Unconventional but Different After All? A Unified Series of Narrative Monetary Policy Shocks*

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Abstract

We construct a unified series of narrative monetary policy shocks for the U.S. that spans both conventional and unconventional policy episodes, combining Romer and Romer's identification with Wu and Xia's shadow rate. The methodological consistency across regimes allows us to formally test whether monetary policy transmission differs at the zero lower bound. Structural-break tests cannot reject equality of aggregate peak responses, but strongly reject it for wealth inequality. Expansionary unconventional shocks increase wealth inequality—the opposite of conventional easing—because stock prices rise disproportionately relative to house prices, benefiting equity-heavy households at the top of the distribution.

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. A key obstacle in addressing these questions is the lack of a monetary policy shock series that spans both conventional and unconventional episodes and is constructed in a consistent way. Without such a series, it is difficult to determine whether observed differences in the effects of unconventional policy reflect genuine differences in transmission or merely differences in identification.

In this paper, we construct a unified series of narrative monetary policy shocks that covers both conventional monetary policy (CMP) and unconventional monetary policy (UMP) episodes. 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 (2016). The shadow rate is widely used to represent the monetary policy stance, and may fall below zero. This captures the effects of unconventional policy in a single, easy-to-understand measure that can be directly compared with conventional rate changes.

The resulting shock series has three key properties. First, it extends the narrative identification to the ZLB period, where the federal funds rate lacks sufficient variation to identify conventional shocks. Second, combined with Wieland and Yang (2020)'s extension of the original Romer and Romer (2004) shocks—which we further update through the end of 2008 and supplement with the most recently published Tealbook/Greenbook forecasts—it provides the longest available narrative monetary policy shock series for the United States.[1] Third, and most importantly, because the CMP and UMP components are constructed

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

with the same methodology, the unified series enables formal statistical tests of whether the transmission of monetary policy differs across regimes—holding the identification constant.

The UMP shocks pass a comprehensive set of diagnostics. In contrast to the CMP series, which have been shown to be serially correlated and predictable, our new UMP measure appears more robust to these concerns. Moreover, the UMP shocks are uncorrelated with prominent financial, uncertainty, and oil shocks, as well as with the high-frequency UMP decompositions of Swanson (2021, 2024) and Jarociński (2024). At the same time, the impulse responses implied by our unified shock are broadly consistent with those obtained from these alternative measures, suggesting that our identification delivers a complementary series rather than a competing one.

We exploit the consistency of the unified series by estimating full-sample local projections with a structural break at the ZLB. For aggregate variables, we cannot reject equality of peak responses across regimes. Unconventional policy is as expansionary as nominal interest rate cuts. Both lower the interest rate by a comparable amount on impact, and the effects on industrial production, unemployment, and inflation are of similar magnitude—though UMP effects are more persistent. These findings further support the "irrelevance hypothesis" of Debortoli et al. (2020), who argue that monetary policy at the ZLB is as effective as traditional measures.

However, the distributional consequences are different after all. Joint Wald tests strongly reject equality of impulse responses across regimes for wealth shares and the stock-to-house price ratio. Coibion et al. (2017) document that expansionary CMP shocks reduce consumption and income inequality. We find that a 25 basis point cut in the interest rate reduces the wealth share of the top 10% by 0.3% two years after the shock. For UMP shocks, the response flips sign: wealth inequality rises, peaking at a 0.4% 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-to-house price ratio.

This mechanism 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 can fully explain the distributional consequences of monetary policy. We extend this analysis to the bottom of the wealth distribution and show that households in the bottom 10% and bottom 50% are largely "asset excluded," holding little to no equity and often no housing, which limits the direct revaluation channel for these groups.

This paper contributes to three strands of the literature. First, we contribute 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 non-Gaussianity. An advantage of our narrative strategy over these alternatives is that it produces a shock series that is methodologically consistent across conventional and unconventional regimes, enabling direct, like-for-like comparisons while requiring less data and imposing fewer assumptions.

Second, with our novel 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. The key value added of our analysis is that we can test for aggregate equivalence across regimes within a unified framework, rather than comparing results across studies that use different identification strategies.

Third, we contribute to the literature on the impact of monetary policy on inequality. Although there is extensive evidence for conventional monetary policy (e.g., Coibion et al. (2017); Furceri et al. (2018)), evidence for unconventional policy is scarce and mostly inconclusive.[3] Independently, Mangiante and Meichtry (2023) use a SVAR model and Swanson (2021)'s factors to compare the effects

[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.

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

of conventional and unconventional monetary policy on inequality. We find similar results for wealth inequality with our novel shock series. Regarding the transmission channel, Lenza and Slacalek (2024) argue that the effect of UMP on inequality is largely determined by its impact on employment. Our analysis suggests that asset prices are the main channel through which monetary policy affects wealth inequality, and the formal structural-break tests confirm that this distributional wedge is a statistically robust feature of the data, not an artifact of comparing across different identification schemes.

The paper is organized as follows: Section 2 derives our novel UMP shocks and provides diagnostics. Section 3 reports empirical evidence on the aggregate and distributional effects of UMP, comparing them to CMP. Section 4 then formally tests whether these differences are statistically significant using the full sample and structural-break regressions. Section 5 concludes.

2 Identification of Monetary Policy Shocks

Our identification strategy is designed to produce a unified shock series that is methodologically consistent across the conventional and unconventional policy environments. We build on the narrative approach of Romer and Romer (2004), implementing their Taylor rule-type regressions but replacing 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 ZLB period by a one-dimensional metric, which we then use to derive a series of policy shocks that is directly comparable to the conventional series.

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 estimated for that specific period as resulting from unconventional monetary policy.

An important conceptual point is that Equation (1) is not a structural policy rule in the behavioral sense. Rather, it is a *forecasting equation* that partials out the systematic, information-driven component of policy changes by conditioning on the Fed's own Greenbook/Tealbook forecasts. The residual captures the

[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.

surprise component of policy, regardless of whether the left-hand-side variable is the observed federal funds rate or the shadow rate. During the ZLB, all unconventional policy actions—asset purchases, forward guidance, changes in collateral requirements—ultimately manifest in movements of the yield curve. The shadow rate synthesizes these movements into an implied short rate. Thus, Equation (1) asks: given the Fed's macroeconomic forecasts, what component of the change in the overall policy stance (as reflected in the yield curve) was predictable? The residual is the unpredictable component. The diagnostics in Section 2.2 confirm that this residual satisfies the standard properties expected of a well-identified shock.

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.

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

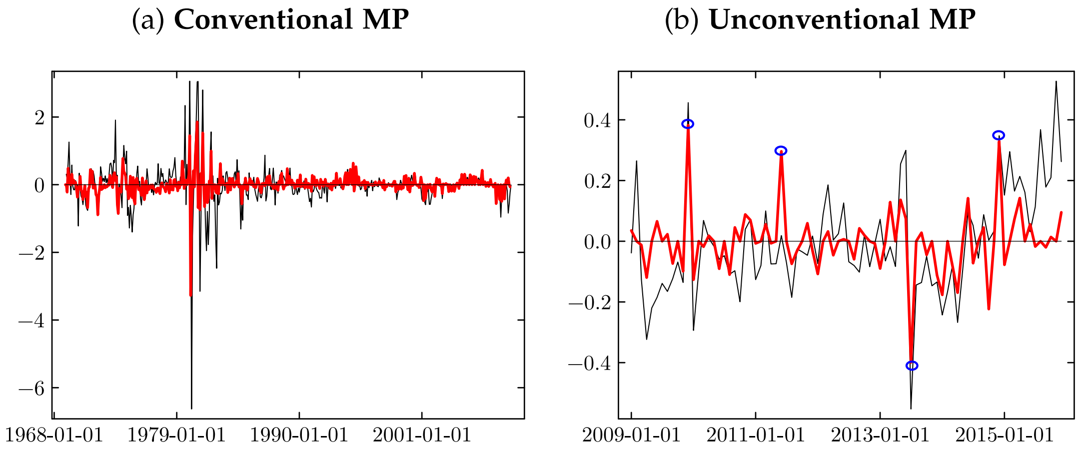
where sff_{m-1} is the level of the shadow rate prior to the m-th meeting. $F_m \Delta y_{m,i}$ is the forecast of output growth made for the m FOMC meeting. The subscript i indicates the horizon of the forecast relative to the date the forecast was made. Specifically, -1 refers to the previous quarter, 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 unconventional monetary policy shocks and the first-difference of the shadow rate.

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

Figure 1: New measure of unconventional monetary policy shocks



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.

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 basis points, which is comparable to the standard deviation of 15 basis points 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 large-scale asset purchases (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 circle 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 set of diagnostics that are widely used in the literature. In particular, we assess (i) serial correlation, (ii) predictability, and (iii) the extent to which our UMP shocks comove with other prominent shock measures over the ZLB period.

Figure 2 summarizes the evidence on serial correlation by plotting the autocorrelation function for UMP shocks (panel (b)) alongside the corresponding CMP series (panel (a)). For UMP, none of the autocorrelations at the considered lags exceed the 95% confidence bands in absolute value, indicating that serial correlation is not a salient feature of the series. This visual conclusion is supported by the formal AR-based tests reported in Table 2 (Panel A): the F-tests for joint significance do not reject the null for UMP, and this finding is robust when increasing the number of included lags. In contrast, CMP exhibits a clear rejection of joint insignificance once additional lags are considered. Importantly, if one were to rely only on the AR(4) specification, CMP would also fail to reject, which is not aligned with the original conclusions in Miranda-Agrippino and Ricco; the extended-lag specifications in Table 2 (Panel A) therefore provide a more informative comparison across series.

We then evaluate predictability using standard macro-financial predictors and the factor-based controls proposed by Miranda-Agrippino and Ricco. Table 1 reports Granger causality tests for a set of common macroeconomic and financial variables. As shown in column (3), none of the selected variables Granger-cause the UMP shock series. Consistently, Table 2 (Panel B) reports joint significance tests for the factor-based specification; the corresponding test outcomes do not provide evidence that these factors predict the UMP shocks.

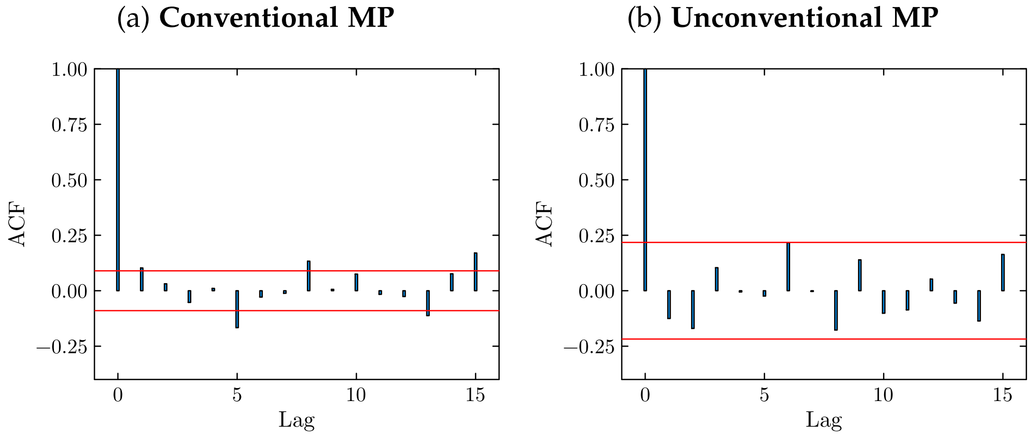
Finally, we assess whether our UMP shocks are correlated with alternative shock measures that capture monetary, financial, uncertainty, and oil-related disturbances during the ZLB period. Table 3 reports pairwise correlations and associated p-values. Across categories, the correlations are small in magnitude and statistically indistinguishable from zero, including with prominent UMP decompositions based on forward guidance and asset purchase surprises (Swanson, 2021, 2024; Jarociński, 2024).[7] Overall, this evidence suggests that our UMP

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

[7] In Appendix C we provide similar diagnostics for these alternative UMP shock series and

shock series is not simply proxying for other well-known shocks (financial, uncertainty, or oil). Moreover, although correlations with alternative UMP shock series are also weak, this indicates that our identification provides a complementary measure of policy surprises rather than a re-labeling of any single existing series. At the same time, it moves in the expected direction relative to asset-purchase surprises, as reflected in positive—though statistically insignificant—correlations with LSAP-based measures.

