Lastly alternative measures of wealth constructed from alternative methodological approaches are also important to confirm that results are not a statistical artifact of any one measure. Therefore, we conduct robustness exercises which address each of these considerations.

4.2.1 Effects of expansionary monetary policy during different periods

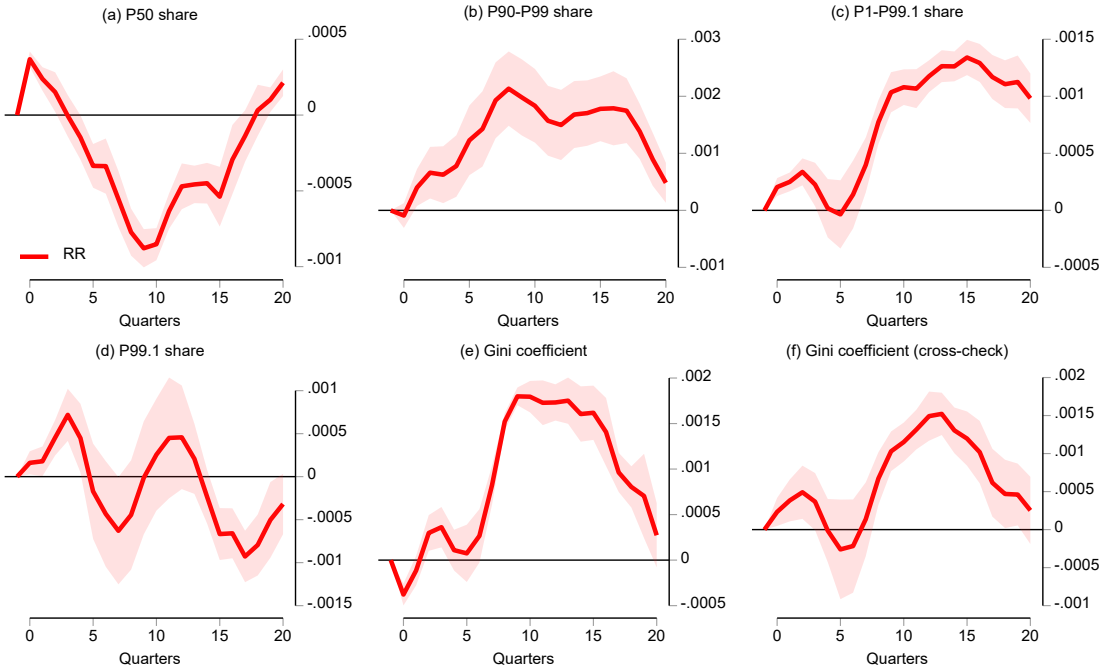
An advantage of high-frequency data, in this case quarterly time series, is that more observations are available to estimate relationships between variables with more granularity and more degrees of freedom in the sense that delineating between different time periods of study carries less risk of overfitting. In this instance, we split the observations into two main periods of interest: (1) the two decades before the pre-

Greenspan era Fed and (2) during Greenspan's tenure in which asset prices, particularly the stock market, were an implicit target of monetary policy. How do these two eras compare in terms of the effects of expansionary monetary policy?

Figure 6 plots the wealth share responses to 100bp expansionary monetary policy estimated between 1976.Q1 and 1980.Q4. 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 Figure 4. Only instrumental RR shocks are presented because GK shocks are unavailable for the 1970s.

