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Inflation Targeting, Monetary Policy Surprises, and Capital Misallocation

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ABSTRACT

We examine whether a more predictable monetary policy framework improves the allocation of capital across firms. Using firm-level data from the Indian manufacturing sector for 2005-2024, we study this in the context of India's adoption of flexible inflation targeting (FIT) in 2015. We find that firms with high pre-FIT average revenue per unit of capital (ARPK) subsequently accumulate more capital and experience a relative decline in ARPK, consistent with capital being reallocated toward previously under-capitalized firms. Event-study estimates show that these changes emerge after the reform. To further examine the role of monetary policy predictability in capital allocation, we use high-frequency measures of monetary policy surprises. We document a decline in the volatility of these surprises following FIT and show that larger surprises are associated with higher ARPK and lower capital accumulation, particularly among firms with high ex-ante ARPK. Together, these findings are consistent with greater monetary policy predictability contributing to improved capital allocation following FIT.

Keywords: Flexible inflation targeting; monetary policy; capital misallocation; firm investment; monetary policy surprises.

JEL Code: E22, E52, E58, D24, O16.

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Abstract

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1 Introduction

Does a more credible monetary policy framework improve not only aggregate stability, but also the allocation of capital across firms? This question is especially important in emerging economies, where inflation is often more volatile, expectations are less firmly anchored, and substantial differences in firms' access to capital coexist with wide dispersion in returns to capital. When aggregate price signals and the monetary policy response to them are difficult to predict, firms and investors may find it harder to distinguish changes in firm-specific fundamentals from movements in the general price level. Unpredictable monetary policy may also tighten financing conditions and amplify existing financial frictions. In either case, capital may fail to reach firms where its return is highest. Such distortions can generate dispersion in the revenue products of capital across firms and lower aggregate productivity by preventing resources from being allocated to their most productive uses (Hsieh and Klenow, 2009). Yet, despite an extensive literature on whether inflation targeting stabilizes inflation and anchors expectations, there is limited evidence on whether the adoption of such a framework improves the allocation of capital across heterogeneous firms.

This paper examines this question using India's transition to flexible inflation targeting (FIT) in 2015. India provides a particularly useful setting. The reform represented a major change in the monetary policy framework of a large emerging economy: it established an explicit numerical inflation target (4 percent Consumer Price Index inflation) and strengthened the institutional commitment to price stability. Existing evidence suggests that inflation expectations became more firmly anchored after the reform and that financial markets perceived the Reserve Bank of India (RBI) as more responsive to inflation (Pattanaik et al., 2023; Garga et al., 2026). At the same time, Indian manufacturing is characterized by substantial heterogeneity in firm size, productivity, financing conditions, and returns to capital. The setting therefore allows us to ask whether the benefits of greater monetary policy credibility extend beyond lower aggregate volatility to the allocation of capital within the productive sector.

Our main contribution is to show that the introduction of FIT was followed by a reallocation of capital toward firms with relatively high ex-ante returns to capital. We measure a firm's return to capital using average revenue per unit of capital (ARPK), normalized relative to the mean in its four-digit industry. Firms with high ARPK before the reform can be understood as firms that were relatively under-capitalized given the revenue generated by their capital stock. Following the introduction of FIT, these firms accumulate more capital and experience a decline in ARPK relative to firms with initially low ARPK. This convergence in returns is consistent with an improvement in capital allocation. We complement this regime-change evidence with high-frequency measures of monetary policy surprises. Larger surprises are associated with higher ARPK and lower capital, and these responses are more pronounced among firms with high ex-ante ARPK. Taken together, the two sets of results point to a common pattern: a less volatile and more predictable monetary policy environment is associated with capital moving toward firms with initially high returns.

We use annual firm-level data from the Centre for Monitoring Indian Economy's Prowess database for 2005-2024 covering non-government-owned manufacturing firms. We construct real sales using industry-level wholesale price indices and deflate gross fixed assets using a gross fixed capital formation deflator. ARPK is measured as real sales relative to real gross fixed assets. To identify firms that had relatively high returns before the reform without allowing post-reform outcomes to affect their classification, we classify firms using their average industry-normalized ARPK over 2005-2014. Firms above the median of this pre-FIT distribution are designated high-ARPK firms.

Our empirical analysis proceeds in two parts. We first estimate a difference-in-differences specification comparing changes in ARPK and capital after 2015 between firms with high and low pre-FIT ARPK. The specification includes firm and year fixed effects. We progressively add industry-specific linear trends and firm-size-by-year fixed effects, allowing industries and firms of different initial sizes to follow different trajectories. We also estimate event-study specifications to examine the dynamics of the effects and assess differential pre-trends. Because conventional pre-trend tests may have limited power, we further evaluate sensitivity to violations of parallel trends using the procedure developed by Rambachan and Roth (2023).

The second part of the analysis uses the high-frequency monetary policy shocks constructed by Lakdawala and Sengupta (2025). These measures isolate the unexpected component of RBI announcements using movements in overnight indexed swap (OIS) rates in narrow windows around announcement dates. We use both the Target Factor, which captures surprises in the contemporaneous short-term policy stance, and the first principal component of movements across the OIS yield curve, which summarizes the broader surprise embedded in the announcement. We first document that the volatility of these monetary policy surprises declined following the introduction of FIT, consistent with a more predictable monetary policy environment. We then next examine whether the magnitude of these surprises is related to firm-level capital allocation. Since our interest is in uncertainty and the magnitude of unexpected policy news rather than whether a particular announcement is expansionary or contractionary, we use the absolute value of each shock. If reduced monetary policy uncertainty facilitates capital allocation, larger policy surprises should be associated with higher ARPK and lower capital, especially among firms that were initially under-capitalized. Evidence of such a relationship would provide a complementary link between the decline in monetary policy surprises following FIT and the improvement in post-FIT capital allocation documented in our analysis.