Figure 2: 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.

compare the results with those of our shock series.

Table 2: Serial correlation and predictability of the shock series

	Panel A: Serial correlation AR(10)		*Panel B: Predictability* Factor regression	
	CMP	UMP	CMP	UMP
Constant	-0.0022	0.0003	0.0199	0.0193
	(0.0002)	(0.0002)	(0.0002)	(0.0017)
$x_{1,t-1}$	0.1089	-0.1241	-0.0270	0.0320
	(0.0266)	(0.0135)	(0.0003)	(0.0056)
$x_{2,t-1}$	0.0107	-0.1751	0.0203	0.0005
	(0.0053)	(0.0230)	(0.0003)	(0.0006)
$x_{3,t-1}$	-0.0372	0.0506	-0.0300	0.0384
	(0.0045)	(0.0094)	(0.0003)	(0.0032)
$x_{4,t-1}$	0.0283	0.0576	-0.0413	-0.0335
	(0.0035)	(0.0192)	(0.0007)	(0.0082)
$x_{5,t-1}$	-0.1543	0.0467	0.0179	0.0279
	(0.0056)	(0.0125)	(0.0011)	(0.0045)
$x_{6,t-1}$	-0.0042	0.2050	-0.0153	0.0074
	(0.0254)	(0.0237)	(0.0003)	(0.0010)
$x_{7,t-1}$	-0.0076	0.0577	-0.0087	-0.0153
	(0.0472)	(0.0094)	(0.0008)	(0.0012)
$x_{8,t-1}$	0.1223	-0.1222	-0.0296	0.0110
	(0.0210)	(0.0162)	(0.0003)	(0.0008)
$x_{9,t-1}$	-0.0196	0.0587	-0.0062	0.0180
	(0.0073)	(0.0179)	(0.0016)	(0.0022)
$x_{10,t-1}$	0.0464	-0.1558	0.0129	-0.0367
	(0.0048)	(0.0125)	(0.0005)	(0.0004)
R^2	0.0598	0.1412	0.0590	0.1537
F-statistic	2.92	1.04	2.18	1.09
p-value	0.001	0.425	0.019	0.385
Observations	470	74	359	71
F-statistic [AR(4)]	1.78	1.03		
p-value [AR(4)]	0.131	0.399		

Note: Panel A regresses each shock on ten lags of itself ($x_{k,t-1}$ = shock$_{t-k}$); the last two rows report the F-statistic and p-value from the AR(4) specification. Panel B regresses each shock on one lag of ten macro-financial factors ($x_{k,t-1} = f_{k,t-1}$) constructed by Miranda-Agrippino and Ricco (2021) from variables of McCracken and Ng (2016). Heteroskedasticity-robust standard errors in parentheses.

Table 3: Correlations between the UMP shock and alternative shock measures

Shock	Source	ρ	p-value
Monetary policy			
Forward guidance	Swanson (2021)	-0.0239	0.8289
LSAP	Swanson (2021)	0.1103	0.3180
Forward guidance (orth.)	Swanson (2024)	-0.0140	0.8994
LSAP (orth.)	Swanson (2024)	0.0912	0.4092
Odyssean FG	Jarociński (2024)	-0.1658	0.1317
LSAP	Jarociński (2024)	0.1011	0.3602
Delphic FG	Jarociński (2024)	0.1798	0.1017
Financial			
Excess bond premium	Gilchrist and Zakrajšek (2012)	-0.0287	0.7956
Credit supply	Bassett et al. (2014)	-0.3890	0.2371
Uncertainty			
Economic policy	Baker et al. (2016)	-0.0593	0.5918
Financial	Jurado et al. (2015)	-0.0058	0.9585
Macroeconomic	Jurado et al. (2015)	0.0704	0.5243
Real	Jurado et al. (2015)	-0.0090	0.9350
Oil shocks			
Oil shock	Känzig (2021)	0.0647	0.5587
Oil shock	Baumeister and Hamilton (2019)	0.0294	0.7904

Note: With the exception of the financial shock of Bassett et al. (2014), which is quarterly and spans 2009Q1–2010Q4, the remaining series are monthly (2009M1–2015M12), with a sample size of 84 observations.

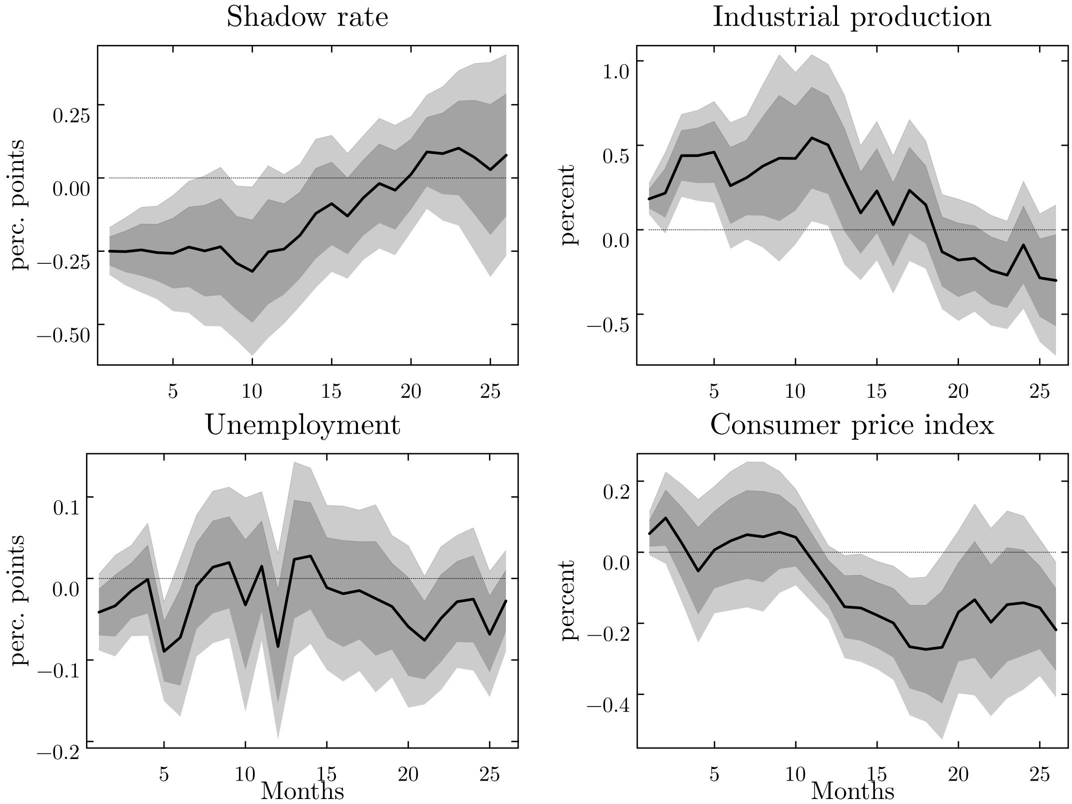
3 Aggregate and Distributional Effects

We now document what unconventional monetary policy does. To estimate the dynamic causal effects of the identified shocks, we use the local projection method of Jordà (2005):

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

where x_{t+h} is the variable of interest h periods after the shock, ε_t is the identified monetary policy shock, $\boldsymbol{Z}_{t-1}$ is a vector of controls, and standard errors are computed following Newey and West (1987). For aggregates, the sample covers the ZLB period (2009–2015); we also report pre-ZLB results based on the conventional shocks as a benchmark. The central question—whether the aggregate and distributional effects genuinely differ across regimes—is then tested formally in Section 4.

Figure 3: Empirical responses for aggregate variables



Note: Impulse responses to an expansionary UMP shock that lowers the shadow rate by 25 basis points on impact. Light (dark) gray areas are 90 percent (68 percent) confidence intervals based on Newey and West (1987) standard errors.

3.1 Aggregate effects

First, we examine the dynamic effects of UMP shocks on aggregate macroeconomic variables. For controls, we largely follow Ramey (2016) and include four lags of the monetary policy shock and standard macroeconomic variables such as the log of industrial production, the log of the CPI, the commodity price index, the unemployment rate, and the rate as controls.

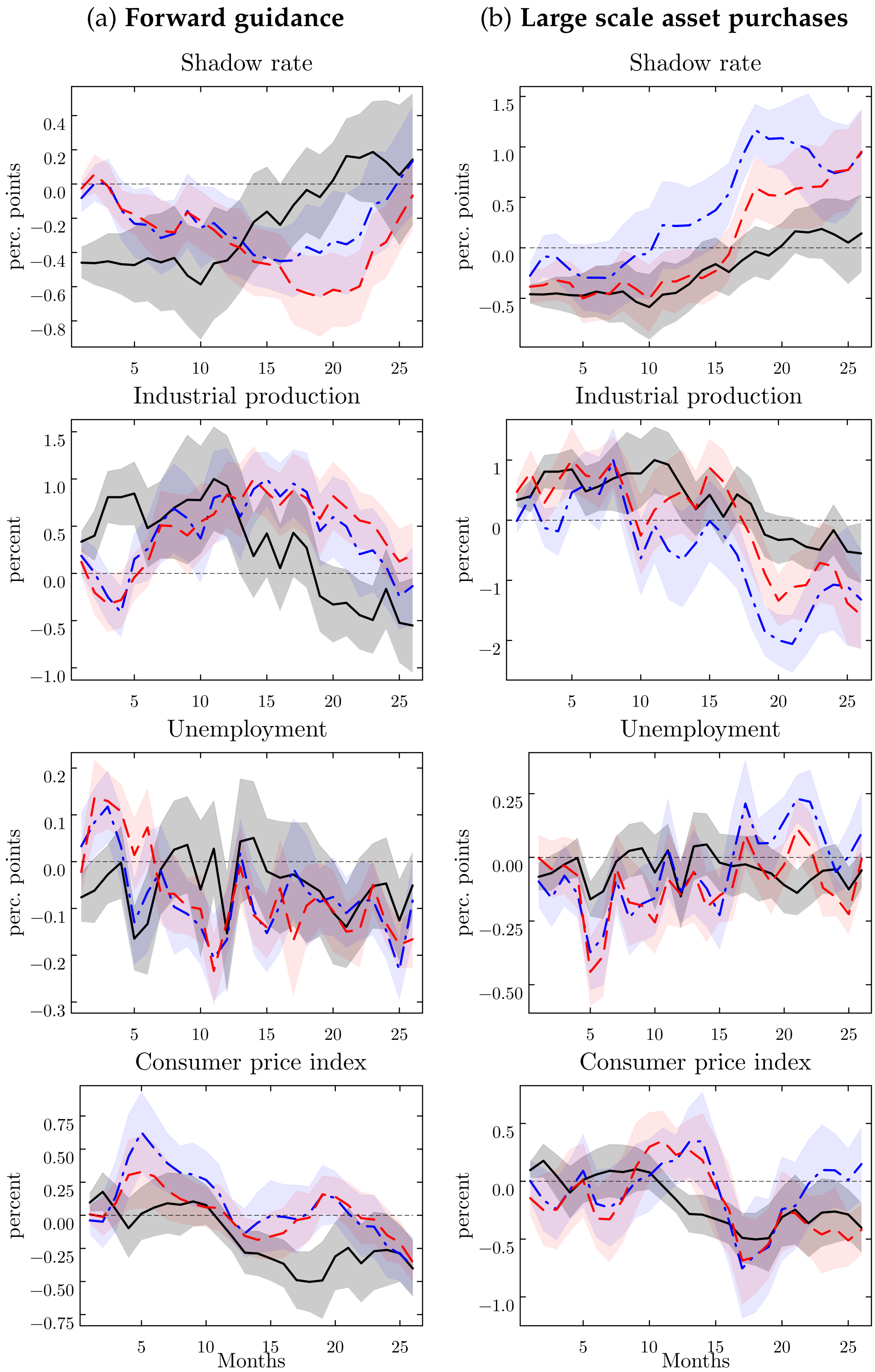
In Figure 3, we report the impulse responses of UMP shocks normalized to a 25 basis point reduction in the shadow federal funds rate on impact. Starting with the effect on the interest rate, we find that it falls by an amount similar to that usually found for CMPs. Compared to rate cuts, the effect of UMP shocks on the interest rate appears to be quite persistent. After the initial drop, it continues to fall slowly for about ten months, reaching a trough of 41 basis points. This higher persistence is also transmitted to other variables. Industrial production barely reacts on impact, building up slowly and peaking at around 1% twelve

