# Household Portfolio and Deposit Insurance: Implications for the Supply of Safe Assets*

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**Abstract**

This paper investigates the effect of deposit insurance (DI) on household portfolio allocation between bank deposits and risky assets. Theoretically, limited DI creates a kink in the capital allocation line, causing depositor bunching at the DI threshold and increased equity holdings. Using a natural experiment in India and individual holdings on stocks, deposits, and mutual funds, we confirm depositor bunching at the DI threshold. Leveraging a bunching-in-differences design, we show that DI expansion shifts portfolios from equities and mutual funds to deposits, driven by unmet demand for safe assets. Bunchers increase their deposits between 3.6% and 5.1% by liquidating their stock holdings, which were more exposed to safer state-owned enterprises, transiently affecting the asset prices of these stocks. We show that the share of bunchers is a sufficient statistic to measure the depositor-implied risk of bank default. Our estimates of the welfare effect of changes in DI show that depositors gain at least 4% as DI increases, even after accounting for the resulting moral hazard by banks.

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# 1 Introduction

A safe asset can be broadly characterized as a security that is liquid, insensitive to informational asymmetries, and expected to retain its value even amid systemic crises (Dang, Gorton, and Holmström, 2020; Barro et al., 2022; Brunnermeier, Merkel, and Sannikov, 2024). Due to these properties, safe assets are a key component of household and investor portfolios worldwide, serving as reliable stores of value and collateral (Gorton, 2017). Consequently, investors assign a premium to safe assets, highlighting the strong demand for such securities (Krishnamurthy and Vissing-Jorgensen, 2012). Despite the high demand, the supply of such assets is limited and is significantly shaped by institutional frameworks and government guarantees. Deposit insurance is a prominent example of such an institutional mechanism. The seminal work of Diamond and Dybvig (1983) highlights that uninsured deposits are susceptible to runs and deposit insurance serves as a critical policy tool that reduces this risk, allowing households to safely hold their wealth within the banking system. Therefore, the deposit insurance threshold imposes a natural limit on the supply of safe assets to households, especially when banks are risky and can significantly alter household portfolio allocation.

While deposit insurance can play a crucial role in shaping portfolio allocation by influencing the supply of safe assets, empirical evidence on this front is limited. Most studies focus on depositor behaviour during severe banking crises (Iyer and Puri, 2012; Iyer, Puri, and Ryan, 2012; Martin, Puri, and Ufier, 2025; Artavanis et al., 2022) or on deposit fluctuations following changes in insurance limits (Iyer et al., 2019; Atmaca et al., 2023; De Roux and Limodio, 2023; Cucic et al., 2024). Although bank runs are an extreme form of portfolio reallocation, they leave an important gap: how does deposit insurance affect household portfolios across asset classes? Addressing this gap is crucial for understanding how fluctuations in the supply of safe assets influence household portfolio choice and the demand for other assets, as well as evaluating the broader impact of deposit insurance and informing the design of optimal policies à la Dávila and Goldstein (2023). However, answering this question requires overcoming two significant challenges. First, it requires an environment where changes in DI coverage are exogenous – that is, independent of financial crises – so that we can distinguish policy-driven rebalancing from crisis-induced behaviour. Second, it requires detailed household data, including both deposit holdings and investments in other financial assets, to examine deposit insurance's impact on overall portfolio allocation.

This paper attempts to address these challenges and examine how the expansion of safe assets through deposit insurance influences household portfolio allocation. We begin by presenting a theoretical framework of portfolio allocation, where individuals allocate their endowments between a safe asset – deposits – and a risky asset. Deposit insurance (DI) plays a crucial role in this decision as it limits the supply of safe deposits, i.e., deposits are safe up to the DI threshold, after which they are subject to risk. This generates a kink in the capital allocation line, affecting the optimal portfolio choice. We show that when bank failure carries a positive probability, a limited DI leads to bunching in the deposit distribution at the threshold, which results in a higher level of securities-holding than in the presence of unlimited insurance. Furthermore, we show that raising the DI threshold prompts depositors – especially those whose balances meet or exceed the previous threshold – to optimize along a higher indifference curve. This shift results in an increase in deposits and a decline in stock holdings. We bring together theory and empirics by estimating the welfare gains of deposit insurance and showing the benefits of insurance and their relation to risk aversion.

We provide empirical support for our framework using a granular depositor-level dataset drawn from a 4% random sample of depositors at a major private sector bank in India. This dataset uniquely links deposit accounts with stock and mutual fund transactions, long-term illiquid asset investments, spending patterns, loan data, credit scores, and demographic details. By incorporating information on family members, we also analyze intra-household transfers. Unlike prior studies that treat deposits and investment portfolios separately, our dataset integrates individual balance sheets to study in detail depositor behavior and portfolio choices.

Identifying the effect of DI on portfolio choice ideally requires individual-level exogenous changes in the DI threshold – an infeasible empirical scenario. While our theoretical model shows that all depositors holding deposits at the threshold and above are affected by an increase in DI, we take advantage of a key prediction revealing a source of cross-sectional variation in the response of depositors to deposit insurance: "bunchers", depositors with a balance at the DI threshold, respond more strongly to the increase in DI, since they are the ones facing the tightest constraint on safe assets. In implementing this methodology, our study follows the work established by Chetty et al. (2011), Luttmer and Singhal (2014) and Kleven (2016) in public economics.

Exploiting a natural experiment from February 2020 – when India raised its DI limit from ₹100,000 to ₹500,000 – we implement a bunching-in-differences approach to estimate the impact of DI changes on household portfolio allocation. The bunching-in-differences design combines the bunching behaviour in response to a policy threshold with a differences-in-differences design that examines the response of these bunchers to a shock in the policy threshold. Specifically, our design analyzes the response of depositors who cluster around the former threshold of ₹100,000 to changes in the threshold following the DI expansion, compared to those who do not cluster around this threshold. The key coefficient of interest is the interaction term of a time indicator variable, which denotes the period after the policy change, and a buncher indicator that identifies depositors clustering at the ₹100,000 threshold prior to the policy change.

This empirical design offers three primary advantages. First, by comparing a depositor's response before and after the policy change, we can incorporate depositor fixed effects, allowing us to control for any unobserved, time-invariant differences among depositors. Second, our estimator is resilient to concerns about the threshold acting as a reference point for reasons unrelated to DI policy – such as the preference for round numbers – since it compares the change in mass at the same point both before and after the policy change. Third, we can include ZIP code × time (month-year) fixed effects to account for time-varying local and aggregate shocks.

The identification of the estimate of interest relies on two key assumptions. First, the parallel trends assumption, which asserts that the two groups would have followed similar trajectories in the absence of the policy change. We provide support for this assumption using a pre-trend analysis. Second, the smoothness assumption requires that no structural changes occur at the threshold, aside from changes in DI eligibility. While our empirical design mitigates the impact of changes in other policies at the DI threshold, provided that the timing of those changes does not coincide with the DI threshold adjustment, there may still be concerns about changes in deposit rates at the threshold due to changes in DI coverage. We verify that deposit rates remain stable around this threshold. Furthermore, a review of our data provider's deposit and lending policies reveals no structural changes affecting depositors with balances above it, reinforcing the validity of the smoothness assumption.

We begin our analysis by documenting that bunchers increase their deposits – relative to non-bunchers – following the expansion of DI. This finding is not driven by pre-trends and remains robust across various bandwidth choices, comparing both bunchers and non-bunchers within the same household, as well as accounting for potential optimization errors and other concurrent shocks, such as those from the COVID-19 pandemic. Additionally, our results hold true when employing alternative estimators, different transformations of the dependent variable, and a continuous measure of exposure to policy changes, alongside diverse clustering methodologies. Finally, through a placebo test, we establish that these results are unlikely to be the result of spurious factors.

In terms of economic magnitude, our results suggest that a 1 percentage point increase in DI coverage is associated with a 2.1-3.0% increase in deposits. This result resonates with the findings of De Roux and Limodio (2023) who document an elasticity of 2.3% for Colombia using depositor-level data and an elasticity of 3.4% for the US using bank-level data.

Our theoretical model shows that relative to a scenario with unlimited DI, bunchers tend to invest less in safe assets while investing more in either riskier securities or illiquid assets. We test this assertion by presenting a parsimonious summary of the characteristics comparing bunchers with non-bunchers before the DI expansion. Consistent with our model predictions, bunchers tend to allocate a larger portion of their wealth to risky assets, such as stocks and mutual funds, or maintain a greater share in illiquid long-term investments. Lastly, we note that bunchers do not systematically differ from non-bunchers across a host of demographic and economic variables such as age, gender, marital status, household size, income, credit scores, and whether the depositor is self-employed.

Next, we assess a key prediction of our model, which posits that bunchers will reallocate their investments from risky assets into deposits after DI expansion. To support this hypothesis, we begin by presenting indicative evidence of portfolio reallocation, focusing on how baseline responses differ among bunchers who engage in retail trading of stocks and mutual funds. We document that the increase in deposits among bunchers is primarily driven by those who trade. The assessment of pre-trends suggests that the observed behaviors are not attributable to pre-existing trends among different depositor types. Overall, this heterogeneity in behavior among bunchers, contingent on their trading activity, reinforces our model's prediction that, in response to an increased supply of safe assets following the DI expansion, depositors are likely to shift their portfolios from risky assets toward deposits.

While the heterogeneous response among bunchers based on their trading activity is informative about the source of the increase in deposits, it is not direct. Particularly, it may be driven by other characteristics of bunchers that are correlated with investment in the stock market or mutual fund, such as financial literacy. We address this issue by directly examining the portfolio holding data for depositors for twelve months before and after the DI expansion. However, a straightforward comparison of aggregate stock holdings between bunchers and non-bunchers and attributing the changes in the aggregate portfolio to DI expansion is empirically challenging. Specifically, in the presence of non-random matching between depositors and securities, the estimated average difference in the aggregate security portfolio between bunchers and non-bunchers may not reflect the effect of DI expansion, but rather differences in the fundamentals of the securities they invest in.

We address this issue by leveraging granular security-level holdings data for each depositor and including ISIN $\times$ time fixed effects. These fixed effects allow us to identify the response of bunchers, relative to non-bunchers, from the same security at the same time, thereby abstracting away from the confounding factor of non-random matching of depositors to securities. Moreover, this fixed effect allows us to control for all fundamental shocks to the underlying security. Our results, with ISIN $\times$ time, depositor, and ZIP $\times$ time fixed effects, indicate that bunchers are more likely to liquidate their security holdings following DI expansion. Specifically, they liquidate their holdings in both the stock market and mutual funds.

A key hypothesis this paper posits is that bunchers have an unmet demand for safe assets. Consequently, they allocate funds to the stock market due to constraints on the availability of safe assets imposed by the DI limit. An implication of this hypothesis is that even when bunchers engage in stock market investments, they are likely to tilt their portfolios towards safer securities in the market as they have an unmet demand for safety. Furthermore, they are more likely to liquidate these safer securities in their portfolio after DI expansion.

We test for this proposition by constructing monthly portfolio tilts for each investor and stock characteristics following the methodology outlined in Balasubramaniam et al. (2023).[1] Prior to DI expansion, the portfolio of bunchers exhibits a greater tilt towards SOE stocks relative to non-bunchers. Meanwhile, we do not observe any differential portfolio tilts among bunchers and non-bunchers across several other stock characteristics. After the increase in deposit insurance, we observe that bunchers liquidate their holdings in the stocks of state-owned enterprises (SOEs), which are backed by government guarantees and regarded as safe investments in India.

We also investigate the asset price implications of liquidating SOE stocks and find that such liquidation, driven by the expansion of DI, can exert downward pressure on the prices of these safer stocks, up to 5%. However, we note that this effect is transient, with prices reverting back within a month. This pattern of an initial price drop after liquidation pressure, followed by a recovery, aligns with models of limits to arbitrage, particularly those that account for slow-moving capital (Shleifer and Vishny, 1997; Gabaix, Krishnamurthy, and Vigneron, 2007; Mitchell, Pedersen, and Pulvino, 2007; Duffie, 2010).

We combine our model with the empirical observations to present some quantitative exercises. First, we note that the share of bunchers is a sufficient statistic to estimate the depositor perceptions of bank failure risk. Therefore, we calibrate our model to target the observed mass of depositors around that threshold in the data to estimate the implied probability of bank failure as perceived by depositors. The underlying intuition is that, given their risk aversion, the mass of bunchers is driven by the probability that depositors anticipate the bank to fail. The model fits the data well, especially with reasonable values of risk aversion. Specifically, while it does a good job matching the targeted mass of bunchers it also fits well with other parts of the distribution of depositors, that were not explicitly targeted.

Furthermore, the identified model allows us to conduct welfare analysis. We find that welfare increases following DI expansion and this increase crucially depends on the risk aversion of the underlying population; specifically, greater risk aversion corresponds to a larger welfare increase. Additionally, the welfare improvement arises from two key sources. First, there is a reallocation of risky assets into deposits from depositors with an unmet demand for safety before the expansion. This feature makes the share of bunchers a sufficient statistic to compute welfare changes driven by portfolio reallocation due to marginal changes in the DI limit. Second, even individuals with substantial endowments experience an increase in utility without any change in their portfolio composition, as the expansion of DI reduces their overall exposure to risk. We estimate that in the absence of any moral hazard effect of DI on banks, depositor welfare increases by 4.3-18.6%.

[1]The stock characteristics we consider are (1) firm ownership: state-owned and business group affiliation; (2) sector of operations: manufacturing, financial, wholesale, diversified, construction, information and communication, and agriculture; (3) market characteristics: market alpha, market beta, realized returns, realized volatility, and market capitalization; and (4) accounting characteristics: dividend payer, market to book value ratio, age, size, leverage, interest coverage ratio, cash to assets ratio, operating margin, and tangibility.

We conduct a counterfactual analysis to assess the welfare effects of expanding deposit insurance (DI), incorporating the potential moral hazard effects of DI expansion. Existing literature suggests that DI expansion may incentivize risk-taking behaviour by banks (see Demirgüç-Kunt and Kane (2002), Calomiris and Jaremski (2016) and Anginer and Demirgüç-Kunt (2018) for a review). To account for this, we model moral hazard by allowing the likelihood of bank failure to increase following DI expansion. Our results indicate that moral hazard can diminish the welfare gains from expanding DI, particularly adversely affecting depositors with high endowments. Nonetheless, the welfare benefits are robust to moderate moral hazard effects. Specifically, even when we assume the probability of bank failure increases by 15%, the overall welfare impact remains positive, with gains ranging from 4.0% to 18.2%. This indicates that the welfare advantages of DI expansion are unlikely to be fully offset by moral hazard unless the associated risks are extraordinarily high.

Lastly, we rule out several alternative mechanisms that may account for the relative deposit growth observed among bunchers following the DI expansion. We examine several potential sources of monetary reallocation: moving cash-in-hand to bank accounts, redistributing funds among family members within the household, shifting money across different banks, reducing overall spending, and increasing lending to bunchers, which could create additional deposits in their bank accounts. We document that, on average, none of these alternative mechanisms can quantitatively explain the rise in deposits among bunchers.

The primary contribution of our paper is to introduce a new dimension to the discussion on optimal deposit insurance by examining it through the lens of depositor portfolio allocation. A long tradition in the theoretical literature has concentrated on how deposit insurance influences banks, particularly in terms of their liquidity creation and risk-taking behaviors.[2] Consequently, empirical work has largely mirrored this focus, analyzing the effect of deposit insurance on bank behavior.[3] While some research has utilized detailed depositor-level data to explore depositor-run behaviour and its relationship with DI, these studies still relate back to bank stability or liquidity creation (Iyer and Puri, 2012; Iyer, Puri, and Ryan, 2012; Iyer et al., 2019; Artavanis et al., 2022; Atmaca et al., 2023; De Roux and Limodio, 2023; Martin, Puri, and Ufier, 2025). Thus, the discussion on optimal deposit insurance has primarily been shaped by considerations of its costs and benefits from the standpoint of banks, as highlighted in the recent work of Dávila and Goldstein (2023). We contribute to this discussion

[2]See Merton (1977); Kareken and Wallace (1978); Bryant (1980); Diamond and Dybvig (1983); Pennacchi (1987, 2006); Calomiris and Kahn (1991); Chan, Greenbaum, and Thakor (1992); Matutes and Vives (1996); Hazlett (1997); Allen and Gale (1998); Diamond and Rajan (2001); Duffie et al. (2003); Goldstein and Pauzner (2005); Uhlig (2010); Keister (2016); Egan, Hortaçsu, and Matvos (2017); Liu (2023), and Schilling (2023) among others. We refer readers to Gorton and Winton (2003) for a review of this large theoretical literature.

