Online Appendix: Effects of Monetary Policy on Wealth Inequality

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A The Gini coefficient from the binned data

An important question for this paper is how the Gini coefficient is constructed from the binned data provided by *the Distributional Financial Accounts*(DFA). In particular, it is essential to clarify how the so-called "pseudo Gini" is computed and what are the advantages and limitations of this method. This section explains the construction of the Gini coefficient based on grouped wealth shares and discusses the implications for accurately measuring inequality.

I fully acknowledge the limitation that binned data do not capture within-group heterogeneity. Nevertheless, I adopt this approach because (1) the time series trends from the DFA and SCF(*the survey of consumer finance*) Gini measures are broadly consistent, and (2) using grouped data eliminates the complications of rank correlations in Gini decomposition, thereby clarifying the transmission channels of inequality changes. Below, I provide detailed responses to the specific points raised.

A.1 Method of pseudo Gini

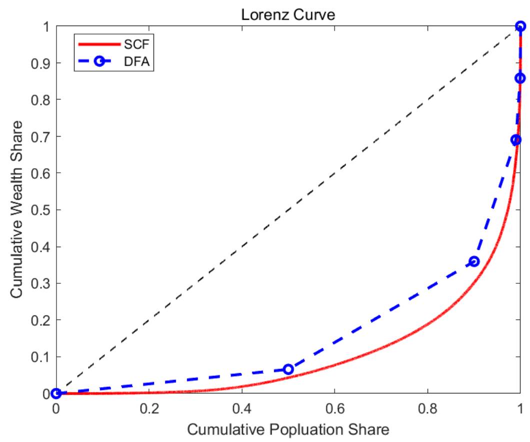
The Gini coefficient can be computed by treating each binned data point as a single observation, and the formula itself remains unchanged. In the equation below, w_i represents the population weight of each bin (or group), and y_i denotes the wealth per capita within bin i, calculated as the wealth share divided by the population share.

$$G = \frac{1}{2\bar{y}} \sum w_i w_j |y_i - y_j|$$

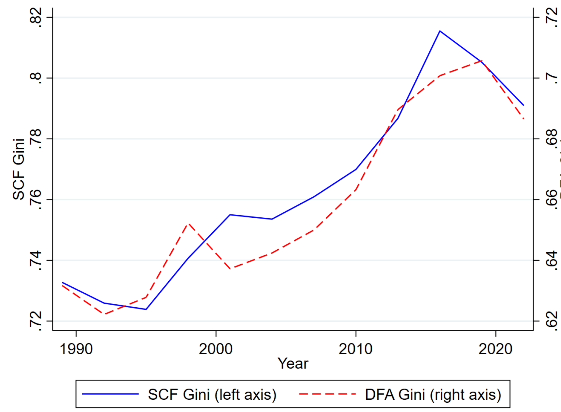
This relative mean absolute difference approach is equivalent to the area between the Lorenz curve and the line of perfect equality (the 45-degree line), divided by 0.5.

A.2 Limitation of DFA Gini

The Gini coefficient based on DFA relies on five wealth bins and thus cannot capture within-group heterogeneity. Van Ourti and Clarke (2011) pointed out such downward bias is inherent in using grouped data. As illustrated in Figure 1 (panel (a)), the Lorenz curve for DFA (blue dashed) is linear within the bottom 50%, whereas the SCF curve (red) exhibits greater convexity. Consequently, the DFA-based Gini is downward biased relative to the SCF Gini



(a) Lorenz curve



(b) Time series

Figure 1: Comparison of Wealth Inequality Measures: SCF and DFA

computed from over 20,000 individual observations.

A.3 Advantages of the DFA Gini

Despite its limitations, the pseudo Gini based on DFA binned data offers several important advantages. First, it is externally validated: although it slightly understates the level of inequality compared to the "true" Gini from the Survey of Consumer Finances (SCF), it closely tracks the SCF Gini over time. The correlation between the two series is **0.9611**, and a simple linear regression yields an $R^2 = 0.92$, a slope of 1.00, and an intercept of 0.10—implying a stable level gap but nearly identical cyclical dynamics.