We obtain three main findings. First, high-ARPK firms experience a substantial decline in ARPK after the introduction of FIT. The baseline results are robust and stable after controlling for industry-specific trends and firm-size-specific time patterns. The event-study estimates show that this decline begins after the reform and persists through the post-FIT period, with no evidence of differential pre-trends. The Rambachan-Roth sensitivity analysis yields a breakdown value of approximately $\bar{M} = 1.05$: the confidence interval would include zero only if post-treatment deviations from parallel trends were slightly larger than the largest deviation observed before the reform.

Second, the decline in ARPK is accompanied by an increase in the capital stock of firms with high pre-FIT ARPK. The event-study estimates show that this increase emerges after the introduction of FIT and persists throughout the post-reform period. The capital estimates are, however, more sensitive to potential violations of parallel trends than the ARPK estimates, with a Rambachan-Roth breakdown value of approximately $\bar{M} = 0.26$. We therefore interpret the evidence on capital accumulation with some caution. Nevertheless, the combined finding that initially high-return firms accumulate capital while their ARPK declines is consistent with capital being reallocated toward firms that were relatively under-capitalized before FIT.

Third, the high-frequency monetary-shock analysis provides complementary evidence consistent with this interpretation. Larger Target Factor and first-principal-component surprises around RBI announcements are followed by higher firm-level ARPK and generally lower capital accumulation. These relationships are particularly pronounced among firms with high ex-ante ARPK: larger October and August shocks disproportionately increase their ARPK and reduce their capital relative to initially low-ARPK firms. Although some estimates weaken after the inclusion of industry-specific trends, the results remain qualitatively similar when the sample is restricted to 2009-2024. Overall, the findings suggest that monetary policy surprises impede capital accumulation, particularly among firms with the highest initial returns to capital, thereby contributing to greater capital misallocation.

Our findings are consistent with two related mechanisms. Greater monetary policy predictability may improve capital allocation through two related channels. In the misallocation framework, firms with high ARPK face larger distortions to capital accumulation: despite high returns to additional capital, they operate with inefficiently low levels of capital. First, greater predictability may reduce uncertainty about future inflation, interest rates, and monetary policy, lowering the option value of delaying irreversible investment. High-ARPK firms, for which the returns to additional capital are particularly high, therefore have the strongest incentive to undertake investments that may previously have been postponed. Second, high ARPK may reflect financial constraints that prevent firms from undertaking otherwise profitable investments. By reducing uncertainty about future cash flows, interest rates, and refinancing conditions, greater monetary policy predictability may reduce the risks faced by lenders, lowering external-finance premia or relaxing credit constraints. Financially constrained high-ARPK firms can then raise additional financing and expand their capital stocks. Both channels therefore predict greater capital accumulation and declining ARPK among initially high-ARPK firms, but differ in the underlying friction: in the first, uncertainty leads firms to delay investment, while in the second, limited access to finance prevents them from undertaking it.

The paper contributes to three strands of literature. First, we contribute to the literature evaluating inflation targeting. Much of this work examines inflation, inflation volatility, output growth, and the anchoring of expectations, with mixed evidence on the causal effects of adopting an inflation target (Ball and Sheridan, 2005; Mishkin and Schmidt-Hebbel, 2007; Gonçalves and Salles, 2008; Lin and Ye, 2007, 2009; Brito and Bystedt, 2010; Sethi and Mishra, 2026). Recent work has begun to document real effects at the firm level: inflation targeting is associated with stronger firm performance and private investment in developing economies, while better-anchored inflation expectations may particularly benefit credit-constrained sectors (Bambe et al., 2024; Bambe, 2023; Choi et al., 2022). We extend this literature by shifting attention from average firm performance or aggregate investment to the distribution of capital across firms. Our results show that the relevant real effects of a credible monetary framework may lie not only in how much firms invest, but also in which firms receive capital.

Second, the paper relates to a growing literature on heterogeneous firm responses to monetary policy. Existing studies show that investment responses depend on leverage, age, dividend status, liquidity, default risk, collateral, and debt maturity (Ottonello and Winberry, 2020; Durante et al., 2022; Cloyne et al., 2023; Jeenas, 2023; Deng and Fang, 2022; Jungherr et al., 2024). This literature has largely focused on the transmission of discrete monetary policy shocks in advanced economies. We study a persistent change in the monetary policy regime in a large emerging economy and organize firm heterogeneity around ex-ante returns to capital. This allows us to connect heterogeneous investment responses directly to whether monetary policy reallocates capital toward higher-return uses.

Third, we contribute to the emerging literature linking monetary policy to capital misallocation. Closest to our analysis, Albrizio et al. (2026) show that monetary easing reduces capital misallocation in Spain by inducing greater investment among firms with high marginal revenue products of capital, particularly when such firms are highly leveraged. We provide complementary evidence from India and study a different policy margin: the adoption of a more credible and predictable monetary framework. By combining the FIT regime change with high-frequency measures of RBI policy surprises, we show that both lower policy uncertainty and the post-FIT period are associated with capital moving toward firms with high initial returns. More broadly, the results identify capital allocation as an important channel through which improvements in monetary institutions may generate real gains in emerging economies.

The remainder of the paper is organized as follows. Section 2 describes the firm-level data and monetary policy shock measures. Section 3 presents the empirical strategy. Section 4 reports the results, and Section 5 concludes.

2 Data

2.1 Firm Level Data

We use annual firm-level data from the Prowess database maintained by the Centre for Monitoring Indian Economy (CMIE). Prowess provides detailed financial and firm-level information for Indian companies across a broad range of industries. Our analysis covers the period from 2005 to 2024. We restrict the sample to manufacturing firms classified under NIC 2008 two-digit industry codes 10 to 30 and exclude government-owned firms. To ensure sufficient information for the analysis, we further exclude firms with fewer than three years of available observations during the sample period.

We use firms' sales and gross fixed assets, measured in rupees millions, to construct the measures of average revenue per capital (ARPK) and capital, respectively. To obtain real measures, we deflate sales using the Wholesale Price Index (WPI) at the NIC 2008 two-digit industry level. Gross fixed assets are deflated using a gross fixed capital formation (GFCF) deflator constructed from the GFCF series reported in the Database on Indian Economy (DBIE) maintained by the Reserve Bank of India (RBI). We winsorize ARPK and capital at the 2nd and 98th percentiles to limit the influence of extreme observations.