months after the shock. The effect on unemployment is more subdued and erratic, but overall falls by about 0.15 percentage points twenty-four months after the shock. For these variables, the effects are more persistent, but the implied elasticities are comparable to those for the CMP. Appendix B 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 shows no initial price puzzle. In the first twelve months, the CPI rises by 0.37% at its peak, then starts to fall and becomes insignificant as the stimulative effects fade.
In Appendix D we show that these results are robust to alternative models. In particular, we use an internal instrument VAR ordering the UMP shock series first and a Proxy VAR with the shock as an external instrument for the shadow rate. Overall, the results are very similar in terms of magnitude, with a less erratic downward path for unemployment and slightly more persistent rise in inflation. Section 4 formally tests whether these aggregate effects differ from those of conventional policy using structural-break regressions with a pooled sample.

3.2 Comparison to alternative shocks

Before moving on to the effects of wealth inequality, we briefly examine how the effects of our estimated shocks compare with some alternative measures of unconventional monetary policy. One advantage of our shock is that it captures the effects of all types of unconventional monetary policy in a unified way. Thus, our measure is not a direct substitute for other available shock series, which separate forward guidance from large-scale asset purchases.
In particular, we make this comparison against Swanson (2024) and Jarociński (2024) forward guidance and LSAP factors. We choose these because they represent some of the most popular and well-established identified series in the literature and thus provide a good baseline. In addition, Swanson's factors are robust to the "Fed reaction to news" and Jarocinski's factors are robust to the "Fed information effect." These are two persistent concerns within estimated monetary policy shocks, and something we do not directly address in our shock series. Thus, a comparison with these alternative measures also allows us to indirectly assess whether our shocks might suffer from such problems.
Figure 4 shows that the impulse responses implied by our unified UMP shock are broadly consistent with those obtained using alternative UMP measures. Moreover, the responses do not reveal a sharp empirical distinction between

Figure 4: Comparison of empirical responses for aggregate variables



Note: Impulse responses normalized for an increase in industrial production of 1% at the peak. *Black solid line*: UMP shock. *Blue dashed-dotted line*: Swanson (2024) FG/LSAP factors. *Red dashed line*: Jarociński (2024) FG/LSAP factors. Sample between 2009m1-2015m12. Shaded areas around point estimates are 68 percent confidence intervals based on Newey and West (1987) standard errors.

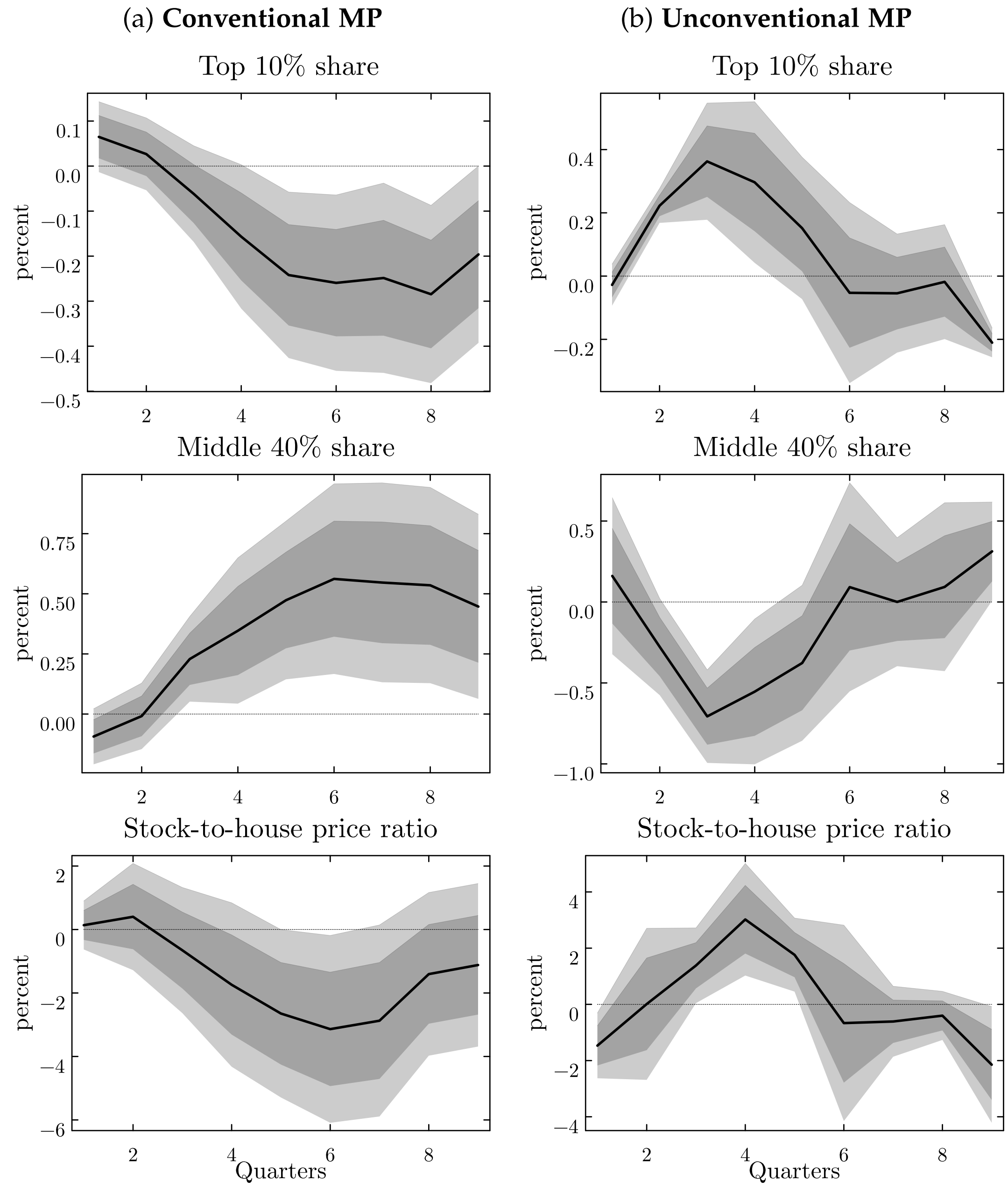
the effects of forward guidance and LSAP surprises. For the shadow federal funds rate, the response to our UMP shock most closely resembles the response to the LSAP factors, particularly the series in Jarociński (2024), which displays substantial persistence. The responses based on forward-guidance factors are nevertheless similar in terms of peak impact, although the adjustment occurs more gradually and at longer horizons, as expected. For industrial production and unemployment, our estimates track the LSAP-based responses at short horizons, and at medium to longer horizons they resemble a combination of the forward-guidance and LSAP responses. Finally, the inflation response is also comparable across measures, featuring a modest initial increase followed by a decline after roughly 12 months.

3.3 Effects on wealth inequality

To see the impact on inequality, we use data from the 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 class" portion between the 50 and 90 percentiles, which we call the middle 40%. In Appendix E.1 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 controls used in the monetary policy analysis of Ramey (2016). Figure 5 plots the impulse responses of the wealth shares for conventional (1989-2008) and unconventional monetary policy (2009-2015), both normalized for an immediate 25 basis point decline in the interest rate. 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 0.3%, while the wealth share of the middle class increases by 0.56%. 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 0.36%, while the share of the middle

Figure 5: Empirical responses for wealth inequality and asset prices



Note: Impulse responses to expansionary CMP and UMP shocks, normalized such that each implies a 25 basis points fall in the interest rate on impact. Light (dark) gray areas are 90 percent (68 percent) confidence intervals based on Newey and West (1987) standard errors.

class falls by 0.7%.

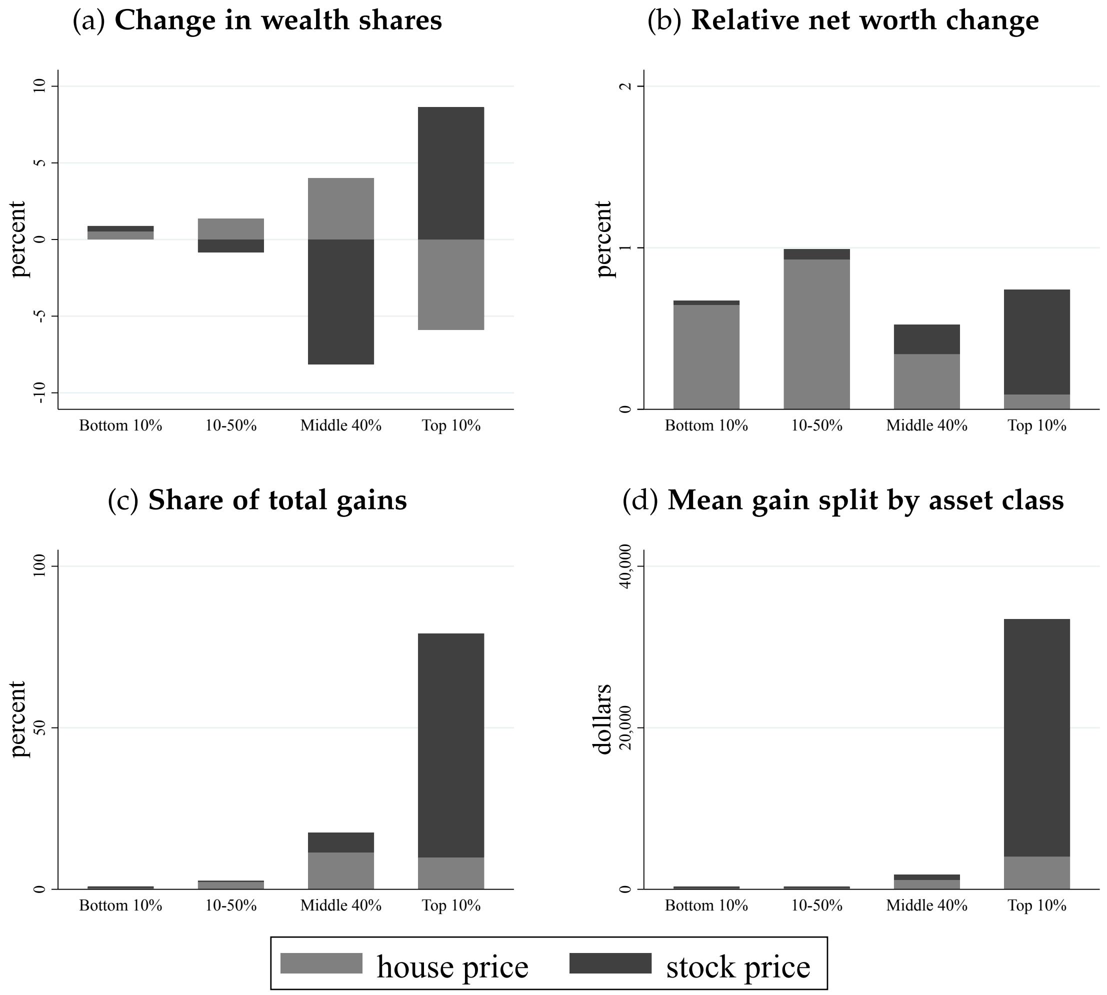
As we do find similar effects on output and unemployment for conventional and unconventional monetary policy, we turn to asset prices as potential explanation for the differential impact on wealth inequality. Households in the top 10% of the wealth distribution hold a sizable fraction of their wealth 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-to-house price ratio, which we also show in Figure 5. This ratio corresponds to the S&P 500 divided by the Case-Shiller house price index in logs. 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-to-house price ratio falls by about 3.13%. This U-shape is very similar to the dynamics of the top 10% wealth measure. For unconventional policy, the stock-to-house price ratio rises rapidly by over 3%, following very similar dynamics to the wealth inequality response.