[3]See Gorton (1988); Brewer (1995); Saunders and Wilson (1996); Calomiris and Powell (2001); Martinez Peria and Schmukler (2001); Demirgüç-Kunt and Detragiache (2002); Cooper and Ross (2002); Demirgüç-Kunt and Huizinga (2004); Cull, Senbet, and Sorge (2005); Demirgüç-Kunt, Kane, and Laeven (2008a,b); Calomiris and Jaremski (2019), and Kim, Kundu, and Purnanandam (2024) among others. We refer the reader to Demirgüç-Kunt and Kane (2002); Calomiris and Jaremski (2016), and Anginer and Demirgüç-Kunt (2018) for a review of the empirical literature on this topic.

by introducing a new perspective on the role of deposit insurance (DI) in shaping portfolio choices. While welfare gains in models like those proposed by Diamond and Dybvig (1983) primarily arise from decreased bank run risk, we propose a new mechanism through which DI can affect depositor welfare by changing the supply of safe, liquid assets.

Our novel channel of portfolio reallocation through which DI can affect depositors is important for three reasons. First, it offers a depositor's perspective on how adjustments in DI thresholds can affect household portfolio allocation and, subsequently, their welfare by altering the supply of safe, liquid assets. Second, our findings indicate that an expansion of DI may lead depositors to shift their funds from other sectors of the economy, such as equity markets and mutual funds, to bolster deposit growth. This suggests potential costs to other economic segments that policymakers should consider. Therefore, while our findings do not solve the challenging question of optimal deposit insurance, they do inform the discussion. Specifically, these considerations are likely to be more important in emerging market, where deposits often represent the sole safe and liquid asset for households. For example, while households in emerging economies might invest in U.S. Treasuries – considered globally safe assets – they frequently face volatile exchange rates that introduce currency risk for those holding foreign securities. Additionally, Krishnamurthy and Li (2023) demonstrate that U.S. Treasuries and bank transaction deposits are not perfect substitutes, even within the United States. Similarly, Cram, Kung, and Lustig (2024, 2025) and Cram et al. (2025) raise concerns over considering government debt a safe asset. Finally, our framework, which identifies the share of bunchers as a sufficient statistic for estimating depositor-implied probabilities of bank failure, provides valuable guidance for regulators in assessing bank risk.

Lastly, our work contributes to the literature on the supply and demand of safe assets.[4] We contribute to this literature by presenting a household demand perspective. Specifically, we identify the role of DI threshold in limiting the supply of safe assets. As a result, these households have an unmet demand for safe assets and they seek alternative options to salvage this unmet demand and operate at a lower indifference curve.

## 2 Institutional Details

This section presents the specifics of deposit insurance in India. We begin by outlining the structure of the deposit insurance system, followed by a discussion of the changes made to the deposit insurance limit in February 2020, contemporaneous aggregate economic conditions, and other events in the Indian banking sector.

Deposit insurance was introduced in India in 1962, making it the second country in the world

[4]See Krishnamurthy and Vissing-Jorgensen (2012, 2015); Gorton, Lewellen, and Metrick (2012); Sunderam (2015); Caballero, Farhi, and Gourinchas (2016, 2017); Gorton (2017); Lenel (2017); Caballero and Farhi (2018); He, Krishnamurthy, and Milbradt (2019); Kacperczyk, Perignon, and Vuillemey (2021) and Gorton and Ordonez (2022) among others.

to implement such a scheme – the first being the United States in 1933. Deposit Insurance and Credit Guarantee Corporation (DICGC), a wholly-owned subsidiary of the Reserve Bank of India (RBI), is in charge of supplying deposit insurance to depositors in Indian banks. Specifically, DICGC protects depositors' money kept in all commercial and foreign banks located in India; central, state, and urban co-operative banks; regional rural banks; and local banks, provided that the bank has opted for DICGC cover.

DICGC insures all kinds of bank deposit accounts, such as savings, current, recurring, and fixed deposits up to a limit of ₹500,000 per account holder per bank. In case an individual's deposit amount exceeds ₹500,000 in a single bank, only ₹500,000, including the principal and interest, will be paid by DICGC if the bank becomes bankrupt. The deposits kept in different branches of a bank are aggregated for the purpose of insurance coverage and a maximum amount of up to ₹500,000 is paid. However, if funds are deposited into separate banks, they would then be separately insured. Appendix A presents a more detailed discussion of the organization and operational structure of the DICGC.

The insurance limit has experienced a series of adjustments over the decades. Appendix Table A.1 presents the timeline of these changes. Initially set at ₹5,000 on January 1, 1968, it was raised to ₹10,000 on April 1, 1970, and further increased to ₹20,000 on January 1, 1976. The limit was then elevated to ₹30,000 on July 1, 1980. A significant increase occurred on May 1, 1993, when the insurance limit was raised to ₹100,000. Following this adjustment, the limit remained largely stagnant for nearly three decades. However, in 2020, it was dramatically raised to ₹500,000, representing a five-fold increase and substantially enhancing the coverage offered to depositors.

The announcement of the change in the deposit insurance limit was made on February 1, 2020, by the Indian Finance Minister during the 2020 Union Budget speech. The actual change in the deposit insurance coverage was effective from February 4, 2020.

The primary motive for the revision of deposit insurance limits was to ensure it remained commensurate with rising per capita income levels. In India, per capita income surged from $500 in 1993 to $1,900 in 2019; however, the deposit insurance ceiling stagnated at ₹100,000 (≈$1,350) throughout this period. This disconnect led to increasing pressure from the banking sector to raise the deposit insurance limit, highlighting concerns over depositor protection amidst evolving economic conditions. Soumya Kanti Ghosh, the Group Chief Economic Advisor at the State Bank of India – India's largest state-owned bank – articulates this challenge effectively: *"In particular, over the years, the level of insured deposits as a percentage of assessable deposits has declined from a high of 75% in 1981-82 to 28% in 2017-18. Given this backdrop, we believe, there is a dire need to revisit the insurance coverage of the bank deposits. In particular, the current upper limit of ₹100,000 per depositor, we believe, has outlived its shelf life and there is a need to revisit it."* (SBI Ecowrap, 2019)

Another important consideration for the proposed change in India's deposit insurance policy was the government's objective to align the ratio of deposit insurance to per capita income with those of other BRICS nations (Brazil, Russia, China, and South Africa) as part of its club convergence agenda (Panda, 2019). Before 2020, India's deposit insurance was a modest \$1,350, while its GDP per capita stood at approximately \$1,913, resulting in a ratio of just 0.71, the lowest among the BRICS countries. In contrast, Brazil and China had much higher ratios of 7.07 and 6.97, respectively. Russia's deposit insurance amount of \$19,460 yielded a ratio of 1.91, and South Africa, with \$6,110 in deposit insurance, reached a ratio of 1.06. The stark disparity highlighted India's need to increase its deposit insurance limit to improve its ratio and match those of its peers in the BRICS club. Additionally, developed economies demonstrate significantly higher deposit insurance relative to per capita income. For instance, the USA offers \$250,000 in deposit insurance with a ratio of 3.94, the UK provides \$109,114 with a ratio of 2.71, and Canada offers \$74,620, resulting in a ratio of 1.71. We direct readers to Appendix Table A.2 for detailed calculations. This context emphasizes the need for India to enhance its deposit insurance framework relative to its peers in BRICS and other advanced economies, which India aspires to match in the long run.

Next, we discuss other significant aggregate events that coincided with the adjustment of deposit insurance in February 2020. A major global development during this period was the outbreak of coronavirus (COVID-19), which only became a prominent issue in India in late March 2020. Similar to many economies worldwide, India experienced a decline in economic growth during this time. However, before the COVID-19 outbreak, the Indian economy was on a stable trajectory, as reflected in actual and expected GDP growth rates (see Appendix Figure A.1). At the same time, the Reserve Bank of India continued its policy of reducing interest rates; however, this decline was not a direct response to the pandemic, as the rate cuts had commenced in late 2018 (see Appendix Figure A.2).

It is also noteworthy to highlight major events in the Indian banking sector during the period. A key event before the deposit insurance limit change was the imposition of withdrawal restrictions on a regional cooperative bank – Punjab & Maharashtra Co-operative Bank Limited (PMC) – by the RBI on 23 September 2019.[5] Many have argued – though ex-post – that the fraud case of PMC bank was the immediate reason for the Indian government to re-evaluate India's deposit insurance system (Nayak and Chandiramani, 2022). On 5 March 2020, RBI took over the management of Yes Bank – a private sector bank in India.[6] The bank came out of the moratorium and resumed full-fledged banking operations on 18 March 2020 (within 2 days), after the Union Cabinet approved the reconstruction

[5]The restrictions were imposed following the accusation of fraud involving the bank and Housing Development Infrastructure (HDIL). As an immediate effect of this restriction, the bank account holders were not allowed to withdraw more than ₹1,000 from their accounts. On 26 September 2019, the restrictions were eased and a total of ₹10,000 could be withdrawn by customers. On 5 November 2019, the RBI decided to increase the prescribed withdrawal limit to ₹50,000. The limit was further increased to ₹100,000 on 19 June 2020.

[6]After the asset quality review of the bank it was found that its actual non-performing assets (NPA) were seven times than the one reported in their audit books. The RBI cited Yes Bank's failures to raise new funding to cover its NPA, inaccurate statements of confidence in its ability to receive new funding, and its underreporting of its non-performing assets, among other factors, as the reasons for the moratorium.

program for Yes Bank.[7] Similarly, on 17 November 2020, RBI imposed a month-long moratorium on Lakshmi Vilas Bank – a small private sector bank – due to a deterioration in its financial position.

# 3 Theoretical Framework

This section builds upon the framework of deposit insurance described in De Roux and Limodio (2023) to develop a portfolio allocation model. In this model, individuals decide how to allocate their endowments between deposits and a risky asset (market), taking into account that the availability of risk-free deposits is limited by the deposit insurance threshold.

## 3.1 Setup

Consider individuals deciding how to allocate an endowment over two assets. The utility function is defined as $U(E, \sigma)$, defined over the expected return of the underlying portfolio, $E$, and its variance, $\sigma^2$, as a measure of risk. This function satisfies all standard regularity assumptions, as well as the Inada conditions.

Each individual is endowed with a positive endowment, denoted as $Y_i > 0$, which is distributed according to the density function $f(Y)$. They must decide how to allocate this endowment between the stock market, $M$, and an asset called deposits, $D$. The stock market offers an expected return $E(\widetilde{R}M) > 1$ with a variance of $\sigma M^2$. The specifics of the return and risk for deposits are described in equation 1. The model assumes smoothness in terms of endowment distribution and preferences à la Chetty et al. (2011) and Kleven (2016).

In this model, bank deposits carry risk since there is a probability $\pi \in (0, 1)$ of bank failure. We assume the probability of bank failure to be constant and determined exogenously. A deposit insurance policy exists with a coverage threshold of $\delta > 0$. This policy guarantees that a depositor whose deposits do not exceed this threshold ($D \leq \delta$) will always receive the full amount deposited, $R_D D = D$, since $R_D$ is assumed to be unit for tractability. However, if a depositor has amounts exceeding the threshold ($D > \delta$), they receive only the insured amount $\delta$ in case of bank failure. For tractability, we also set a zero recovery rate. Equation 1 describes the expected gross returns on deposits.

$$\mathbb{E}(\widetilde{R}_D D) = \begin{cases} D & if \quad D \leq \delta \\ (1-\pi)D + \pi\delta & if \quad D > \delta \end{cases} \tag{1}$$

Equation 1 states that deposits are reimbursed in all circumstances if the total deposits are below the deposit insurance threshold, $D \leq \delta$, thus carrying zero risk and making deposits under the threshold

[7] The program involved infusing money in the Yes bank by investors including State Bank of India, ICICI Bank, HDFC Bank, Axis Bank, Kotak Mahindra Bank, Rakesh Jhunjhunwala, Radhakishan Damani and Azim Premji trust investors including State Bank of India, ICICI Bank, HDFC Bank, Axis Bank, Kotak Mahindra Bank, Rakesh Jhunjhunwala, Radhakishan Damani and Azim Premji trust.

a safe asset. However, if the total deposits exceed the threshold ($D > \delta$), the depositor receives $D$ if the bank does not fail, which occurs with probability $1 - \pi$. In the event of a bank failure, which occurs with probability $\pi$, the depositor receives only the threshold amount $\delta$. This situation implies a positive risk associated with holding bank deposits. We assume that this risk is lower than the risk of holding stocks; hence, we have $\sigma_D^2 \in (0, \sigma_M^2)$. Specifically, the variance of deposits is given by the expression $\sigma_D^2 = \pi(1-\pi)(1-\frac{\delta}{D})^2 \cdot \mathbb{I}(D-\delta)$. This expression implies that a higher level of insurance threshold makes deposits safer. Equation 1 can be alternatively described using equation 2, with the expected gross return on deposits being equal to the level of deposits, $D$, minus a share of deposits lost in case of bank failure, $\pi \times (D - \delta)$, which only involves individuals holding more than the insurance threshold, denoted by the indicator function $\mathbb{I}(D - \delta)$.

$$\mathbb{E}(\widetilde{R}_D D) = D - [\pi \times (D - \delta) \times \mathbb{I}(D - \delta)] \tag{2}$$

## 3.2 Solution to the Investor Problem

Individuals choose the share of their endowment invested in the stock market, $\omega = \frac{M}{Y}$, and deposits, $1 - \omega = \frac{D}{Y}$. As a result, the investor problem can be rewritten as follows:

$$\max_{\omega} E(\widetilde{R}_M)\omega + E(\widetilde{R}_D \frac{D}{Y}) - \gamma \left[\sigma_M^2 \omega^2 + \sigma_D^2 (1-\omega)^2\right] \tag{3}$$

Plugging in the expression for $\mathbb{E}(\widetilde{R}_D D)$ from equation 2 into equation 3, allows us to re-write the optimization problem as in equation 4, where $\hat{\delta} = \frac{\delta}{Y}$ denotes the insurance threshold level relative to the endowment.

$$\max_{\omega} E(\widetilde{R}_M)\omega + (1-\omega) + \left[\pi \times (1 - \omega - \hat{\delta}) \times \mathbb{I}(D-\delta)\right] - \gamma \left[\sigma_M^2 \omega^2 + \sigma_D^2 (1-\omega)^2\right] \tag{4}$$

Figure 1 presents the effect of the kinked capital allocation line (CAL) on optimal portfolio through a classical example in the bunching literature. The CAL is defined between $\omega = 0$ denoting the case with all the endowment is invested in deposits and $\omega = 1$ if only stocks are chosen. The CAL line has a convex kink due to kink in expected deposit returns as shown in equation 2.

In fact, the set is linear with slope $f(R)$ from $\omega = 1$ to $\omega^{\delta *}$, with this slope changing to $f(R, \pi, \delta)$, between $\omega^{\delta *}$ and $\omega = 0$. This occurs because the portfolio return drops when deposits exceed the deposit insurance threshold $\delta$. As the portfolio contains marginally more deposits after $\omega^{\delta *}$, the expected return for a given variance declines, since the investor prices in the likelihood of a bank default and only reimbursement of deposits up to $\delta$.

The left panel of Figure 1a shows an individual with endowment $Y^{KI}$ and an optimal portfolio with the optimal $\omega^{\delta*}$ and a set $(E^*, \sigma^*)$. This individual is labelled as *kink insensitive*, as she would always choose the share of deposits $\omega^{\delta*}$, implying a level of deposit holding at the insurance threshold $\delta$, both in the presence of the kink and also in a counterfactual scenario in which there is a zero probability of bank failure. This is evident from the fact that her indifference curve is tangent both to the kinked budget set and to the counterfactual linear budget set, which continues from the kink through the dashed line with slope $f(R)$.

Figure 1b presents the case of an individual with endowment $Y^{MB}$, who is the marginal buncher since $Y^{MB} > Y^{KI}$. In the case of a zero probability of bank failure, her deposits are determined by the point of tangency between the highest indifference curve and the dashed capital allocation set, choosing a higher share of optimal deposits $\omega^{\pi} < \omega^{\delta*}$. However, because of the kink due to a strictly positive probability of bank failure, her optimal deposit is bunched at the deposit insurance threshold $\delta$ implied by $\omega^{\delta*}$. Given the assumptions on the utility function and the smoothness of the endowment function, this behaviour produces an excess mass in the deposit distribution at the kink and includes all individuals with an endowment between $Y^{KI}$ and $Y^{MB}$.

