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The beginning of the trend: Interest rates, profits, and markups

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Abstract

Recent highly cited research uses time-series evidence to argue the decline in interest rates led to a large rise in economic profits and markups. We show the size of these estimates is sensitive to the sample start date: The rise in markups from 1984 to 2019 is 14% larger than from 1980 to 2019, a difference amounting to a \$3000 change in income per worker in 2019. The sensitivity comes from a peak in interest rates in 1984, during a period of heightened volatility. Our results imply researchers should justify their time-series selection and incorporate sensitivity checks in their analysis.

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1. Introduction

Since the early 1980s, the labor share of value-added and the real interest rate have declined significantly. These declines have led to a debate about the magnitude of an implied rise in market power (Barkai, 2020; Farhi and Gourio, 2018; Karabarbounis and Neiman, 2019; Davis et al., 2023). As a leading example, Barkai (2020) delineates these trends from 1984 to 2014: The decline in interest rates led to a 5 pp decline in the cost of capital and a 7 pp decline in the capital share; the implied economic profit share increased by 14 pp, amounting to over \$1 trillion in economic profits in 2014.

However, researchers question how much market power has really changed. Different methods and samples lead to disparate magnitudes. Basu (2019) finds markups measured using aggregate data in 1984-2014 (Barkai, 2020), industry data in 1988-2015 (Hall, 2018), and firm data in 1980-2016 (De Loecker et al., 2020) produce a wide range of estimates. In this paper, we ask: How does sample selection influence the estimated growth in market power?

Time-series selection heavily influences the economic size of these results, challenging their robustness. We contribute to the market power literature by quantifying the role of sample selection on the estimated trends implied by decreasing interest rates. Extending our 4-decade sample back by just 4 years explains 25% of the trend in the real interest rate, 37% in the cost of capital, 14% in the economic profit share, and 14% in implied markups. This sensitivity amounts to a difference of \$260 billion of economic profits in 2019.

Time-series selection sensitivity is one of many time-series inference traps in research. Card and Krueger (1995) show how publication bias in minimum wage studies can lead to overestimation of employment effects. White (2000) addresses the problem of multiple comparisons in time-series analysis, developing methods to assess the reliability of results when testing different hypotheses on the same dataset. Jensen et al. (2023) discusses the factor zoo in asset pricing using out-of-sample tests. Although each of these papers, as well as ours, focuses on a particular topic, they all illustrate broader methodological concerns in empirical research of time series.

More generally, we show sensitivity is pronounced when analyzing any trend using high-volatility time series, as with real interest rates in the 1980s. Data points far from the time value mean, or the dependent variable mean, have higher influence on time-series regression results. Hence, points at the beginning or end of a sample are mechanically influential, and points drawn from a highly volatile time series are more likely influential. Therefore, the volatility in financial markets poses a challenge in accurately quantifying trends. Our empirical contribution indicates this challenge is plausibly significant, calling for justified sample selection and robustness checks.

We emphasize the application to quantifying secular trends in market power for two reasons. First, researchers use these different magnitudes to estimate models and inform policies. Following Executive Order 14036, the Council of Economic Advisors (2023) uses evidence from Shapiro (2018) and Philippon (2019) to reorient competition policy. Precise measurements of economic profits and markups are also key targets for modeling and welfare (Edmond et al., 2023; Farhi and Gourio, 2018; Eggertsson et al., 2021). For instance, Blanchard (2019) cites the scale of rising profits to argue the cost of public debt is small.

Second, as we’ve already highlighted, there is a substantial disagreement about how much markups have really increased. Our analysis therefore contributes to ongoing empirical research on secular trends in the US economy. Key debates continue over rising national-level concentration (Barkai, 2020; Covarrubias et al., 2020), the dominance of superstar firms (Autor et al., 2020), and conflicting measures of public-firm markups (De Loecker et al., 2020; Traina, 2018), all of which hinge on precise estimation of long-term economic trends and their underlying drivers. We clarify one major reason for these disparate magnitudes: Sample selection.

