Unconventional Monetary Policy Shocks and their Distributional Implications*

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Abstract

We identify a novel series of unconventional monetary policy shocks for the U.S. by combining Romer and Romer's narrative identification strategy with Wu and Xia's shadow federal funds rate. This yields a unified metric of monetary shocks during the zero-lower bound period. We find that unconventional monetary policy is effective in stimulating the economy, but comes at the cost of higher wealth inequality. In particular, stock prices rise more than house prices, benefiting wealthier households over the middle class.

Keywords: Monetary policy and shocks, Wealth inequality, Household portfolios

JEL-Codes: E32, E52, G51

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1 Introduction

In the 15 years since the Great Recession, the lower bound on policy rates has forced many central banks into uncharted territory. During this period, monetary authorities have used unconventional monetary policy (UMP) in various forms, including forward guidance, asset purchases, collateral requirements, and others. The impact of these measures on the stance of monetary policy, their effectiveness in stimulating economic activity, and their association with side effects such as increased inequality remain unresolved. In this paper, we introduce a novel approach to measure UMP shocks through the shadow rate concept developed by Wu and Xia (2016), which captures the comprehensive effects of UMPs in a unified metric. Our results suggest that UMP shocks increase economic activity in comparable ways to conventional policy rate adjustments, but come with a trade-off in terms of exacerbated wealth inequality.

Our identification strategy follows the narrative approach of Romer and Romer (2004). The idea behind Romer and Romer's methodology is to regress changes in the federal funds rate on the Federal Reserve's own forecasts. In this way, they are able to control for the central bank's information set and thus obtain a measure that captures the exogenous component of monetary policy changes. However, given the effective lower bound on the federal funds rate from 2009 to 2016, this method was not feasible and has so far not been used to study unconventional policies. To address this limitation and maintain the transparent strategy of Romer and Romer, we combine their approach with the shadow rate of Wu and Xia. The shadow rate is widely used to represent the monetary policy stance, and has the advantage that it can be below zero. This captures the effects of unconventional policy in a single, easy-to-understand measure that can be directly compared with conventional monetary policy (CMP).

CMP shocks were relatively small during the Great Moderation, with a standard deviation of about 15 bps. We find that this trend continues for UMP shocks, with a standard deviation of about 10 bps. Moreover, unlike the CMP series, which have been shown to be serially correlated and predictable, our new UMP measure appears to be more robust to these concerns according to a number of diagnostics. Finally, we update Wieland and Yang (2020) through the end of 2008, which, in combination with the new UMP series and the inclusion of the most recently published Tealbook/Greenbook forecasts, allows us to provide the most comprehensive series of monetary shocks currently available for the Romer and Romer identification approach.[1]

[1] https://github.com/ralphluet/ump_shocks

We find that unconventional policy is as expansionary as nominal interest rate cuts. In both cases, a negative shock lowers the interest rate on impact, but while the CMP typically leads to a minimum interest rate just three months after the shock, the effect of the UMP builds up much more slowly, reaching a trough of 45 basis points almost a year later. The higher persistence is also present in the remaining variables. Industrial production experiences an immediate positive effect that rises slowly to reach a peak of almost 3%, around the same time as the interest rate is at its minimum. The reaction of inflation is muted, but does not show a price puzzle. In particular, the CPI rises in the first year, with a maximum increase of just over 0.5%.

Although this suggests high substitutability between the two types of monetary policy, we show this is not the case when considering distributional consequences. Coibion et al. (2017) document that expansionary CMP shocks reduce consumption and income inequality. We find that the wealth share of the top 10% falls by 1.2% two years after the shock. However, UMP shocks increase wealth inequality, peaking at a 1.5% increase in the top 10% share. This difference arises from the distinct effects on stock and house prices. Expansionary UMP shocks significantly boost stock prices relative to house prices, while CMP lowers the stock-house-price ratio, aligning with wealth dynamics. This is consistent with Kuhn et al. (2020), who show that the evolution of wealth inequality in the U.S. is strongly influenced by relative changes in these asset prices. Using the Survey of Consumer Finances, we find that asset price reevaluations explain up to half of the distributional consequences of monetary policy.

This paper contributes to identifying and assessing the effects of monetary policy, particularly unconventional measures. Most of the literature relies on the narrative approach or high-frequency event studies, following Romer and Romer (2004) and Kuttner (2001).[2] The identification of UMP shocks typically uses the high-frequency method. Gürkaynak et al. (2005) highlight the importance of forward guidance for asset prices, further explored by Gertler and Karadi (2015). More recently, Swanson (2021) adds asset purchases to this analysis. Inoue and Rossi (2021) suggest identifying UMP effects by examining shifts in the entire term structure, obtaining "functional" monetary policy shocks. Following Wright (2012), Jarociński (2024) identifies UMP shocks based on heteroskedasticity. Our narrative strategy contrasts these measures for UMP while requiring less data and imposing fewer assumptions.

[2]Several studies have improved these strategies. For example, Aruoba and Drechsel (2023) uses machine learning to improve the narrative approach, while Jarociński and Karadi (2020) and Miranda-Agrippino and Ricco (2021) address the information effect in central bank announcements that may distort high-frequency identified shocks.

With our novel monetary shocks, we contribute to the empirical literature on the aggregate effects of unconventional monetary policy. Our results align with Miranda-Agrippino and Ricco (2023), who use factors derived by Swanson (2021). Swanson (2024) extends this by including the Fed's response to news, finding smaller but puzzling effects on output and inflation compared to ours. Bundick and Smith (2020) and D'Amico and King (2023) find, like us, more persistent effects from UMP. In terms of magnitude, D'Amico and King (2023) also indicates larger effects of UMP compared to CMP. Overall, we provide further evidence supporting the "irrelevance hypothesis" by Debortoli et al. (2020), who find that monetary policy at the ZLB is as effective as traditional measures in influencing interest rates, output, and inflation.

Our final contribution concerns the impact of monetary policy on inequality. Although there is extensive literature on conventional monetary policy (e.g., Coibion et al. (2017); Furceri et al. (2018)), evidence for unconventional policy is scarce and mostly inconclusive.[3] The closest paper to ours is Mangiante and Meichtry (2023), which uses a SVAR model and Swanson (2021)'s factors to compare the effects of conventional monetary policy and forward guidance on consumption inequality. We find similar results for wealth inequality. Regarding the transmission channel, Lenza and Slacalek (2024) argue that UMP's effect on inequality is largely determined by its impact on employment. However, our analysis suggests that asset prices are the main channel through which monetary policy affects wealth inequality.