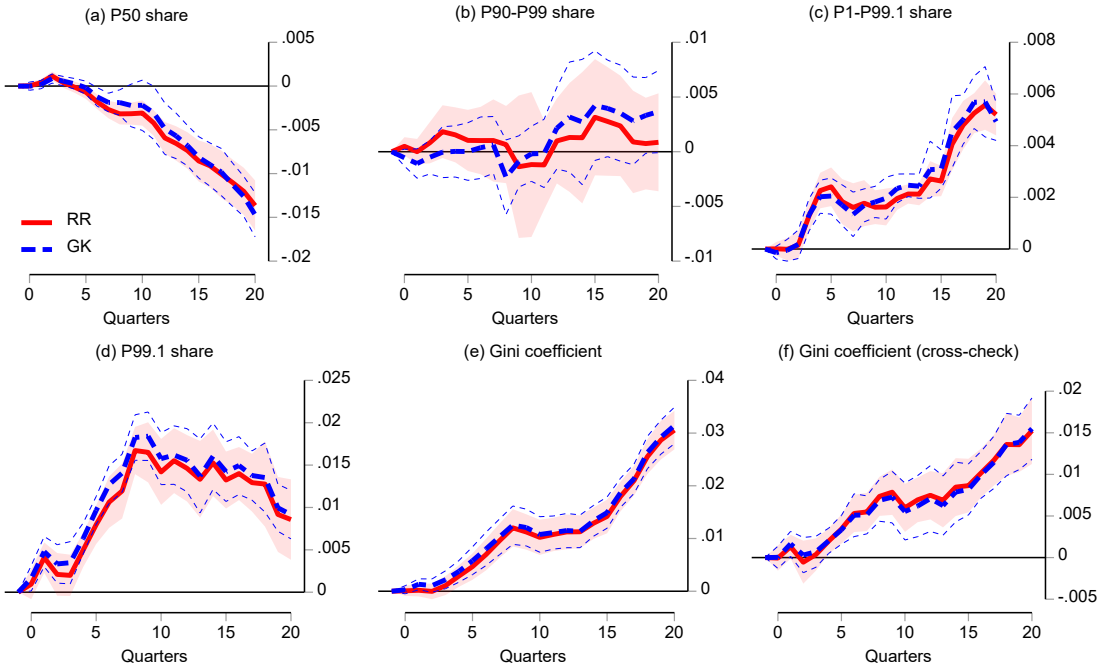
The results indicate that the effects of expansionary policy were both more modest and transitory over the medium term. The bottom 50% wealth share declines by 0.05 percentage points while the top 10 percent gain, more precisely, the group between the top 10 percent and top 1 percent (P90-99) and the group between the top 1 and 0.1 percent as shown in panels (b) through (c). Overall wealth inequality, as measured by the Gini coefficient in panels (e) and (f), indicates a rise between 0.0015 and 0.002 after ten quarters, or two and half years, but eventually subsides after five years.

Fig. 6: The effect of monetary policy from the mid-1970s through the 1980s.



Notes: This figure shows response estimates to a 100bp expansionary policy using RR shocks as the instrument. Only the RR measure is available going back to the mid-1970s to estimate the effect with the LP-IV approach. Results are 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. Panel (e) Gini coefficient is 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; see Appendix A.2 for the methodology.

Fig. 7: Effect of monetary policy during the 1990s through the mid-2000s.



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

Figure 7 reports response estimates between 1990.Q1 and 2006.Q4 using, again, both 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 Figure 4. On average, net wealth shares for bottom 50 percent fall by 0.01 percentage points after five years, while rising for the top 1 percent overall and with much of the accrual going to the top 0.1 percent. Per panel (e) of figure 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 that could be overstated, increasing around only 0.015. In either case, the effect registers more than double the Gini increase of 0.005 found in Figure 4.