Figure 1c shows that the distribution of deposits would be smooth in the case of a zero probability of bank failure and no kink, as indicated by the downward sloping curve labelled "prekink density". However, because of the kink due to a non-zero probability of bank failure, there emerges an excess mass of individuals who bunch at the $\delta$ threshold. These agents deposit $\delta$, instead of choosing an optimal amount of deposits given by their maximization with zero probability of bank failure. As a result, the distribution of deposits in the presence of the kink exhibits an excess mass or bunching at $\delta$ and a discontinuity in the distribution to the right of the threshold, labelled as "Postkink density". These findings can be summarized by the following proposition.

*Proposition 1: In the presence of a positive probability of bank failure, a limited threshold of deposit insurance induces excessive bunching in the deposit distribution at the threshold and a higher purchase of stocks than in the presence of unlimited insurance.*

## 3.3 Depositor behavior and an increase in deposit insurance

This conceptual framework aids in examining how depositors react to a rise in the DI threshold, which is the primary focus of this paper. In particular, the definition of the gross deposit rate in equation 2 indicates that an increase in DI threshold results in a lower risk on deposits. This creates two opposing effects: a) it incentivizes depositors whose balances meet or exceed the prior threshold to increase their deposits; and b) it leads to a reduction in stock market investments among depositors who were previously constrained by the DI limit.

At the same time, our paper highlights a crucial source of cross-sectional variation with respect to the impact of this change: individuals who cluster around the former threshold, defined as $\delta_1$, display the strongest uptick in deposits and drop in stock holding, while those with deposits exceeding $\delta_1$ present a milder expansion in deposits and decline in stocks as the threshold grows from $\delta_1$ to $\delta_2$. In addition to this, individuals who face a higher cost of transforming their endowment into deposits, for example, those who invest in other less liquid assets, present a lower response to deposit insurance. Appendix B presents a formal proof of these statements based on the solution to the investor problem discussed in section 3.2.

Figure 2 presents a simple summary of the effect of DI expansion on the portfolio choice of depositors. Figure 2a shows the response of the marginal buncher – with an endowment $Y^{MB}$, presented in Figure 1b – to an increase in deposit insurance. Specifically, as the DI threshold increases from $\delta_1$ to $\delta_2$ with $\delta_2 > \delta_1$, the capital allocation set of the individual expands and the new kink in the CAL moves to the left of the old kink along the allocation set. As a result, the new share of deposit is determined by the point of tangency between the highest indifference curve and the expanded set, leading to an increase in deposits denoted by the amount $\Delta D^{MB}$.

Figure 2b presents the case for an individual with endowment $Y^{NB}$ with $Y^{NB} > Y^{MB}$. This individual was not bunching at the old threshold and has an endowment of $Y^{NB} > Y^{MB}$. Similar to the marginal buncher, she also increases her deposits. However, the increase in her deposits denoted by $\Delta D^{NB}$ is smaller in magnitude than the increase in deposits by the marginal buncher, i.e., $\Delta D^{MB} > \Delta D^{NB}$. The discussion in Section 3.3 can be summarized by the following proposition.

*Proposition 2: An increase in the deposit insurance threshold leads to a rise in deposits and a decline in stock holding for individuals with deposits higher or equal to the old threshold. Individuals who were bunching at the old threshold exhibit the largest increase in deposits, individuals holding more than the old threshold expand their deposits and lower their stock holding less than the former bunchers. Investors holding stocks exhibit a stronger reaction to the increase in insurance than those involved in less liquid investment.*

# 4 Data & Key Patterns

We collect granular depositor-level data from a large private-sector bank in India. Specifically, we extract a 4% random sample of all retail customers who hold a savings deposit account with the bank. Our sample includes 321,350 unique depositors, with 7,933,335 observations spread across 8,034 ZIP codes, covering the period from February 2019 to February 2021. The data provides detailed information on three deposit accounts for each depositor: savings, time, and recurring deposits.[8] We can also observe the total investment in the stock market, mutual funds and public provident funds

[8] Recurring deposits are a saving product where the depositor contributes a fixed amount of money at regular intervals.

for our sample depositors. Lastly, the data also includes information on loans taken from the bank, depositor credit scores from the credit bureau, and demographic details like age, gender, location, and family linkages. This rich set of information allows for a thorough analysis of depositor behaviour.

## 4.1 Summary Statistics

Table 1 presents the summary statistics of the key variables in our sample. Panel A presents the summary statistics of the month-end balance for these variables. We define total deposits as the sum of savings, time and recurring deposits. The average (median) deposits in our sample are ₹327,480 (₹59,298) with a large standard deviation of ₹715,401. The majority of the total deposits come from savings deposits which have an average (median) value of ₹212,053 (₹31,746) followed by time deposits with an average month-end balance of ₹96,485.

A key advantage and novelty of our data is that, in addition to observing the deposits, we can also observe detailed holdings of depositors in the stock market and mutual funds. We can track the mutual fund and stock market holdings of depositors because a DEMAT (Dematerialized) account, required in India since 1996 for holding and trading financial securities, can only be opened through a linked bank account.[9] The DEMAT account number –linked to a unique customer – is used for all transactions to facilitate the electronic settlement of trades. By merging each customer's deposit account number with their DEMAT account number, we can track both their deposits and their holdings in mutual funds and stocks.

The DEMAT account activity data allows us to track the ISIN level purchases and sales by the depositor. Panel B of Table 1 reports the number of shares and the amount for each ISIN (stock or mutual fund). On average, depositors hold 850 shares with an investment of ₹160,388. The decrease in the number of observations related to mutual funds is indicative of the limited investment in these securities by depositors within our sample. Lastly, we can also observe the depositors' investment in the Public Provident Fund (PPF), which is a voluntary savings-cum-tax-reduction social security instrument in India with a maturity of 15 years.

We define banked wealth as the wealth that we can observe in the bank data as the sum of total deposits, investment in the stock market, mutual funds, and PPF. The average (median) banked wealth for our sample is $\approx$ ₹1 million (₹102,486) with a large amount of heterogeneity denoted by a large standard deviation of $\approx$ ₹3 million.

Panel C of Table 1 documents the characteristics of depositors in our sample. The average depositor in our data is 38 years old, with $\approx$ 3.6 members in the household, and has an account with

[9] A DEMAT account, short for dematerialized account, is used in India to hold financial securities digitally, specifically for shares traded in the stock market. These accounts are managed by two main depositories – the National Securities Depository Limited (NSDL) and the Central Depository Services Limited (CDSL). A depository participant (DP), a bank, serves as an intermediary between the investor and the depository. In India, a DP acts as the depository's agent, with their relationship governed by an agreement under the Depositories Act, 1996. While the DEMAT account stores the securities, a bank account is required for handling the financial settlements.

our bank for 8.13 years as of February 2020. 44% of depositors in our sample are female. Around 50% of depositors in our sample do not have a credit score, and conditional on having a credit score, their average score is 760, denoting an excellent credit history. Only 5% of depositors in our sample have PPF and around 37% of the depositors have taken any type of loan from the bank. The dataset contains imputed income and profession of the customers, collected by the bank in compliance with the Prevention of Money-Laundering Act (PMLA), 2002. 34% of the depositors in our sample are self-employed. The average (median) monthly income in our sample is ₹72,761 (₹40,071) with a large standard deviation of ₹134,697. The large heterogeneity in the distribution of income closely mirrors the distribution of banked wealth reported in Panel A.

Moreover, panel C of Table 1 shows that 23% of the bank customers in our sample had some investment in the stock market and around 14% had some investment in mutual funds during our sample period. The average month-end amount in stocks and mutual funds is ₹571,042 and ₹57,119, respectively. The observation that depositors in our sample allocate significantly more of their portfolios to stocks compared to mutual funds aligns with the discussions presented in Campbell, Ramadorai, and Ranish (2014, 2019); Anagol, Balasubramaniam, and Ramadorai (2021), and Balasubramaniam et al. (2023). They argue that Indian households, even those with equity investments, tend to avoid holding bonds or mutual funds, reinforcing the notion of a pronounced preference for direct equity ownership over alternative investment vehicles.

Two noteworthy points emerge about our sample from Table 1. First, the wealth distribution is highly skewed. This is evident from the large standard deviation of ≈ ₹3 million. Moreover, the $25^{th}$ percentile value of banked wealth is ₹8,635 and the $75^{th}$ percentile value is ₹598,410 denoting a rightward skewness in the wealth distribution. Second, the average bank depositor in our sample is unlikely to be representative of the average Indian household, but more likely to represent middle- to upper-middle-class individuals or households. The second observation is not surprising, given that our bank is a large private-sector institution. The distribution of the imputed monthly income data for the depositors supports this conjecture. This provides an advantage for our data, as our analysis is likely to reflect the responses of relatively affluent and sophisticated customers. Consequently, our results may be less susceptible to concerns regarding external validity.

## 4.2 Deposits & Expansion of DI Limit

Next, we examine the impact of increasing the deposit insurance (DI) limit on deposit levels by tracking the month-end balances of depositors in our sample. This analysis aims to capture the association between DI expansion and deposit behaviour.

First, we compare the proportion of insured deposits and the share of fully insured depositors over the 12 months before and after the DI limit expansion. Appendix Figure C.1a presents the fraction of fully insured accounts before and after the expansion and Appendix Figure C.1b shows the share of insured deposits during the same periods. We observe a 27 percentage point increase in fully insured depositors and a 20 percentage point rise in insured deposits post-expansion, both of which are statistically significant at the 1% level. The economic impact aligns with the policy change, which quintupled the insurance limit.

Next, we examine deposit growth following the DI limit increase. Figure 3 presents the temporal trends in median (Panel 3a), average (Panel 3b), and total bank deposits (Panel 3c) over the sample period, with the vertical grey dashed line marking the DI expansion event. Our results indicate that deposits increased by 13.4% after the DI limit increase. Specifically, Figure 3 suggests that median and average month-end balances, as well as total bank deposits, remained stable before February 2020 but increased following the DI expansion.

In summary, Figures C.1 and 3 present two key takeaways. First, the share of depositors and deposits covered by insurance increased significantly. While this may be a largely mechanical effect, it is crucial for understanding the scale of the policy's impact. Second, total deposit levels grew following the DI expansion, indicating a response from depositors.

## 4.3 Depositor Distribution & Bunching Behavior

Next, we examine the distribution of depositors within our sample, particularly focusing on the period preceding the DI expansion in February 2020. Figure 4a presents a histogram that illustrates the distribution of depositors based on their average month-end balances for the twelve months leading up to February 2020.

Three significant observations emerge from this analysis. First, we observe a power-law distribution, indicating that the number of depositors declines exponentially as the deposit amount increases. This pattern mirrors the wealth distribution across households, which similarly exhibits power-law characteristics.

Second, we document round number bunching, suggesting that depositors are influenced by specific numerical reference points. This behaviour is likely attributable to intrinsic psychological biases or behavioural discontinuity and has been documented in a range of contexts, as discussed in Kleven (2016).

Third, we observe a significant concentration of depositors around the ₹100,000 deposit insurance (DI) threshold during the pre-policy period. This phenomenon of bunching is not isolated to our analysis; it has been documented in other contexts as well. For instance, Iyer et al. (2019) document bunching at the DI threshold in Denmark, De Roux and Limodio (2023) report similar clustering in Colombia, and Atmaca et al. (2023) observe comparable behavior among depositors in Belgium.

It is important to highlight that, unlike traditional bunching – which typically displays missing mass in the post-kink region – in our case, the missing mass is located in the pre-kink region. This shift can be attributed to the interest accrued on deposits. For example, if a depositor places exactly ₹100,000 in a bank account to achieve complete deposit insurance coverage, the total balance will naturally increase over time as interest accumulates. If the depositor does not periodically adjust their account to maintain an exact balance of ₹100,000, they will likely find their deposits exceeding the DI threshold, resulting in an accumulation of excess mass in the post-kink region. This phenomenon of excess mass in the post-kink region of DI threshold is also evident in the bunching figures of Atmaca et al. (2023). Therefore, the excess mass observed in the post-kink region can likely be attributed to optimization frictions, as discussed in the review article by Kleven (2016).

Next, we examine the effect of changes in the DI threshold on the distribution of depositors. Figure 4b presents the distributions of depositors before and after the policy change within a narrow range of ₹80,000 to ₹150,000. For a comprehensive view, we also provide the full pre- and post-policy distributions for all deposit amounts in Appendix Figure C.2. The solid blue line represents the pre-policy distribution, while the dashed maroon line indicates the post-policy distribution. The vertical dashed grey line marks the ₹100,000 threshold, standardized to zero. A key finding from Figure 4b is the substantial reduction in bunching around the ₹100,000 threshold following the increase in the DI limit. Specifically, the degree of bunching at this threshold decreases by approximately 35%, i.e., 35% of depositors moved their deposits away from the ₹100,000 threshold. This suggests that the incentives for depositors to concentrate their balances at ₹100,000 were reduced after the DI limit was raised to ₹500,000 in February 2020.

# 5 Empirical Strategy

We use the February 2020 increase in the DI limit from ₹100,000 to ₹500,000 as a natural experiment to examine its impact on portfolio allocation. Specifically, we exploit the bunching behaviour of depositors around the prior DI limit of ₹100,000, documented in Section 4.3. We compare the response of bunchers with non-bunchers – below and above the cutoff of ₹100,000 – to the expansion in deposit insurance limit. Therefore, our empirical design is a bunching-in-differences design that examines the response of bunchers – relative to non-bunchers – before and after the DI limit expansion. Specifically, we estimate the following regression specification at the depositor level:

$$LN(Deposits_{i,t}) = \beta \times Buncher_i \cdot Post_t + \theta_i + \theta_{z(i \in z),t} + \varepsilon_{i,t} \quad (5)$$

where, $LN(Deposits_{i,t})$ denotes the natural logarithm of total bank deposits of depositor $i$ (residing in ZIP code $z$) at time (month-year) $t$. $Buncher_i$ is an indicator variable taking a value of one for depositors with pre-policy deposits below the ₹100,000 DI limit, and 0 otherwise. $Post_t$ is an indicator variable taking a value of one for all months since February 2020. $\theta_i$ and $\theta_{z(i \in z),t}$ denote depositor and ZIP $\times$ time (month-year) fixed effects, respectively.

A key advantage of our granular data is the ability to use depositor fixed effects, enabling us to compare the behavior of the same depositors before and after the expansion of deposit insurance (DI) limits. This controls for any unobserved, time-invariant differences across depositors. We also include ZIP code $\times$ time fixed effects to account for time-varying local and aggregate shocks. This fixed effect is crucial for controlling local variations in COVID-19 exposure that emerged after the policy was implemented. Therefore, $\beta$ can be viewed as a within-depositor estimator that captures changes in the dependent variable for both groups before and after the policy change, while controlling for all time-varying local and aggregate shocks. Alternatively, we can interpret our estimator, $\beta$, as a within-ZIP estimator, comparing ”bunchers” and ”non-bunchers” within the same ZIP code, exposed to the same shocks, while controlling for depositor-level, time-invariant factors.

## 5.1 Identifying Assumptions

The identification of $\beta$ relies on three key assumptions. First, the parallel trends assumption, which asserts that the two groups would have followed similar trajectories in the absence of the policy change. While this assumption cannot be directly tested, examining pre-trends offers a useful validation of its plausibility. We assess this assumption by estimating equation 6, a dynamic version of equation 5, which tracks the temporal responses of bunchers compared to non-bunchers around the policy event.

$$LN(Deposits_{i,t}) = \sum_{j=-9, j\neq -1}^{j=+12} \beta_j \times Buncher_i \cdot \mathbb{1}\{t = j\} + \theta_i + \theta_{z(i \in z),t} + \varepsilon_{i,t} \tag{6}$$

The second key assumption for interpreting $\beta$ as the structural parameter that presents the economic effect of deposit insurance is the smoothness assumption. This assumption requires that no structural changes occur at the threshold, aside from changes in insurance eligibility. A major concern for this assumption would arise if deposit rates increased at the DI threshold, as banks might offer higher returns to compensate depositors for the added risk of uninsured balances. To address this, we examine deposit rates from four major banks in India, including our data provider (see Appendix Table A.3). We do not observe deposit rate changes around the threshold; in fact, deposit rates remain constant up to ₹5,000,000, ten times the new DI limit of ₹500,000. Additionally, we conduct a thorough review of our data provider’s deposit policy and do not observe any other structural changes affecting depositors with balances above the threshold.

A potential issue with using this policy change is that it may have been anticipated, especially after incidents like the PMC Bank, as discussed in section 2. While the policy change may have been anticipated, it is uncertain whether the specific timing and the magnitude of the increase were foreseen, especially considering that discussions about deposit insurance have been ongoing since 2009. For instance, the 2009 report from the Committee on Financial Sector Assessment, chaired by Rakesh Mohan, emphasized the necessity of reviewing and fortifying the deposit insurance system to bolster financial stability (CFSA Report, 2009). Similarly, the 2013 Financial Sector Legislative Reforms Commission report advocated for an expansion of the coverage of traditional deposit insurance (FSLRC Report, 2013). Furthermore, if the policy was anticipated, it would lead to an underestimation of the actual effect, suggesting that our estimate represents a lower bound of the true effect.