The Survey of Consumer Finances (SCF) allows us to directly quantify how asset price revaluations translate into wealth gains across the distribution. Following Kuhn et al. (2020), we take each household's portfolio composition from the SCF and apply the estimated stock and house price responses at the four-quarter horizon to revalue asset holdings mechanically. We partition households into four wealth groups—Bottom 10%, 10–50%, 50–90%, and Top 10%—and report the implied gains from several complementary perspectives. Figure 6 presents the results. Panel (a) shows how the revaluation shifts each group's share of total wealth. Panel (b) reports the percentage change in net worth relative to each group's baseline. For the Bottom 10%, whose baseline net worth is negative, the sign is reversed so that a reduction in indebtedness corresponds to a positive value. To complement this measure and avoid denominator issues more broadly, panels (c) and (d) use dollar-gain based measures: the share of aggregate gains accruing to each group and mean gains decomposed by asset class (equity vs. housing), respectively.

The results confirm the asset-price channel as a key driver of the distributional wedge between CMP and UMP. Under an expansionary UMP shock, the Top 10%—whose portfolios are equity-heavy—capture the lion's share of to-

Figure 6: Wealth gains from asset price revaluations (SCF)



Note: The figure reports the SCF-based revaluation exercise for four wealth groups (Bottom 10%, 10–50%, 50–90%, Top 10%) after a 25 basis points expansionary UMP shock. Panel (a) shows the implied change in each group's share of total wealth. Panel (b) reports relative net worth changes; for the Bottom 10%, whose baseline net worth is negative, the sign is reversed so that a reduction in indebtedness corresponds to a positive value. Panels (c)–(d) report dollar-gain based measures (share of total gains and mean gains by asset class) that do not rely on a group-level wealth denominator.

tal revaluation gains (panel (c)), driven almost entirely by stock price increases (panel (d)). The 50–90% group benefits primarily through housing revaluations, while the bottom groups receive comparatively little from either channel, consistent with their limited asset-market participation. Panel (a) shows that these differential gains translate into a rising wealth share for the Top 10% and a declining share for the middle class, mirroring the impulse response evidence from the DFA. We do not account for return heterogeneity within groups or portfolio rebalancing, both of which could further amplify these effects.

4 Full-sample local projections with a ZLB structural break

The preceding section documented the effects of unconventional monetary policy on aggregates, asset prices, and the wealth distribution, and compared them to those of conventional policy. A natural question is whether the apparent similarities in aggregate responses and the stark differences in distributional responses are statistically significant. A key advantage of our unified shock construction is that it spans both the pre-ZLB and ZLB periods within a single, methodologically consistent framework, making it possible to carry out a full-sample estimation and test this directly.

To do so, we augment the baseline local projection in equation (2) to allow for a structural break at the ZLB.

4.1 Empirical specification

Let D_t denote an indicator variable that equals one during the ZLB period and zero otherwise. We consider two local projection specifications.

"Simple" break. We augment the baseline local projection by allowing the coefficient on the monetary policy shock to differ in the ZLB period:

$$x_{t+h} = \alpha_h + \theta_h \varepsilon_t + \delta_h(\varepsilon_t \times D_t) + \boldsymbol{\beta}_h' \boldsymbol{Z}_{t-1} + u_{t+h} \tag{3}$$

Here, θ_h corresponds to the impulse response in the non-ZLB period and $\theta_h + \delta_h$ would imply the impulse response in the ZLB period. This corresponds to an estimation where only the shock effects differ across regimes, while the rest of economic mechanisms remain the same.

"Full" break. To allow for broader regime changes, both in the shock transmission and in the relationship between outcomes and controls, we additionally estimate:

$$x_{t+h} = \alpha_h + \theta_h \varepsilon_t + \boldsymbol{\beta}_h' \mathbf{Z}_{t-1} + D_t \times \left[\delta_h \varepsilon_t + \boldsymbol{\zeta}_h' \mathbf{Z}_{t-1}\right] + u_{t+h} \tag{4}$$

Once again, now the ZLB-period IRFs to the shock correspond to the sum of θ_h and δ_h.

Both specifications are estimated using the same controls as in Section 3.1 for aggregates and Section 3.3 for distributional effects, respectively.

4.2 Testing for differences across regimes

Given these specifications, we now proceed to test whether the dynamic effects of the monetary policy shocks differ across the ZLB and non-ZLB episodes.

For aggregate variables, equality of impulse responses "at all horizons" is not always the most informative metric because conventional and unconventional policy responses can differ in timing (e.g., more persistent interest-rate effects in the ZLB) as shown in Section 3.1. Thus, testing whether the entire IRFs are different can potentially reject the null even when the economic magnitudes are quantitatively similar. We therefore focus on a transparent and economically meaningful comparison. In particular, for each variable we test whether the peak response in the ZLB differs from the peak response in the non-ZLB episode. Table 4 reports the corresponding p-values.

For wealth shares and the stock-to-house price ratio, given that the effects should go in opposite directions we concentrate on the entire dynamic path. Accordingly, we report joint Wald tests of $H_0 : \delta_0 = \delta_1 = \cdots = \delta_H = 0$, over the relevant horizons. Table 5 reports test statistics and p-values.

4.3 Results

Aggregate dynamics. Table 4 shows that we do not reject equality of peak effects across regimes for the key aggregate variables. Figure 7 compares the baseline estimates with the pooled-sample break estimates and illustrates that the implied aggregate responses are broadly similar in magnitude.

At the same time, Figure 7 also shows that pooling the samples can materially affect the estimated inflation response. Relative to the baseline ZLB estimates, both pooled-break specifications tend to generate a more pronounced price puzzle. Hence, the pooled specification reintroduces issues present in the pre-ZLB

Romer and Romer (2004) conventional monetary policy series, that are better handled by the baseline sample-specific estimation strategy in the main text.

Table 4: t-test IRF peak difference (p-values)

	Simple Break	Full Break
Interest Rate	0.43	0.56
Industrial Production	0.09	0.20
Unemployment	0.15	0.25
Consumer Price Index	0.30	0.42

Wealth inequality and asset prices. For distributional outcomes, Table 5 strongly rejects equality across regimes. Additionally, we can see in Figure 8 that the qualitative distributional pattern is preserved, and the stock-to-house price ratio remains a key summary of the distributional transmission channel. In this sense, the full-sample structural-break exercise reinforces the central message of Section 3.3: the distributional consequences differ significantly across the conventional and unconventional episodes, while aggregate magnitudes are broadly comparable.

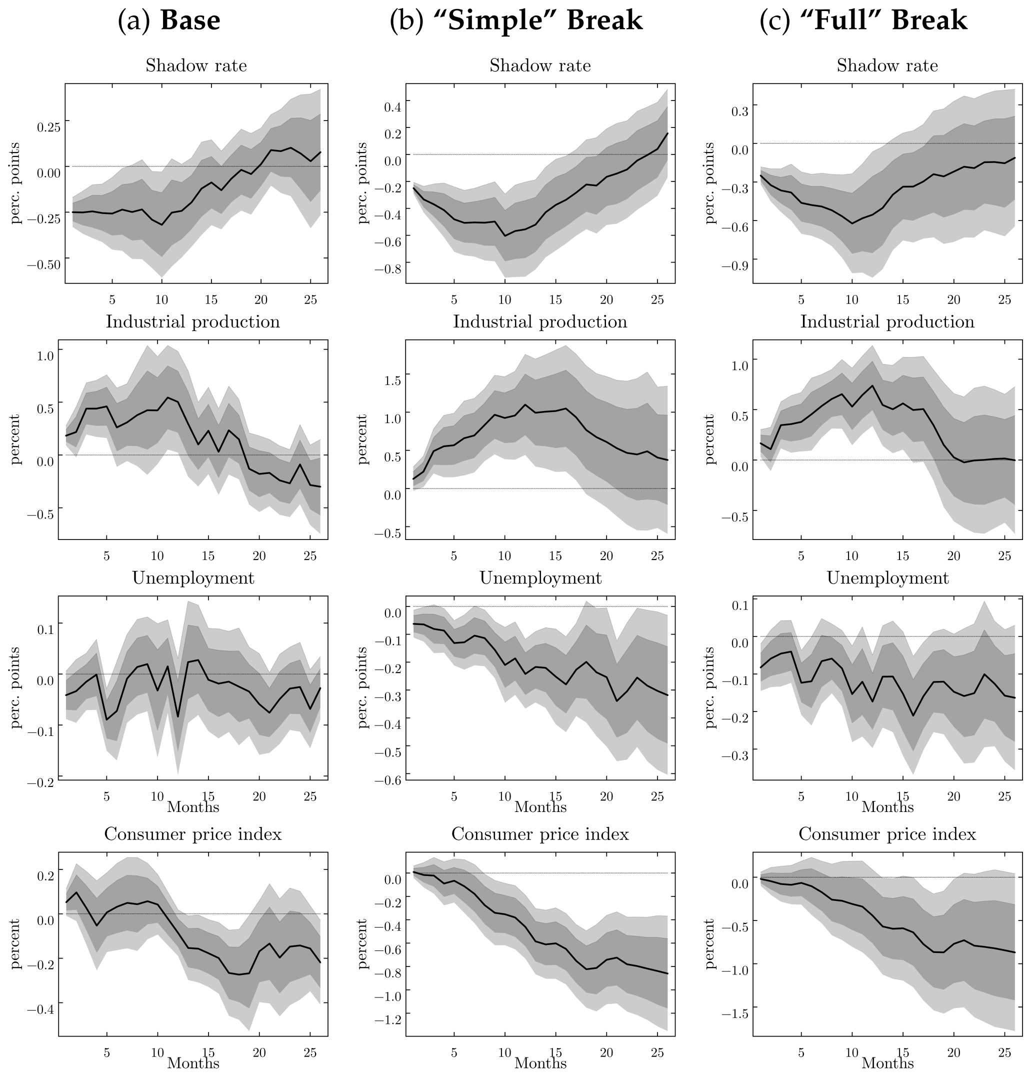
Table 5: Joint Wald test

	Simple Break		*Full Break*	
	$\chi^2(9)$	p-value	$\chi^2(9)$	p-value
Price ratio	22.387	0.0077	18.451	0.0303
Top 1%	24.257	0.0039	14.744	0.0982
Top 10%	24.480	0.0036	30.022	0.0004
Middle 40%	31.787	0.0002	22.905	0.0064
Bottom 50%	23.111	0.006	21.764	0.0097