The paper is organized as follows: Section 2 derives our novel UMP shocks and provides diagnostics. Section 3 reports empirical evidence on the effects of UMP on aggregates, wealth inequality, and stock and house prices. Section 4 concludes.

2 Identification of Unconventional Monetary Policy Shocks

We construct a time series of unconventional monetary policy shocks by building on the identification strategy of Romer and Romer (2004). Specifically, we implement their Taylor rule-type regressions but replace the federal funds rate with the shadow federal funds rate derived in Wu and Xia (2016). Using the shadow rate, we are able to summarize the monetary policy stance during the

[3] Colciago et al. (2019) provides a detailed review of the literature on UMP's effects on income and wealth inequality.

ZLB period by a one-dimensional metric, which we then use to derive a series of monetary policy shocks.

As Wu and Xia (2016) show, their computed shadow rate has similar dynamic correlations with standard macroeconomic variables in the 2009-2016 period as the federal funds rate had with the same variables in the earlier period.[4] The shadow rate uses the entire yield curve to impute the implied, possibly negative, short rate. Therefore, because the federal funds rate was effectively constant from 2009 to 2016, we interpret the series of monetary shocks as resulting from unconventional monetary policy.

To accomplish this, we regress the change in the shadow rate at each FOMC meeting m, Δsff_m, on the Greenbook forecasts of real GDP growth, inflation and unemployment.

$$\Delta sff_m = \alpha + \beta sff_{m-1} + \sum_{i=-1}^{2} \gamma_i F_m \Delta y_{m,i} + \sum_{i=-1}^{2} \lambda_i (F_m \Delta y_{m,i} - F_{m-1} \Delta y_{m,i}) + \sum_{i=-1}^{2} \varphi_i F_m \pi_{m,i} + \sum_{i=-1}^{2} \theta_i (F_m \pi_{m,i} - F_{m-1} \pi_{m,i}) + \mu_i F_m ue_0 + \varepsilon_m^{UMP}, \quad (1)$$

where sff_{m-1} is the level of the shadow rate prior to the m meeting. $F_m \Delta y_{m,i}$ is the forecast of output growth made for the m FOMC meeting. The subscript i indicates the horizon of the forecast relative to the date the forecast was made. Specifically, -1 refers to the previous quarter, 0 refers to the current quarter, and 1 and 2 correspond to one and two quarters ahead, respectively.[5] Similarly, $F_m \pi_{m,i}$ for inflation and $F_m ue_0$ for unemployment. For the latter, as usual, we only consider the forecast for the current quarter. Thus, similar to Romer and Romer (2004)'s definition of policy shocks, the residuals ε^{UMP} of this regression are defined as exogenous *unconventional* monetary policy shocks.

2.1 Descriptive evidence

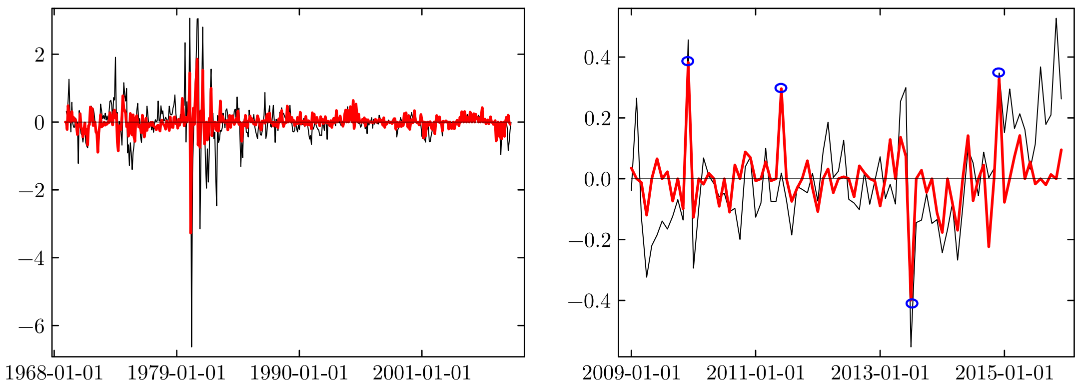
Figure 1 shows the monetary policy shocks along with changes in the (shadow) federal funds rate. Specifically, panel (a) of this figure shows the first-difference of the federal funds rate and Romer and Romer (2004)'s conventional monetary policy shocks, which we re-estimate and extend to December 2008 building on Wieland and Yang (2020)'s corrections. Panel (b) plots our new measure of un-

[4]Bullard (2012) and Krippner (2012) also point to the use of the shadow rate as an appropriate proxy for describing the stance of monetary policy.

[5]The forecast of the previous quarter is substituted for the realized value.

Figure 1: New measure of unconventional monetary policy shocks

(a) **Conventional MP** (b) **Unconventional MP**



Note: Monetary policy shocks (thick red line) and changes in (shadow) federal funds rate (thin black line). Conventional MP corresponds to the period from 1969 to 2008, while unconventional MP spans 2009 to 2016.

conventional monetary policy shocks and the first-difference of the shadow rate. At first glance, the UMP shock series appears to be more moderate in magnitude, following the trend of the CMP shocks during the Great Moderation. The standard deviation of the UMP shocks is 10 bps, which is comparable to the standard deviation of 15 bps for the CMP shocks prior to the ZLB.

Overall, the UMP shock series captures some of the most important policy announcements. We highlight some of these relevant periods with the blue circles in Figure 1 panel (b). From left to right, the first circle corresponds to the December 2009 FOMC meeting. On that date, the Fed made two important announcements that are consistent with the large contractionary shock we identify. First, it announced its intention to gradually reduce the pace of LSAPs from the QE1 program. Second, it announced the end of most of the special liquidity facilities by February 1, 2010. The contractionary shock marked by the second circle coincides with the announcement of the end of QE2 at the June 2011 FOMC meeting. The UMP series is also able to capture the so-called "taper tantrum" episode. We clearly identify a contractionary shock when the Federal Reserve signaled a likely end to LSAPs around May 2013, followed by a large expansionary shock marked by the third blue cycle when the FOMC unexpectedly decided not to begin tapering. Finally, the last circle corresponds to December 2014. At that meeting, the Fed issued several forward guidance statements that signaled a possible increase in the federal funds rate "sooner than currently anticipated".