4.2.2 Accounting for business cycles

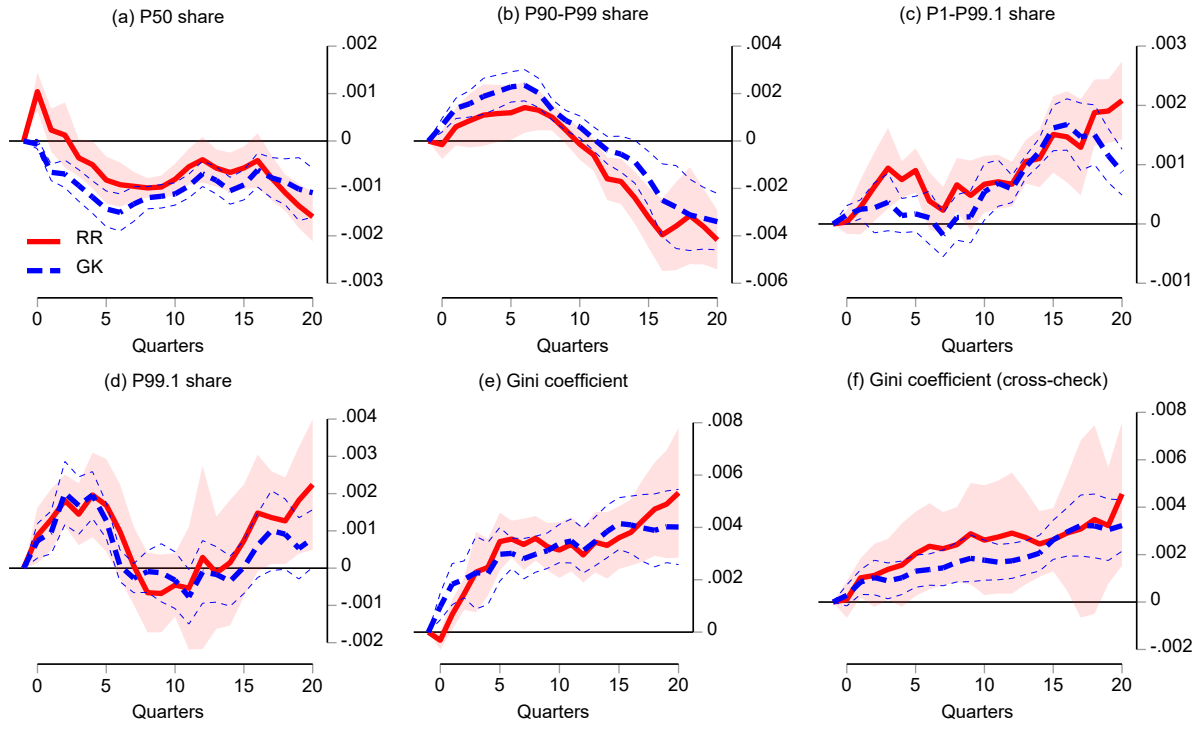
Fed officials set monetary policy in response to the business cycle, increasing the policy rate when economic expansions are perceived to carry the risk of inflation and cutting the rate at signs of a recession—in many cases the recession is the result of Fed tightening itself. Previous empirical evidence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

Figures 8 and 9 present our results of 100bp expansionary MP shock on the wealth shares and the Gini coefficient during economic recessions and expansions, respectively. To obtain the estimates both figures, we modify the specification of lag control variables in equation (2), substituting the vector of macro variables of the unemployment rate, GDP growth rate, 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 figure 8, to determine the effects during recessions, we constrain observations between 1980.Q1 and 2012.Q4 to those in which the recession indicator is equal to 1 or was equal to 1 in the past two quarters, i.e., up to 6 months after a recession has occurred. We believe this is a reasonable (and even conservative) constraint formulation given that recessions have long lasting