Table 1 presents summary statistics for High-ARPK and Low-ARPK firms separately for the pre- and post-FIT periods. High-ARPK firms have substantially higher ARPK and lower capital than Low-ARPK firms in the pre-FIT period, consistent with greater differences in capital allocation across firms. Following the introduction of FIT, the average ARPK of firms classified ex ante as High-ARPK firms decreases, while their average capital increases. At the same time, the average ARPK of Low-ARPK firms increases. These changes suggest a reduction in the differences in resource allocation between High- and Low-ARPK firms following the introduction of FIT, pointing towards a decline in misallocation in the post-FIT period.

2.2 Shock Data

We obtain the monetary policy shock measures from Lakdawala and Sengupta (2025), who construct high-frequency monetary policy shocks for India using movements in Overnight Indexed Swap (OIS) rates around Reserve Bank of India (RBI) monetary policy announcements. Their approach is designed to isolate the unexpected component of monetary policy decisions from changes that were anticipated by financial markets. The use of high-frequency OIS rate movements around policy announcements therefore provides a market-based measure of monetary policy surprises rather than simply relying on changes in the policy rate.

We use two shock measures from their dataset: the Target Factor (TF) and the First Principal Component (FPC). The Target Factor is intended to capture unexpected changes in the RBI's contemporaneous short-term policy rate target. The First Principal Component (FPC) provides an alternate measure of the monetary policy surprise associated with an RBI policy announcement. It captures the common unexpected movement in interest rates across different maturities of the OIS curve following the announcement and therefore summarizes the overall surprise in market expectations regarding monetary policy in a single measure. In this sense, the FPC reflects the extent to which an RBI announcement unexpectedly changes the market's assessment of the monetary policy stance. Figure 1a and Figure 1b plot the year-wise standard deviation of Target Factor and First Principal Component Shocks, respectively.

To construct annual measures from the high-frequency monetary policy shock data, we use the absolute values of the October and August shocks and match them to the firm-level data for the subsequent year in Prowess. We use the absolute value of the shocks because we are more interested in the magnitude of monetary policy shocks, rather than their direction. In this sense, larger absolute shocks capture a greater degree of unexpected monetary policy news, regardless of whether the surprise is contractionary or expansionary.

For October, when shock values are unavailable for the years 2011, 2015, 2016, and 2023, we use the corresponding September shock values. Similarly, since August shock values are unavailable for the period before 2014, we use the corresponding July shock values (most of them being in the last week of July) for the pre-2014 period. The resulting annual shock measures are then assigned to firm-level observations in the subsequent year.

3 Empirical methodology

Our empirical analysis proceeds in two steps. First, we examine whether the introduction of flexible inflation targeting (FIT) was associated with a change in the allocation of capital across firms with different ex-ante levels of average revenue per capital (ARPK). In particular, we compare the evolution of ARPK and capital for firms classified as ex-ante High-ARPK firms with that of Low-ARPK firms. Second, we examine how monetary policy shocks impact firm-level ARPK and capital, and whether these effects differ systematically between High-ARPK and Low-ARPK firms.

3.1 Effect of Flexible Inflation Targeting on High-ARPK Firms

We first examine the average effect of the introduction of FIT using a difference-in-differences specification:

$$Y_{it} = \alpha_i + \lambda_t + \beta \left(High_i \times Post_t \right) + \delta_{j(i)} \times t + \gamma_{s(i)} \times \lambda_t + \varepsilon_{it}, \tag{1}$$

where Y_{it} denotes the outcome variable for firm i in year t. $High_i$ is an indicator equal to one if firm i is classified as an ex-ante High-ARPK firm and zero otherwise. Firms having an average $ARPK/\overline{ARPK}$ for the period FY 2005-2014 above the median are defined as High-ARPK firms, where $\overline{ARPK}$ is the NIC 4-digit industry-level mean. $Post_t$ is an indicator equal to one for the post-IT period, 2015-2024, and zero otherwise. The baseline specification includes firm fixed effects, α_i, which absorb all time-invariant firm characteristics, and year fixed effects, λ_t, which capture aggregate shocks common to all firms.

The coefficient of interest is β, which captures the change in the outcome of High-ARPK firms relative to Low-ARPK firms following the introduction of FIT. The specification includes firm fixed effects and year fixed effects. For robustness, we additionally include industry-specific time trends, $\delta_{j(i)} \times t$, where $j(i)$ denotes the industry of firm i, and interactions between firm-size groups and year fixed effects, $\gamma_{s(i)} \times \lambda_t$, as controls. Firm size group is measured using the firm size decile group reported in the Prowess database for 2014. The firm-size-by-year effects allow firms of different size groups to experience different aggregate time patterns, thereby accounting for differential changes across firm-size categories.

We estimate equation (1) separately for ARPK and capital. A negative coefficient for the High-ARPK $\times$ Post interaction in the ARPK specification, together with a positive coefficient in the capital specification, would indicate that the post-FIT period is associated with a reduction in ARPK and an increase in capital among firms that had relatively high ARPK prior to the introduction of FIT.

We next employ an event-study specification to examine the dynamic effects of the introduction of flexible inflation targeting. The event-study specification is given by

$$Y_{it} = \alpha_i + \lambda_t + \sum_{k \neq 2014} \beta_k \left(\text{High}_i \times \mathbf{1}\{t = k\}\right) + \delta_{j(i)} \times t + \varepsilon_{it}, \tag{2}$$

where Y_{it} denotes the outcome variable for firm i in year t, measured alternatively by ARPK and Capital. The indicator $\mathbf{1}\{t = k\}$ identifies each calendar year, with 2014 omitted as the reference year. Thus, the interaction coefficients β_k capture the difference in the outcome between High-ARPK and Low-ARPK firms in year k, relative to the omitted reference year, 2014. The specification includes firm fixed effects, α_i, which absorb all time-invariant firm characteristics, and year fixed effects, λ_t, which capture aggregate shocks common to all firms. We additionally control for industry-specific linear time trends, $\delta_{j(i)} \times t$, where $j(i)$ denotes the industry of firm i.