2.2 Shock diagnostics

The standard Romer and Romer (2004) narratively identified monetary policy shocks for conventional policy have been criticized for lacking a number of properties that are desirable in shock series.[6] Since we base our new measure of UMP shocks on the same strategy, we conduct a number of diagnostics that are widely used in the literature. In particular, we test for serial correlation and predictability of the shock series using two sets of tests for each of these issues.[7] Using the autocorrelation function, we find that none of the lags considered are larger than the 95% confidence bands in absolute terms. Therefore, serial correlation is not an issue compared to CMP shocks. This is also supported by looking at the F statistic and the corresponding p value of an AR(4) regression, which clearly do not reject the joint insignificance of the estimated coefficients. For the predictability of the shock series, using several common macro-financial variables, we do not find any to Granger-cause the UMP shock series. Moreover, testing for the joint significance of the coefficients in the regression with Miranda-Agrippino and Ricco (2021)'s factors leads to a clear rejection of the null hypothesis and thus also of the predictability of the shock series.

3 Effects of Unconventional Monetary Policy Shocks

To estimate the dynamic causal effects of the UMP shocks, we use the local projection method of Jordà (2005). Specifically, we estimate the following regression,

$$x_{t+h} = \alpha_h + \theta_h \varepsilon_t^{UMP} + \boldsymbol{\beta}_h' \boldsymbol{Z}_{t-1} + u_{t+h}, \tag{2}$$

where x_{t+h} is the variable of interest, h periods after the shock. ε_t^{UMP} is the UMP shock. $\boldsymbol{Z}_{t-1}$ is a vector of controls. Finally, u_{t+h} is a serially correlated error term.

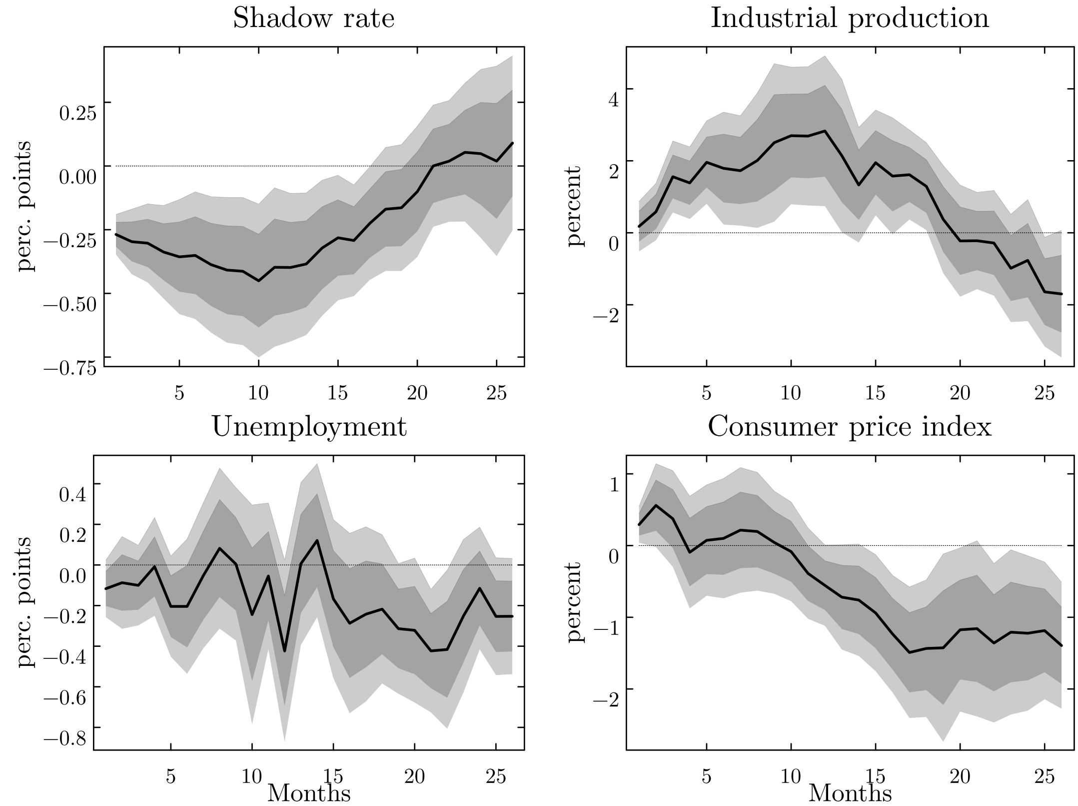
3.1 Aggregate effects

First, we examine the dynamic effects of UMP shocks on aggregate macroeconomic variables. Following Ramey (2016), we include two lags of the monetary policy shock, the federal funds rate, the log of industrial production, the log of

[6]See, for example, Ramey (2016) and Miranda-Agrippino and Ricco (2021).

[7]In the Appendix B we provide more details on the results of these diagnostics.

Figure 2: Empirical responses for aggregate variables



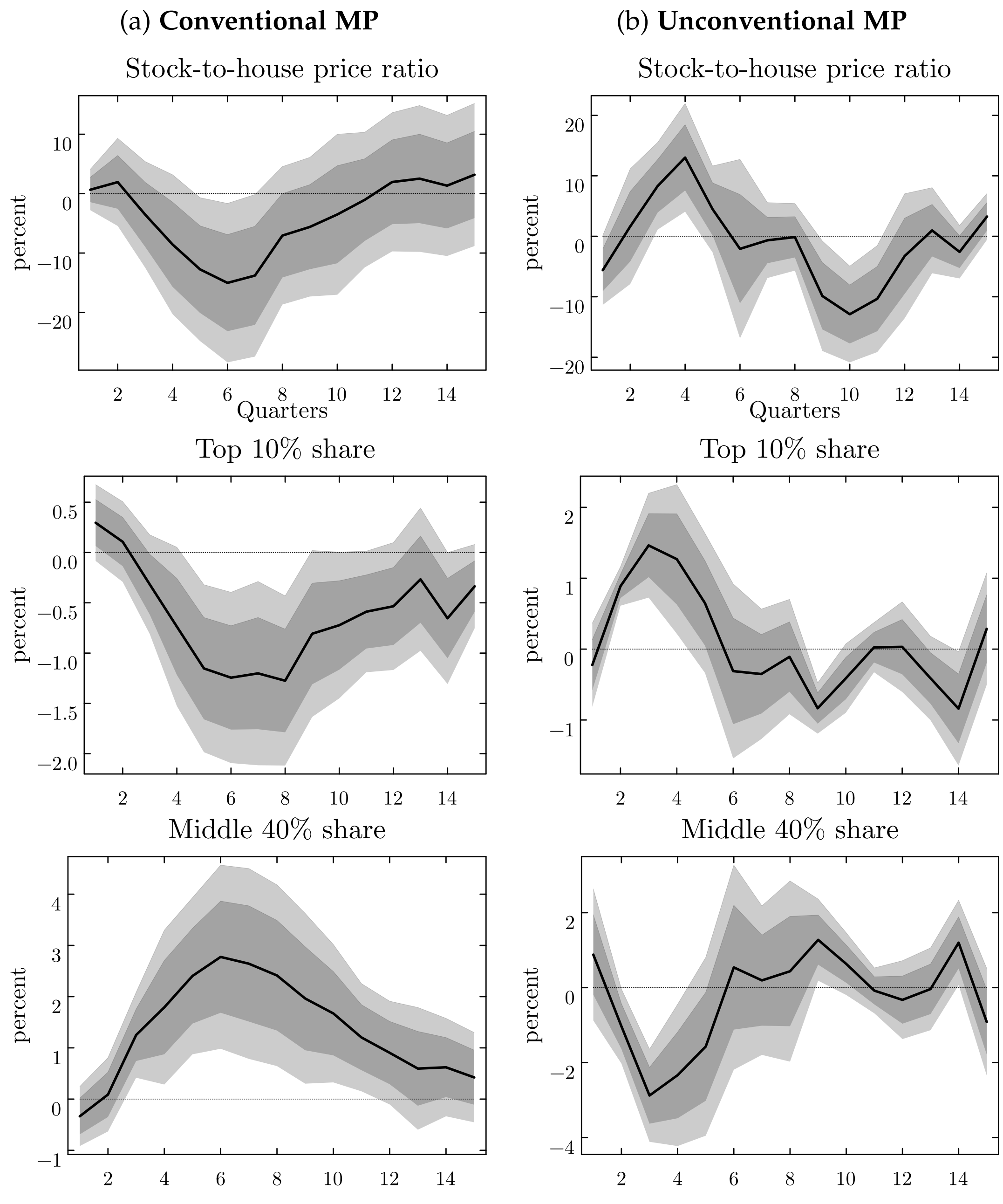
Note: Impulse responses to a one standard deviation expansionary UMP shock. Light (dark) gray areas are 90 percent (68 percent) confidence intervals based on Newey and West (1987) standard errors.