Another potential challenge in identifying the structural parameter lies in the possibility that the DI threshold may function as a reference point for reasons that are unrelated to policy considerations. In particular, the threshold of ₹100,000 represents a prominent round number, which may be influenced by the phenomenon of round-number bunching discussed in Section 4.3. However, our empirical approach is likely resilient to this issue, as our estimator exploits the change in DI limit over time and the response of that change across the cross-section. Therefore, as long as the behavioural discontinuity that induces reference dependence at round numbers remains stable over time, our identification is immune to this threat.

# 6 Bank Deposits & DI Expansion

The objective of this paper is to examine the reaction of depositors to expansion in the DI limit. To do so, this section examines the response of bank deposits among bunchers compared to non-bunchers following the expansion of deposit insurance (DI) in February 2020. Overall, this section presents robust evidence that bunchers increase their deposits – relative to non-bunchers – following DI expansion.

We begin our analysis by comparing depositors in the ₹25,000 bandwidth around the ₹100,000 threshold. Depositors are categorized as bunchers or non-bunchers based on their average monthly deposits in the 12 months prior to February 2020. Specifically, we compare the response of bunchers – with pre-policy deposits in the $(75, 100]$ range – to non-bunchers – whose pre-policy deposits fall within $(100, 125]$. We use a shorthand notation for numbers in each set, i.e., 100 means ₹100,000.

Panel A of Table 2 presents the results. Columns 1-4 display estimates for the interaction term between Buncher and Post across various fixed-effect specifications, with our preferred specification (equation 5) in column 4, which includes depositor and ZIP $\times$ time fixed effects. Across all specifications, the interaction term is positive and statistically significant, indicating that bunchers increased their deposits relative to non-bunchers following the DI expansion. Specifically, bunchers raised their deposits by 4.2% over the 12 months after the DI expansion.

## 6.1 Choosing Bandwidth

Despite the informativeness of the results presented in Panel A of Table 2, a shortcoming of the analysis is that the choice of the bandwidth of 25 – around the 100 K threshold – is somewhat arbitrary. The selection of bandwidth around the threshold represents a trade-off between bias and variance. As the bandwidth shrinks, bias decreases, but variance increases due to the smaller sample size. Conversely, increasing the bandwidth raises the sample size, reducing variance, but at the cost of increased bias.[10]

We address the issue of bandwidth selection by performing a grid search around the threshold. Specifically, we estimate the coefficient of the interaction term in specification 5 across a broad range of bandwidths. We compare the response of bunchers – with pre-policy deposits in the $[max\{100 - \Delta_k, 50\}, 100]$ range – to non-bunchers – whose pre-policy deposits fall within $(100, 100 + \Delta_k]$ range, where $\Delta_k$ is the increment in bandwidth set at 1.[11] For the bunchers, we limit our analysis to depositors on the left of the threshold, ensuring that we do not extend beyond 50,000, as this would distance us from depositors we can confidently classify as bunchers.

Figure 5 presents the results from the grid search, showing the point estimate of the interaction term on the Y-axis across a range of bandwidths around the threshold on the X-axis. The estimate of the interaction term remains consistently positive throughout the grid search and the confidence intervals around the estimate decrease as we increase the bandwidth. Furthermore, the point estimates across these bandwidths are statistically indistinguishable from each other, with only minor changes in the economic magnitude of the estimate. Therefore, a key takeaway from this analysis is that expanding the bandwidth appears to introduce little additional bias while increasing the bandwidth helps reduce the variance of the estimate.

Based on the observation from Figure 5, we choose our sample where we define bunchers as depositors with pre-policy deposits in the $(70, 100]$ range and the non-bunchers are defined as depositors whose pre-policy deposits fall within the $(100, 500)$ range. We will use this definition of bunchers and non-bunchers throughout the paper and will refer to it as the baseline sample, henceforth. Appendix Table C.1 presents the summary statistics for this sample of depositors.

## 6.2 Baseline Results

Panel B of Table 2 presents the analysis using the baseline sample. The estimate of interest is the coefficient associated with the interaction term of Bunchers and Post. Column 1 presents the results without any fixed effects. Columns 2-4 present estimates for various combinations of fixed-effect

[10]The theoretical bias-variance trade-off in selecting an optimal bandwidth is similar to that in regression discontinuity (RD) designs. However, the econometrics literature on bunching estimators has yet to address the challenge of optimal bandwidth selection fully. A generalized solution is beyond this paper's scope due to a key difficulty: optimal bandwidth algorithms in RD designs assume a smooth density of observations at the threshold. This assumption is inherently violated in bunching designs, where observations are intentionally concentrated around a specific point.

[11]Note that, as before, we use the shorthand notation for numbers, i.e., 100 means ₹100,000.

specifications, with our preferred specification (equation 5) in column 4, which includes depositor and ZIP × time fixed effects. Across all specifications, the interaction term is positive and statistically significant at 1%, indicating that bunchers increased their deposits relative to non-bunchers following the DI expansion. Our estimate indicates that bunchers increase their deposits by 5.2% relative to non-bunchers following the DI expansion. This result is consistent with the key prediction of our model that bunchers react more strongly to expansion in the DI limit.

Moreover, the magnitude of the estimate of interest is fairly stable across different specifications. Specifically, as we move from column 1 to 4, the model $R^2$ increases from 4.2% to 59.7%, while the estimate of interest slightly increases in magnitude. Therefore, under the Oster (2019) framework, the omitted variables are likely to downward bias the estimate of interest.

### 6.2.1 Assessment of Pre-Trends

A key identifying assumption is that, absent the DI expansion, the deposit trends for bunchers and non-bunchers would have evolved similarly. A suggestive way to test this assumption is to examine if the deposits for the two groups have common trends before the DI expansion. We test this by estimating a dynamic version of the baseline regression (equation 6), which allows us to observe deposit trends over time. Figure 6 illustrates the monthly deposit trends for both bunchers and non-bunchers before and after the DI expansion, using the baseline sample.

There are three key takeaways from Figure 6. First, we do not observe economically meaningful or statistically significant differences in deposits, relative to $t = -1$, for the two groups in the months preceding the DI expansion. This lack of pre-trends suggests that the parallel trends assumption likely holds. Second, following the DI expansion in February 2020, bunchers' deposits respond immediately relative to non-bunchers, as indicated by the positive and statistically significant coefficient at $t = 0$. Third, the effect grows over time and stabilizes around 7–8 months post-expansion, as seen in the trajectory of $\beta_j$ for the post-treatment time indicators.

Overall, the pre-trends assessment suggests that common trends are unlikely to influence our findings. Additionally, high-frequency analysis around the event timing indicates that the expansion of DI insurance is associated with an increase in deposits among bunchers compared to non-bunchers.

### 6.2.2 Heterogeneous Response Among Non-Bunchers

Our model also predicts that the response of non-bunchers, compared to bunchers, diminishes as we move further right along the DI threshold. This section provides evidence supporting this prediction.

To test this prediction, we divide the non-bunchers in the baseline sample into four groups, each with a bandwidth of 100 or ₹100,000. We then estimate the baseline specification to evaluate the effect of bunchers relative to each of the four non-buncher groups. Figure 7 presents the results for the heterogeneous response and the results in Appendix Table D.1 complement this analysis. Our findings indicate that bunchers increase their deposits relative to each category of non-bunchers. The deposit response of bunchers is both economically meaningful and statistically significant compared to all non-buncher groups. Additionally, we observe that the non-bunchers' response to the DI expansion diminishes as their pre-policy deposit levels move further from the DI threshold of ₹100,000.

Overall, the heterogeneous response of non-bunchers suggests that the depositor's behavior is sensitive to their position relative to the Deposit Insurance (DI) threshold, even for those who do not bunch. Specifically, individuals or entities with deposits close to this threshold exhibit a stronger response, likely motivated by the greater marginal benefit of the increase in deposit insurance coverage. In contrast, those with deposits significantly above the threshold experience diminishing incremental gains from any further deposit adjustments. Thus, the findings indicate that proximity to the DI threshold serves as a critical determinant of the depositor's response to the expansion of the DI.

### 6.2.3 Discussion of Magnitude: The Elasticity of Deposits to Deposit Insurance

The analysis so far is pertinent to identifying the behavior of depositors most responsive to Deposit Insurance (DI). However, interpreting the magnitude of this effect is challenging. This section addresses this limitation by estimating the elasticity of deposit growth with respect to deposit insurance. Such an elasticity measure is critical for broadly understanding depositor behavior and for calibrating models involving deposit insurance, as in Dávila and Goldstein (2023).

To estimate the elasticity, we examine how much deposits increase in response to an expansion in insurance coverage. This estimate leverages the variation in shocks to the share of insured deposits, which differ across individuals based on their pre-policy deposit levels.

Specifically, we collapse the data at the depositor level and compute two key quantities for each depositor. First, we calculate deposit growth for each depositor by taking the difference between the natural logarithm of their average deposits twelve months after the policy change and the natural logarithm of their average deposits twelve months prior. Second, we construct a measure of the change in insurance coverage by dividing the increase in the DI threshold of ₹400,000 by each depositor's average deposit in the pre-policy period. This measure reflects the relative impact of the DI threshold increase based on pre-existing deposit levels, with the intuition that depositors experiencing a larger change in coverage are more likely to respond, as shown in Section 6.2.2.

Appendix Table D.2 presents the estimate of the elasticity of deposits to deposit insurance based on the abovementioned methodology. Column 1 shows that an increase in insurance coverage of 1 percentage point (pp) is associated with a 2.1% increase in the level of deposits. Column 2 includes ZIP code fixed effects and finds that a 1 pp increase in coverage is associated with an increase of 3.0% in the level of deposits (column 2). Overall, the results indicate that a 1 pp increase in coverage is associated with a 2.1-3.0% increase in deposits.

This estimate aligns well with the existing literature. For example, De Roux and Limodio (2023) use U.S. bank-level data to analyze the 2008 increase in the DI threshold, finding that banks with a 1 percentage point higher share of insured deposits experience a 3.4% higher deposit growth rate following the policy change. Similarly, they document an estimate of 2.3% for Colombia. Overall, the key message from this comparison is that our estimate, using depositor-level data from the DI expansion in India, is very close in magnitude to the estimates presented in the literature for Colombia, an emerging economy, and the US, an advanced economy. This comparison is valuable as it helps us assess the external validity of our estimate. Specifically, the closeness in the elasticities across three very different economies indicates that our theoretical model, in principle, seems applicable to other settings and valuable to guide policy in other contexts.

#### 6.2.4 Robustness

This section examines the robustness of our main results. Specifically, we show that our results hold even after comparing bunchers and non-bunchers within the same household, are not explained by optimization error discussed in Section 4.3, are unlikely to be driven by the fact that the post-analysis period substantially overlaps with the COVID-19 period, and are robust to a series of sensitivity analysis: alternative estimators, transformations of the dependent variable, a continuous measure of policy change exposure, and different clustering approaches. Finally, using a placebo test we show that the results are unlikely to be spurious or unrelated to the DI threshold.

A primary concern is that bunchers and non-bunchers may face different household-level budget constraints. More broadly, household-level omitted variables may explain the differential response of bunchers and non-bunchers. We address this concern by re-estimating our baseline specification with household $\times$ time fixed effects. Appendix Table D.3 presents the results. We find that our results are robust to the inclusion of household $\times$ time fixed effects, i.e., bunchers exhibit a greater response to expansion in DI insurance, relative to non-bunchers within the same household. Additionally, the effect size increases when household $\times$ time fixed effects are included, suggesting that the omitted variable bias due to not comparing bunchers and non-bunchers within the same household likely biases our estimate downward. The parallel trends analysis presented in Appendix Figure D.1 further supports these results and suggests that within-household estimates are unlikely to be driven by pre-trends.

Next, we address the potential impact of post-kink excess mass, arising from optimization frictions discussed in Section 4.3, on our estimates. This concern is unlikely to alter the qualitative inferences from our analysis, as the baseline estimation groups post-kink excess mass with non-bunchers. Depositors forming the excess mass in the post-kink region are actually bunchers who appear in this region because their deposits have accrued interest over time. Including them with non-bunchers likely biases our estimates in Table 2 downward. To address this, we re-estimate our baseline specification to account for this post-kink excess mass. Based on the interest rate schedule, these post-kink bunchers would still have had deposits below ₹104,000.[12] We re-define baseline bunchers to also include all depositors with pre-policy deposits above ₹100,000 and below ₹104,000. Appendix Table D.4 presents the results. Comparing the baseline estimate in column 1 with the estimate of the interaction term based on the adjusted buncher definition confirms our argument that combining the bunchers prone to optimization error with non-bunchers biases our baseline estimate downward. Moreover, note that while the magnitude of the effect is greater in column 2, the two estimates are statistically indistinguishable from each other, indicating that the post-kink excess mass is unlikely to affect our inference.

The within-household estimation result also helps us to address another concern that the post-analysis period substantially overlaps with the COVID-19 period, which may influence our findings. While ZIP × month fixed effects should address this concern under the assumption that the COVID-19 effects are homogeneous within ZIP codes, varying exposure to COVID-19 across households may still impact results. This test effectively rules out COVID-19 exposure differences as a concern, under the assumption of similar exposures for bunchers and non-bunchers within households.

We further test the robustness of our results by exploring alternative estimators, transformations of the dependent variable, a continuous measure of policy change exposure, and different clustering approaches. Appendix Table D.5 replicates the baseline results using Poisson estimation with deposit levels as the dependent variable, yielding consistent findings. Appendix Table D.6 uses monthly deposit growth as the dependent variable and documents similar results. Appendix Table D.7 employs a continuous measure of coverage change at the depositor level, as outlined in Section 6.2.4, confirming that our results hold with this alternative measure of exposure to the DI threshold change. Lastly, Appendix Table D.8 demonstrates that our inference remains robust under various clustering choices.

A concern about the validity of the empirical results is that the point estimate of the interaction term may capture a spurious relationship, unrelated to the deposit insurance threshold. We address this concern by conducting a placebo test. We randomly select a DI threshold between ₹231,000 and ₹600,000 from a uniform distribution. The random threshold thus generated is to classify depositors into bunchers and non-bunchers. Specifically, the depositors with pre-policy deposits less than or equal to the random threshold and greater than or equal to threshold minus ₹30,000 are defined as placebo bunchers and all other depositors are defined as non-bunchers. We estimate the coefficient of $Placebo - Buncher \times Post$ in the baseline specification and repeat this exercise 1,000 times. To negate the validity of the baseline results, the null hypothesis that the point estimate associated with $Placebo - Buncher \times Post$ is zero must be rejected.

[12] We calculate this upper bound on deposits assuming that bunching depositors re-balance their deposits annually. If all such depositors adjust their balances after twelve months, given an interest rate of 3.5-4%, the maximum deposit amount would reach ₹103,500 - ₹104,000. This figure likely represents an upper limit, as bunchers are strategic by nature and may choose to re-balance more frequently than once per year.

Appendix Figure D.2 presents a visual assessment of the cumulative density of $\beta$, the coefficient of the interaction term $Placebo{-}Buncher{\times}Post$, estimated using 1,000 simulations. The distribution of $\beta$ is centered around 0, with a standard deviation of 0.0217. We fail to reject the null hypothesis that the average point estimate from the placebo analysis is equal to zero. The red dashed line denotes the location of the coefficient of the interaction term from column 4 of Table 2 with none of the estimates, among the 1,000 simulated placebo $\beta$, lying to the right of the red dashed line. The results of the placebo test add confidence to the argument that the baseline results are neither spurious nor unrelated to the DI threshold.

#### 6.2.5 Supplementary Results

This section presents four supplementary findings to offer a comprehensive view of the impact of DI expansion on bank deposits. First, we analyze the effect across various types of deposits. Second, we assess the response of depositors around the new DI threshold of ₹500,000. Third, we investigate the heterogeneous response among bunchers, based on individual depositor characteristics. Fourth, we investigate the role of trust in banks and the government in explaining the baseline finding.

**Heterogeneity across deposit types:** Appendix Table D.9 shows that the increase in bank deposits following deposit insurance (DI) expansion is primarily concentrated in savings and recurring deposit accounts, while the impact on time deposits is smaller in magnitude and statistically insignificant. This result indicates that while DI expansion increases overall depositor confidence, it is especially effective in promoting liquid savings behaviors rather than longer-term commitments in the form of time deposits.