effects—well beyond 6 months—which are likely to influence the wealth dynamics of households. For figure 9, we constrain the indicator to only observations in which the dummy is equal to zero.

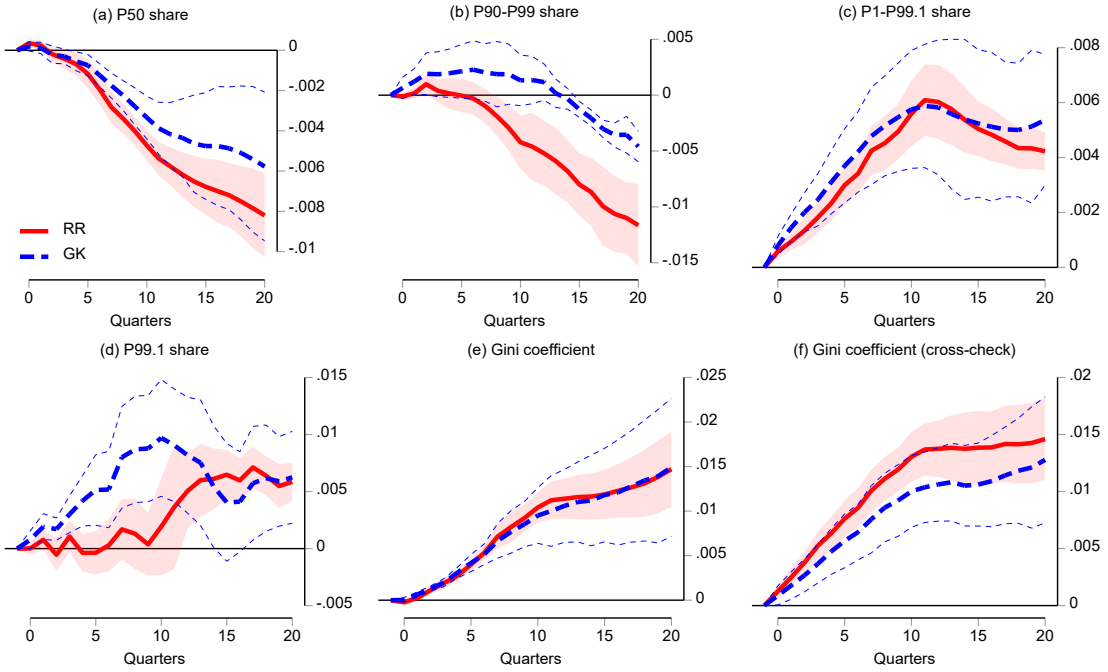
The results shown in figures 8 and 9 suggest that expansionary MP has larger effects during economic expansions than contractions. The patterns are similar in both cases, but the magnitudes vary in terms of the change in the distribution. The bottom 50 percent (panel (a)) share declines, as does the next 9 percent (panel (b)), while the top 1 percent generally gain (panels (c) and (d)). The Gini coefficient (panel (e)) rises by about 0.005, which is the outcome effect in our baseline results in figure 4. This suggests economic recessions may have larger countervailing effects that push in the other directions and are more influential on wealth dynamics—which is also evident in this particular measure as wealth inequality has declined since the Great Recession. In figure 9, a 100bp expansionary MP shock increases the Gini coefficient by 0.015. The cross-check Gini in panel (f) of figure 9 also indicates approximately the same magnitude by RR shock estimates but a little less by GK shock estimates.