The event-study specification allows us to examine both the dynamics of the response following the introduction of FIT and the validity of the identifying assumption. In particular, the coefficients in the pre-FIT period provide a test for differential pre-trends between High-ARPK and Low-ARPK firms. The absence of statistically significant pre-treatment coefficients would indicate that the two groups followed similar trends prior to the introduction of FIT.

While the conventional event-study framework provides evidence on pre-treatment trends, it relies on the assumption that these trends would have remained parallel in the absence of the treatment. To assess the sensitivity of our results to possible violations of this assumption, we additionally implement the robustness procedure proposed by Rambachan and

Roth (2023). This approach allows for deviations from exact parallel trends and evaluates whether the estimated treatment effects remain robust under increasingly larger departures from the standard parallel-trends assumption.

3.2 Monetary Policy Shocks and Firm Outcomes

We first estimate the following specification:

$$Y_{it} = \alpha_i + \beta Shock_{t-1} + \delta_{j(i)} \times t + \varepsilon_{it}, \tag{3}$$

where $Shock_{t-1}$ denotes the absolute value of the monetary policy shock measured in the preceding year. We estimate equation (3) separately using the Target Factor and the First Principal Component, and separately for October and August shocks. The dependent variable Y_{it} is alternatively ARPK and capital. A positive coefficient on the shock variable in the ARPK specification indicates that larger monetary policy surprises are associated with higher ARPK, while a negative coefficient in the capital specification indicates an association between larger shocks and lower capital.

To check whether there is a differential impact of shocks on ex-ante high ARPK firms, we next estimate:

$$Y_{it} = \alpha_i + \lambda_t + \beta \left(Shock_{t-1} \times High_i\right) + \delta_{j(i)} \times t + \gamma_{s(i)} \times \lambda_t + \varepsilon_{it}. \tag{4}$$

The coefficient of interest is β, which captures the differential association between the monetary policy shocks and the outcome of High-ARPK firms relative to Low-ARPK firms. We define ex-ante high ARPK firms as those whose average $ARPK/\overline{ARPK}$ for the period FY 2005-2009 above the median are defined as High ARPK firms, where $\overline{ARPK}$ is the NIC 4-digit industry-level mean. We restrict the sample to the period 2009-2024 for this specification.

We estimate equation (4) separately for ARPK and capital, using both the Target Factor and the First Principal Component and considering both October and August shocks. A positive coefficient on the shock $\times$ High-ARPK interaction in the ARPK specification implies that larger monetary policy shocks are associated with a relative increase in ARPK among High-ARPK firms. Conversely, a negative coefficient in the capital specification implies that larger shocks are associated with a relative reduction in capital among High-ARPK firms. Taken together, a positive effect on ARPK and a negative effect on capital among High-ARPK firms would be consistent with greater capital misallocation following larger monetary policy shocks.

4 Results

4.1 Average Effects

We first estimate the differential change in outcomes between High-ARPK and Low-ARPK firms using the difference-in-differences specification. Table 2 presents the average treatment effect of the introduction of FIT on ARPK. The coefficient on the High-ARPK × Post interaction is negative and statistically significant across all specifications for ARPK. The coefficient ranges from -1.466 to -1.583, indicating that, relative to Low-ARPK firms, High-ARPK firms experienced a decline in ARPK of around 1.5 units following the introduction of FIT. The stability of the estimates across specifications with industry time trends and firm-size $\times$ year effects suggests that the result is robust to controlling for differential industry trends and firm-size-specific time patterns.

Table 3 presents the corresponding results with capital as the outcome variable. The coefficient on the High-ARPK × Post interaction is positive and statistically significant across specifications, although the magnitude declines with the inclusion of additional controls. The estimates range from 0.494 to 1.278, suggesting that High-ARPK firms experienced a relative increase in capital following the introduction of FIT. Taken together, the results indicate that firms with high pre-FIT ARPK subsequently accumulated more capital while their ARPK declined relative to Low-ARPK firms. This pattern is consistent with an improvement in the allocation of capital across firms following the introduction of FIT.

We next estimate the dynamic response to the introduction of FIT on the ARPK and Capital of ex-ante High ARPK firms as compared to ex-ante Low ARPK firms. Figure 2 provides the event-study estimates for ARPK. We find a consistent decrease in ARPK of ex-ante High ARPK firms after the introduction of FIT. All pre-treatment coefficients are statistically indistinguishable from zero, indicating the absence of pre-trends. Furthermore, Figure 3 shows a sustained increase in Capital after the introduction of FIT. Although there is some movement in the pre-treatment coefficients, most of them are statistically indistinguishable from zero.

To assess the robustness of our event-study estimates to potential violations of the parallel-trends assumption, we follow Rambachan and Roth (2023). Rather than assuming that parallel trends hold exactly, we allow for post-treatment deviations from parallel trends and examine how large these deviations would need to be, relative to the largest pre-treatment deviation, to overturn our conclusions. We consider different values of the relative magnitude restriction, $\bar{M}$. A value of $\bar{M}$=0 imposes the standard parallel-trends assumption, while $\bar{M}$=1 allows post-treatment deviations from parallel trends to be as large as the largest deviation observed in the pre-treatment period.

Figures 4 present the corresponding sensitivity analysis for ARPK and Capital. For ARPK, the estimated breakdown value is approximately $\bar{M}$=1.05. This implies that the negative post-treatment effect on ARPK would cease to be statistically significant only if the magnitude of the post-treatment violation of parallel trends were approximately 1.05 times as large as the largest pre-treatment violation. Thus, the ARPK results are robust to post-treatment deviations from parallel trends that are smaller than this threshold. For Capital, the estimated breakdown value is approximately $\bar{M}$=0.26, indicating that the statistical significance of the estimated increase in Capital would be lost if post-treatment deviations from parallel trends were around 0.26 times as large as the largest pre-treatment deviation. Hence, the evidence for an increase in Capital is more sensitive to potential violations of the parallel-trends assumption than the evidence for a reduction in ARPK.