Second, the DFA Gini provides timely quarterly estimates, whereas the SCF is available only triennially, limiting its usefulness for analyzing the short-run effects of monetary policy.

Third, binned data offer analytical tractability when applying the Lerman and Yitzhaki (1985) decomposition. Since the wealth bins (e.g., bottom 50%, 50–90%, 90–99%, top 1%) are coarse and the per capita rankings of asset components are stable—with the top 1% consistently holding the most—the rank correlation terms R_i can reasonably be assumed to equal one. This removes the need to estimate R_i and allows for a clean attribution of Gini changes to shifts in asset shares or within-component inequality.

In sum, the DFA pseudo Gini, while not a perfect measure, is a reliable, high-frequency proxy that enables meaningful decomposition and policy analysis.

B Supplementary Robustness Results

This section shows the results of three important points regarding the local projection (LP) specification. First, I confirm that adding standard macroeconomic controls did not materially affect the impulse responses. Second, following the guidance of Montiel Olea and Plagborg-Møller (2021), I replaced the originally reported HAC (Newey-West) standard errors with Eicker-Huber-White robust errors. Under this adjustment, the IRF estimates lose statistical significance. Third, I attempted the bias correction method proposed by Herbst and Johannsen (2024) and the resulting IRFs remained nearly unchanged. Fourth, the first-stage F-statistic is small in the quarterly specification, raising concerns about weak instruments. To address this issue, I present results based on monthly frequency data, where the weak instrument problem does not arise.

B.1 Inclusion of control variables

Following Gertler and Karadi (2015), I include additional control variables—namely, real GDP, inflation (CPI), and the excess bond premium (EBP)—in the local projection regressions. As shown in Figure 2, the resulting impulse responses remain qualitatively similar. The inclusion of these controls does not lead to any significant change in the estimated effects of m onetary policy shocks on the Gini coefficient.

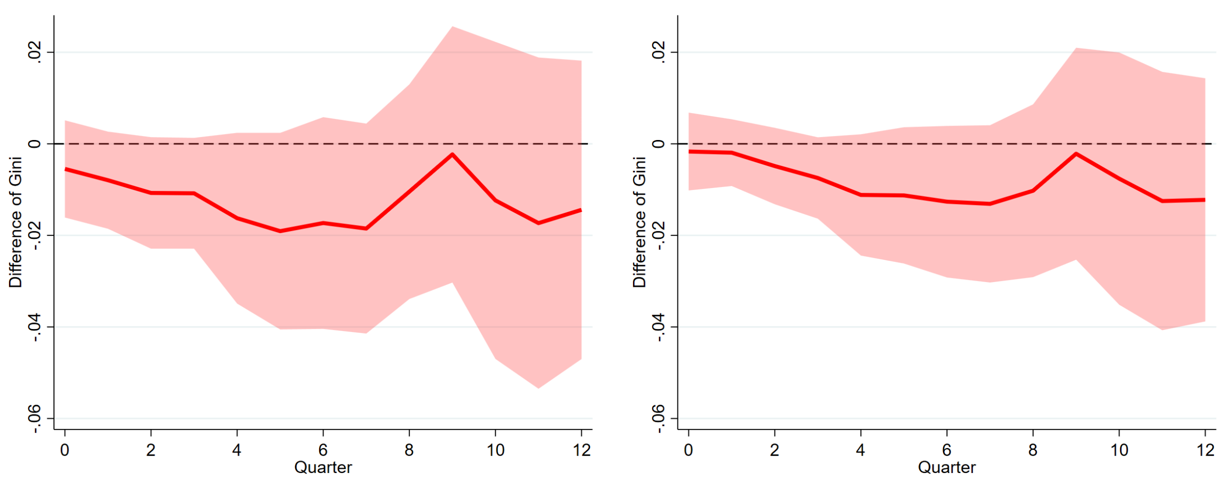


Figure 2: Effect of Monetary Policy on Wealth Inequality: Baseline(left) vs. With Macroeconomic Controls(right)

Note: The red line shows the impulse response of the wealth Gini coefficient to a 100 basis point interest rate increase. The shaded red area indicates the ±1 standard deviation confidence band, based on Eicker-Huber-White robust standard errors. The x-axis shows the horizon (in quarters), and the y-axis shows the change in the Gini coefficient.