2. Interest Rates, Profits, and Markups

We use the standard method of Hall and Jorgenson (1967) to measure the cost of capital using financial-market rates, which track the decline in the 10-year Treasury yield (Barkai, 2020; Karabarbounis and Neiman, 2019; Davis et al., 2023). We then measure profits and markups as the residual from national income less payments to labor and capital. Our measurement follows Barkai (2020): The main variables come from the Bureau of Economic Analysis (BEA) National Income and Product Accounts Table 1.14 (value added, labor compensation), Fixed Assets Accounts Table 4.1 (capital, depreciation, and inflation), and Integrated Macroeconomic Accounts Table S.5.a (inventories); tax rates come from the Organisation for Economic Cooperation and Development and the Tax Foundation.

Our approach calculates the change in the estimated linear trend through 2019 for different start dates in the 1980s. For each time series, we estimate the simple linear regression:

$$y_t = \beta * t + \alpha + \varepsilon_t \tag{1}$$

In the left panels, we plot the entire time series at the highest frequency available on the Federal Reserve Economic Data database. In the right panels, we plot the percentage change in the trend for every starting year in the 1980s compared to a base year of 1980.

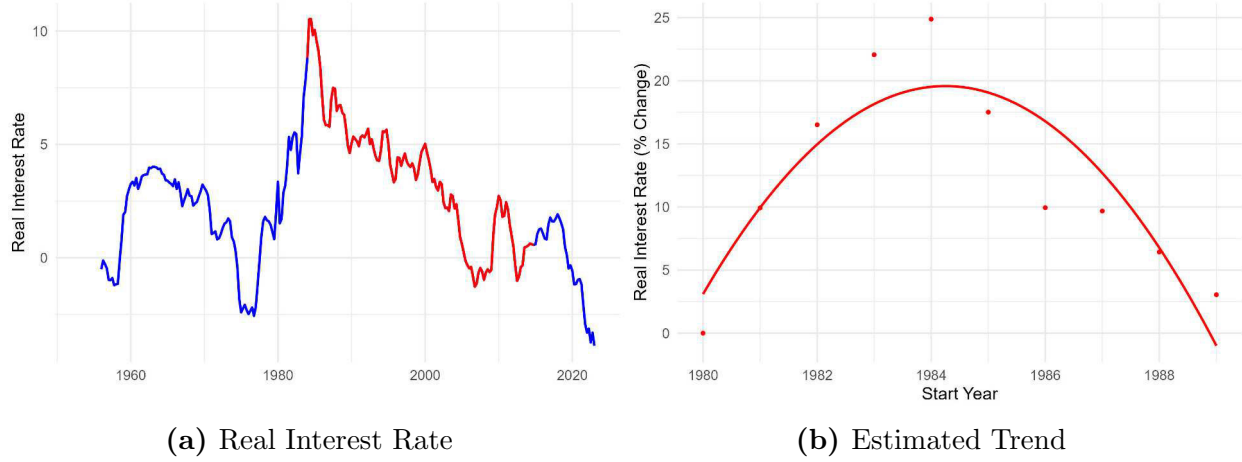
Figure 1a displays the real interest rate. The part in red is from 1984 to 2014, the period referenced in the literature. Figure 1b plots the percentage change in the linear trend of the real interest rate, starting from different years. We fit a quadratic function over these points.

The linear trend for the real interest rate is steepest when starting the series in 1984, which is the most commonly cited start date in the literature. Data points from the beginning of the sample are highly influential. The real interest rate was 7 pp lower in 1980 than in 1984. The peak in the real interest rate occurred in 1984.

The Hall and Jorgenson (1967) cost of capital R_c is:

$$R_c = (\rho - \nu + \delta) \frac{1 - z\tau}{1 - \tau} \tag{2}$$

Figure 1: Real Interest Rate: $i - \nu$



Note: The real interest rate is measured as the 10-year Treasury yield less expected capital inflation, constructed as the three-year moving average of realized capital inflation from the BEA. Shown at a quarterly frequency.