5 Conclusion

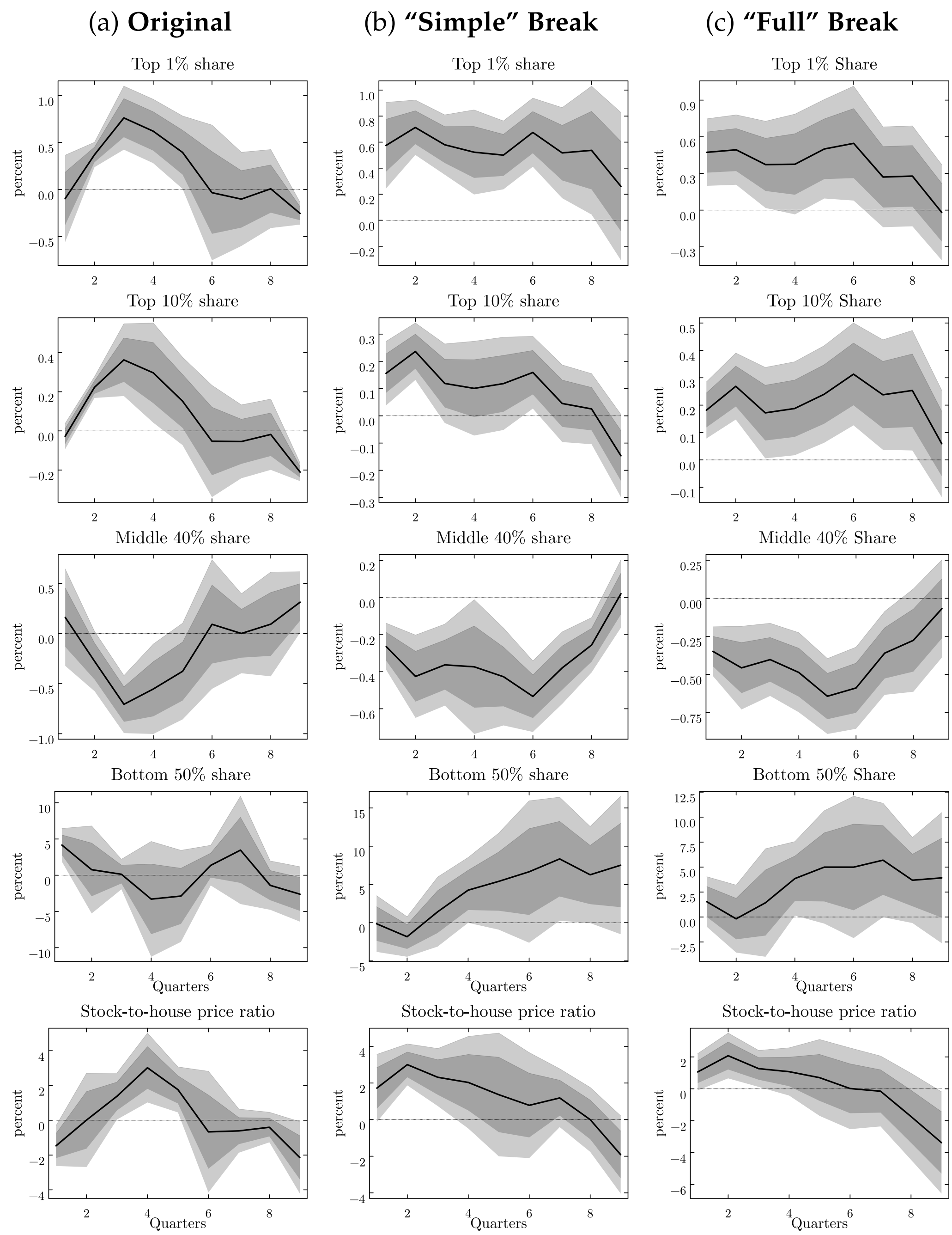
This paper constructs a unified series of narrative monetary policy shocks that spans both the conventional and unconventional policy environments. Our measure is continuously updated to generate the longest unified sample of monetary policy shocks. By replacing the federal funds rate with Wu and Xia (2016)'s shadow rate in the Romer and Romer (2004) identification framework,

Figure 7: IRF comparison with structural breaks - Aggregates



Note: Impulse responses to an expansionary UMP shock that lowers the shadow rate by 25 basis points on impact. Light (dark) gray areas are 90 percent (68 percent) confidence intervals based on Newey and West (1987) standard errors.

Figure 8: IRF comparison with structural breaks - Inequality and asset prices



Note: Impulse responses to an expansionary UMP shock that lowers the shadow rate by 25 basis points on impact. Light (dark) gray areas are 90 percent (68 percent) confidence intervals based on Newey and West (1987) standard errors.

we obtain a methodologically consistent measure that covers the pre-ZLB period (1969–2008) and the ZLB period (2009–2016) in a comparable way. The resulting shock series passes standard diagnostics for serial correlation and predictability, and is largely uncorrelated with alternative UMP shock measures based on high-frequency forward guidance and LSAP surprises, suggesting it captures a complementary dimension of policy surprises. At the same time, the aggregate responses it generates are broadly in line with those implied by these established series.

Using this unified series, we address the question of whether unconventional monetary policy works differently from conventional rate cuts. Pooled-sample local projections with a structural break at the ZLB show no significant difference in peak effects for output, unemployment, or the interest rate, with p-values well above conventional thresholds. In this sense, unconventional policy is about as effective as conventional policy in stimulating aggregate activity.

The distributional consequences, however, are strikingly different. Joint Wald tests strongly reject equality of impulse responses across regimes for wealth shares and the stock-to-house price ratio ($p < 0.001$ in most cases). Expansionary UMP shocks increase the wealth share of the top 10% and decrease the share of the middle class — the opposite of what conventional rate cuts produce. We trace this to the differential response of stock and house prices: UMP shocks raise equity valuations relative to housing, benefiting equity-heavy portfolios at the top of the distribution. A micro-simulation using SCF household portfolios confirms that this revaluation channel accounts for a substantial share of the estimated distributional effects.

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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]
- **GDP growth**. 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 full- and ZLB-specific samples we use S&P Goldman Sachs Commodity Index. For the CMP-only sample we use the CRB Commodity Price Index, as in Ramey (2016).

[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.
- **10-year Treasury yield**. McCracken and Ng (2016) FRED-MD and FRED-QD: Monthly and Quarterly Databases for Macroeconomic Research.
- **Wealth shares**. The share of each portion of the wealth distribution is computed as the ratio of that particular portion net worth over the total net worth across the entire distribution. Households' net worth is the difference between all their assets minus all their liabilities. For this we use the Federal Reserve Distributional Financial Accounts.

B Aggregate Effects of CMP Shocks

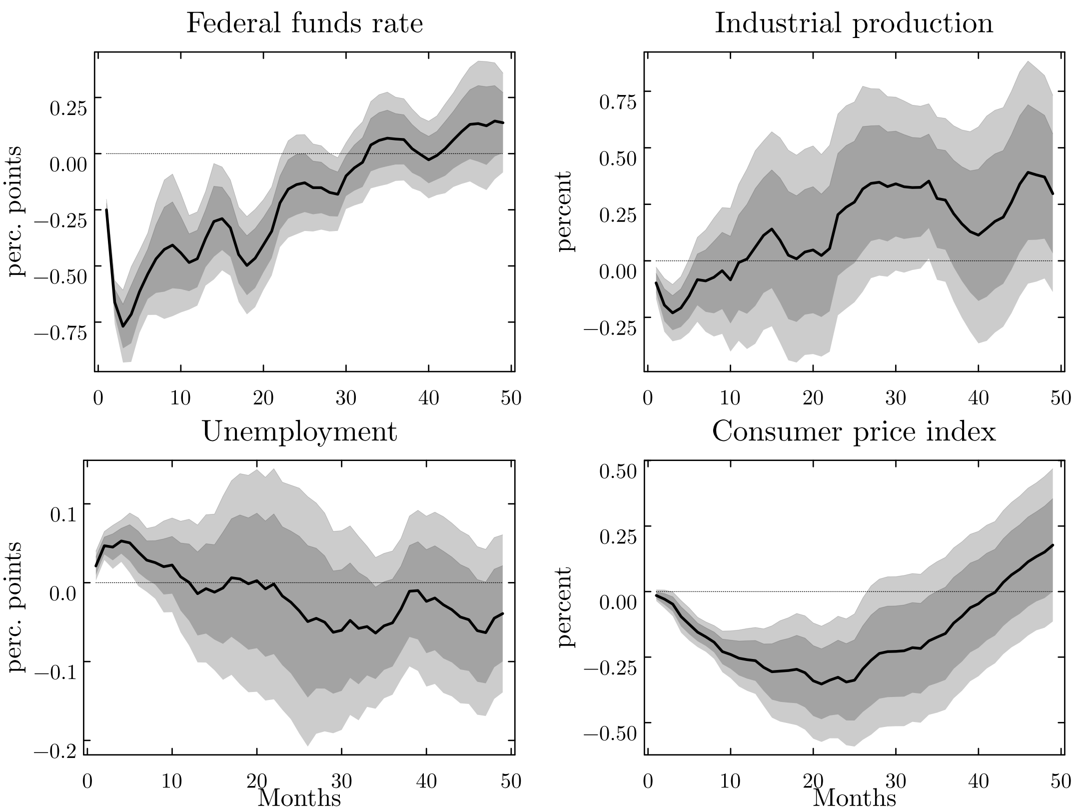
The Wieland and Yang (2020) update of the original Romer and Romer (2004) narrative shock series is a standard benchmark in the literature, but it ends in December 2007. We implement their corrections and extend the series through the end of 2008, which delivers the conventional-policy portion of the unified sample used in Section 4.[9]

Figure 9 reports aggregate impulse responses estimated with the same specification and controls as in Section 3.1. For completeness, Figure 10 compares our updated CMP series with the original Romer and Romer (2004) series over the common sample, and Figure 11 compares it with the Wieland and Yang (2020) update. In both cases, the black solid line and red dashed line are very close, indicating that the results are not driven by the specific update used.

Relative to UMP, the CMP responses are less persistent, but the peak effects on the interest rate, industrial production, and unemployment are similar in magnitude. This reinforces the main-text conclusion that unconventional policy is broadly as effective as conventional rate cuts in stabilizing aggregate activity. Inflation is the main exception: the CMP series continues to display the familiar price puzzle that is much less pronounced for UMP.

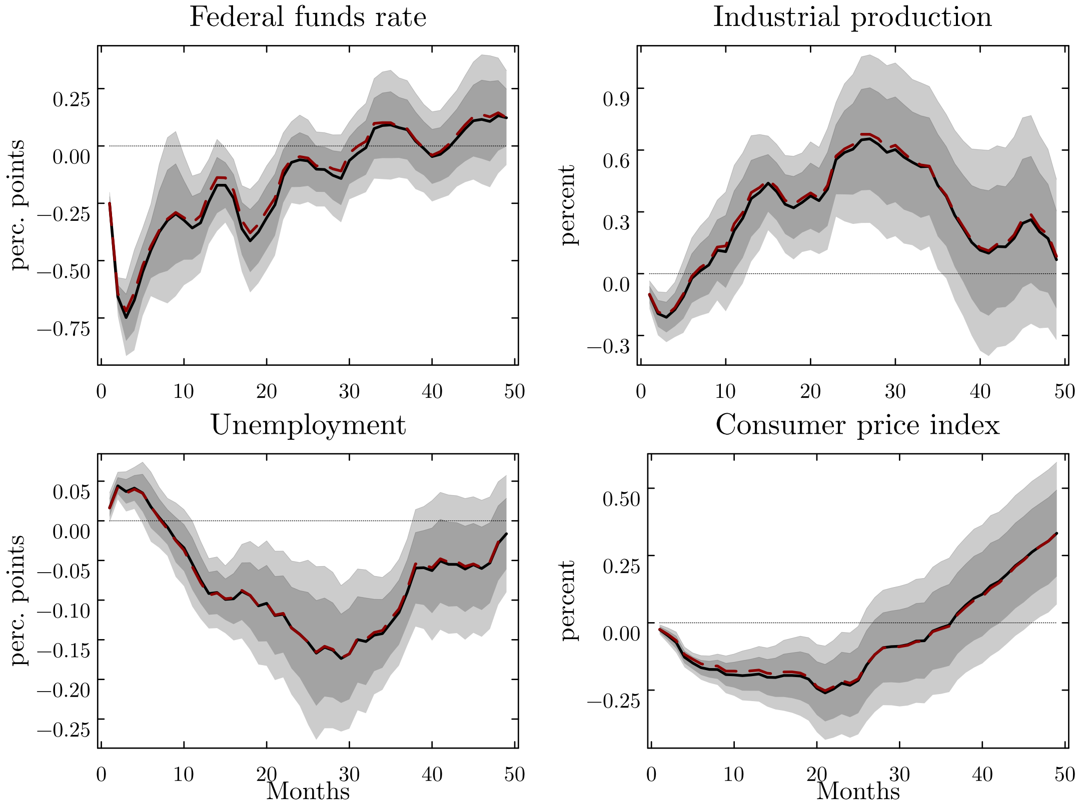
[9] Our code can also be extended easily as additional Tealbook forecasts become available.