**Response above the new limit:** Second, we examine the response of depositors with pre-policy deposits above ₹500,000. The intuition of this test is that perhaps these depositors reduce their deposits after the DI expansion to be fully covered by insurance. Appendix Table D.10 presents the results. The estimate of interest is the coefficient associated with the $Non - Buncher s_5$ [500-600] × Post, where $Non - Buncher s_5$ denotes non-bunchers with pre-policy deposits in the $[500 - 600]$ range who are most likely to respond by reducing their deposits to ensure full insurance. We do not find any economically meaningful or statistically significant response by deposits with pre-policy deposits above ₹500,000. This result is consistent with the observation that we do not observe excess bunching of depositors at the ₹500,000 threshold after the DI expansion (see Appendix Figure C.2). The lack of repose by these depositors may be driven by the fact that ₹500,000 is a very large amount in India. For instance, India's per capita Net National Income (NNI) at constant (2011-12) prices was ₹72,805 in 2014-15 and ₹98,374 in 2022-23 (MOSPI, 2023).

**Heterogeneity by depositor characteristics:** Third, we investigate the heterogeneous response among bunchers, based on individual depositor characteristics. Appendix Table D.11 presents results on how the effect of deposit insurance expansion varies across depositor characteristics. These characteristics include demographic variables (gender, age, and family size) and bank relationship variables (years of relationship with the bank, ownership of other savings products such as time and recurring deposits, or holding a loan or PPF account with the bank). Two key results stand out from this analysis. First, the policy change results in an increase in deposits among bunchers. Second, there are no heterogeneous effects within bunchers across any of the heterogeneity dimensions considered. In other words, once we condition on a borrower being a buncher, there is no differential response along different dimensions. The lack of variation in responses across individual depositor characteristics is important for external validity. Since the differential response among bunchers is not concentrated within specific demographic or financial groups, our findings are more likely to generalize to depositors at other banks and in different countries.

**Heterogeneity by income:** Fourth, we examine the heterogeneous responses among bunchers based on their pre-policy income levels, focusing on income relative to the DI threshold. The rationale is that income relative to the threshold likely influences depositor responses: depositors with income near the threshold may face constraints limiting their ability to expand deposits, while those with income well above the threshold may see limited marginal benefits from additional insurance, reducing their incentive to respond. To test this, we segment depositors in our baseline sample into ten deciles based on their income-to-DI-threshold ratio, calculated by dividing their pre-policy monthly income by ₹100,000. Additionally, depositors with zero income are classified into a separate group, resulting in a total of eleven groups. We then estimate our baseline model for each group individually and plot these estimates with 95% confidence intervals in Appendix Figure D.3. The results display a non-linear pattern across the distribution: initially, the effect size increases with the income-to-threshold ratio but then declines as the ratio continues to rise, producing an inverted U-shaped response across the distribution.

This finding is important for two reasons. First, it informs that the aggregate effect of DI expansion crucially depends on the income distribution of the affected population. Specifically, the inverted U-shaped response suggests that the impact is strongest among depositors with income levels moderately above the DI threshold, where the benefits of expanded insurance are most attractive and accessible. For lower-income depositors constrained by their income relative to the threshold, limited resources may prevent them from increasing their deposits, despite the added insurance. Conversely, higher-income depositors may view the marginal benefits of additional insurance as minimal, given that a larger portion of their wealth likely exceeds the threshold.

Second, this result is also important from an external validity perspective. The inverted U-shaped response pattern implies that the increase in deposits following DI expansion is not uniformly distributed across all income levels, but rather is influenced by the relative positioning of depositors' incomes to the insurance threshold. This means that for DI policies implemented in different settings – such as in countries with varied economic conditions or among banks serving different socioeconomic demographics – the income-to-threshold ratio will play a key role in determining the strength of depositor responses.

**Role of Trust:** Fifth, we examine how trust in banks and the government influences the response of bunchers to deposit insurance (DI) expansion. The rationale is that DI expansion is likely to have a greater impact on depositors who lack confidence in banks. Additionally, because DI is typically provided by the government, its expansion is expected to have a greater effect in regions where trust in the government is strong. We construct district-level measures of trust in banks and in the government by using responses from the 2012 India Human Development Survey (IHDS).[13] We then map this trust data to our depositor-level dataset by hand-matching district identifiers in the two datasets. Appendix Table D.12 presents the results wherein we classify each depositor as living in an area of high, medium, or low trust in banks or the government. Our results indicate that the success of DI in stimulating deposit growth depends on depositor trust in the government, i.e., the effect is higher in regions where the trust in the government is high. Moreover, in regions where bank trust is low, DI acts as a substitute for that trust by providing an external safety assurance, thus encouraging depositors to engage more confidently with the banking system. This implies that DI can partially offset a lack of confidence in individual banks by transferring depositor reliance to the government as a guarantor of financial security. Overall, these results are consistent with trust playing an important role in financial markets, in general, (La Porta et al., 1996; Glaeser et al., 2000; Guiso, Sapienza, and Zingales, 2008; Cole et al., 2013; Gennaioli, Shleifer, and Vishny, 2015; Gennaioli et al., 2022) and the banking sector, in specific (Karlan et al., 2009; Johnson, Meier, and Toubia, 2019; Bachas et al., 2021; Park, Sarkar, and Vats, 2021; Limodio and Strobbe, 2023; Thakor and Merton, 2024).

## 6.3 Characteristics of Bunchers

By definition, bunchers are "special depositors" who strategically limit their deposits to align with the DI threshold. The results so far indicate that these bunchers increase their deposits following DI expansion, indicating that the threshold holds significant importance for them. This raises a critical

[13]These measures are based on survey questions regarding confidence in banks to safeguard money and confidence in the government's role in supporting citizens. Appendix Figures C.3 and C.4 present the spatial distribution and summary statistics of the trust measures, respectively.

question: How do these bunchers finance their increased deposits? A first step towards assessing the explanations for their response requires a parsimonious summary of the characteristics of these bunchers relative to non-bunchers. The objective of this section is to provide such a characterization.

Table 3 compares the characteristics of bunchers and non-bunchers using depositor-level attributes measured prior to the deposit insurance (DI) expansion. The analysis employs a linear probability model with buncher as the dependent variable, which equals 1 for depositors classified as bunchers and 0 otherwise. The table sequentially presents results, adding different types of variables from columns 1 to 4. Specifically, column 1 incorporates demographic information, while column 2 adds financial data. Column 3 includes lending market information, and column 4 incorporates the occupational details of the depositors. Finally, columns 5 and 6 introduce ZIP code and household fixed effects, alongside the previously mentioned characteristics. The depositor-level characteristics include age, gender, marital status, household status, number of household members, tenure of the banking relationship, income, wealth, portfolio composition, credit scores, various loans, and whether the depositor is self-employed.

A key result that emerges from the analysis is that financial variables that include income, wealth and portfolio composition increase the model's explanatory power by 4.3%. Specifically, we find that bunchers tend to have a greater share of stocks, mutual funds and PPFs in their portfolio before the DI expansion. This difference between the two groups of depositors is consistent with our theoretical model that bunchers tend to invest less in safe assets – deposits – and invest more in other risky securities such as stocks and mutual funds and illiquid securities such as PPF. Moreover, we find that bunchers tend to have lower wealth relative to non-bunchers.[14]

Next, we report that the inclusion of ZIP fixed effects increases the model's explanatory power by 12%, suggesting that the geographic location of depositors significantly influences their incentives to strategically limit their deposits to match the DI threshold. Lastly, we note that the inclusion of household fixed effects increases the model's explanatory power by over 60%, indicating that the household-level omitted variables may play a key role in explaining the depositors' incentives to bunch.

Table 4 presents further analysis of bunchers in our baseline sample. Specifically, it examines the differences between bunchers who trade – defined by investment in stocks or mutual funds – versus those who do not. Similar to the analysis in Table 3, Table 4 sequentially presents results by adding different types of variables from columns 1 to 4. The depositor-level characteristics include age, gender, marital status, household status, number of household members, tenure of the banking relationship, income, wealth, portfolio composition, credit scores, various loans, and whether the depositor is self-employed.[15]

[14]This result on differences in banked wealth may be mechanical, driven by our baseline sample wherein non-bunchers have greater deposits than bunchers, before the DI expansion.

[15]We do not conduct this analysis with household fixed effects as that leaves us with a very small sample with limited power.

In terms of demographic characteristics, we document that female bunchers are less likely to trade. This result on gender is consistent with the large literature documenting that women are less likely to participate in the stock market than men.[16] On credit side characteristics we document that bunchers who are credit card holders and had a personal loan are also more likely to trade.

The most significant result that emerges from the analysis is that financial variables that include income, wealth and share of the portfolio in PPF increase the model's explanatory power by 35%. Notably, our results indicate that trading bunchers generally possess greater wealth and allocate a smaller share of their portfolios to PPF. This observation suggests a potential segmentation of bunchers into two distinct groups: those who invest in risky but liquid assets, such as stocks and mutual funds, and those who prefer safer but illiquid investments like PPF.

The key takeaway from this analysis is that the differences in portfolio composition provide prima facie evidence that bunchers tend to invest more in securities due to constraints on the availability of safe assets imposed by the DI threshold. Moreover, bunchers can be categorized into two groups: those who invest in risky but liquid assets, such as stocks and mutual funds, and those who prefer safe but highly illiquid assets, such as the PPF. The expansion of the DI threshold may incentivize these bunchers to liquidate their security holdings to finance increased deposits. In Section 7, we present more direct evidence of this behavior, specifically showing that trading bunchers increase their deposits, while those invested in illiquid securities do not exhibit similar increases.

# 7 Portfolio Reallocation & DI Expansion

This paper seeks to evaluate the hypothesis that depositors, especially those identified as bunchers, reallocate their investments from the stock market and mutual funds into deposit accounts. This section provides evidence of this behavior, showing that depositors liquidate their stock and mutual fund holdings to increase their bank deposits. Additionally, we find that these liquidations are predominantly concentrated in specific categories of stocks that are perceived to be safer than the broader market.

## 7.1 Heterogeneous Response among Traders & Non-Traders

We begin by offering suggestive evidence of this portfolio reallocation by examining how baseline responses vary between depositors who participate in the retail trading of stocks and mutual funds. To achieve this, we replicate our baseline dynamic specification and categorize bunchers into traders $(B,T)$ and non-traders $(NB,T)$. We then estimate the dynamic responses for these groups relative to non-bunchers.

Figure 8 presents the results. We find that the sharp increase in deposits among bunchers is

[16] See Barber and Odean (2001); Agnew, Balduzzi, and Sunden (2003); Neelakantan and Chang (2010); Van Rooij, Lusardi, and Alessie (2011); Halko, Kaustia, and Alanko (2012); Almenberg and Dreber (2015); Ke (2021); Bucher-Koenen et al. (2021); Kaustia, Conlin, and Luotonen (2023) among others.

primarily driven by depositors who trade (represented in blue). Specifically, non-trading bunchers (represented in red) show minimal response compared to non-bunchers. Overall, the analysis indicates that depositors categorized as bunchers experience the most pronounced increase in deposits following the expansion of DI, primarily driven by those who actively engage in trading. This heterogeneity in behavior among bunchers, depending on their trading activity, supports the prediction that, in response to unmet demand for safe assets, depositors may reallocate their portfolios towards deposits following an expansion of DI.

## 7.2 Liquidation of Securities

While the analysis presented in Section 7.1 is informative about the source of the increase in deposits, it is far from direct and may be driven by other characteristics of bunchers that are correlated with investment in the stock market or mutual fund. This section addresses this issue by directly examining the portfolio holding data for depositors for twelve months before and after the DI expansion.

### 7.2.1 Identification of Effect of DI Expansion on Portfolio Reallocation

A straightforward comparison of aggregate stock holdings between bunchers and non-bunchers and attributing the changes in the aggregate portfolio to DI expansion is empirically challenging. If depositors randomly chose securities in their portfolios and bunching was randomly assigned to depositors, we could measure the effect of DI expansion by comparing the aggregate portfolio or share of wealth in the stock market of depositors who bunch with the depositors who do not. However, depositors are unlikely to randomly choose securities in their portfolio. For instance, bunchers have an unmet demand for safe assets and may invest more in safer securities in the market relative to non-bunchers.[17]

In the presence of such non-random matching, the estimated average difference in the aggregate security portfolio between bunchers and non-bunchers may not reflect the effect of DI expansion, but rather differences in the fundamentals of the securities they invest in. Moreover, bunching is an equilibrium outcome and therefore unlikely to be random and may be correlated with other time-invariant characteristics of the depositor, such as upbringing, education, prior work experience, or attitudes towards certain industries or firms.

We address this issue by using granular security-level holdings data for each depositor. Specifically, we include ISIN $\times$ time (month-year) fixed effects in our analysis which removes the above confounding factors. The inclusion of ISIN $\times$ time fixed effects ensures that we identify the response of bunchers, relative to non-bunchers, from the same security at the same time, thereby abstracting away from the confounding factor of non-random matching of depositors to securities. Such an identification strategy has been employed previously in Fracassi, Petry, and Tate (2016) and Kempf and

[17] Section 7.3 provides evidence that supports the assertion that bunchers are inclined to overinvest in stocks perceived as safer alternatives, particularly those associated with state ownership. The state-owned enterprises are considered safe due to the state guarantees. This behavior indicates a strategic preference among bunchers for securities that are likely to offer lower associated risks.

Tsoutsoura (2021) to address the non-random matching between credit rating analysts and the firms they cover. More recently, Cramer et al. (2024) employ this identification strategy in the context of banking to address non-random matching between lenders and regions. Overall, this approach ensures that our analysis more accurately captures the effects of the depositors' behaviors without confounding influences.

### 7.2.2 Results: Effect of DI Expansion on Portfolio Reallocation

Table 5 presents the results documenting the differential effect of DI expansion on portfolio holdings of bunchers and non-bunchers. Panel A presents the results using the natural logarithm of the total amount invested in security $j$ by depositor $i$. The estimate of interest is the coefficient associated with the interaction term of Buncher × Post. Column 1 reports the results with ISIN × time fixed effects. The estimate of interest is negative and statistically significant. The estimate indicates that bunchers liquidate 1.7% of their holding, relative to a non-buncher, for the same security after DI expansion. Columns 2 and 3 include depositor fixed effects and ZIP × time fixed effects, respectively. The inclusion of these fixed effects is in line with our baseline specification and controls for all time-invariant differences across depositors and time-varying differences across ZIPs. The estimate of interest is negative and statistically significant. Moreover, the magnitude of the effect is relatively stable despite these fixed effects being able to explain 20% of additional variation in the dependent variable relative to column 1. The results documented in columns 1-3 indicate that bunchers are more likely to liquidate their security holdings following DI expansion.

One concern regarding the results thus far is that the total investment in securities is recorded at market price, which can fluctuate independently of investor activity due to market changes. Panel B of Table 5 addresses this concern by using the natural logarithm of the total number of shares held of security $j$ by depositor $i$. The primary advantage of this approach is that changes in the number of shares held provide more direct evidence of active liquidation. Specifically, these findings suggest that the observations in Panel A are unlikely to be attributed to fluctuations in market valuations. Instead, they indicate that the decline in the number of shares held by bunchers, relative to non-bunchers for the same security, reflects active liquidation activity.

Next, we document that the results presented in Table 5 are not confined to a single type of investment vehicle. To this end, we categorise securities into stocks and mutual funds based on their ISIN identifiers. Appendix Table E.1 presents the results. The coefficients for both stocks and mutual funds are negative and statistically significant. The results show that bunchers liquidate their holdings in both stocks and mutual funds following DI expansion.

Furthermore, we conduct several robustness tests to increase confidence in our findings. First, Appendix Table E.2 documents heterogeneous responses among non-bunchers regarding their security holdings. This observation is consistent with the heterogeneous responses among bunchers related to deposits, as documented in Table D.1. Second, our results, as shown in Appendix Table E.3, remain robust to alternative bandwidths. Third, Appendix Table E.4 shows that our results are robust to incorporating buncher × ISIN fixed effect. This fixed effect allows us to control for time-invariant potential preference differences between bunchers and non-bunchers, which could contribute to non-random matching between depositor types and securities. Collectively, these robustness checks strengthen the validity of our conclusions.

Overall, our results indicate that bunchers liquidate their security holdings after DI expansion. This result is consistent with the theoretical argument made earlier in the paper that the DI threshold limits the availability of safe assets to households, compelling them to adjust their investment strategies.

## 7.3 What Do Bunchers Liquidate?

The key hypothesis this paper posits is that bunchers have an unmet demand for safe assets. Consequently, they allocate funds to the stock market, due to constraints on the availability of safe assets imposed by the DI limit. An implication of this hypothesis is that even when bunchers engage in stock market investments, they are likely to tilt their portfolios towards safer assets and are more likely to liquidate these assets after DI expansion.[18] This section presents evidence consistent with this corollary of our main hypothesis.