Equation (2) maps the cost of finance¹ to the cost of capital used in real investment decisions by adjusting it for expected capital inflation ν , depreciation δ , taxes τ , and depreciation allowances z . The formula is widely used in the capital investment literature because it holds in a large class of models, relying only on a simple arbitrage argument. Here, ρ is the cost of finance and is defined as $dR_d + (1 - d)R_e$, where d is the debt share of financial assets, R_d is the expected return on debt measured as the Moody's Baa bond yield, and R_e is the expected return on equity measured as the 10-year Treasury yield plus a 5% risk premium. Barkai (2020), Karabarounis and Neiman (2019), and Davis et al. (2023) all show the cost of finance ρ closely tracks the interest rate i ; we focus on ρ to make it easy to compare with Barkai (2020).

Figure 2a displays the cost of capital. The part in red is from 1984 to 2014, the period referenced in the literature. Figure 2b plots the percentage change in the linear trend of the cost of capital, starting from different years. We fit a quadratic function over these points.

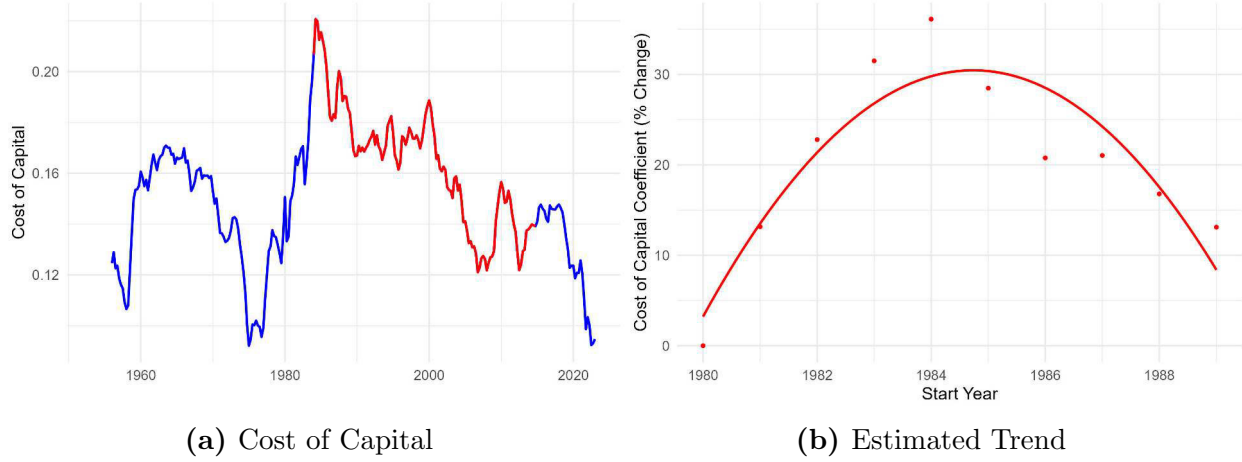
The trend for the cost of capital is steepest when starting the series in 1984. Data points from the beginning of the sample are highly influential. The cost of capital was 7 pp lower in 1980 than in 1984. Comparing the endpoints of the sample, the cost of capital was nearly the same in 1980 and 2019.

The economic profit share measures earnings in excess of production costs, including the cost of capital. It's fundamentally a residual after subtracting labor and capital payments from value-added:

$$\Pi = 1 - \frac{WL}{Y} - \frac{R_c K}{Y} \quad (3)$$

¹The cost of finance is also known as the weighted average cost of capital (WACC) in financial economics.

Figure 2: Cost of Capital: R_c



Note: The cost of capital, otherwise known as the weighted average cost of capital (WACC) is composed of the equity and debt costs of capital measured as the weighted average of Moody’s Baa bond yield and the 10-year Treasury yield plus a 5% risk premium. Shown at a quarterly frequency.

Following Basu (2019), we can convert (3) to an implied markup on gross output, as in De Loecker et al. (2020). Assuming constant returns to scale and an intermediate input share of revenue of 0.5, we have:

$$\mathcal{M} = \frac{2}{2 - \Pi}. \quad (4)$$

Figures 3a and 3c display the economic profit share and implied markups on gross output. Figures 3b and 3d plot the percentage change in the linear trend of the economic profits and implied markups, starting from different years. Again, we fit a quadratic function over these points.