the CPI, the commodity price index, and the unemployment rate as controls. For the UMP shock, we replace the federal funds rate with the shadow rate.
In Figure 6, we report the impulse responses from UMP shocks. Starting with the effect on the interest rate, we find it falls by an amount similar to that usually found for CMP. Compared to interest rate cuts, the effect of UMP shocks on the interest rate appears quite persistent. After the initial drop, it continues to fall slowly for about ten months, reaching a trough of 45 bps. This higher persistence is also passed to other variables. Industrial production barely reacts on impact, building up slowly and peaking at around 2.8% twelve months after the shock. The effect on unemployment is more erratic, but the average effect is a decrease of around 0.18 percentage points, with a minimum decrease of 0.42 percentage points twelve months after the shock. For these variables, the effects are more persistent but the implied elasticities comparable to CMP. Appendix C reports analogous impulse responses from the extended CMP shocks, which are similar to those in Ramey (2016). Finally, the effect on inflation is moderate and does not show an initial price puzzle. In the first twelve months, the CPI rises by 0.56% at its peak, then starts to fall as the stimulative effects fade.

3.2 Effects on wealth inequality

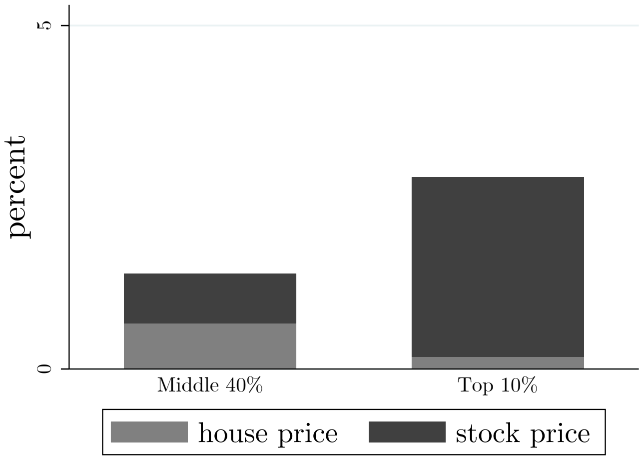
To see the impact on inequality, we use data from Survey of Consumer Finances (SCF) and the Distributional Financial Accounts (DFA). The latter is a quarterly dataset produced by the Federal Reserve Board based on the SCF and aggregate measures from the Financial Accounts. This allows us to study the impact of monetary shocks on different parts of the wealth distribution. Specifically, we summarize the effect on wealth inequality by looking at the wealth shares of the top 10% and the middle 40%. In the Appendix we show the response for more percentiles individually.
Since the DFA variables are only available quarterly, we transform the previously identified shocks to a quarterly frequency. Finally, due to the smaller sample size, for inference with more degrees of freedom, we include only one lag of the same controls used for the aggregates. Figure 3 plots the impulse responses of the wealth shares for conventional (1989-2008) and unconventional monetary policy (2009-2015). The results for conventional policy are consistent with those found by Coibion et al. (2017) in the case of income inequality. Specifically, after an expansionary CMP shock, wealth inequality persistently decreases. At the trough, the decline in the top 10% share is about 1.2%, while

Figure 3: Empirical responses for wealth inequality and asset prices



Note: Impulse responses to a one standard deviation expansionary CMP and UMP shocks. Light (dark) gray areas are 90 percent (68 percent) confidence intervals based on Newey and West (1987) standard errors.

Figure 4: Wealth growth from asset price reevaluations



Note: Growth in wealth attributable to changes in house and stock prices after a UMP shock. This is calculated by taking, for each wealth group, the holdings of each asset multiplied by the asset price change resulting from the impulse response in Figure 3, divided by the total wealth of the specific group. The asset holdings and total wealth correspond to the 2009-2016 period averaged from the Survey of Consumer Finances.

the wealth share of the middle class increases by almost 3%. This contrasts with the case of unconventional policies. Specifically, we find that wealth inequality rises rapidly after an expansionary UMP shock, with a maximum increase of the top 10% share of 1.5%, while the share of the middle class falls by 2.9%.

As we do find similar effects on output and unemployment for conventional and unconventional monetary policy, we turn to asset prices as potential explanation for the differential impact on wealth inequality. Households in the top 10% of the wealth distribution hold a sizable fraction of their wealth in stocks. On the other hand, the typical asset portfolio of the middle class is dominated by housing. Kuhn et al. (2020) show how the different evolution of stock and house prices explains the observed dynamics for wealth inequality in the U.S. over the last 70 years. We find strong evidence that this argument also applies conditional on monetary shocks.