Figure 9: Empirical responses for aggregate variables



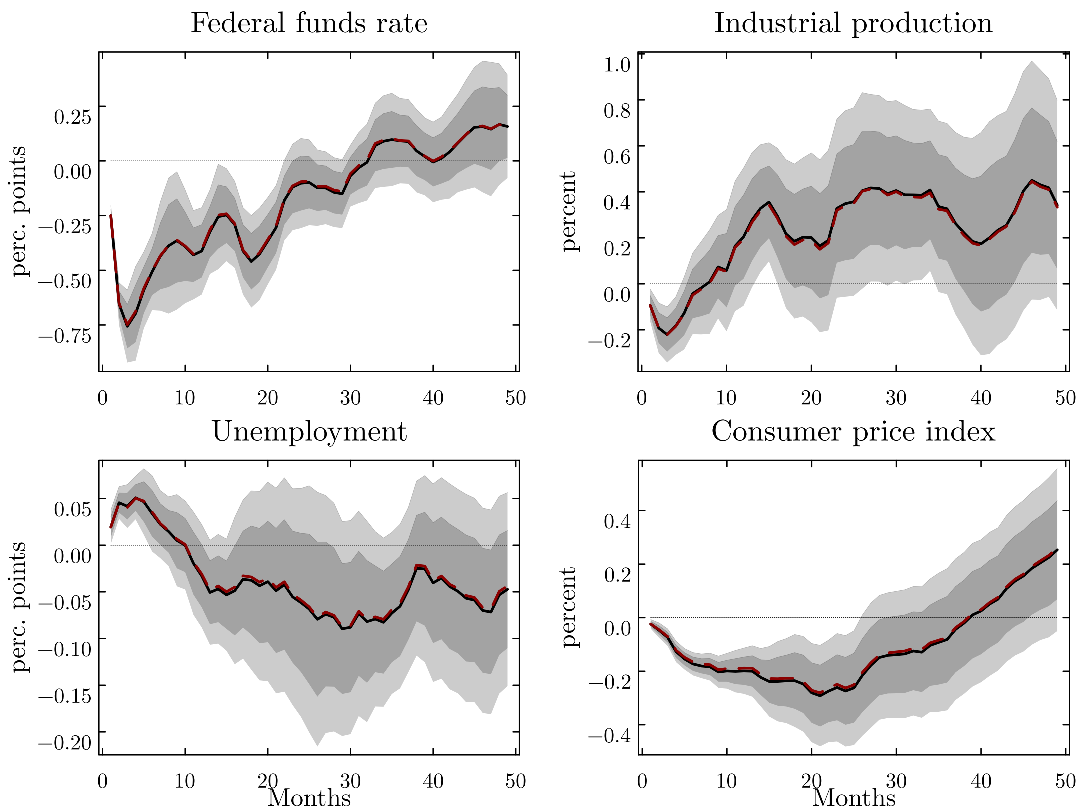
Note: Impulse responses to an expansionary CMP shock that lowers the Federal funds rate by 25 basis points. Own updated CMP series between 1969m3-2008m12. Light (dark) gray areas are 90 percent (68 percent) confidence intervals based on Newey and West (1987) standard errors.

Figure 10: Empirical responses for aggregate variables



Note: Impulse responses to an expansionary CMP shock that lowers the Federal funds rate by 25 basis points. *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 11: Empirical responses for aggregate variables



Note: Impulse responses to an expansionary CMP shock that lowers the Federal funds rate by 25 basis points. *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.

C Diagnostics for Alternative Shocks

The main text shows that our unified shock series has the properties typically expected of an externally identified policy shock: little serial correlation and no predictability from standard macro-financial information. This appendix applies the same diagnostics to the leading alternative UMP shock measures and compares their behavior with our series.

Figure 12 plots autocorrelation functions up to 15 lags. The benchmark is our UMP series in panel (a), for which no autocorrelation exceeds the 95% confidence bands in absolute value. Several alternative measures display more pronounced serial dependence, with some lags closer to or outside those bands.

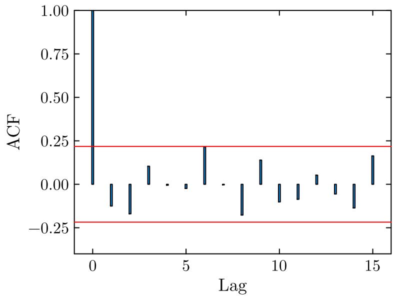
Table 6 formalizes this comparison with AR(10) tests. The clearest rejection arises for Swanson's orthogonalized LSAP series, while the orthogonalized forward-guidance series and Jarociński's Odyssean forward-guidance component are closer to the margin. Overall, detectable serial correlation is more common in the alternative measures than in our UMP series.

Table 7 reports Granger-causality tests. Several of the Swanson LSAP measures show clear evidence of predictability from lagged industrial production and CPI, with additional significance for consumption and equity prices in some specifications. The Jarociński LSAP series also displays statistically significant predictability, especially from CPI.

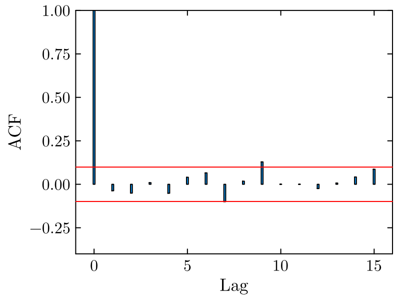
Table 8 repeats the factor-based predictability test from the main text using the macro-financial factors of Miranda-Agrippino and Ricco (2021). The same pattern emerges: several alternative UMP measures, including Jarociński's LSAP series and the Swanson (2021) forward-guidance and LSAP series, are more predictable than our benchmark UMP series.

Figure 12: Serial correlation of narrative monetary policy shocks - Autocorrelation function

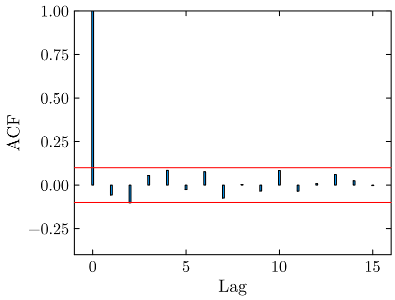
(a) **Unconventional MP**



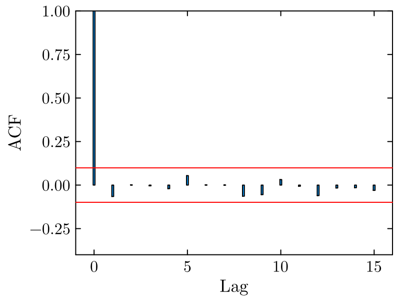
(b) **JK - Odyssean FG**



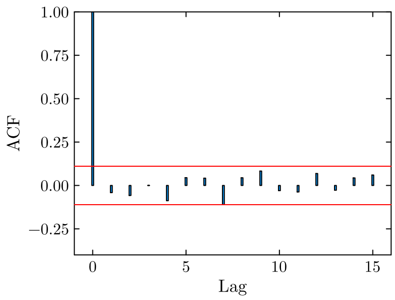
(c) **JK - Delphic FG**



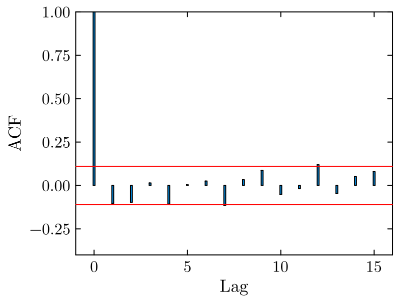
(d) **JK - LSAP**



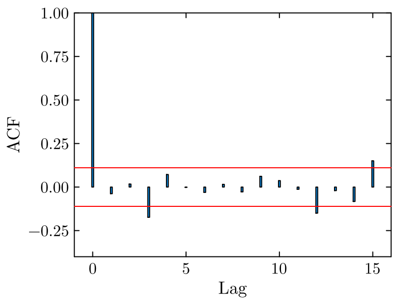
(e) **SW - FG**



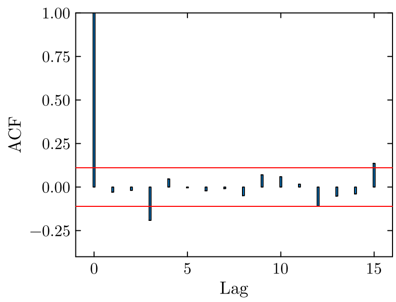
(f) **SW - FG Orthogonal**



(g) **SW - LSAP**



(h) **SW - LSAP Orthogonal**



Note: Autocorrelation function with 15 lags for our UMP shocks and other UMP shocks. Red lines correspond to the 95% confidence intervals. *JK* corresponds to the series of Jarociński (2024), and *SW* correspond to the series of Swanson (2021) or Swanson (2024) if they are orthogonalized to control for the “Fed reaction to news” effect.