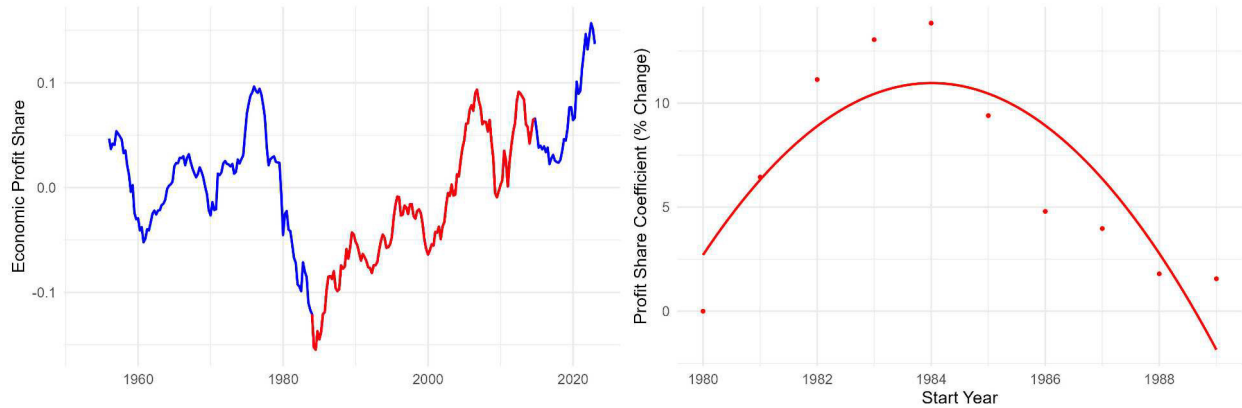
The trends for profits and markups are steepest when starting the series in 1984. The points at the start are highly influential. Economic profits were 4 pp higher in 1980 than in 1984.

While our primary analysis focuses on start-date sensitivity, we recognize end-date choice can also significantly impact trend estimates. Figure A.1 illustrates how varying the end date affects our key variables. As evident from Figure A.1, the choice of end date can substantially alter trend estimates, particularly in recent years characterized by increased volatility. For instance, ending the sample in 2020 versus 2014 changes the estimated trend in both the economic profit share and implied markups by 16%.

3. Time-Series Volatility and Influence

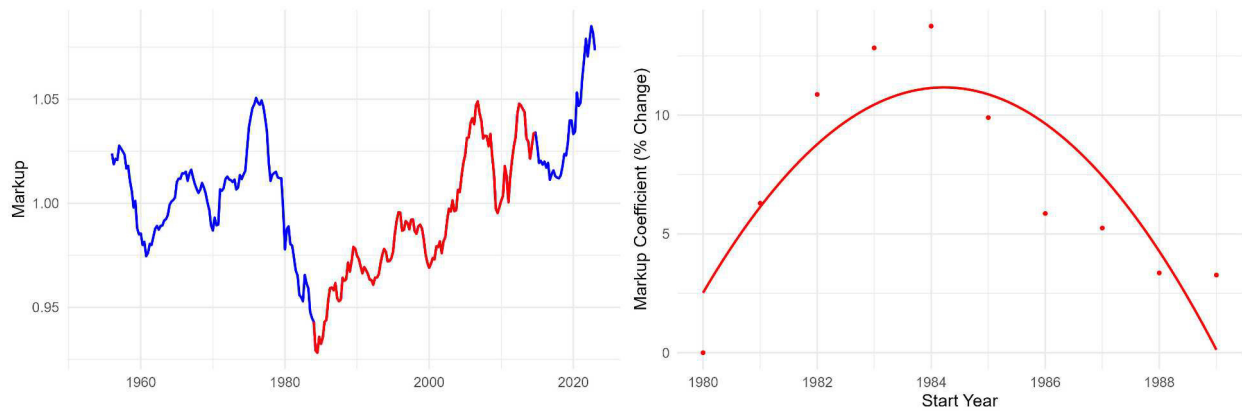
The secular trends of rising profits and markups are due to variation in real interest rates. However, real interest rates are notoriously volatile, and their fluctuations can significantly impact our understanding of the economic environment. This issue is particularly salient with financial-market time series, where the data are commonly volatile. In this section, we conclude with a discussion of statistical influence.