We capture this with the stock-house-price ratio, which we also show in Figure 3. Consistent with our hypothesis, the distributional dynamics follow the pattern of the difference between stock and house prices. A conventional interest rate cut leads to a sustained decline in the relative price of stocks. At the trough, the stock-house-price ratio falls by about 15%. This U-shape is very similar to the dynamics of the top 10% wealth measure. For the unconventional policy, the stock-house-price ratio rises rapidly to a peak of just over 13%, again following very similar dynamics to the wealth inequality response.

The Survey of Consumer Finances allows us to directly estimate the effect of asset prices on individual household portfolios and wealth shares. We follow Kuhn et al. (2020) and construct a decomposition of wealth gains from monetary shocks based on our estimated asset price responses. Figure 4 takes household portfolios from the SCF and then applies the price changes induced by monetary policy to reevaluate asset positions. The relatively larger increase in stock prices after unconventional monetary policy primarily benefits households in the top 10% of wealth holdings. Households in the middle 40% over-proportionally benefit from house price gains because of leverage, but this is not enough to compensate for the smaller increase in house prices relative to stock prices. Overall, this direct effect of household portfolio revaluation explains 22% of the increase in the wealth share of the top 10% and about 44% of the decrease in the wealth share of the middle 40% in Figure 3. We do not take into account return heterogeneity within the top 10% or additional portfolio rebalancing that would further amplify the effect of asset price changes.

4 Conclusion

We construct a new series of unconventional monetary policy shocks by replacing the federal funds rate with Wu and Xia (2016)'s shadow rate in the Romer and Romer (2004) narrative method. By focusing on the effective lower bound period between 2009 and 2016, any variation in the shadow rate after controlling for the Fed's information set must be due to unexpected changes in unconventional monetary policy.

Our empirical evidence shows that unconventional monetary policy is as effective as conventional interest rate policy in stimulating the economy. However, UMP and CMP have opposite effects on wealth inequality. Expansionary UMP shocks increase wealth inequality, while interest rate cuts reduce it. We provide evidence that the transmission works through asset prices and the differential exposure of households to stock vs. house prices. Stock prices respond disproportionately to expansionary unconventional policies, redistributing wealth to households at the top of the wealth distribution.

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A Data

A.1 Data for UMP shock identification

To obtain the new measure of unconventional monetary policy we use the following monthly data between 2009M1 and 2015M12,

- **Nominal interest rate**. Wu and Xia (2016) shadow federal funds rate available at the Federal Reserve Bank of Atlanta.[8]
- **Industrial Production**. Tealbook forecast for Q/Q growth in real Gross Domestic Product (gRGDP).
- **Inflation**. Tealbook forecast for Q/Q growth in the price index for GDP (gPGDP).
- **Unemployment**. Tealbook forecast for unemployment rate (UNEMP).

A.2 Data for local projections

To study the aggregate effects, we use monthly series available for the period from 1969M1 to 2015M12. The distributional variables are only available at quarterly frequency from 1989Q3 onwards. Thus, for the analysis of cross-sectional dynamics, we use aggregate variables with the same frequency and time frame. Unless otherwise stated, all variables are obtained from the St. Louis Fed - FRED database.

- **Nominal interest rate**. Federal funds effective rate (FEDFUNDS). From 2009Q1 till 2015Q4 we use the Wu and Xia (2016) shadow federal funds rate.
- **Industrial Production**. Industrial Production: Total Index (INDPRO)
- **Inflation**.Consumer Price Index for All Urban Consumers: All Items in U.S. City Average (CPIAUCSL)
- **Unemployment**. Unemployment Rate (UNRATE).
- **Commodity inflation**. For UMP we use FRED's Global Price Index of all Commodities (PALLFNFINDEXM). For CMP we use CRB Commodity Price Index available in Ramey (2016) dataset.

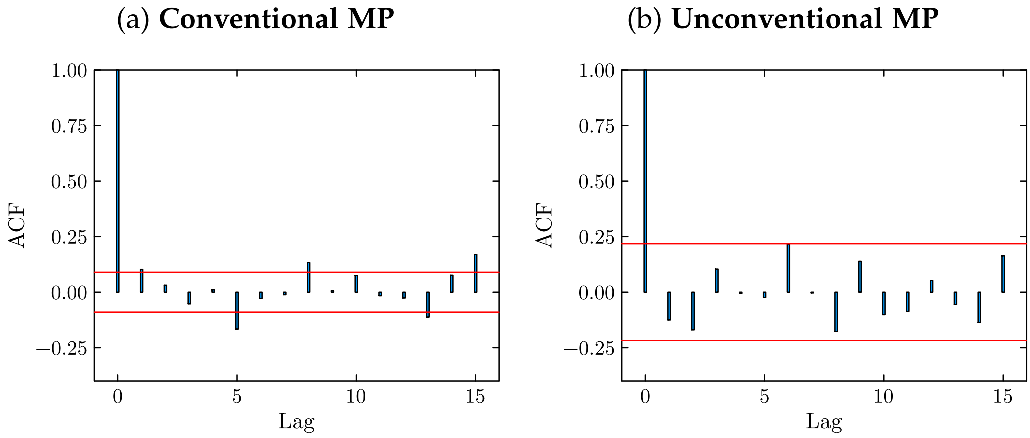
[8]https://www.atlantafed.org/cqer/research/wu-xia-shadow-federal-funds-rate

- **House prices**. S&P/Case-Shiller U.S. National Home Price Index (CSUSHPISA) from 1987M1 onwards.
- **Stock Prices**. Robert Shiller Online Data.
- **Wealth inequality**. Ratio of Top 10% Households divided by Bottom 90% Households from the Fed Distributional Financial Accounts dataset.

B Shock Diagnostics

In this section, we provide more details on the shock diagnostics. As mentioned in the main text, we test for serial correlation and predictability of the shock series, as these are two important concerns in the shock identification literature. Similar to Känzig (2021), we examine each of these properties by looking at the autocorrelation function and Granger causality tests, respectively. In addition, following Miranda-Agrippino and Ricco (2021), we test for serial correlation by regressing the shock on four lags of itself. Whether the shocks can be predicted by past information is tested through the use of ten factors obtained by Miranda-Agrippino and Ricco (2021) through principal component analysis over a hundred of time series. Regardless of the test, we do not find that the series exhibit any serial correlation nor can be predicted by other variables.
Figure 5 (b) shows the autocorrelation function for the UMP shocks. Visually, we can see that none of the lags considered are larger than the 95% confidence bands in absolute terms. Therefore, serial correlation is less of an issue compared to CMP in panel (a) of the same figure. This is also supported by the F statistic and the corresponding p value of the AR(4) regression, which clearly indicate that the joint insignificance of the estimated coefficients cannot be rejected. If we relied only on this test, the CMP would also reach the same conclusion, which is not consistent with the original findings of Miranda-Agrippino and Ricco. However, as can be seen in Table 2, we also consider more lags and find that for UMP it remains insignificant while for CMP there is a clear rejection of the null.