We match our equity holdings data to stock characteristics data from the Center for Monitoring Indian Economy (CMIE) Prowess database. The characteristics we consider are (1) firm ownership: state-owned and business group ownership;[19] (2) sector of operations: manufacturing, financial, wholesale, diversified, construction, information and communication, and agriculture; (3) market characteristics: market alpha, market beta, realized returns, realized volatility, and market capitalization; and (4) accounting characteristics: dividend payer, market to book value ratio, age, size, leverage, interest coverage ratio, cash to assets ratio, operating margin, and tangibility. We use the average value of these characteristics from 2017 until 2019 to compute stock-level characteristics.

We follow the methodology outlined in Balasubramaniam et al. (2023) to compute monthly portfolio tilts for each investor and characteristic. Specifically, we create a holdings-weighted measure of the investor's portfolio characteristics, using portfolio shares as holdings. This approach effectively captures the degree to which an investor favors or disregards particular characteristics within their portfolio. While this methodology is straightforward for discrete characteristics, it can present concerns

[18]Households often hold portfolios that differ substantially from the predictions of CAPM (Balasubramaniam et al., 2023). We direct readers to Curcuru et al. (2010) for a survey of the empirical literature documenting considerable heterogeneity in portfolio composition.

[19]Business group firms – a common occurrence in emerging markets – are legally independent entities with a large ownership stake and common control by a single entity (Khanna and Yafeh, 2007).

with continuous characteristics as they often display skewness and fat tails, which can render the measure prone to outliers. We address this by following the suggestion outlined in Balasubramaniam et al. (2023). Specifically, we rank stocks according to their characteristic values and use the demeaned rank as our stock-level characteristic measure. This method produces a demeaned rank uniformly distributed from -0.5 to 0.5, with a mean of zero, thereby providing a more reliable assessment of the continuous characteristics.

To examine what type of securities bunchers liquidate, we run a difference-in-difference specification examining the change in portfolio tilts for each stock characteristic for bunchers following the DI expansion. Specifically, we estimate regression specification 7 with the depositor and ZIP × time fixed effects. Table 6 presents the results. We report the coefficient of the estimate associated with the interaction term of buncher and post along with the standard error of the estimate, the number of observations in the regression, and the model $R^2$ for each portfolio characteristic.

$$Portfolio - Tilt^c_{i,t} = \beta^c \times Buncher_i \cdot Post_t + \theta_i + \theta_{z(i \in z),t} + \varepsilon_{i,t} \tag{7}$$

The majority of the coefficients associated with changes in portfolio tilts are economically small and statistically insignificant, with a notable exception of state ownership. We find that bunchers tilt their portfolio away from state-owned firms following DI expansion. This result suggests that bunchers liquidate their holdings in state-owned enterprises (SOE), which enjoy guarantees from the government and are considered a safe investment in India. Therefore, this result is consistent with our hypothesis that bunchers are more likely to liquidate their other safer assets to finance their deposit increase after DI expansion.

We further expand the regression for portfolio tilt based on SOE in Table 7. There are two key advantages of this exercise. First, we can observe the estimate of bunchers in addition to the interaction term, which allows us to examine the differences in portfolio tilts based on SOE between bunchers and non-bunchers before the DI expansion. Second, we can incorporate additional controls and validate that the change in portfolio tilt is unlikely to be driven by other characteristics of SOE that these bunchers value or correspond to characteristics of other stocks that are usually co-held in a portfolio.

Column 1 of Table 7 presents the results without any fixed effects. This allows us to observe the estimate of bunchers, in addition to the interaction term. The estimate of bunchers is positive and statistically significant, indicating that bunchers tend to tilt their portfolio towards SOE. The estimate of the interaction term of post and buncher is negative and statistically significant, indicating that bunchers liquidate their holdings in SOE after DI expansion. Furthermore, the F-statistic associated with the test $Bunchers \times Post + Bunchers = 0$ is statistically insignificant, indicating we cannot reject the null that bunchers liquidate their entire excess portfolio tilt in SOE.

This result supports our hypothesis that bunchers exhibit a preference for safer assets when constrained by a binding DI limit and liquidate these safer assets once the constraint is relaxed. Moreover, the existence of the clientele effect among bunchers is consistent with the theories in which investors categorize risky assets into distinct styles (Barberis and Shleifer, 2003).

The results in columns 2 and 3 resonate with the results discussed in column 1 indicating that our results are robust to ZIP and month-year fixed effects. Moreover, the addition of ZIP fixed effects increases model $R^2$ by 10 percentage points. This increase in model explanatory power is consistent with the importance of local biases in stock holdings as discussed in Coval and Moskowitz (1999). Column 4 adds depositor fixed effects and column 5 replicates the baseline specification, reported earlier in Table 6. Overall, from columns 1-5, the model $R^2$ increases by 86 percentage points and the point estimate of interest associated with the interaction term is negative and statistically significant. Moreover, the stability in the magnitude accompanied by a large increase in model explanatory power suggests that omitted variables are unlikely to explain our results, under the Oster (2019) framework.

Column 6 includes portfolio tilts associated with all other characteristics as control variable. Despite the addition of these controls, the estimate of interest is negative and statistically significant. This indicates that our result on the change in portfolio tilt is unlikely to be driven by other characteristics of SOE that these bunchers value or correspond to characteristics of other stocks that are usually co-held in a portfolio.

Overall, the results indicate that bunchers tend to tilt their portfolio towards safer stocks of state-owned enterprises. This result suggests that bunchers have an unmet demand for safe assets when the DI limit constrains the supply of safe assets. Moreover, when the DI limit is relaxed these bunchers tend to liquidate these safer stocks to finance their increase in deposits.

## 7.4 Asset Pricing Implications of SOE Liquidation

This section examines the asset price implications of the liquidation of SOE stocks. To this end, we conduct an event study analysis comparing the cumulative abnormal returns (CAR) for non-financial firms. Specifically, we compare the CAR for SOE with business group firms and other non-financial firms by estimating the regression specification 8, where other non-financial firms are the omitted category:

$$CAR_{i,t} = \sum_{j=-20, j\neq -1}^{j=+20} \beta_j \times SOE_i \cdot \mathbb{1}\{t=j\} + \sum_{j=-20, j\neq -1}^{j=+20} \gamma_j \times BG_i \cdot \mathbb{1}\{t=j\} + \theta_i + \theta_t + \varepsilon_{i,t} \quad (8)$$

where, $CAR_{i,t}$ denotes the cumulative abnormal returns for stock $i$ on trading day $t$. $SOE_i$ takes a value of one for SOE firms and zero otherwise. Similarly, $BG_i$ takes a value of one for business group firms and zero otherwise. $\mathbb{1}\{t = j\}$ is the time indicator variable taking a value of one if the date is

$j$ days before or after the DI expansion date. February 1, 2020 is denoted by $j = 0$. $\theta_i$ and $\theta_t$ denote stock and trading day fixed effects, respectively.

In this analysis, we split all non-SOE firms into business group and other non-financial firms. Such a split has two key advantages. First, it allows us to create two comparison groups and examine if the results are driven by the movements of the comparison group firms or SOEs. Second, business group firms – independent entities with a large ownership stake and common control by a single entity – may serve as a better comparison group for SOE as they may be considered relatively safer than an average non-financial firm due to their access to internal capital markets.[20]

Figure 9 presents the results of the estimation of equation 8. We document a decline in cumulative abnormal returns (CAR) for SOEs following the event date. However, this decrease is fully reversed within 20 days. This finding indicates that while the liquidation of SOE stock causes prices to drop, other market participants, such as arbitrageurs, step in to counteract this decline. However, it takes some time for these players to restore prices to their previous levels. In contrast, we do not observe any economically or statistically significant changes for business group firms during the same period. Additionally, our results indicate that the observed effect on SOEs is unlikely to be attributable to pre-existing trends.

Overall, our results suggest that although the liquidation of relatively safer stocks related to DI expansion can create negative price pressures, this effect is likely to be transient. Our results on asset price implications of DI expansion would be consistent with models of limits of arbitrage, especially slow-moving capital (Shleifer and Vishny, 1997; Gabaix, Krishnamurthy, and Vigneron, 2007; Mitchell, Pedersen, and Pulvino, 2007; Duffie, 2010).

# 8 Discussion on Welfare Implications

This section applies the theoretical framework outlined in Section 3 to quantify the welfare implications of expanding DI for households. We also provide estimates of household welfare under different levels of moral hazard associated with DI expansion. To do so, we calibrate the model parameters and estimate the expected probability of bank failure by matching the empirical distribution at the initial DI threshold with the distribution generated by the model at the same point.

## 8.1 Calibration

Appendix Table B.1 presents the calibrated parameters used in our model. The parameter $\rho$ is defined as $\frac{1+r_m}{1+r_f}$, where $r_m$ represents the market return and $r_f$ the risk-free rate. We extract data on market returns and risk-free rates for India for 2019 from the Indian Fama-French-Momentum website that

[20]See Ghatak and Kali (2001); Gopalan, Nanda, and Seru (2007); Hann, Ogneva, and Ozbas (2013); Matvos and Seru (2014); Almeida, Kim, and Kim (2015); Santioni, Schiantarelli, and Strahan (2020); Faccio, Morck, and Yavuz (2021) and Faccio and O'Brien (2021), among others. Khanna and Yafeh (2007) present a detailed review of the literature on business groups and their prevalence across emerging markets.

follows the methodology outlined in Agarwalla, Jacob, and Varma (2014). We calculate $\rho$ using the average monthly market returns and risk-free rates for India during that year. Additionally, $\sigma_M^2$ represents the variance of $\frac{1+r_m}{1+r_f}$. For our calibration, we set the initial deposit insurance level $\delta_{initial}$ at ₹100,000 and the new level $\delta_{new}$ at ₹500,000.

## 8.2 Identification & Estimation

The remaining parameters are the risk aversion coefficient $\gamma$ and bank failure probability denoted by $\pi$. We target the observed mass of bunchers in the data to identify these parameters. Equation 9 plays a key role in this process, as it relates the model-generated distribution of bunchers to their observed frequency at the threshold, allowing us to identify the pair $\{\pi, \gamma\}$ that best fits the empirical data.

$$\delta + \frac{\rho - 1}{2\gamma\sigma_M^2} < Y < \delta + \frac{\pi + \rho - 1}{2\gamma\pi(1-\pi)} \tag{9}$$

However, we cannot jointly identify $\gamma$ and $\pi$ based on equation 9 alone. Therefore, we estimate the values of $\pi$ for various levels of risk aversion. Specifically, we consider the cases when $\gamma = 1$, $\gamma = 3$, $\gamma = 5$, and $\gamma = 10$. We also consider a case of heterogeneous risk aversion with $ln(\gamma) \sim \mathcal{N}(\mu, \sigma^2)$, where we calibrate $\mu = 2.01$ and $\sigma = 0.134$ à la Calvet et al. (2021).

We use the density of bunchers as our key target moment. We begin with observed bank wealth data, which we fit to a generalized power distribution to estimate its parameters. Using these distribution parameters, we generate 100 simulated endowments. We determine the optimal deposit level for each endowment. We then apply the Simulated Method of Moments (SMM) to estimate the bank failure probability ($\pi$) by matching the key target moment from the simulated data to that observed empirically. As shown in Appendix Figure B.1, this approach successfully identifies $\pi$, with a clear global minimum within the feasible range.

Next, we assess the model fit. Figure 10 compares the empirical distribution of depositors with the distribution generated by our simulated data. Overall, the simulation closely replicates the observed patterns, particularly capturing the mass at the bunching point, which was our key target moment. Additionally, it accurately reproduces the distribution of depositors' optimal deposit amounts across the range, demonstrating that our model provides a good fit to the empirical data.

## 8.3 Depositor Implied Probability of Bank Failure

The identification exercise enables us to estimate the implied probability of bank failure ($\pi$), based on depositor behavior. The table below Figure 10 shows the estimated values of $\pi$ corresponding to different levels of risk aversion. Notably, $\pi$ increases as risk aversion rises. For instance, at a moderate risk aversion level of $\gamma = 3$, $\pi$ is approximately 0.54%, whereas at a high risk aversion level of $\gamma =$

10, $\pi$ rises to 1.74%. The positive correlation between $\pi$ and risk aversion reflects the fact that as depositors become more risk-averse, the model requires a higher bank failure probability to replicate their bunching behavior accurately. In the case of heterogeneous risk aversion, we estimate $\pi$ to be approximately 1.28%, representing the average bank failure probability when depositors have a wide range of risk preferences.

This estimation methodology is one of the key contributions of this paper. Specifically, it provides regulators with a straightforward method to infer the depositor-implied probability of bank failure using a single, simple metric: the fraction of depositors at the DI threshold. Regulators can easily collect this data from all banks and calculate the implied failure probability, using equation 9. Unlike previous measures – which often rely on stock market data or risk indicators – our metric is, to the best of our knowledge, the first to directly reflect depositors' expected probability of bank failure, thereby offering a more intuitive measure of bank runs.

## 8.4 Welfare Implications of DI Expansion

Finally, we use this estimated model to quantify the welfare implications of DI expansion. Figure 11 presents the distribution of welfare effects of DI expansion corresponding to different risk aversion levels. The X-axis plots the distance of the endowment from the initial DI limit. The Y-axis plots the percentage change in utility when the initial DI limit is increased by five times. Different lines represent levels of risk aversion ($\gamma = 1, 3, 5, 10$) and a case with heterogeneous risk aversion. The table below the figure presents the total welfare gain corresponding to different risk aversion values.

The distribution of the welfare effects presents four key results. First, depositors with endowments below the initial DI limit experience no welfare gains from DI expansion. This is because their deposits are already fully covered by the existing insurance, rendering additional coverage redundant. Second, the welfare gains from DI expansion are most pronounced for depositors with endowments exceeding the initial DI limit. For these individuals, the increase in deposit coverage reduces their expected loss, leading to an increase in utility. The utility gains tend to peak for depositors with moderate endowments – those who are close enough to the coverage threshold that the expansion markedly decreases their risk exposure without offering diminishing marginal benefits. Third, depositors with very large endowments experience smaller incremental welfare gains, as their deposits are already well above the coverage limit, and further increases in DI provide a limited gain in utility. Fourth, welfare gains from DI expansion become increasingly significant as risk aversion rises, since risk-averse depositors place a higher value on safety.

Overall, our findings suggest that the welfare benefits of expanding deposit insurance are concentrated among depositors with moderate endowments near the coverage threshold, where the potential gains are most substantial. In contrast, depositors with very high endowments experience limited benefits, and those with low endowments see no improvement. Additionally, these welfare gains become significantly larger as risk aversion increases, highlighting that more risk-averse depositors derive greater utility from expanded coverage.

### 8.5 Role of Moral Hazard

Finally, we extend our welfare analysis to incorporate the potential moral hazard effects of DI expansion. The central intuition is that, as DI coverage increases, banks may become more willing to engage in riskier investment activities, which in turn raises the expected probability of bank failure. To model this behavior, we estimate counterfactual distributions of welfare effects under different levels of moral hazard, characterized by an increase in the probability of bank failure. This approach allows us to assess how the benefits of DI expansion might be attenuated by the increased risk-taking incentives induced by greater safety nets. It highlights the trade-off policymakers face, i.e., expanding insurance can improve depositor welfare, but it may also encourage riskier bank behavior.

We analyze the distribution of welfare effects resulting from the expansion of DI under various scenarios of moral hazard, characterized by changes in the post-expansion probability of bank failure. Specifically, the new probability is modeled as $\pi^* = (1 + \Delta)\pi$, with $\Delta$ taking values of 5%, 7.5%, 10%, 12.5%, and 15%, representing increasing levels of moral hazard. For benchmarking, the scenario with $\Delta = 0$ is included to represent the case of no moral hazard.

Figure 12 summarizes the key findings across these different moral hazard levels, illustrating how the welfare distribution shifts as the probability of bank failure increases after DI expansion. The accompanying table reports the estimated welfare changes for various combinations of risk aversion ($\gamma$) and moral hazard ($\Delta$). The results indicate that moral hazard has a minimal impact on the welfare gains for depositors with moderate endowments, whose benefits remain relatively stable regardless of the increased failure risk. In contrast, depositors with high endowments experience welfare reductions due to moral hazard. Moreover, these high endowment depositors experience a larger reduction in their welfare as moral hazard increases. This reduction stems from the fact that, even after DI expansion, some of their deposits remain uninsured, and heightened moral hazard incentives lead to an increased perceived probability of bank failure. Consequently, the Sharpe ratio on these uninsured deposits falls, reducing the utility gains for these wealthier depositors.