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 100bp expansionary cut to the policy rate. Observations are constrained to periods with an economic expansion, as indicated by the NBER business cycle indicator.

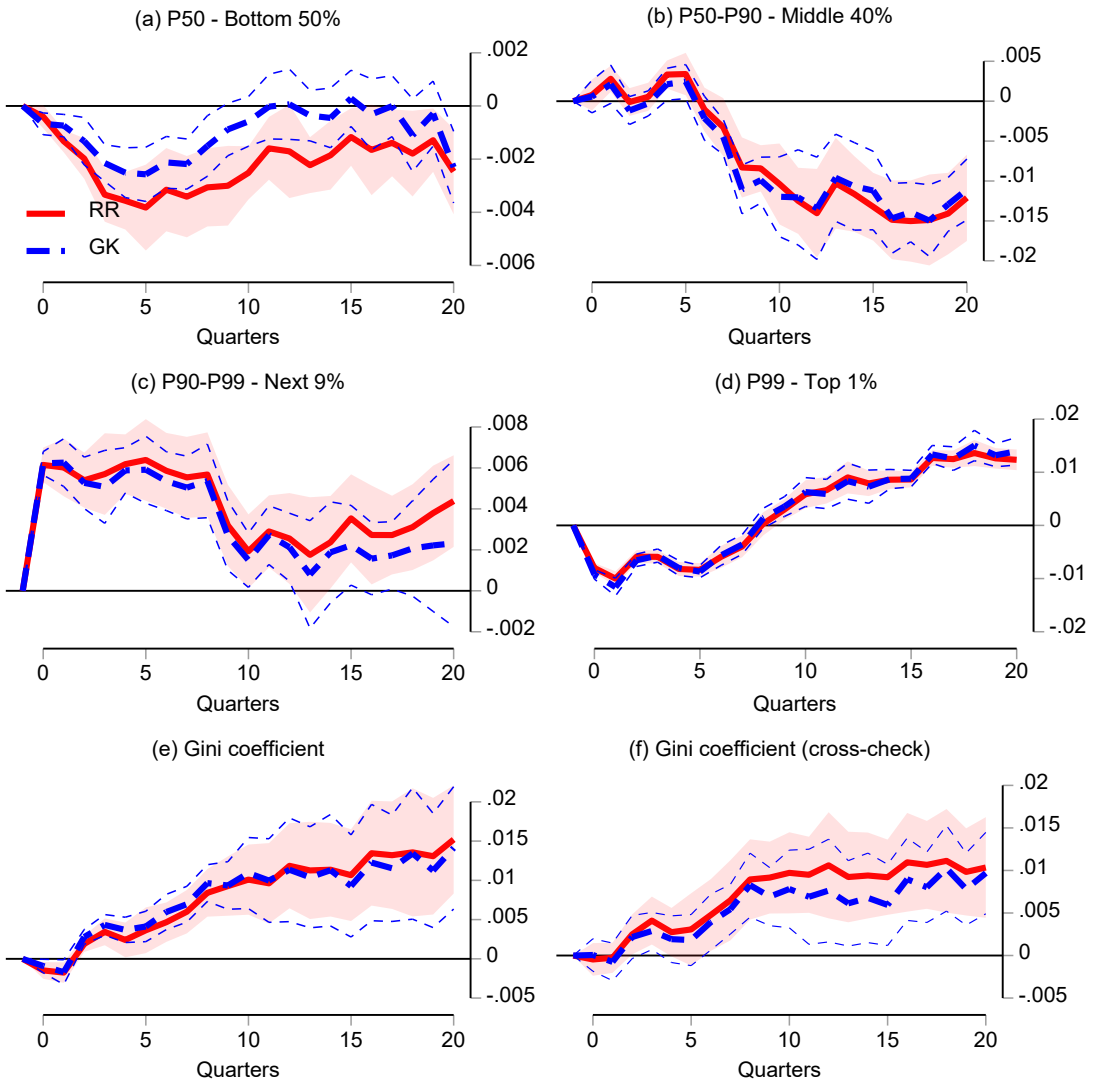
4.2.3 DFA wealth data

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

To this end, we estimate impulse responses of wealth shares using data from the DFA as the dependent variable. The results are reported in figure 10 for four mutually exclusive percentile groups: the bottom 50 percent (P50), the middle 40 percent (P50-90), the next 9 percent, i.e., the top 10 percent minus the top 1 percent, and the top 1 percent. 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). To reiterate, the definition of net wealth with this dependent variable differs from the one from Realtime Inequality—this measure contains only marketable assets and liabilities. The observation period is also shorter, extending from 1989.Q3 to 2012.Q4.

The results from figure 10 also indicate expansionary monetary policy has a statistically significant and sustained effect on the wealth distribution. Both the bottom 50- and middle-40 percent shares decline, but more significantly for the latter, while the next 9 percent and top 1 percent increase (see panels (a) through (d). The Gini coefficient in panel (e) indicates the overall distribution becomes more unequal as the Gini index rises to 0.015 after five years. The cross-check Gini in panel (f) suggests the increase may be lower, around 0.01. Overall, the results confirm the same relationship to expansionary monetary policy despite being from an alternative construction of the wealth distribution from the Federal Reserve itself.

Fig. 10: Response of DFA wealth statistics to 100bps expansionary policy rate shock**.**



Notes: This figure shows response estimates of the wealth shares to surprise 100bps expansionary shock to the policy rate. The measure is real net wealth shares by percentile group computed from the DFAs. 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 G.K. shocks. Confidence intervals are obtained from Newey-West robust standard errors.

4.3 Estimating the historical contribution of monetary policy to wealth inequality

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 that all else is constant over the horizon estimated. 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 has heterogenous 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' purport 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.[4] 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 Figure 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.

Figure 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.