Table 6: Serial correlation of unconventional monetary policy shocks - AR(10) regression

	UMP	JK - Ody. FG	JK - Delph. FG	JK - LSAP	SW - FG	SW - FG Orth.	SW - LSAP	SW - LSAP Orth.
Constant	0.0003	-0.0149	-0.0019	-0.0156	0.0198	0.0037	0.0020	0.0132
	(0.0002)	(0.0020)	(0.0017)	(0.0019)	(0.0025)	(0.0023)	(0.0009)	(0.0007)
shock_{t-1}	-0.1241	-0.0399	-0.0503	-0.0766	-0.0361	-0.1235	-0.0296	-0.0633
	(0.0135)	(0.0021)	(0.0031)	(0.0048)	(0.0021)	(0.0021)	(0.0071)	(0.0049)
shock_{t-2}	-0.1751	-0.0432	-0.1056	-0.0081	-0.0487	-0.1216	0.0067	-0.0558
	(0.0230)	(0.0024)	(0.0042)	(0.0020)	(0.0038)	(0.0054)	(0.0015)	(0.0029)
shock_{t-3}	0.0506	-0.0221	0.0619	-0.0188	-0.0232	-0.0456	-0.1862	-0.2248
	(0.0094)	(0.0079)	(0.0134)	(0.0571)	(0.0072)	(0.0072)	(0.0090)	(0.0118)
shock_{t-4}	0.0576	-0.0601	0.0848	-0.0210	-0.0964	-0.1311	0.0776	0.0333
	(0.0192)	(0.0020)	(0.0054)	(0.0014)	(0.0019)	(0.0020)	(0.0065)	(0.0034)
shock_{t-5}	0.0467	0.0343	-0.0035	0.0367	0.0411	-0.0349	-0.0006	-0.0271
	(0.0125)	(0.0027)	(0.0013)	(0.0150)	(0.0046)	(0.0059)	(0.0043)	(0.0020)
shock_{t-6}	0.2050	0.0582	0.0816	0.0078	0.0352	-0.0159	-0.0542	-0.0536
	(0.0237)	(0.0073)	(0.0036)	(0.0070)	(0.0024)	(0.0020)	(0.0051)	(0.0064)
shock_{t-7}	0.0577	-0.0935	-0.0882	-0.0117	-0.0961	-0.1092	0.0534	0.0260
	(0.0094)	(0.0052)	(0.0052)	(0.0012)	(0.0056)	(0.0058)	(0.0038)	(0.0026)
shock_{t-8}	-0.1222	0.0190	0.0114	-0.0726	0.0310	-0.0012	-0.0301	-0.0572
	(0.0162)	(0.0037)	(0.0013)	(0.0052)	(0.0044)	(0.0052)	(0.0037)	(0.0025)
shock_{t-9}	0.0587	0.1370	-0.0529	-0.0623	0.0900	0.0680	0.0453	0.0533
	(0.0179)	(0.0064)	(0.0034)	(0.0044)	(0.0045)	(0.0052)	(0.0067)	(0.0086)
shock_{t-10}	-0.1558	0.0230	0.0762	0.0213	-0.0159	-0.0315	0.0598	0.0676
	(0.0125)	(0.0023)	(0.0039)	(0.0014)	(0.0033)	(0.0040)	(0.0012)	(0.0015)
R^2	0.1412	0.0397	0.0453	0.0178	0.0372	0.0592	0.0492	0.0670
F-statistic	1.04	1.55	1.78	0.68	1.14	1.86	1.53	2.12
p-value	0.4249	0.1203	0.0626	0.7429	0.3319	0.0511	0.1291	0.0231
Observations	74	386	386	386	306	306	306	306

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

Table 7: Granger causality tests of different UMP shock series

Variable	p-value							
	UMP	JK - Ody. FG	JK - Delph. FG	JK - LSAP	SW - FG	SW - FG Orth	SW - LSAP	SW - LSAP Orth
Industrial Production	0.3461	0.9010	0.9917	0.0151	0.0268	0.1067	9e-05	6e-05
Unemployment rate	0.2740	0.9981	0.9847	0.9925	0.1947	0.7897	0.7887	0.7437
CPI	0.6796	0.0778	0.3035	2e-08	0.0004	0.0021	2e-05	5e-05
Consumption	0.3987	0.9987	0.9211	0.8087	0.3323	0.1948	0.0097	0.0065
S&P 500	0.3735	0.9801	0.4126	0.1490	0.3457	0.8972	0.0245	0.0287

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

Table 8: Predictability of the UMP shock series

	UMP	JK - Ody. FG	JK - Delph. FG	JK - LSAP	SW - FG	SW - FG Orth.	SW - LSAP	SW - LSAP Orth.
Constant	0.0193	-0.0003	0.0159	0.0092	0.0359	0.0245	0.0099	0.0075
	(0.0017)	(0.0030)	(0.0054)	(0.0030)	(0.0029)	(0.0029)	(0.0011)	(0.0011)
$f_{1,t-1}$	0.0320	-0.0238	-0.0377	-0.1854	-0.1106	0.0567	0.0066	-0.0433
	(0.0056)	(0.0057)	(0.0045)	(0.0388)	(0.0067)	(0.0072)	(0.0105)	(0.0095)
$f_{2,t-1}$	0.0005	0.0615	-0.0100	-0.1219	0.0536	0.0278	-0.0614	-0.0765
	(0.0006)	(0.0020)	(0.0020)	(0.0241)	(0.0035)	(0.0043)	(0.0059)	(0.0053)
$f_{3,t-1}$	0.0384	0.0132	0.0600	-0.0012	0.0873	0.0818	-0.0193	-0.0457
	(0.0032)	(0.0050)	(0.0095)	(0.0123)	(0.0053)	(0.0053)	(0.0032)	(0.0028)
$f_{4,t-1}$	-0.0335	0.0209	0.0171	-0.0999	0.0247	-0.0480	-0.1175	-0.0811
	(0.0082)	(0.0064)	(0.0071)	(0.0528)	(0.0090)	(0.0093)	(0.0130)	(0.0115)
$f_{5,t-1}$	0.0279	0.0663	-0.0337	-0.0342	0.0104	0.0524	0.0627	0.0350
	(0.0045)	(0.0060)	(0.0102)	(0.0318)	(0.0085)	(0.0082)	(0.0084)	(0.0079)
$f_{6,t-1}$	0.0074	-0.0840	0.0489	0.0823	-0.0818	-0.0529	0.0794	0.0612
	(0.0010)	(0.0057)	(0.0034)	(0.0126)	(0.0046)	(0.0049)	(0.0033)	(0.0031)
$f_{7,t-1}$	-0.0153	-0.0249	0.0182	-0.2095	-0.0707	0.0065	0.0046	-0.0485
	(0.0012)	(0.0055)	(0.0070)	(0.0260)	(0.0095)	(0.0093)	(0.0059)	(0.0055)
$f_{8,t-1}$	0.0110	-0.0368	-0.0440	0.0563	-0.0220	0.0381	0.0395	0.0038
	(0.0008)	(0.0029)	(0.0043)	(0.0031)	(0.0029)	(0.0030)	(0.0008)	(0.0009)
$f_{9,t-1}$	0.0180	-0.0536	0.0200	0.0263	-0.0737	-0.0055	0.0837	0.0299
	(0.0022)	(0.0032)	(0.0035)	(0.0137)	(0.0038)	(0.0038)	(0.0035)	(0.0032)
$f_{10,t-1}$	-0.0367	-0.0095	0.0063	-0.0640	-0.0424	-0.0357	-0.0324	-0.0092
	(0.0004)	(0.0035)	(0.0030)	(0.0029)	(0.0036)	(0.0036)	(0.0009)	(0.0008)
R^2	0.1537	0.0352	0.0138	0.0686	0.0708	0.0228	0.0694	0.0522
F-statistic	1.09	1.01	0.39	2.03	2.06	0.63	2.01	1.49
p-value	0.3848	0.4380	0.9522	0.0303	0.0282	0.7866	0.0321	0.1435
Observations	71	287	287	287	281	281	281	281

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 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.

D Robustness to Alternative Models

In the main text, we estimate the dynamic effects of UMP shocks using the local projection method of Jordà (2005). Specifically, we estimate

$$x_{t+h} = \alpha_h + \theta_h \varepsilon_t^{UMP} + \boldsymbol{\beta}_h' \boldsymbol{Z}_{t-1} + u_{t+h}, \tag{5}$$

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

This section reports robustness checks based on alternative econometric models. We first remain within the local-projection framework but use the shock series as an instrument rather than as the shock itself. We then estimate an internal instrument VAR and a Proxy VAR.

For the local projection IV specification, we follow Jorda et al. (2015) and Ramey (2016) and estimate the first-stage regression

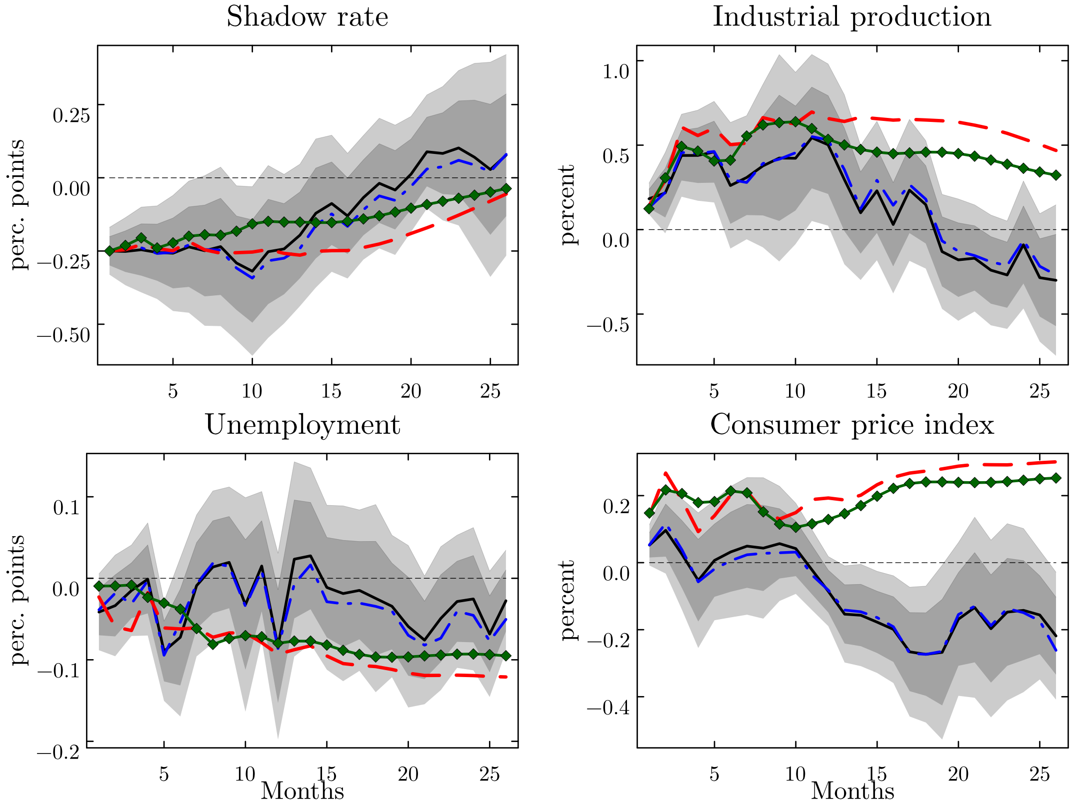
$$\Delta sffr_t = \alpha + \theta^{FS} \varepsilon_t^{UMP} + \boldsymbol{\beta}' \boldsymbol{Z}_{t-1} + u_t, \tag{6}$$

where $\Delta sffr_t$ is the monthly change in the shadow federal funds rate, instrumented with ε_t^{UMP}, and $\boldsymbol{Z}_{t-1}$ contains the same controls as in the main text. We then estimate Equation 5 and recover the IV impulse response as $\theta_h^{IV} = \frac{\theta^{RF}}{\theta^{FS}}$.

For the internal instrument VAR, we order the UMP shock series first and use recursive identification. For the Proxy VAR, we use the UMP series as an external instrument for the shadow federal funds rate. In both VARs, the remaining variables and lag length match the specification in Section 3.1.

Figure 13 compares the aggregate responses from the baseline local projection with those from the three alternative models. The LP-IV estimates are nearly identical to the baseline responses. The two VAR specifications deliver the same qualitative conclusions, with somewhat smoother unemployment dynamics and a more persistent increase in inflation. Overall, the main aggregate findings are not sensitive to the econometric framework.

Figure 13: Empirical responses for aggregate variables in different models



Note: Impulse responses to an expansionary UMP shock that lowers the shadow rate by 25 basis points. *Black solid line*: Local projection. *Blue line with circles*: Local projection IV. *Red dashed line*: Internal instrument VAR. *Green line with diamonds*: Proxy VAR. Light (dark) gray areas are 90 percent (68 percent) confidence intervals based on Newey and West (1987) standard errors for the original local projection.

E Further Distributional Results

The main text focuses on the middle and upper parts of the wealth distribution, where asset revaluations are quantitatively most important. This section extends the analysis to the bottom half of the distribution by documenting participation, wealth levels, and portfolio composition, and by relating these patterns to the mechanism emphasized in the paper.