Figure 5: Serial correlation of narrative monetary policy shocks - Autocorrelation function



Note: Autocorrelation function with 15 lags for CMP and UMP shocks. Red lines correspond to the 95% confidence intervals.

Table 1: Granger causality tests of the UMP shock series

Variable	p-value	
	CMP	UMP
Industrial Production	0.2483	0.3461
Unemployment rate	0.2159	0.2740
CPI	0.7090	0.6796
Consumption	0.9454	0.3987
S&P 500	0.9002	0.3735

Note: Variables are in first differences to ensure stationarity. Each regression contains 12 lags of the independent variable and a constant.

In Table 1 we report the results for the Granger causality tests. As seen in column 3, we find that none of the macroeconomic variables selected Granger-cause the UMP shock series. Moreover, testing for the joint significance of the coefficients in the regression with Miranda-Agrippino and Ricco's factors, leads, as depicted in Table 3, to a clear rejection of the null hypothesis, and hence of predictability of the shock series.

Table 2: Serial correlation of narrative monetary policy shocks - AR regression

	AR(4)		AR(10)	
	CMP	UMP	CMP	UMP
Constant	-0.0019	0.0009	-0.0022	0.0002
	(0.0002)	(0.0001)	(0.0002)	(0.0001)
shock_{t-1}	0.1035	-0.1403	0.1088	-0.1241
	(0.0257)	(0.0119)	(0.0282)	(0.0149)
shock_{t-2}	0.0267	-0.1775	0.0106	-0.1750
	(0.0056)	(0.0208)	(0.0054)	(0.0253)
shock_{t-3}	-0.0628	0.0713	-0.0371	0.0505
	(0.0042)	(0.0102)	(0.0048)	(0.0101)
shock_{t-4}	0.0180	-0.0061	0.0283	0.0576
	(0.0024)	(0.0152)	(0.0037)	(0.0222)
shock_{t-5}	–	–	-0.1542	0.0466
			(0.0055)	(0.0132)
shock_{t-6}	–	–	-0.0041	0.2049
			(0.0254)	(0.0257)
shock_{t-7}	–	–	-0.0075	0.0577
			(0.0530)	(0.0096)
shock_{t-8}	–	–	0.1223	-0.1222
			(0.0243)	(0.0173)
shock_{t-9}	–	–	-0.0195	0.0587
			(0.0078)	(0.0204)
shock_{t-10}	–	–	0.0464	-0.1557
			(0.0057)	(0.0139)
R^2	0.0151	0.0562	0.0597	0.1411
F-statistic	1.78	1.03	2.92	1.04
p-value	0.131	0.399	0.001	0.425
Observatons	470	74	470	74

Note: Regression of each type of monetary policy shock on four/ten lags of itself. In brackets we report the heteroskedaticity robust standard errors.

Table 3: Predictability of the UMP shock series

	CMP	UMP
Constant	0.0198	0.0192
	(0.0002)	(0.0560)
$f_{1,t-1}$	-0.0270	0.0319
	(0.0003)	(0.1059)
$f_{2,t-1}$	0.0203	0.0005
	(0.0003)	(0.0277)
$f_{3,t-1}$	-0.0299	0.0384
	(0.0003)	(0.0845)
$f_{4,t-1}$	-0.0413	-0.0335
	(0.0007)	(0.1769)
$f_{5,t-1}$	0.0179	0.0279
	(0.0012)	(0.1902)
$f_{6,t-1}$	-0.0152	0.0074
	(0.0003)	(0.0148)
$f_{7,t-1}$	-0.0087	-0.0152
	(0.0008)	(0.0418)
$f_{8,t-1}$	-0.0295	0.0110
	(0.0004)	(0.0255)
$f_{9,t-1}$	-0.0062	0.0180
	(0.0017)	(0.0756)
$f_{10,t-1}$	0.0129	-0.0366
	(0.0005)	(0.0303)
R^2	0.0589	0.1536
F-statistic	2.18	1.09
p-value	0.0185	0.3848
Observations	359	71

Note: Regression of each type of monetary policy on one lag of a set of factors. These factors are constructed by Miranda-Agrippino and Ricco (2021) from a list of macro-financial variables set by McCracken and Ng (2016). In brackets we report the heteroskedaticity robust standard errors.

C Aggregate Effects of CMP shocks

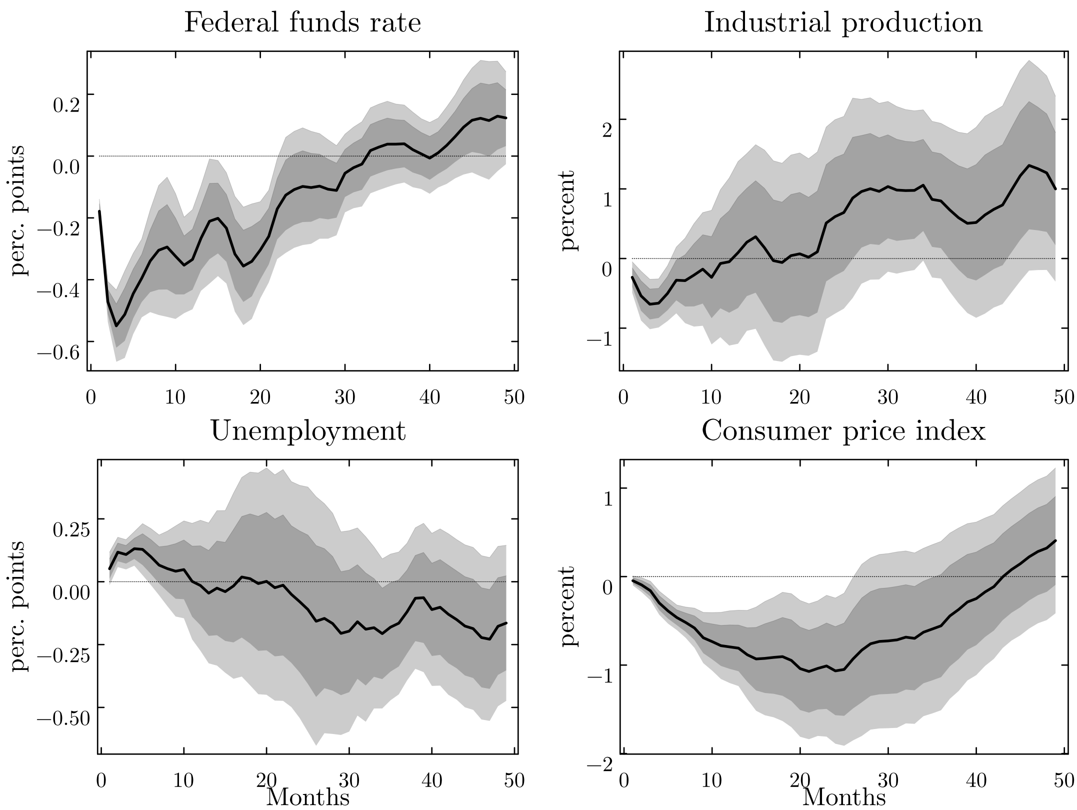
Wieland and Yang (2020)'s update of the original Romer and Romer (2004) narratively identified monetary policy shocks is probably one of the most widely used versions of this shock series. Unfortunately, their extension only goes to December 2007. In this paper, we implement their corrections and further extend the series up to the ZLB.[9]