4.2 Target Factor and First Principal Component Shocks

We next estimate how the reduction in shock volatility is related to the ARPK and Capital of firms. We consider the absolute values of Target Factor and First Principal Component Shocks in the months of October and August. Table 4 presents the results for the impact of shocks on ARPK. For the October shock, an increase in both Target Factor and First Principal Component Shocks leads to an increase in firms' ARPK, which is consistent with our hypothesis that an increase in shocks leads to greater misallocation. The coefficient for the August shock regression remains positive but is not statistically significant.

Table 5 presents the results for the impact of shocks on Capital. For the October shocks, an increase in the Target Factor shock is associated with a decrease in Capital in both specifications, while the coefficient on the First Principal Component Shock is negative and significant in the specification without Industry Time Trends but becomes statistically insignificant after their inclusion. For the August shocks, an increase in both Target Factor Shock and First Principal Component Shock results in a negative and significant impact on capital. The results are robust to the inclusion of Industry time trends as controls. Overall, the results suggest that greater shocks are associated with higher ARPK and lower Capital, which is consistent with an increase in misallocation.

We next look at how Target Factor and First Principal Component Shocks affect firms with ex-ante High ARPK. Here, we define ex-ante High ARPK firms as firms having average $ARPK/\overline{ARPK}$ for the period FY 2005-2009 above the median, where $\overline{ARPK}$ is the NIC 4-digit industry-level mean. The regressions are done for the period 2009-2024. Table 6 presents the results for the impact of shocks on the ARPK of ex-ante High ARPK firms. A positive coefficient for the interaction between the shock and the ex-ante High ARPK dummy would mean that an increase in the shock leads to an increase in ARPK of ex-ante High ARPK firms, and hence a decrease in the shock would mean a decrease in ARPK of ex-ante High ARPK firms. Panel (a) presents the results for the October shock. An increase in both Target Factor and First Principal Component Shocks leads to an increase in ARPK of ex-ante High ARPK firms. The coefficients remain positive and statistically significant across the different specifications. August shocks present similar results, with the coefficient being positive and significant for both Target Factor and First Principal Component Shocks.

Table 7 presents the corresponding results for Capital. For October shocks, the interaction between the First Principal Component Shock and the ex-ante High ARPK dummy is negative and statistically significant across all specifications, suggesting that an increase in the First Principal Component Shock is associated with a decline in Capital of ex-ante High ARPK firms. The interaction coefficient for the Target Factor shock is negative in all specifications, but becomes statistically insignificant after the inclusion of Industry Time Trends. For August shocks, the interaction coefficient for both the Target Factor and First Principal Component shock is negative and statistically significant, and the results are robust to inclusion of industry time trends and firm size $\times$ year fixed effects.

5 Conclusion

This paper examines whether a more credible monetary policy framework can improve the allocation of capital across firms. Using India's transition to flexible inflation targeting in 2015, we find that firms with high pre-FIT ARPK accumulated more capital and experienced a relative decline in ARPK after the reform. The event-study estimates indicate that these changes emerged following the introduction of FIT and persisted during the post-reform period. Although the capital estimates are more sensitive to potential violations of parallel trends, the joint increase in capital and decline in ARPK among initially high-return firms is consistent with capital being reallocated toward firms that were relatively under-capitalized before the reform.

The analysis of high-frequency monetary policy shocks provides complementary evidence. Larger monetary policy surprises are followed by higher ARPK and lower capital accumulation, with these effects concentrated among firms with high ex-ante ARPK. Thus, unexpected monetary policy news appears to impede capital accumulation precisely among firms for which the returns to additional capital are potentially the greatest. Together, the regime-change and shock-based results suggest that a more stable and predictable monetary policy environment can reduce capital misallocation.

These findings broaden our understanding of the real effects of inflation targeting. The benefits of monetary policy credibility may extend beyond stabilizing inflation and anchoring expectations: greater predictability may also improve how capital is distributed within the productive sector. This allocative channel is likely to be particularly important in emerging economies, where both macroeconomic uncertainty and financial frictions are substantial. Our results are consistent with improved information and a relaxation of financing constraints, but the present analysis does not distinguish conclusively between these mechanisms. Examining firms' borrowing, the composition of external finance, and heterogeneity in pre-existing financial constraints offers a useful direction for further research.

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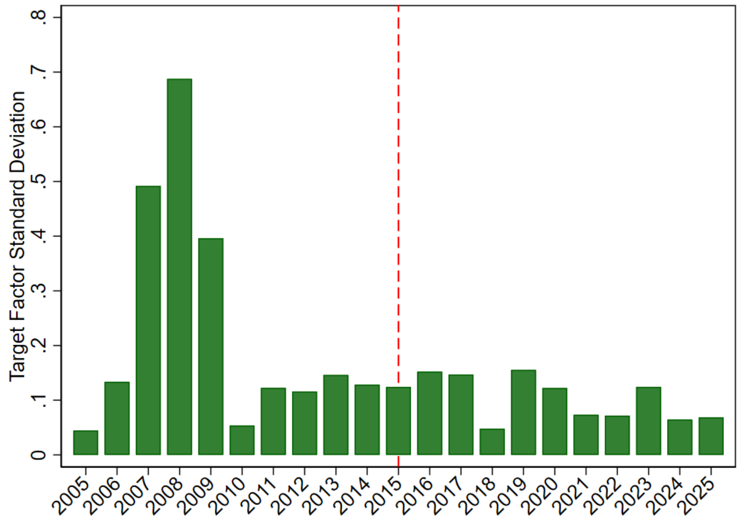
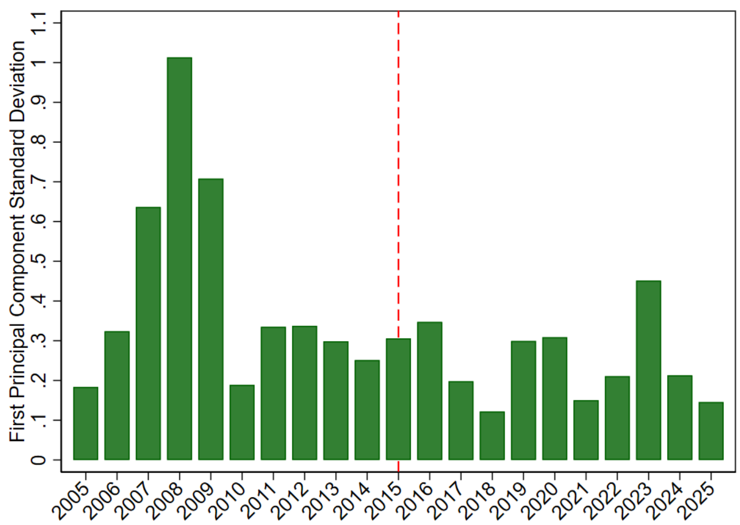
Figure 1: Year-wise Standard Deviation of Monetary Policy Shocks