Overall, the results suggest that, although increased moral hazard can diminish welfare gains for depositors with high endowments, its overall impact remains limited. Specifically, welfare gain remains positive across the entire distribution even when moral hazard raises the probability of bank failure by up to 15%.

To further assess the relevance of moral hazard, we identify the threshold increase in the bank failure probability necessary to entirely erode the welfare gains from DI expansion. This analysis sheds light on the robustness of the benefits achievable despite potential risk-taking incentives induced by moral hazard. Our estimates suggest that, for a low risk aversion coefficient of 1, a 70% increase in the expected bank failure probability would be required for moral hazard to eliminate all welfare gains. For higher risk aversion levels—3, 5, and 10—the required increases are approximately 98.4%, 105.7%, and 105.8%, respectively. When considering heterogeneous risk aversion across households, the threshold rises further to about 106.9%, indicating that moral hazard would need to be substantially large to fully offset the welfare benefits of DI expansion. These findings suggest that moral hazard, while a relevant concern, would need to be substantial – far beyond typical expectations – to completely negate the welfare gains.

# 9 Alternative Sources of Deposit Growth

This section discusses various alternative mechanisms that may account for the deposit growth observed among bunchers following DI expansion. We examine several potential sources of monetary reallocation: moving cash-in-hand to bank accounts, redistributing funds among family members within the household, shifting money across different banks, reducing overall spending, and increasing lending to bunchers, which could create additional deposits in their bank accounts. We document that, on average, none of these alternative mechanisms can quantitatively explain the rise in deposits among bunchers following DI expansion.

**Cash-in-Hand & Deposit Growth:** We start by investigating whether the movement of money from cash to bank accounts among bunchers explains their increased deposits following the expansion of the DI limit. The hypothesis is that depositors concerned about bank safety might prefer holding cash, particularly when the DI limit is binding. The DI expansion could prompt these depositors to switch from cash to bank accounts. We explore this hypothesis through three tests.

First, we create a ZIP-level quasi-exogenous instrument measuring digital payment adoption, based on the uptake of the Unified Payments Interface (UPI). This measure is based on the rationale presented in Dubey and Purnanandam (2023) and this ZIP-level measure has been linked to increased digital transaction usage in India in previous work by Cramer et al. (2024).[21] We refer to this as the UPI exposure index. Appendix section C.3 presents the methodology for the construction of the UPI Index. High UPI exposure suggests greater use of digital transactions and, subsequently, less cash held informally. If bunchers' deposit increases result from moving cash to banks, we would expect a

[21]Moreover, Cramer et al. (2024) document that within a district our measure of UPI exposure is unlikely to be correlated with several ZIP-level observable characteristics such as nightlights, population, geographic area, share of marginalized population, literacy rate, presence of schools and colleges, employment, and the distribution of employment across manufacturing and services sector. We direct readers to Dubey and Purnanandam (2023) and Cramer et al. (2024) for a detailed discussion on the construction of this measure as well as the endogeneity concerns resolved by using this measure instead of actual digital transactions.

stronger effect in areas with low UPI exposure. However, Column 2 of Appendix Table F.1 shows no significant differences between bunchers in high and low UPI exposure regions.

Second, we analyze occupational differences, positing that self-employed individuals tend to hold more cash compared to salaried workers, who typically receive direct deposits into their bank accounts. Column 3 of Appendix Table F.1 provides evidence of no statistically significant differences in responses between self-employed and salaried bunchers. Third, we leverage the pre-policy share of transactions conducted in cash as a proxy for cash holdings. Column 4 of Appendix Table F.1 indicates no significant differences among bunchers with high versus low pre-policy cash usage.

Together, these findings collectively suggest that the transfer of money from cash to bank accounts is unlikely to be a primary driver behind the observed increase in bunchers' deposits after the DI expansion.

**Reallocation Across Banks:** Like the US, DI in India is applied at the bank level, meaning depositors cannot exceed the DI limit by opening multiple accounts at the same bank. However, they can expand their protection by holding accounts at different banks. Under a binding DI limit at a bank, bunchers may distribute their deposits across various banks to protect their savings. This section investigates whether bunchers consolidate their deposits at a single bank, thereby increasing the amount covered under that institution.

To assess this, we compare buncher behavior in regions with multiple banks to areas dominated by a single institution. We posit that if bunchers are reallocating funds, we should see a stronger response in regions without a dominant bank. Results in Appendix Table F.2 show no significant differences in buncher behavior between the two regions, suggesting that cross-bank reallocation is unlikely to affect our findings.

We conduct an additional test to assess whether depositors actively reallocate their funds across multiple banks to maximize their DI coverage. Our hypothesis is that if depositors – particularly bunchers – manage their deposits across different banks to optimize insurance benefits, then their transaction activity should significantly change after the DI expansion, as their incentive to spread funds reduces. As shown in Appendix Table F.3, there are no economically or statistically significant changes in the number of transactions for bunchers following the DI expansion. This suggests that our main findings are unlikely to be driven by depositors coordinating their deposits across multiple banks.

The two results taken together support the idea that most depositors prefer not to manage multiple bank accounts, as doing so can be costly in terms of time, complexity, and tax implications (Egan, Hortaçsu, and Matvos, 2017; Dávila and Goldstein, 2023). This observation also aligns with the fact that, even in developed economies like the US where depositors can easily open online accounts, most (two-thirds) typically maintain depository relationships with only one financial institution (Ganong et al., 2020).

**Reduction in Spending:** Next, we investigate whether bunchers reduce their spending to finance their increase in deposit levels following an expansion of the DI limit. We posit that, in the presence of a DI limit, depositors – particularly those who are bunchers – may worry about the safety of their funds above the DI limit in banks, leading them to overspend initially. Consequently, an increase in the DI limit could prompt these depositors to reduce their expenditures, leading to higher deposit accumulation. We test the relevance of this conjecture by examining changes in spending behavior among bunchers relative to non-bunchers after DI expansion. Results in Appendix Table F.4 indicate no evidence of reduced spending among bunchers relative to non-bunchers following the DI limit increase.

**Reallocation with Household:** Households with bunchers can strategically distribute deposits among family members to maximize coverage under the DI limit. An increase in this limit may lead to funds being transferred back to the bunchers' bank accounts, potentially driving deposit growth. We test this hypothesis by analyzing changes in behavior among bunchers based on their pre-policy share of household deposits. The rationale is that if bunchers are reallocating savings to family members' accounts, we should observe a greater increase in deposits among those with a larger share allocated to other household members. Results in Appendix Table F.5 find no evidence of such an intra-household deposit reallocation following the DI limit increase.

**Role of Lending:** An increase in the DI limit improves bank funding, allowing banks to expand their lending capacities. Consequently, if banks increase their lending to bunchers after the DI expansion, this additional credit could generate new deposits in their bank accounts. To evaluate this hypothesis, we analyze changes in new loans extended to bunchers compared to non-bunchers following the DI limit increase. Results presented in Appendix Table F.6 show no significant evidence of increased lending to bunchers relative to non-bunchers after the DI expansion.

# 10 Conclusion

This paper examines the role of deposit insurance in portfolio allocation. We present a theoretical framework for portfolio selection, where individuals allocate their endowments between a safe asset –deposits – and a risky asset. DI plays a crucial role in this decision, as it limits the supply of safe deposits, i.e., deposits are completely safe up to the DI threshold, after which they become subject to risk. This generates a kink in the capital allocation line, affecting the optimal portfolio choice. We show that when bank failure carries a positive probability, a limited DI leads to bunching in the deposit distribution at the threshold and a higher purchase of stocks than in the presence of unlimited insurance. Furthermore, we show that raising the DI threshold prompts depositors – especially those whose balances meet or exceed the previous threshold – to optimize along a higher indifference curve. This shift results in increased deposits and a decline in stock holdings.

Next, we provide empirical evidence in support of this framework. To this end, we examine a large change in the DI threshold in India, using detailed data on household finances. This data includes information on deposit holdings, consumption, investments in equities and mutual funds, as well as investments in other illiquid long-term assets, along with the deposit holdings of family members. We begin by documenting that depositors often bunch or concentrate their deposits around the DI threshold. These bunchers tend to either over-invest in liquid assets, such as direct equity and mutual funds, or long-term illiquid investments. Following the increase in the DI threshold, we find that these depositors liquidate their equity and mutual fund holdings to increase their bank deposits, particularly opting to sell relatively safer equity investments to fund this growth.

Our results are important for four main reasons. First, they provide a depositor's perspective on how changes in DI threshold can impact household portfolio allocation, informing the design of optimal deposit insurance policies. Second, they highlight the role of DI in determining the supply of safe, liquid assets, particularly in emerging markets where deposits often serve as the primary source of safe, liquid investments. When DI thresholds restrict the supply of these assets, households may be forced to compromise on liquidity or safety. Third, our results suggest that DI expansion may prompt depositors to reallocate funds from other formal economic segments, such as equity markets and mutual funds, to finance their deposit growth, thereby informing policy-makers of the potential costs of DI to other segments of the economy. Finally, our framework for estimating depositor-implied bank failure probabilities based on depositor distribution offers additional guidance to regulators for estimating bank risk.

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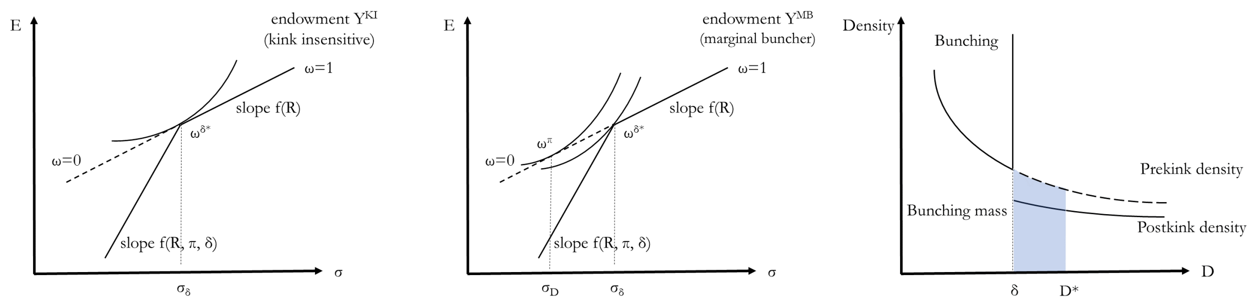
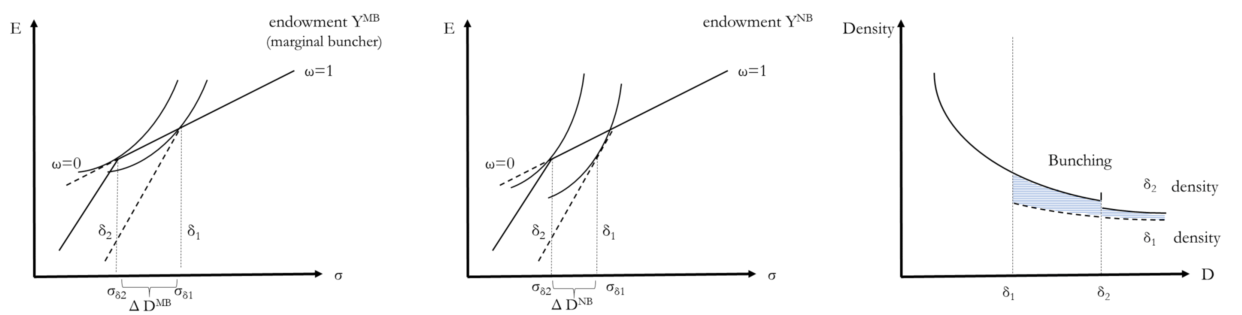
**Figure 1:** Kinked Capital Allocation Set and Optimal Deposit




(a) Kink-Insensitive Individual (b) Marginal Buncher (c) Deposit Distribution

These figures show the portfolio allocation decision problem in the presence of deposit insurance for two individuals, in figures 1a, 1b, and the distribution of deposits figure 1c. Figures 1a, 1b show the kinked capital allocation set, which is generated by the fact that holding deposits generates a unit return when the total deposits are lower or equal than the insurance threshold, $D \leq \delta$. However, the remuneration of deposits drops to the threshold in case of bank default when the total deposits are higher than the insurance threshold, $D > \delta$. Figure 1a shows the deposit decision for an individual with an endowment $Y^{KI}$, who is kink insensitive and would always deposit $\delta$ regardless of whether the probability of bank default is zero or positive. Figure 1b presents the decision of an individual with endowment $Y^{MB}$, who is a marginal buncher. She would deposit more than the threshold, in the presence of a zero probability of bank default, but responds to the kink in remuneration induced by the positive probability of default and the threshold $\delta$ and holds a level of deposits $\delta$. Figure 1c shows the distribution of deposits in the presence of a positive probability of bank default and limited insurance, $\delta$,labelled as Postkink density, and the distribution of deposits without such kink and zero probability of default, indicated as Prekink density. This figure shows the presence of excessive bunching at the $\delta$ threshold, with the shaded area indicating the corresponding bunching mass.

**Figure 2:** Deposits and an Expansion in Deposit Insurance

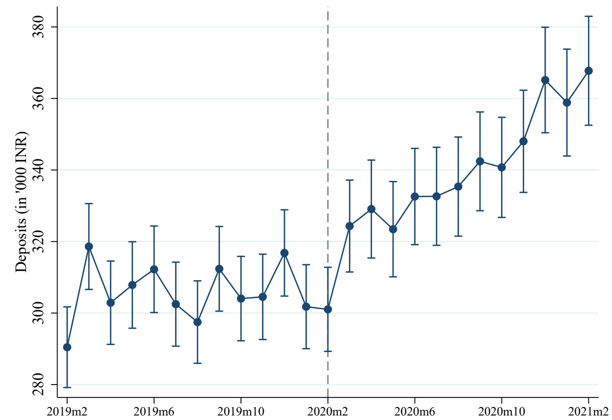



(a) Marginal Buncher (b) Non-Bunching Individual (c) Deposit Distribution

Figures 2a, 2b, and 2c show the portfolio allocation decision problem in the presence of a positive probability of default and when the threshold of deposit insurance increases from $\delta_1$ to $\delta_2$ for two individuals, respectively shown in Figures 2a and 2b. Figure 2c shows the distribution of deposits after the change in deposit insurance. Figures 2a and 2b show the change in the kinked capital allocation set, which is generated by the fact that after the increase in insurance from $\delta_1$ to $\delta_2$, individuals experience a change in the kink to the left of the capital line and an expansion in the deposit rate. Figure 2a shows the deposit decision for the marginal buncher, with endowment $Y^{MB}$, who deposits an additional amount $\Delta D^{MB}$ in response to the increase in insurance. Figure 2b highlights the deposit decision for a non-bunching individual with endowment $Y^{NB} > Y^{MB}$, who deposits an additional amount $\Delta D^{NB} < \Delta D^{MB}$ in response to the increase in insurance.