B.2 Standard errors

Following Montiel Olea and Plagborg-Møller (2021), I replace the previously used HAC (Newey-West) standard errors with Eicker-Huber-White robust standard errors throughout the paper. Notably, after this change, the estimated impulse responses become statistically insignificant under the 1-standard-error band. In the updated figures, the darker shaded area represents the White-based 1-standard-error confidence interval, while the dotted lines indicate the original Newey-West bands. I have revised all figures and tables accordingly and adopt the White standard errors as the default throughout the paper, as recommended.

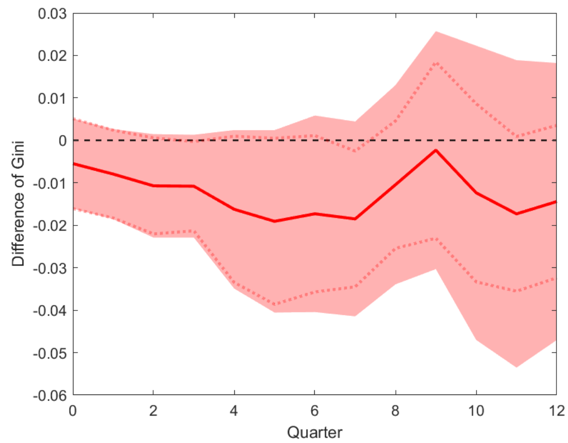


Figure 3: White(shaded-area) vs. Newey-West(dotted line)

Note: The red line shows the impulse response of the wealth Gini coefficient to a 100 basis point interest rate increase. The shaded red area(dotted line) indicates the ± 1 standard deviation confidence band, based on Eicker-Huber-White(the Newey-West) robust standard errors. The x-axis shows the horizon (in quarters), and the y-axis shows the change in the Gini coefficient.

B.3 Bias correction estimator

Herbst and Johannsen (2024) show that the impulse responses function fo the local projection are biased in small samples and propose a method to correct some of that bias. Although my sample size is relatively large (maximum number of sample $N = 133$), I attempted the bias correction method proposed by Herbst and Johannsen (2024) and the resulting IRFs remained nearly unchanged. The red dashed line in the Figure 4 shows the bias-corrected IRF estimates.