(a) Target Factor

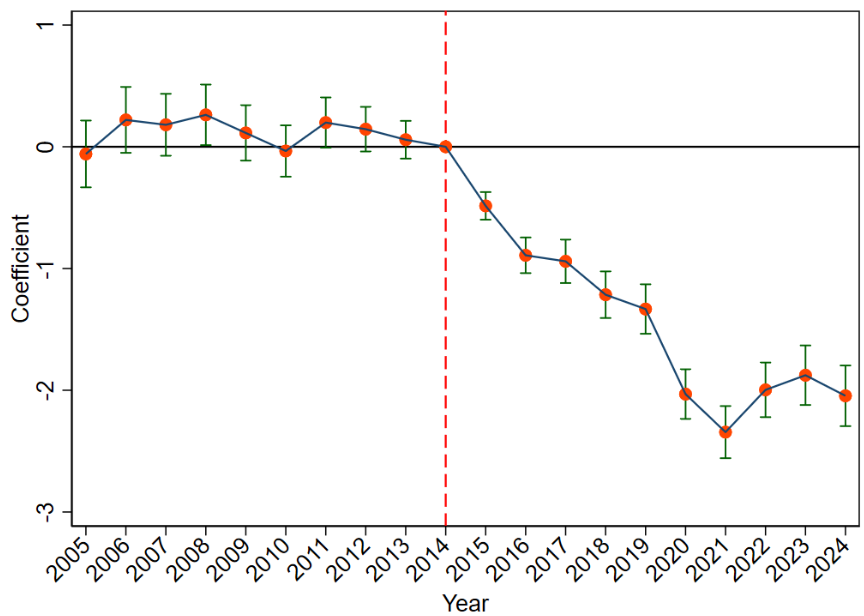


(b) First Principal Component



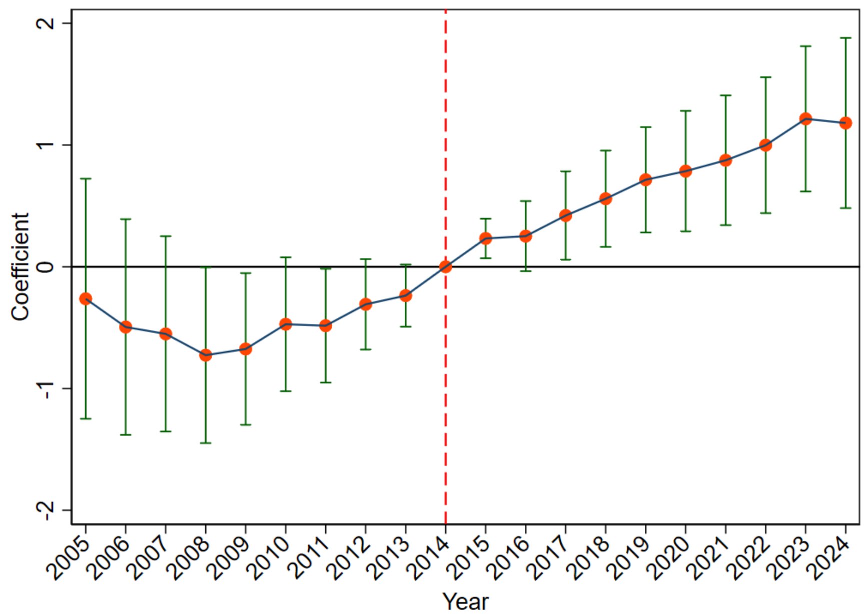
Notes: The figure plots the year-wise standard deviation of (a) target factor and (b) first principal component across the years.

Figure 2: ARPK of ex-ante High-ARPK firms relative to ex-ante Low-ARPK firms



Notes: The figure plots the estimated coefficients from the event-study specification. The dependent variable is average revenue per capital (ARPK). The coefficients are estimated relative to 2014, which is the omitted reference year. The vertical bars represent 95% confidence intervals based on standard errors clustered at the firm level.

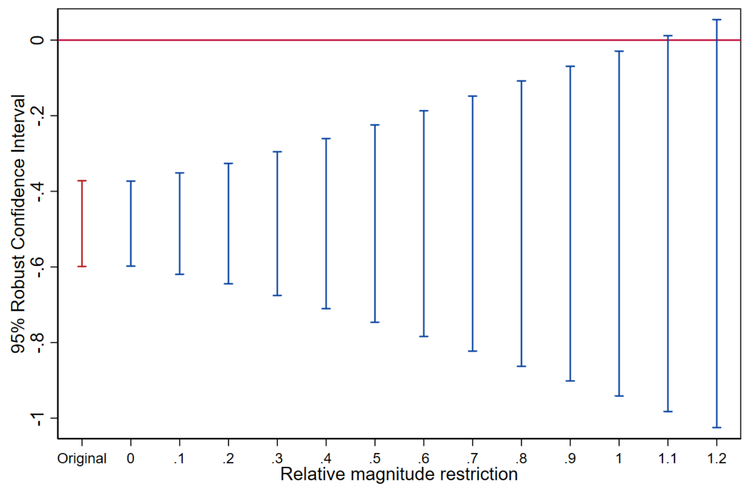
Figure 3: Capital of ex-ante High-ARPK firms relative to ex-ante Low-ARPK firms