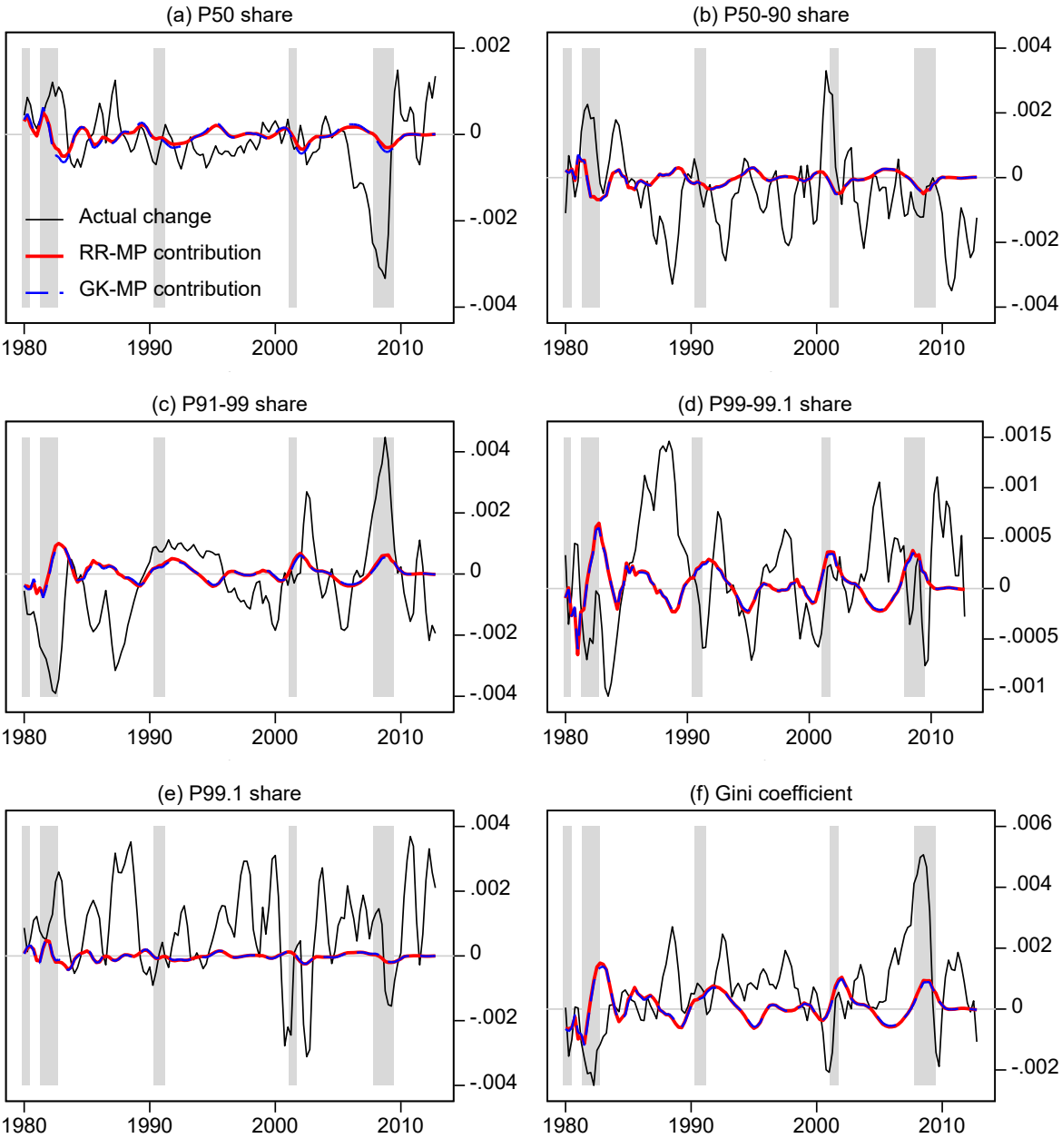
The actual and predicted changes in the Gini coefficient in Figure 11, panel (f), are delineated in Table 2 by decade until the GFC for a cursory comparison. Based on this arbitrary cut, the results in Table 2 indicate that monetary policy has increased in inequality during the 1980s and 1990s and had a relatively neutral effect during 2000s leading up to the GFC with wealth inequality rising in the early 2000s and then declining. During the GFC and subsequent recession, which officially starts in 2008 and ends in the second quarter of 2009, inequality is falling before then rising again, coinciding with the first round of QE between November of 2008 and March of 2010. Per the S&P 500 index, the stock market recovery was also well underway by the end period while the U.S. housing market was still tumbling, only reaching its trough in 2011 before starting to recover 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. But our approach primarily focuses on conventional policy effects through the Federal Funds Rate, not the effects of large-scale securities purchases.

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

On a final note, not too much should be read into the results of Table 2. As should be evident from Figure 11, another delineation would reveal periods when Fed policy is reducing inequality. Furthermore, we conduct this exercise also with the DFA wealth data. The results are reported in Appendix B, Figure B.1 and Table B.2, and we see substantially more correlation between predicted changes in wealth shares and the Gini coefficient and MP shocks. Table B.2 also indicates that the Gini coefficient declined in most periods since 1991. The variation in results between unique methodological constructions of wealth shares confirms no one measure of wealth should be relied on to draw firm conclusions about monetary policy as either an entirely equalizing or disequalizing force on the wealth distribution at this juncture.

[4] It should be noted that this is a substantively different procedure than estimation by local projections. In Coibion et al., 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.

Fig. 11: Contribution of MP shocks to the historical variation in wealth inequality**,** 1980.Q1-2012.Q4



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

Table 2: 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	1980q1-2012q4
Net change, actual Gini	-0.003	0.034	0.021	0.019	0.009	0.080
RR-MP contribution	0.003	0.005	0.000	0.006	0.000	0.013
GK-MP contribution	0.002	0.004	0.000	0.005	0.000	0.012

Notes: Estimates derived from prediction model. Dates 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.