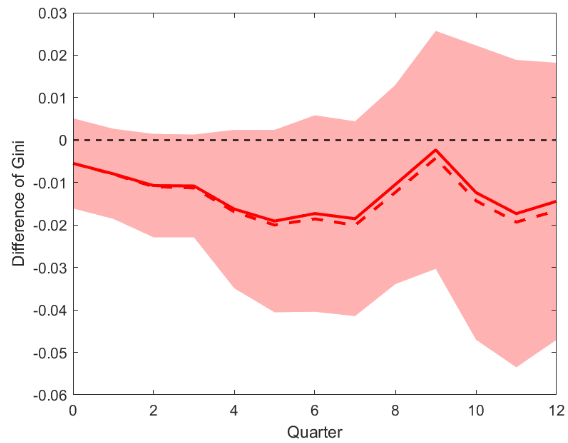
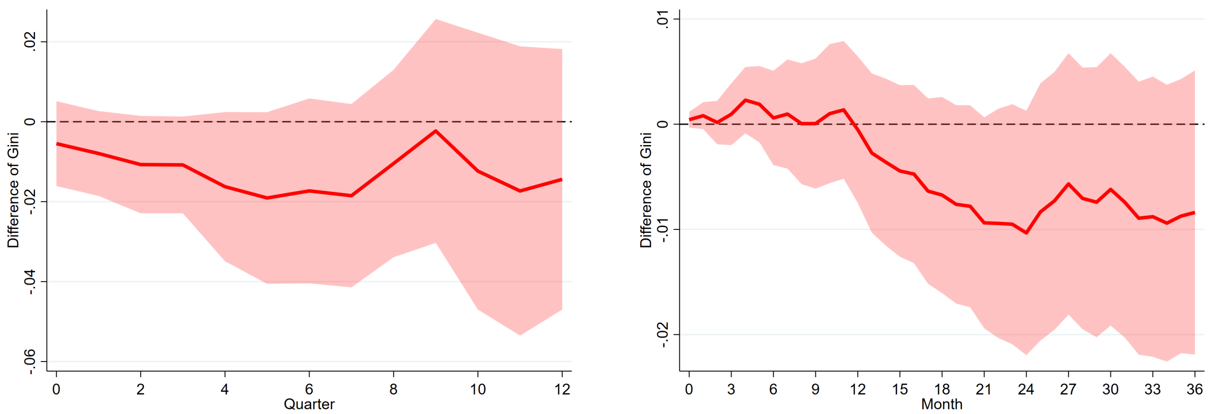


Figure 4: Bias corrected estimates(dashed red line)

Note: The red line shows the impulse response of the wealth Gini coefficient to a 100 basis point interest rate increase, and the red dashed line reflects the small-sample bias correction method proposed by Herbst and Johannsen (2024). The shaded red area indicates the ± 1 standard deviation confidence band, based on Eicker-Huber-White robust standard errors. The x-axis shows the horizon (in quarters), and the y-axis shows the change in the Gini coefficient.

B.4 Concerns with the weak IV

To help assess instrument strength, I report a first-stage F-statistic of **4.88** — which does not exceed the conventional threshold of 10. I follow the approach of Stock and Watson (2018), where the instrument demonstrates strong relevance in monthly data (with F-statistics **25.08**, similar to their findings). However, when aggregated to quarterly frequency, the strength of the instrument diminishes substantially. I suspect that this decline is due to a weak IV problem arising from time aggregation. To address this concern and to acknowledge its potential implications, I conduct a complementary analysis using monthly Gini coefficients constructed from binned data provided by the *Realtime Inequality* project.(Blanchet et al. (2022))[1] The results from this robustness check are presented below.



(a) DFA(quarterly)

(b) RTI(monthly)

Figure 5: Comparison of Wealth Gini IRF: DFA and RTI

Note: The red line shows the impulse response of the wealth Gini coefficient to a 100 basis point interest rate increase. The shaded red area indicates the ±1 standard deviation confidence band, based on Eicker-Huber-White robust standard errors. The x-axis shows the horizon (in quarters), and the y-axis shows the change in the Gini coefficient.

[1] `https://realtimeinequality.org/`

C Details of IRF decomposition

I provide delta-method-based standard errors for the decomposed contributions to the Gini IRF, as shown in Equation (4).

$$\frac{\partial G}{\partial r} = \underbrace{\sum_{i=1}^{n} \frac{\partial S_i}{\partial r} G_i}_{\text{share IRF}} + \underbrace{\sum_{i=1}^{n} S_i \frac{\partial G_i}{\partial r}}_{\text{component Gini IRF}} + \triangle \tag{1}$$

For instance, the variance of the share i's contribution is

$$Var(\text{share } i \text{ contribution}) = G_i^2 Var(\beta^h_{i,share}) + (\beta^h_{i,share})^2 Var(G_i)$$

Here, G_i denotes the time-series average of the Gini coefficient for asset component i, and $\mathrm{Var}(G_i)$ is computed using the time-series variance. $\beta^h_{i,\text{share}}$ represents the impulse response of the share of asset i at horizon h. Since the share effects, component Gini effects, and residual are mechanically derived from point estimates, their standard errors are not separately presented.

References

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