Table 9 reports extensive-margin participation in housing and equity markets for the full population and for the bottom groups. Non-homeownership is much higher in the bottom tail than in the overall population, especially for the bottom 10%, where it rises from 63% to almost 80% between 2010 and 2016. Equity participation is extremely limited throughout: around 95% of households in both the bottom 10% and bottom 50% hold no equity. A large share of bottom households therefore holds neither housing nor equity and is effectively "asset excluded."

Table 9: Asset-market participation in the bottom of the wealth distribution

	2010	2013	2016
Share without a house (%)			
All households	32.78	34.85	36.30
Bottom 10%	63.36	70.12	79.80
Bottom 50%	58.44	61.85	65.08
Share without equity (%)			
Bottom 10%	94.61	96.01	96.18
Bottom 50%	94.59	95.47	94.81
Share with neither house nor equity (%)			
Bottom 10%	61.14	67.95	76.89
Bottom 50%	56.03	59.22	62.25

Note: The values are calculated using the Survey of Consumer Finances, waves 2010/2013/2016.

Table 10 shows that the bottom 10% has uniformly negative net worth. Both mean and median total wealth are negative in all waves, while median housing and equity wealth are zero throughout, consistent with the participation patterns in Table 9. The positive mean housing wealth reflects a minority of homeowners, but that does not overturn the group's negative net worth.

Because the bottom 10% is an extreme tail, Table 11 also reports results for the bottom 50%. Mean total wealth is positive but modest, whereas mean housing

Table 10: Wealth levels in the bottom 10%

	2010	2013	2016
Total wealth			
Mean	-38,107	-37,509	-35,621
Median	-16,724	-18,880	-18,300
House wealth			
Mean	65,429	42,588	28,640
Median	0	0	0
Equity wealth			
Mean	201	345	259
Median	0	0	0

Note: The values are obtained using the Survey of Consumer Finances, waves 2010/2013/2016.

wealth is large relative to mean net worth because many households in this group are highly leveraged. Housing is therefore the main sizable asset for the subset of homeowners in the bottom half, but low ownership rates and substantial liabilities keep group-level net worth low.

Table 11: Mean wealth and portfolio ratios in the bottom 50%

	2010	2013	2016
Mean total wealth	12,944	11,891	15,464
Mean house wealth	53,955	42,806	39,664
Mean equity wealth	317	451	533
House / Total	4.17	3.60	2.56
Equity / Total	0.02	0.04	0.03

Note: The values are obtained using the Survey of Consumer Finances, waves 2010/2013/2016.

For comparison, Table 12 reports the portfolio shares of the main groups emphasized in the main text. The 50–90 group is housing-dominated, whereas the top 10% has much larger equity exposure. This contrast is the key cross-sectional margin behind the different distributional effects of CMP and UMP.
We next extend the SCF-based revaluation exercise from Section 3.3 to the bottom of the distribution.
In the revised main text, Figure 6 already reports the four-group SCF revaluation exercise, including relative net-worth changes in panel (b) and the distri-

Table 12: Portfolio shares by group

Group	House / Total	Equity / Total
50–90%	0.67	0.05
Top 10%	0.19	0.16

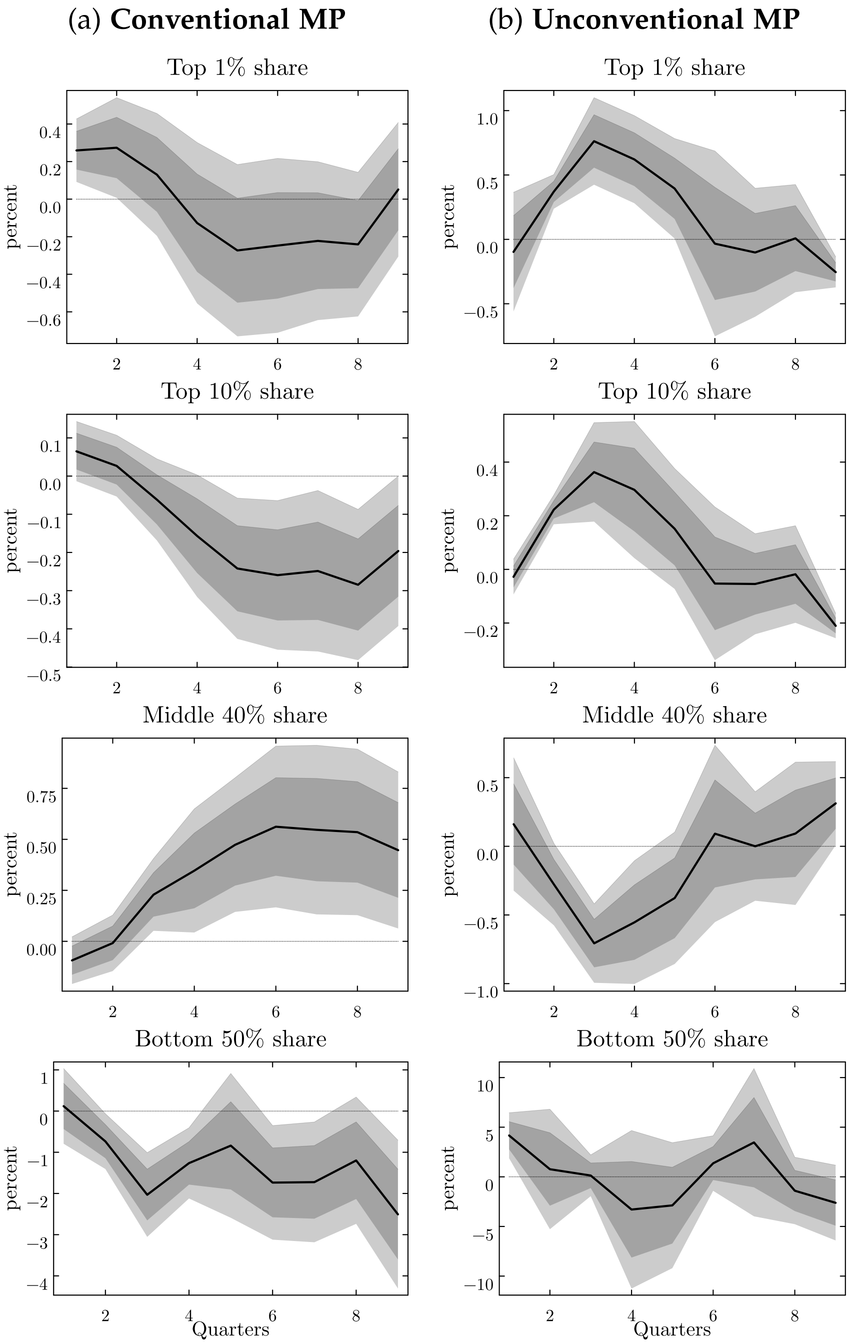
Note: The values are obtained using the Survey of Consumer Finances, wave 2010.

bution of gains across groups and asset classes in panels (c)–(d). Read together with Table 9, the message is clear: near-zero equity participation mechanically limits bottom-household exposure to stock price movements, and when bottom households benefit at all, the gains mostly come through housing for the subset of homeowners.

E.1 Wealth Dynamics by Percentiles

Figure 14 provides a complementary view of the revaluation channel by reporting impulse responses for additional wealth groups. Under UMP, the wealth share of the middle 40% falls, while the top 10% and especially the top 1% gain. This pattern is consistent with the portfolio evidence: middle-class portfolios are housing-heavy, whereas top portfolios are more exposed to equity. By contrast, the bottom 50% shows smaller and less precisely estimated responses, reflecting limited asset holdings. The CMP responses in panel (a) point in the opposite direction.

Figure 14: Empirical responses for wealth inequality: Different percentiles



Note: Impulse responses to expansionary CMP and UMP shocks, normalized such that each implies a 25 basis points fall in the interest rate on impact. Light (dark) gray areas are 90 percent (68 percent) confidence intervals based on Newey and West (1987) standard errors.

Taken together, the appendix evidence reinforces the stock-versus-housing revaluation channel. Bottom households have almost no equity exposure, so stock-price movements matter little for them directly. Even within the bottom 50%, housing matters only for the subset of homeowners, and the extensive margin remains central because a large fraction holds neither housing nor equity. By contrast, the top 10% benefits disproportionately from stock price revaluations, while the 50–90 group is more exposed to housing. These portfolio asymmetries are precisely what make UMP shocks more inequality-increasing than CMP shocks.

Including the bottom tail therefore strengthens, rather than weakens, the main interpretation. The distributional consequences of unconventional policy are largest where exposure to revalued assets is greatest, while households at the bottom participate little in housing and especially equity markets, making their estimated wealth-share responses smaller and less precise.

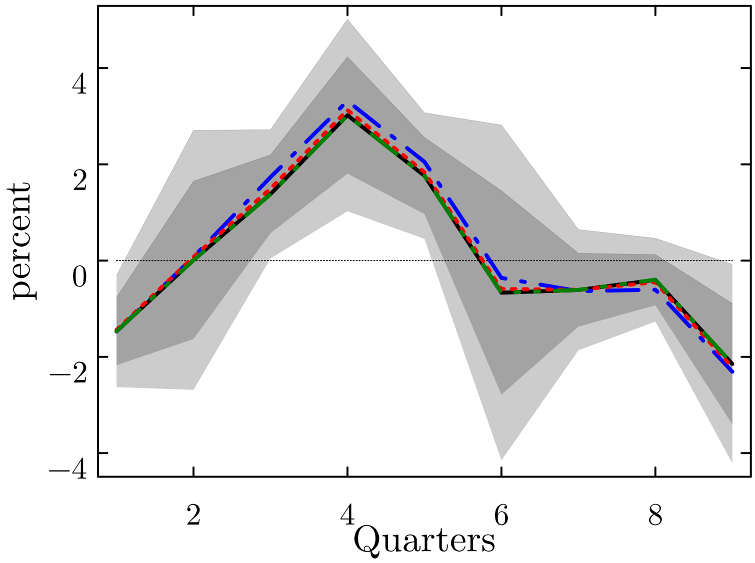
F Robustness to Lingering Subprime Effects

A natural concern is that the increase in the stock-to-house price ratio after expansionary UMP shocks partly reflects lingering features of the post-2008 environment. Our UMP sample overlaps with the repair of household and intermediary balance sheets, elevated risk premia, and tighter credit standards, all of which may have mattered more for housing finance than for public equities. If housing markets remained unusually constrained after the subprime crisis, house prices could have reacted less to monetary accommodation, mechanically raising the relative response of equity prices.

To evaluate this concern, we re-estimate the baseline local-projection response of the stock-to-house price ratio while augmenting the control set with measures of crisis-related financial frictions. In separate specifications, we add: (i) the Excess Bond Premium (EBP), a proxy for credit frictions and intermediary risk-bearing capacity; (ii) the National Financial Conditions Index (NFCI), a broad measure of aggregate financial conditions; and (iii) a mortgage spread, which more directly captures financing conditions in housing markets. Each variable is included analogously to the controls in the baseline specification.

Figure 15 reports the results. Across all three augmented specifications, the response of the stock-to-house price ratio is nearly identical to the baseline: it remains hump-shaped, peaks at a similar horizon, and stays within the baseline confidence bands throughout. Conditioning on crisis-related variation in credit spreads, financial conditions, or mortgage premia therefore does not materially alter either the magnitude or the timing of the response. This makes it unlikely that the main result is driven by lingering post-subprime dynamics rather than by a systematic difference in how UMP affects equity and housing valuations.

Figure 15: Impulse Response Function of stock-to-house price ratio



Note: Black solid line: Original specification. The other lines include additional controls related to the lingering effect of the subprime crisis. *Blue dash-dotted line*: Excess Bond Premium. *Red dotted line*: National Financial Conditions Index. *Green dash-dot-dotted line*: Mortgage spreads.