5 Conclusion

This paper has studied the question of whether monetary policy affects wealth inequality. Prior studies have mainly focused on the effects of unconventional policy on the wealth distribution. However, conventional central bank policy has received relatively less attention. Our findings add to the varied results in the literature so far.

Our empirical analysis focuses on conventional monetary policy in the U.S. post war period. Estimating throughout the 1976-2012 period, we find that, on average, expansionary monetary policy shocks of 100 basis points increase the share of the wealth at the top and lower it for the bottom and middle part of the distribution. We also estimate the effect on the Gini index of net wealth, probably the most well-known inequality metric, and find that the Gini coefficient increases by 0.005 points, or half a basis point, on a Gini scale bounded between 0 to 1. These effects are statistically significant and persistent over the medium term, defined as five years.

Analyzing from the mid-1970s through 1980s, we also find that the effects of expansionary monetary policy on the wealth distribution were weaker and transient. However, the effects of conventional monetary policy appear to have increased in importance over the 1990s and early 2000s. During the Greenspan era as Fed chair, expansionary monetary policy increased the Gini coefficient, on average, between 0.015 and 0.03 points. We also find that the magnitude of the effect is greater during economic expansions versus contractions.

Lastly, we conduct an exercise that 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 wealth shares and the Gini coefficient. Furthermore, the correlation appears larger when estimated on wealth statistics constructed from the Federal Reserve's Distributional Financial Accounts.

The role of the Federal Reserve in exacerbating income and wealth inequality is still a hotly contested question. The public debate has focused chiefly on unconventional monetary policy. However, our results complement the narrative that Fed policy has increasingly used wealth effects to influence the economy through conventional monetary policy, which has at times exacerbated the wealth gap while also ameliorating it at others. In either case, monetary policy is not neutral. More research is required to understand the conditions under which even conventional monetary policy does exacerbate inequality and what policy offsets are necessary under an economic governance structure reliant on interest rate policy to manage economic activity.

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Appendix A

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

The Realtime Inequality conveniently provides data on shares of wealth as well the respective shares of the population attributed to pre-defined percentile groupings. However, Realtime does not report the broad measure of inequality commonly used, the Gini coefficient. 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, 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.

Recall, the wealth percentile groups used in our analysis 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:

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

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

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 pre-defined 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 which represents the total population; the quotient of the 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 pre-defined 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 straight forward and merely involves multiply 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 overtime: 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) 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 many cases there is a small discrepancy as the sum of all cumulative wealth share changes do not always add up to exactly to zero but come very close.