In Figure 6, we depict the impulse responses estimated using the same methodology and controls as in subsection 3.1. For completeness, we also compare the aggregate effects with those obtained using the time samples of the other available shock series. Figure 7 shows the responses using the original Romer and Romer (2004) shock, while Figure 8 shows the responses using the Wieland and Yang (2020) update. As can be seen by comparing the black solid line with the red dashed line, both shock series yield almost identical results.

In all these cases, even if the dynamics are different from those obtained for the UMP shocks, the peaks and troughs for the interest rate, industrial production, and unemployment are of similar magnitude. This provides strong evidence that unconventional policies are as effective as interest rate cuts in stimulating the economy. For inflation, however, the CMP shocks exhibit the usual price puzzle that is less of issue for UMP shocks.

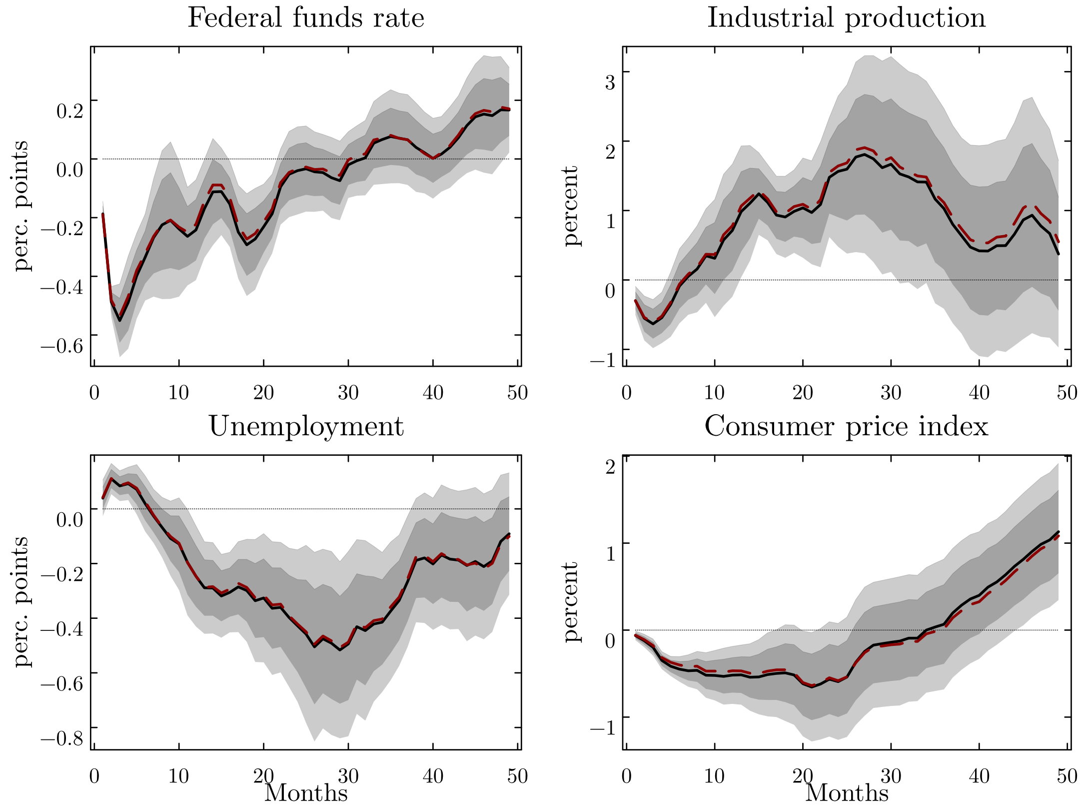
[9] In addition, our code can be easily extended to include newly available data. Here, LINK, you can use the latest available Tealbook forecasts for the period 2016-2018 to estimate monetary shocks using our code.

Figure 6: Empirical responses for aggregate variables



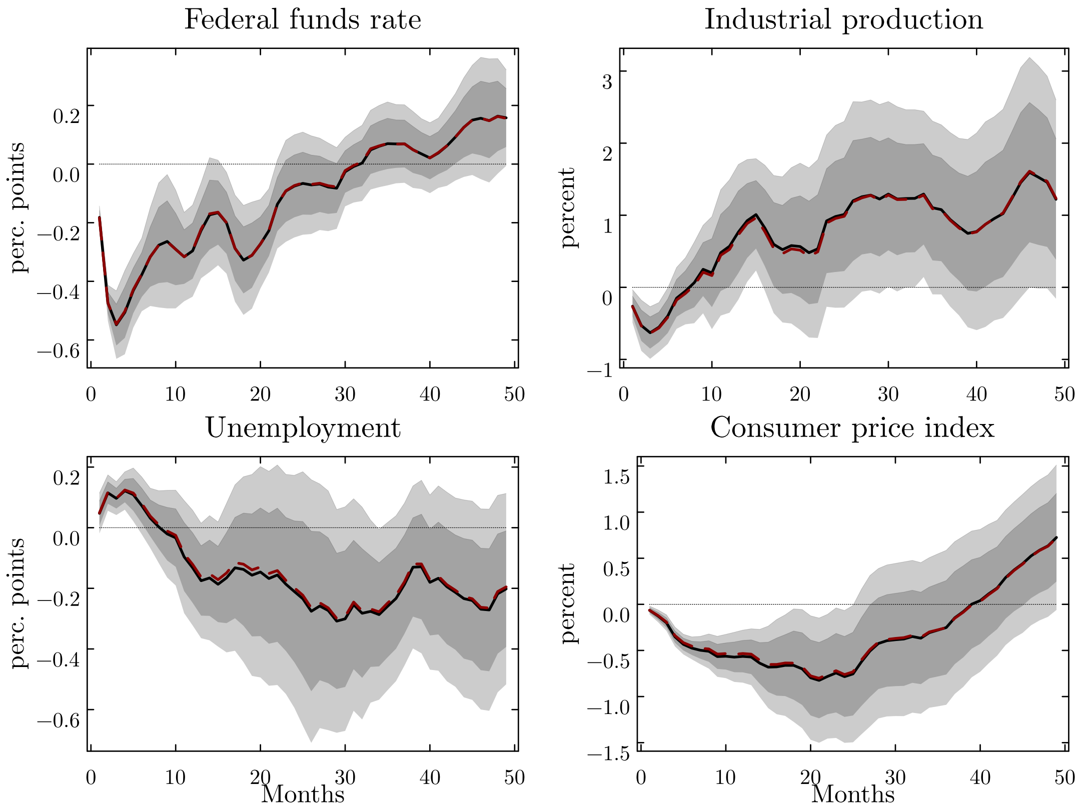
Note: Impulse responses to a one standard deviation expansionary CMP shock. Own updated CMP series between 1969m3-2008m12. Light (dark) gray areas are 90 percent (68 percent) confidence intervals based on Newey and West (1987) standard errors.