Figure 3: Economic Profit: Π , Markup: \mathcal{M}



(a) Economic Profit Share

(b) Estimated Trend



(c) Implied Markup on Gross Output

(d) Estimated Trend

Note: Economic profit is measured as gross value added less compensation of employees less capital costs less taxes on production. Shown at a quarterly frequency.

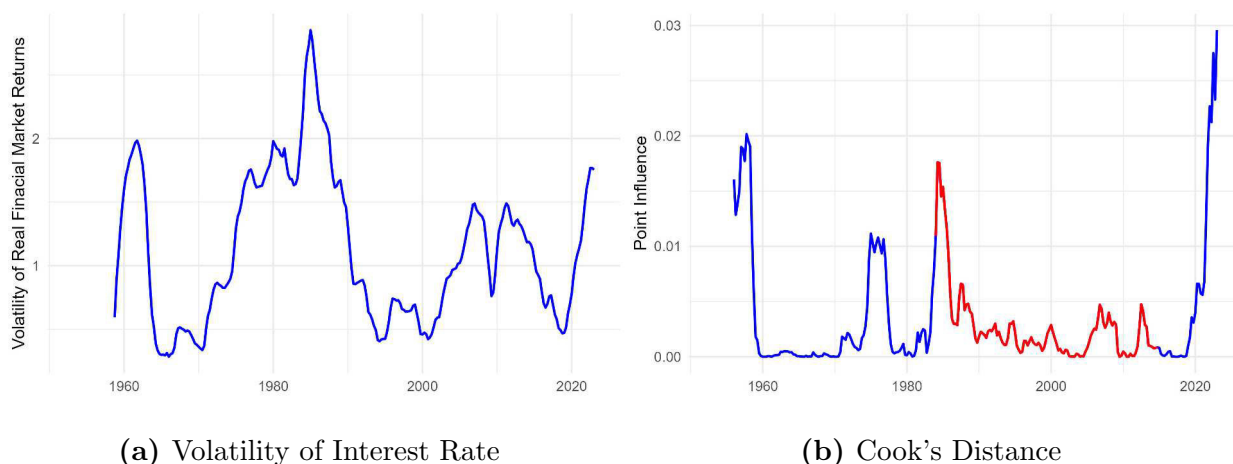
Influence provides an analytic formula that shows how an estimator changes when a single data point is included or excluded, and has been applied in many areas of econometrics (Erickson and Whited, 2000; Andrews et al., 2017; Ichimura and Newey, 2022).

$$\frac{t - \mathbb{E}[t]}{\text{Var}[t]}(y_t - \mathbb{E}[y_t] - \beta(t - \mathbb{E}[t])) \quad (5)$$

Equation (5) indicates points far from the average time value have more impact on the regression, which is mechanically highest for points at the beginning or end of the sample. Moreover, points that are far from the average value of the series, as often with high volatility in a time series, will also have more influence. The influence of a data point is even more pronounced when the estimated beta is far from zero, which is exactly the case in studies that argue for rises or falls in secular trends. Therefore, the choice of the sample start (and end dates) is itself influential; it can significantly alter the conclusions drawn from the regression.

Figure 4a plots the volatility of the real interest rate, measured as the standard deviation in a 5-year rolling window. Figure 4b plots the Cook's distance of each data point. Cook's distance is a common metric of statistical influence in univariate data and summarizes the change in regression coefficients when observation i is removed from the sample.² The secular trends in profits and markups (Figure 3) and the cost of capital (Figure 2) are most exaggerated when plotting across endpoints with the highest real interest rate volatility and influence. Moving across these high-volatility years dramatically changes the trend slope. Coinciding with a spike in volatility after 2019, the economic profit share is at record levels of 15 pp in 2021 and 2022.