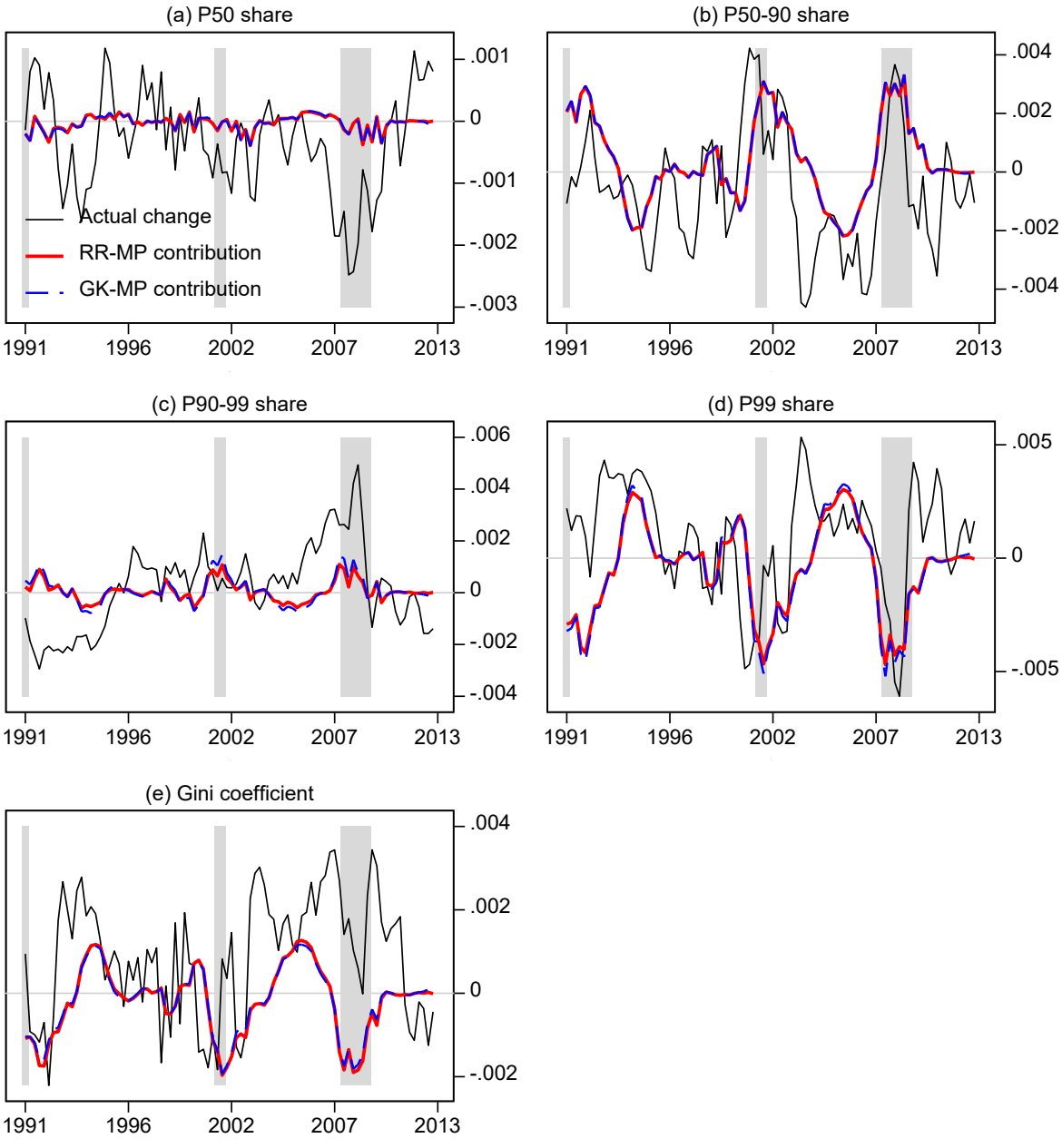
The main point of the cross-check analysis is to ensure that the estimates in wealth shares are consistent with direct estimates on the Gini coefficient as a dependent variable of the LP-IV approach and to detect any major statistical artefacts or anomalies that might lead us to make inaccurate conclusions.

Appendix B

Table B.1: Financial market indices and macroeconomic variables, and their sources

Variable	*Description*	*Time period*	*Source*
Policy rate	Effective Federal Funds Rate	1970q1 - 2022q4	FRED
Equity prices	S&P 500 index	1970q1 - 2022q4	Bloomberg
Gov. bond yields	10-yr constant maturity Treasury note yield	1970q1 - 2022q4	FRED
Real estate prices	Case-Shiller Home Price Index	1970q1 - 2022q4	Shiller (2015)
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
Deflator	R-CPI-U-RS	1977q4 - 2022q4	BLS

Fig. B.1: Historical contribution of MP on the wealth distribution: DFA data, 1990.Q1-2012.Q4



Notes: This figure plots the predicted changes in DFA wealth share levels by percentile group and the Gini coefficient, between 1991.Q1 and 2012.Q4 from monetary policy shocks estimated using RR shock instruments (red line) and from 1991.Q1 to 2012.Q2 using GK shocks instruments (blue line) against actual changes in the dependent variable (thin black line). All plotted series are centered three-quarter moving averages. The gray shaded areas are U.S. recessions according to NBER.

Table B.2: Historical MP contribution to changes in Gini coefficient, DFA data, 1991-2012

	Greenspan [a]	***Greenspan - Bernanke*** [a]	***QE1 - GFC & recession*** [b]	***QE - Recovery*** [b]	***Whole period*** [c]
	1991-1999	2000-2007	2008-2010q1	2010q2-2012q4	1991q1-2012q4
(Net) change, actual Gini	0.0225	0.0367	0.0154	0.0022	0.0767
RR-MP contribution	-0.0056	-0.0020	-0.0107	-0.0001	-0.0184
GK-MP contribution	-0.0052	-0.0018	-0.0099	0.0000	-0.0169

Notes: Estimates derived from 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.