Figure 7: Empirical responses for aggregate variables



Note: Impulse responses to a one standard deviation expansionary CMP shock. *Black solid line*: Own updated CMP series. *Red dashed line*: Original Romer and Romer series. Sample between 1969m3-1996m12. Light (dark) gray areas are 90 percent (68 percent) confidence intervals based on Newey and West (1987) standard errors.

Figure 8: Empirical responses for aggregate variables



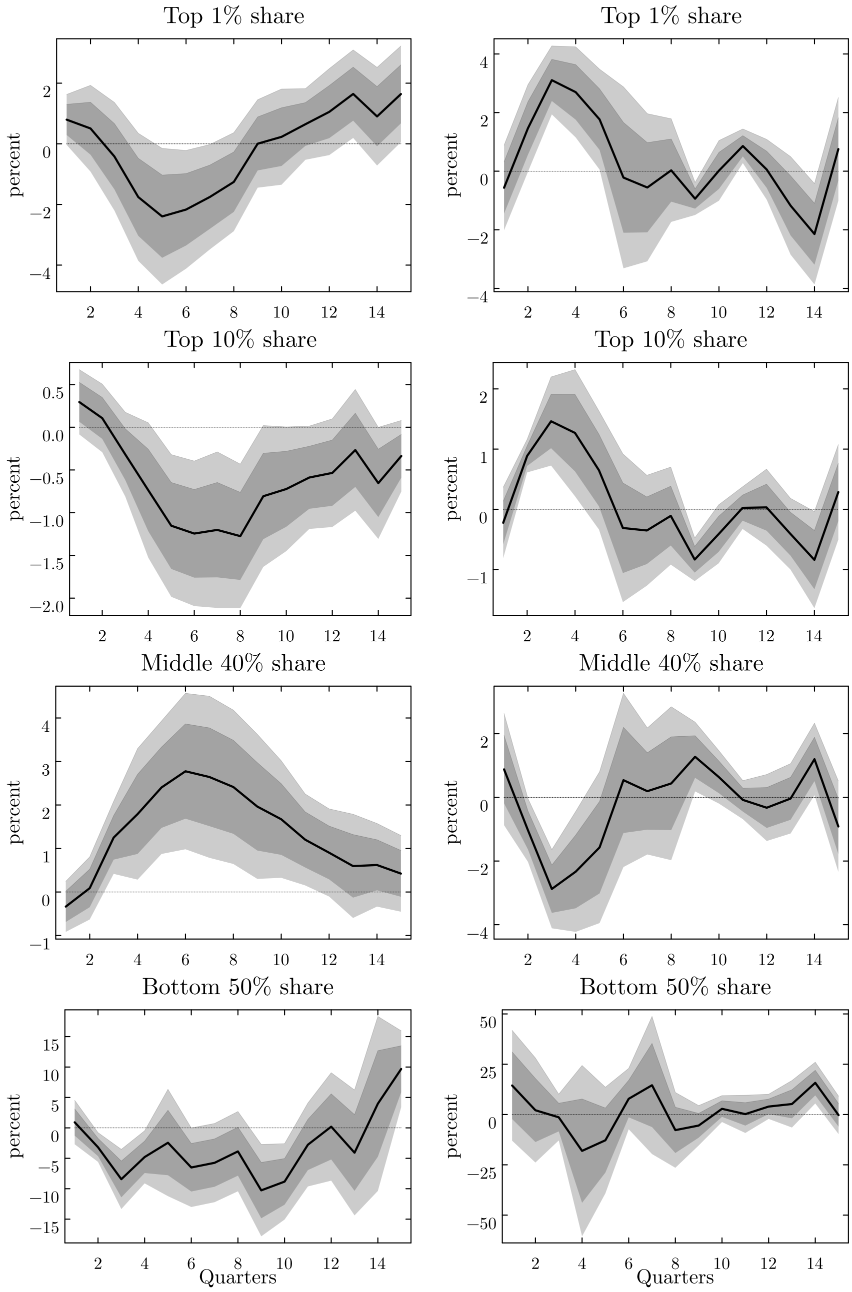
Note: Impulse responses to a one standard deviation expansionary CMP shock. *Black solid line*: Own updated CMP series. *Red dashed line*: CMP Series updated by Wieland and Yang. Sample between 1969m3-2007m12. Light (dark) gray areas are 90 percent (68 percent) confidence intervals based on Newey and West (1987) standard errors.

D Wealth Dynamics by Percentiles

The dynamics of house and stock prices are crucial for understanding the evolution of wealth inequality. More evidence of this channel is seen in the impulse responses of different percentiles of the wealth distribution. In panel (b) of Figure 9, the effect of an expansionary UMP shock is more pronounced for the middle 40 percentile. Middle-class households, whose portfolios are heavily composed of housing, see their wealth share fall when housing prices decline relative to stocks. Conversely, wealthier households, particularly the top 10%, gain from UMP shocks, with the top 1% seeing even stronger increases in wealth share due to their equity-heavy portfolios. Households at the bottom hold little to no wealth, making asset price movements less relevant to them. This is confirmed by the more volatile and uncertain responses of the bottom 50%. Similar conclusions can be drawn from CMP shocks in panel (a).

Figure 9: Empirical responses for wealth inequality: Different percentiles

(a) **Conventional MP** (b) **Unconventional MP**



Note: Impulse responses to a one standard deviation expansionary CMP and UMP shocks. Light (dark) gray areas are 90 percent (68 percent) confidence intervals based on Newey and West (1987) standard errors.