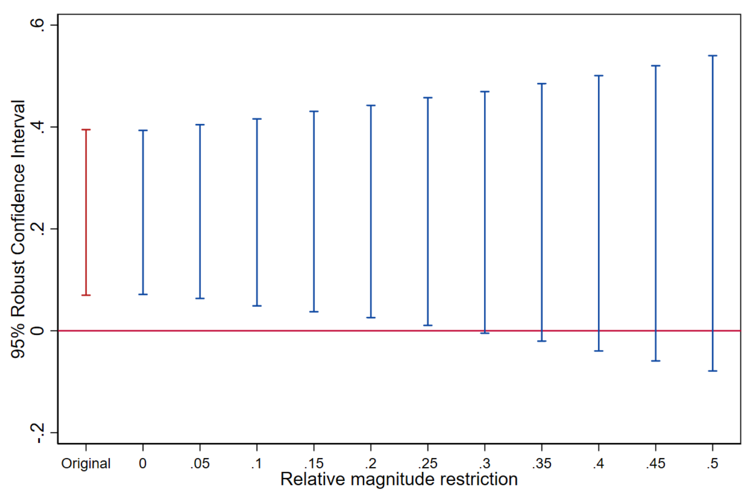
Notes: The figure plots the estimated coefficients from the event-study specification. The dependent variable is capital. The coefficients are estimated relative to 2014, which is the omitted reference year. The vertical bars represent 95% confidence intervals based on standard errors clustered at the firm level.

Figure 4: Sensitivity Analysis for Violations of the Parallel-Trends Assumption

(a) ARPK



(b) Capital



Notes: The figure reports 95% robust confidence intervals for dependent varaiable (a) ARPK and (b) Capital under the relative magnitude restriction of Rambachan and Roth (2023). The horizontal axis shows the relative magnitude restriction, $\bar{M}$, and the Original interval reports the conventional event-study confidence interval. Larger values of $\bar{M}$ allow for larger post-treatment deviations from parallel trends.

Table 1: Summary Statistics of ARPK and Capital across Firm Types

	2005–2014				2015–2024			
	High ARPK Firm		Low ARPK Firm		High ARPK Firm		Low ARPK Firm	
	ARPK	Capital	ARPK	Capital	ARPK	Capital	ARPK	Capital
Mean	6.275476	7.174851	1.485743	11.41408	6.193187	9.674276	2.391616	13.6184
Median	4.186893	1.458315	1.214957	2.533664	3.991373	2.386216	1.673781	3.618394
Observations	26919	26919	27299	27299	37719	37719	34651	34651

Notes: The table presents summary statistics for High ARPK and Low ARPK firms separately for the pre- and post-inflation-targeting periods. Firms with an average $ARPK/\overline{ARPK}$ ratio above the median during FY 2005-2014 are classified as High ARPK firms, while the remaining firms are classified as Low ARPK firms. Here, $\overline{ARPK}$ denotes the mean ARPK at the NIC 4-digit industry level. Capital is measured in Rs. million.

Table 2: Impact of Inflation Targeting on ARPK

	(1) ARPK	(2) ARPK	(3) ARPK
High ARPK x Post	-1.466***	-1.565***	-1.583***
	(0.0784)	(0.0826)	(0.0834)
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Industry Time Trends	No	Yes	Yes
Firm Size x Year	No	No	Yes
Observations	126588	126588	126588
R-squared	0.721	0.725	0.726

Notes: This table reports difference-in-differences estimates of the change in ARPK for ex-ante High ARPK firms following the introduction of Inflation Targeting in 2015, using firm-level data for the period 2005-2024. Firms having average $ARPK/\overline{ARPK}$ for the period FY 2005-2014 above the median are defined as High ARPK firms, where $\overline{ARPK}$ is the NIC 4-digit industry-level mean. The Post dummy takes the value 1 for the post-period (2015–2024). Firm-level data are sourced from Prowess. Standard errors are in parentheses and are clustered at the firm level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3: Impact of Inflation Targeting on Capital

	(1) Capital	(2) Capital	(3) Capital
High ARPK x Post	1.278***	1.063***	0.494*
	(0.308)	(0.304)	(0.268)
Firm FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Industry Time Trends	No	Yes	Yes
Firm Size x Year	No	No	Yes
Observations	126588	126588	126588
R-squared	0.896	0.899	0.921

Notes: This table reports difference-in-differences estimates of the change in Capital for ex-ante High ARPK firms following the introduction of Inflation Targeting in 2015, using firm-level data for the period 2005-2024. Firms having average $ARPK/\overline{ARPK}$ for the period FY 2005-2014 above the median are defined as High ARPK firms, where $\overline{ARPK}$ is the NIC 4-digit industry-level mean. The Post dummy takes the value 1 for the post-period (2015–2024). Firm-level data are sourced from Prowess. Standard errors are in parentheses and are clustered at the firm level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4: Impact of Target Factor (TF) and First Principal Component (FPC) Shock on ARPK

Panel A: October Shocks				
	(1)	(2)	(3)	(4)
	ARPK	ARPK	ARPK	ARPK
TF Shock_$t-1$	0.134***	0.136***		
	(0.0434)	(0.0335)		
FPC Shock_$t-1$			0.101***	0.106***
			(0.0276)	(0.0202)
Firm FE	Yes	Yes	Yes	Yes
Industry Time Trends	No	Yes	No	Yes
Observations	143856	143856	143856	143856
R-squared	0.744	0.747	0.744	0.747
Panel B: August Shocks				
	(1)	(2)	(3)	(4)
	ARPK	ARPK	ARPK	ARPK
TF Shock_$t-1$	0.0158	0.00604		
	(0.0420)	(0.0336)		
FPC Shock_$t-1$			0.0187	0.0119
			(0.0287)	(0.0216)
Firm FE	Yes	Yes	Yes	Yes
Industry Time Trends	No	Yes	No	Yes
Observations	143856	143856	143856	143856
R-squared	0.744	0.747	0.744	0.747