Figure 4: Statistical Influence



Note: Volatility is measured as the rolling standard deviation of the real interest rate from figure 1 over a window of 5-year rolling window. Cook's distance is calculated as in footnote 2. Shown at a quarterly frequency.

²Explicitly for simple regression $D_i = \frac{\sum_{j=1}^n (\hat{y}_j - \hat{y}_{j(i)})^2}{2(MSE)}$ where \hat{y}_j is the j fitted response value, $\hat{y}_{j(i)}$ is the j fitted response value excluding observation i and MSE is the mean-squared error.

The COVID-19 pandemic in 2020 introduced unprecedented volatility into economic time series. Figure 4b shows a sharp spike in Cook’s distance for observations in 2020, indicating their outsized influence on regression estimates. This volatility has significant implications for trend inference. As shown in Figure A.1, ending the sample in 2020 (instead of 2014) has the largest effect on trend estimates for our key variables, further exaggerating the trends in profits and markups.

To illustrate the effect of time-series volatility on sample point-to-point estimates, Table I collects the 15-year long differences of our main variables by sample stop year. As volatility declines in the sample, the long difference in interest rates, the cost of capital, profits, and markups nearly vanish. However, after 2019, a spike in the volatility of the real interest rate increases the difference by a factor of 3. These endpoints also disproportionately influence the time-series trend seen in the spike of point influence after 2020 in Figure 4b.

Table I: 15-Year Long Differences by Sample End Date

Sample	$\Delta(i - \nu)$	ΔR_c	$\Delta \Pi$	$\Delta \mathcal{M}$
1997 – 2012	−3.65	−3.62	7.58	0.39
1999 – 2014	−3.95	−4.28	10.35	0.52
2001 – 2016	−2.54	−2.45	8.40	0.042
2003 – 2018	−0.41	−0.61	2.90	0.014
2005 – 2020	−1.78	−1.64	2.06	0.011
2007 – 2022	−2.32	−2.33	6.64	0.037

Note: Table shows the differences between point estimates for the real interest rate, the cost of capital, profit rate, and markups over a shifting 15-year window.

Volatility in financial-market rates poses a challenge to accurately estimating economic profits and markups. The prevailing methodology for calculating economic profits and implied markups takes into account payments to labor and capital. However, these methodologies often overlook the volatility inherent in financial-market rates compared to more stable returns on capital. Such volatility in capital returns can significantly skew calculated markups and profits, thereby affecting observed trends. Consequently, the notable shifts in profits and markups around 1984 and 2022 are influenced by fluctuations in the cost of capital, which factors like changes in expected capital inflation may drive.

4. Concluding Implications and Discussion

While existing research commonly attributes rising economic profits and markups to broader secular trends, our study adds an important qualifier. We demonstrate the choice of sample start date can significantly influence the size of these trends, particularly when the time series is volatile, as is often the case with financial-market data. In our worked example, extending the sample backward by just 4 years explains 25% of the increase in economic profits since the 1980s, or \$3000 per worker in 2019.

The sensitivity of market power estimates to sample selection has significant implications

for both economic theory and policy. Researchers and policymakers have proposed rising market power as a key driver of various macroeconomic trends (De Loecker et al., 2020; Autor et al., 2020; Council of Economic Advisors, 2023). However, our findings suggest the magnitude of these trends may be less certain than previously thought. This uncertainty is particularly consequential in the market power literature due to the long-term nature of the trends being studied and their substantial policy implications, as antitrust policy and regulatory frameworks are increasingly informed by these empirical estimates (Shapiro, 2018; Philippon, 2019).

Our analysis implies even slight differences in sample selection can lead to serious differences in trend estimation. Given communicating research inevitably loses some detail, it's key that takeaways are not contingent on something as simple as a sample start date. Therefore, we conclude, researchers should justify their choice of time-series sample selection. This justification is consequential when analyzing volatile time series, where endpoints can determine trend estimates.