Notes: This table examines the association between monetary policy shocks and ARPK using firm-level data for the period 2005-2024. Monetary policy shocks are measured using the Target Factor (TF) and the First Principal Component (FPC) from Lakdawala and Sengupta (2025). The annual shock measures are constructed using the absolute values of the October and August shocks and are assigned to firm-level observations in the subsequent year. Firm-level data are sourced from Prowess. Standard errors are in parentheses and are clustered at the firm level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: Impact of Target Factor (TF) and First Principal Component (FPC) Shock on Capital

Panel A: October Shocks				
	(1)	(2)	(3)	(4)
	Capital	Capital	Capital	Capital
TF Shock_$t-1$	-3.594***	-0.241***		
	(0.140)	(0.0601)		
FPC Shock_$t-1$			-2.265***	-0.0436
			(0.0904)	(0.0360)
Firm FE	Yes	Yes	Yes	Yes
Industry Time Trends	No	Yes	No	Yes
Observations	143856	143856	143856	143856
R-squared	0.890	0.901	0.890	0.901
Panel B: August Shocks				
	(1)	(2)	(3)	(4)
	Capital	Capital	Capital	Capital
TF Shock_$t-1$	-3.897***	-0.653***		
	(0.155)	(0.0754)		
FPC Shock_$t-1$			-2.686***	-0.287***
			(0.108)	(0.0449)
Firm FE	Yes	Yes	Yes	Yes
Industry Time Trends	No	Yes	No	Yes
Observations	143856	143856	143856	143856
R-squared	0.890	0.901	0.891	0.901

Notes:This table examines the association between monetary policy shocks and Capital using firm-level data for the period 2005-2024. Monetary policy shocks are measured using the Target Factor (TF) and the First Principal Component (FPC) from Lakdawala and Sengupta (2025). The annual shock measures are constructed using the absolute values of the October and August shocks and are assigned to firm-level observations in the subsequent year. Firm-level data are sourced from Prowess. Standard errors are in parentheses and are clustered at the firm level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 6: Impact of Target Factor (TF) and First Principal Component (FPC) Shock on ARPK

Panel A: October Shocks						
	(1)	(2)	(3)	(4)	(5)	(6)
	ARPK	ARPK	ARPK	ARPK	ARPK	ARPK
TF Shock_$t-1$ x High ARPK	0.466***	0.503***	0.585***			
	(0.166)	(0.167)	(0.174)			
FPC Shock_$t-1$ x High ARPK				0.733***	0.772***	0.828***
				(0.0864)	(0.0880)	(0.0910)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry Time Trends	No	Yes	Yes	No	Yes	Yes
Firm Size x Year	No	No	Yes	No	No	Yes
Observations	71473	71473	71473	71473	71473	71473
R-squared	0.723	0.727	0.728	0.723	0.727	0.728
Panel B: August Shocks						
	(1)	(2)	(3)	(4)	(5)	(6)
	ARPK	ARPK	ARPK	ARPK	ARPK	ARPK
TF Shock_$t-1$ x High ARPK	2.689***	2.814***	2.929***			
	(0.282)	(0.286)	(0.297)			
FPC Shock_$t-1$ x High ARPK				1.297***	1.363***	1.415***
				(0.125)	(0.128)	(0.131)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry Time Trends	No	Yes	Yes	No	Yes	Yes
Firm Size x Year	No	No	Yes	No	No	Yes
Observations	71473	71473	71473	71473	71473	71473
R-squared	0.723	0.727	0.728	0.724	0.728	0.729

Notes: This table examines the heterogeneous association between monetary policy shocks and ARPK for ex-ante High-ARPK firms relative to Low-ARPK firms, using firm-level data for the period 2009-2024. Firms having average $ARPK/\overline{ARPK}$ for the period FY 2005-2009 above the median are defined as High-ARPK firms, where $\overline{ARPK}$ is the NIC 4-digit industry-level mean. Monetary policy shocks are measured using the Target Factor (TF) and the First Principal Component (FPC) from Lakdawala and Sengupta (2025). The annual shock measures are constructed using the absolute values of the October and August shocks and are assigned to firm-level observations in the subsequent year. Firm-level data are sourced from Prowess. Standard errors are in parentheses and are clustered at the firm level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 7: Impact of Target Factor (TF) and First Principal Component (FPC) Shock on Capital

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: October Shocks						
	Capital	Capital	Capital	Capital	Capital	Capital
TF Shock_$t-1$ x High ARPK	-0.942**	-0.722	-0.590			
	(0.461)	(0.454)	(0.452)			
FPC Shock_$t-1$ x High ARPK				-1.152***	-0.972***	-0.717***
				(0.288)	(0.278)	(0.267)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry Time Trends	No	Yes	Yes	No	Yes	Yes
Firm Size x Year	No	No	Yes	No	No	Yes
Observations	71473	71473	71473	71473	71473	71473
R-squared	0.926	0.929	0.940	0.926	0.929	0.940
Panel B: August Shocks						
	(1)	(2)	(3)	(4)	(5)	(6)
	Capital	Capital	Capital	Capital	Capital	Capital
TF Shock_$t-1$ x High ARPK	-4.137***	-3.651***	-2.691***			
	(0.904)	(0.864)	(0.820)			
FPC Shock_$t-1$ x High ARPK				-2.025***	-1.778***	-1.329***
				(0.428)	(0.409)	(0.386)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry Time Trends	No	Yes	Yes	No	Yes	Yes
Firm Size x Year	No	No	Yes	No	No	Yes
Observations	71473	71473	71473	71473	71473	71473
R-squared	0.926	0.929	0.940	0.926	0.929	0.940

Notes: This table examines the heterogeneous association between monetary policy shocks and Capital for ex-ante High-ARPK firms relative to Low-ARPK firms, using firm-level data for the period 2009-2024. Firms having average $ARPK/\overline{ARPK}$ for the period FY 2005-2009 above the median are defined as High-ARPK firms, where $\overline{ARPK}$ is the NIC 4-digit industry-level mean. Monetary policy shocks are measured using the Target Factor (TF) and the First Principal Component (FPC) from Lakdawala and Sengupta (2025). The annual shock measures are constructed using the absolute values of the October and August shocks and are assigned to firm-level observations in the subsequent year. Firm-level data are sourced from Prowess. Standard errors are in parentheses and are clustered at the firm level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.