This recommendation applies not only to studies of market power, but to any empirical work analyzing long-term economic trends. For instance, estimates of equity risk premia can vary by decade because of bull and bear runs, yet many models use a fixed constant for calibration. We also recommend researchers incorporate sensitivity checks to keep these important statistics reliable and portable for future use. Examining time-series volatility around endpoints and presenting results for multiple sample periods can help distinguish genuine economic phenomena from artifacts of arbitrary sample selection.

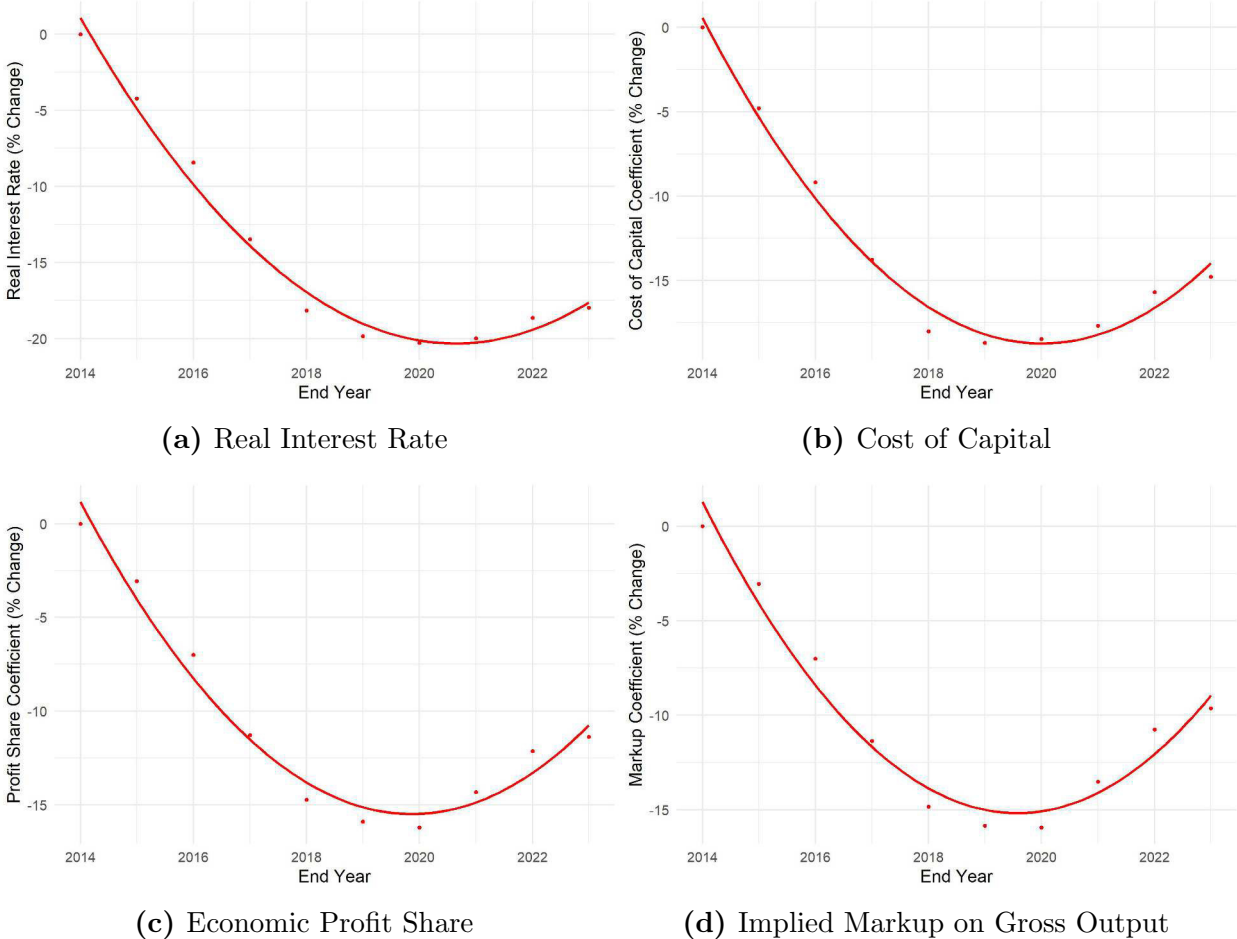
References

- Andrews, I., M. Gentzkow, and J. Shapiro (2017). “Measuring the sensitivity of parameter estimates to estimation moments”. *Quarterly Journal of Economics* **132**(4), 1553–1592.
- Autor, D., D. Dorn, L. Katz, C. Patterson, and J. Van Reenen (2020). “The fall of the labor share and the rise of superstar firms”. *Quarterly Journal of Economics* **135**(2), 645–709.
- Barkai, S. (2020). “Declining labor and capital shares”. *Journal of Finance* **75**(5), 2421–2463.
- Basu, S. (2019). “Are price-cost markups rising in the United States? A discussion of the evidence”. *Journal of Economic Perspectives* **33**(3), 3–22.
- Blanchard, O. (2019). “Public debt and low interest rates”. *American Economic Review* **109**(4), 1197–1229.
- Card, D. and A. Krueger (1995). “Time-series minimum-wage studies: A meta-analysis”. *American Economic Review: Papers & Proceedings* **85**(2), 238–243.
- Council of Economic Advisors (2023). “Protecting competition through updated merger guidelines”. Issue brief, White House.

- Covarrubias, M., G. Gutiérrez, and T. Philippon (2020). “From good to bad concentration? US industries over the past 30 years”. *NBER Macroeconomics Annual* **34**(1), 1–46.
- Davis, C., A. Sollaci, and J. Traina (2023). “Profit puzzles and the fall of public-firm profit rates”. Working paper, Kelley School of Business.
- De Loecker, J., J. Eeckhout, and G. Unger (2020). “The rise of market power and the macroeconomic implications”. *Quarterly Journal of Economics* **135**(2), 561–644.
- Edmond, C., V. Midrigan, and D. Y. Xu (2023). “How costly are markups?”. *Journal of Political Economy* **131**(7), 1619–1675.
- Eggertsson, G., J. Robbins, and E. Wold (2021). “Kaldor and Piketty’s facts: The rise of monopoly power in the United States”. *Journal of Monetary Economics* **124**, S19–S38.
- Erickson, T. and T. Whited (2000). “Measurement error and the relationship between investment and q”. *Journal of Political Economy* **108**(5), 1027–1057.
- Farhi, E. and F. Gourio (2018). “Accounting for macro-finance trends: Market power, intangibles, and risk premia”. *Brookings Papers on Economic Activity* **2018**(2), 147–250.
- Hall, R. (2018). “New evidence on the markup of prices over marginal costs and the role of mega-firms in the US economy”. Working Paper 24574, National Bureau of Economic Research.
- Hall, R. and D. Jorgenson (1967). “Tax policy and investment behavior”. *American Economic Review* **57**(3), 391–414.
- Ichimura, H. and W. Newey (2022). “The influence function of semiparametric estimators”. *Quantitative Economics* **13**(1), 29–61.
- Jensen, T., B. Kelly, and L. Pedersen (2023). “Is there a replication crisis in finance?”. *Journal of Finance* **78**(5), 2465–2518.
- Karabarbounis, L. and B. Neiman (2019). “Accounting for factorless income”. *NBER Macroeconomics Annual* **33**(1), 167–228.
- Philippon, T. (2019). “Causes, consequences, and policy responses to market concentration”. Technical report, Aspen Economic Strategy Group.
- Shapiro, C. (2018). “Antitrust in a time of populism”. *International Journal of Industrial Organization* **61**, 714–748.
- Traina, J. (2018). “Is aggregate market power increasing? Production trends using financial statements”. Working Paper 17, Stigler Center.
- White, H. (2000). “A reality check for data snooping”. *Econometrica* **68**(5), 1097–1126.

A Appendix

Figure A.1: End of Trend Sensitivity, Change in Trend



Note: This figure mirrors panels (b) in Figures 1, 2, and 3 showing the change in the trend estimate compared to the estimated trend from 1984 to 2014.