**Figure 3:** Aggregate Analysis: Bank Deposits and DI Limit Expansion


(a) Median Deposits

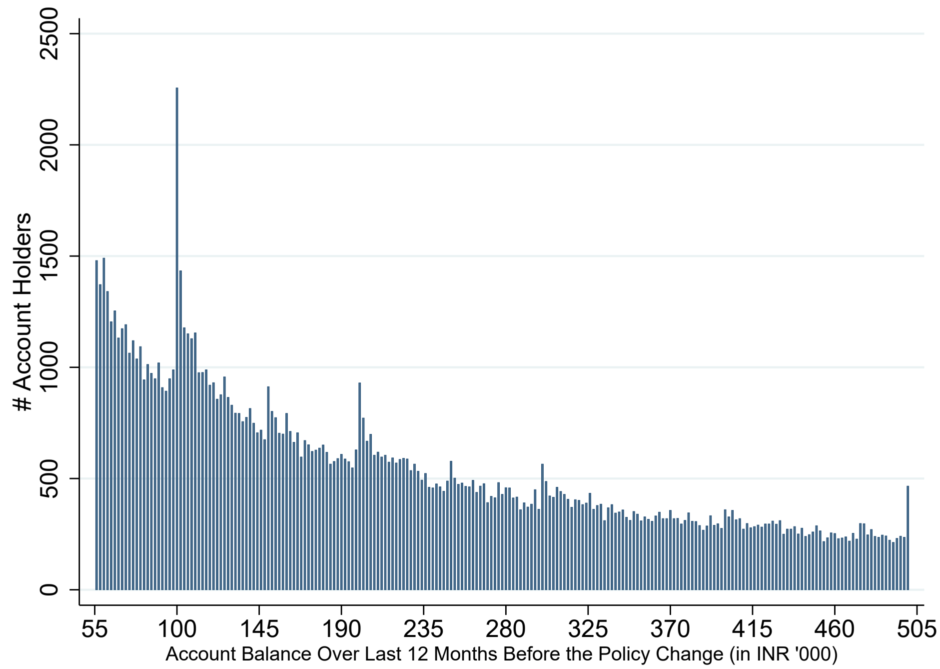



(b) Average Deposits

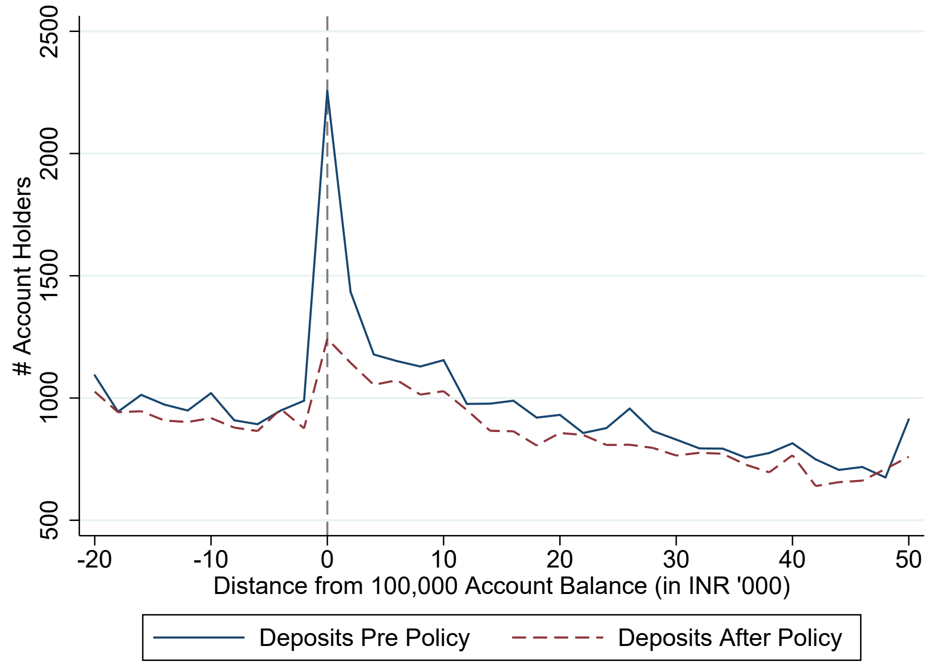

(c) Bank-level Deposits

This figure presents the association between deposits and DI limit expansion. Figure 3a presents the temporal evolution of median deposits. Figure 3b presents the temporal evolution of average deposits along with 95% confidence intervals. Figure 3c presents the temporal evolution of total deposits at the bank level. The dashed grey vertical line denotes February 2020, when the announcement of the DI limit expansion was made. Deposits are defined as the sum of savings, time and recurring deposits.

**Figure 4:** Bunching of Depositors at Pre-policy Deposit Insurance Threshold



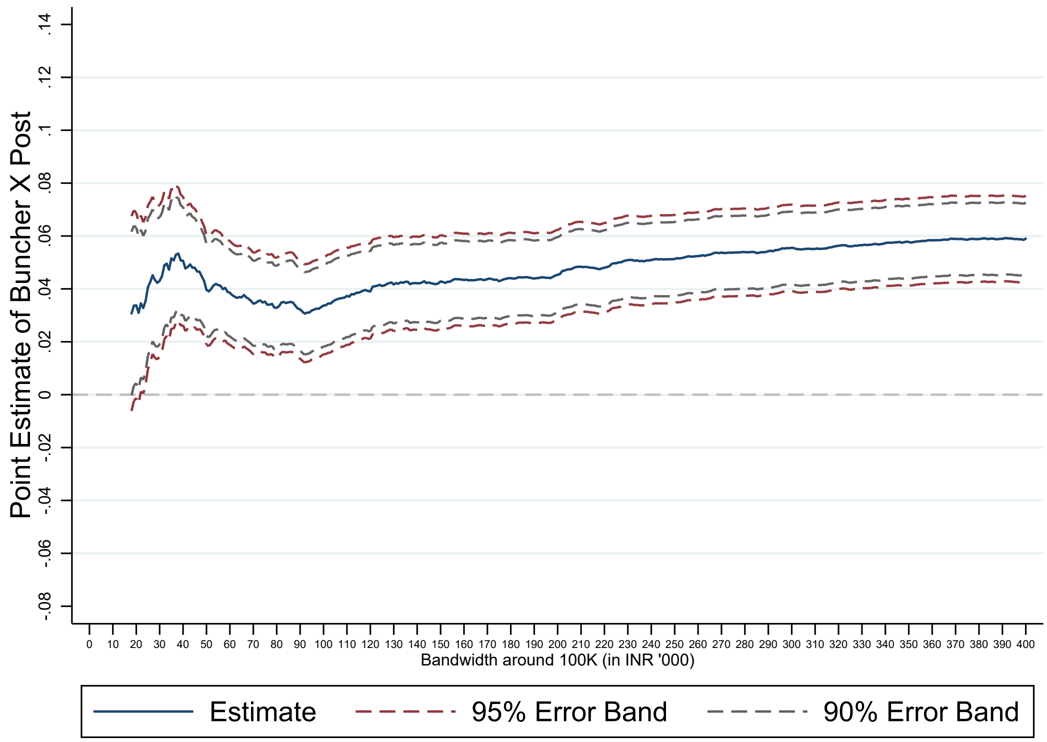

(a) Histogram




(b) Density Plot

This figure presents the distribution of depositors in our sample around the ₹100,000 pre-policy DI threshold. Figure 4a presents the histogram of depositors based on their average month-end balances over the twelve months before the DI expansion in February 2020. Figure 4b compares the density plot of depositors based on their average month-end balances twelve months before and after February 2020. The solid blue line denotes the pre-policy distribution and the dashed maroon line denotes the post-policy distribution. The vertical dashed grey line denotes the ₹100,000 threshold which is standardized to ₹0. The solid blue line is a zoomed-in version of the distribution presented in Figure 4a in a narrow bandwidth of ₹80,000 & ₹150,000. Amounts are reported in '000 ₹(or INR).

**Figure 5:** Grid Search for Bandwidth Around the Threshold

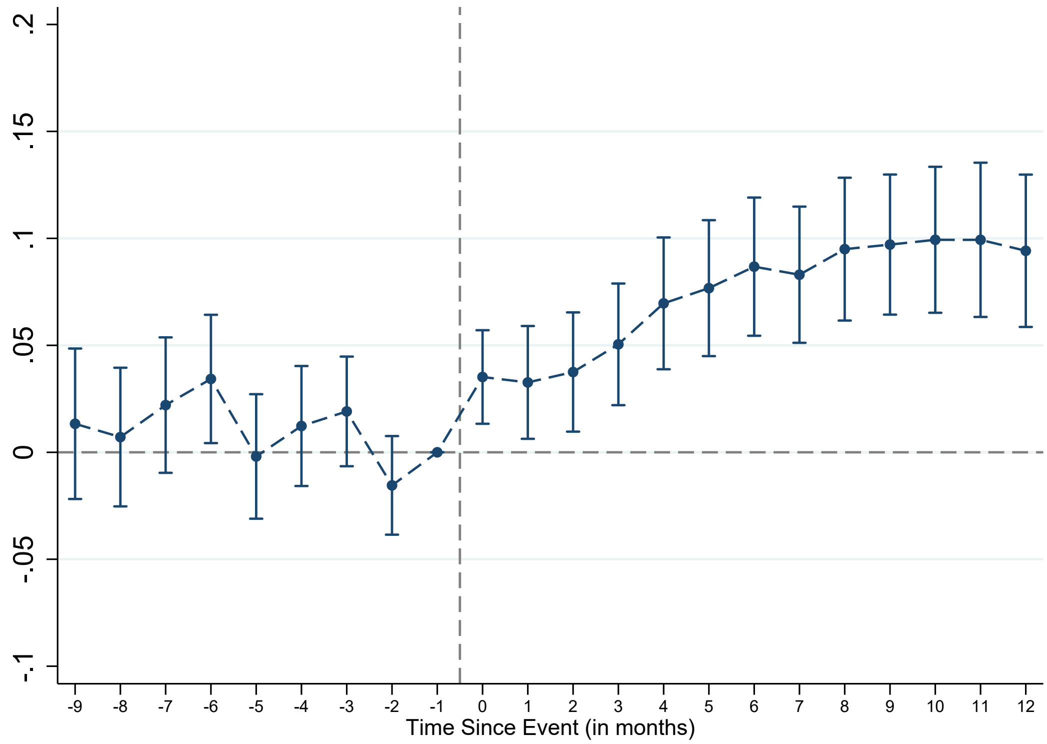



The figure plots the estimated coefficient $\beta$ (Y-axis) from the following specification for a wide range of bandwidths (X-axis):

$$LN(Deposits_{i,t}) = \beta \times Buncher_i \cdot Post_t + \theta_i + \theta_{z(i\in z),t} + \varepsilon_{i,t} \; \forall i \in \underbrace{[max\{100-\Delta_k, 50\}, 100]}_{Buncher} \cup \underbrace{(100, 100+\Delta_k]}_{Non-Buncher}$$

where, $LN(Deposits_{i,t})$ denotes the natural logarithm of total bank deposits of depositor $i$ (residing in ZIP code $z$) at time (month-year) $t$. $Post_t$ is an indicator variable taking a value of one for all months since February 2020. $\theta_i$ and $\theta_{z(i\in z),t}$ denote depositor and ZIP $\times$ time (month-year) fixed effects, respectively. We use the shorthand notation for numbers, i.e., 100 means ₹100,000. Bunchers are defined as depositors with pre-policy deposits in the $[max\{100-\Delta_k, 50\}, 100]$ range and non-bunchers are deposiotrs whose pre-policy deposits fall within $(100, 100+\Delta_k]$. We estimate the above specification for a wide range of bandwidths, where $\Delta_k$ is the increment in bandwidth set at 1. All continuous variables are winsorized at the 1% level. The solid navy blue denotes the point estimate of $\beta$ for each bandwidth. The dashed red and grey lines denote the 95% and 90% confidence intervals, respectively. The confidence intervals are computed from standard errors clustered at the ZIP level.

**Figure 6:** Assessment of Pre-Trends

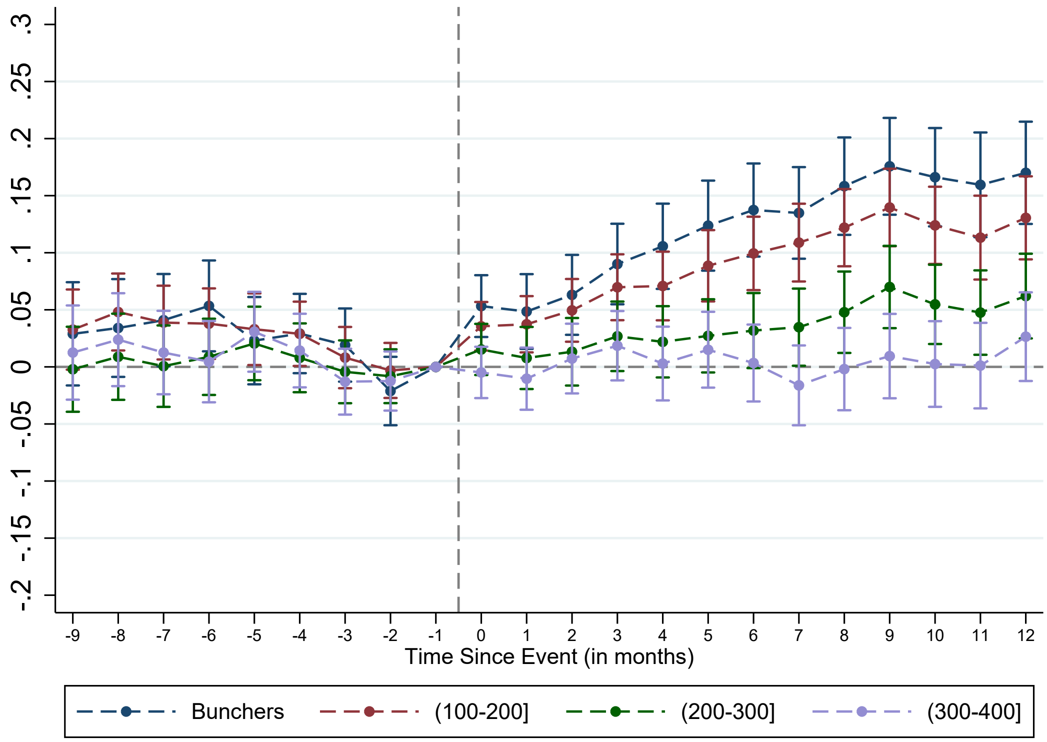



The figure plots the estimates of $\beta_j$ and the 95% confidence intervals from the following regression equation:

$$LN(Deposits_{i,t}) = \sum_{j=-9, j\neq -1}^{j=+12} \beta_j \times Buncher_i \cdot \mathbb{1}\{t = j\} + \theta_i + \theta_{z(i\in z),t} + \varepsilon_{i,t}$$

where, $LN(Deposits_{i,t})$ denotes the natural logarithm of total bank deposits of depositor $i$ (residing in ZIP code $z$) at time (month-year) $t$. $\mathbb{1}\{t = j\}$ is the time indicator variable taking a value of one if the month is $j$ months before/after the month of February 2020. February 2020 is denoted by $j = 0$. $\theta_i$ and $\theta_{z(i\in z),t}$ denote depositor and ZIP × time (month-year) fixed effects, respectively. We use the shorthand notation for numbers, i.e., 100 means ₹100,000. Bunchers are defined as depositors with pre-policy deposits in the $(70, 100]$ range and non-bunchers are depositors whose pre-policy deposits fall within $(100, 500)$. All continuous variables are winsorized at the 1% level. The 95% error bands are estimated by clustering the standard errors at the ZIP level.

**Figure 7:** Assessment of Pre-Trends: Heterogeneous Response of Non-Bunchers

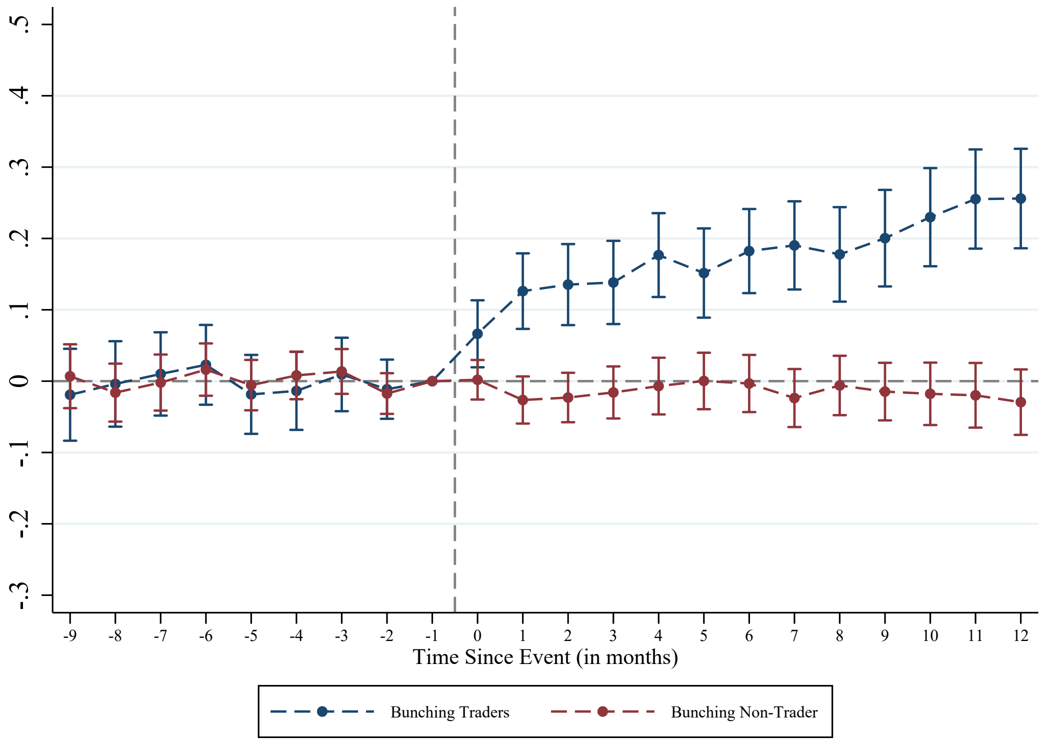



The figure plots the estimates of $\beta_j^k$ and the 95% confidence intervals from the following regression equation:

$$Ln(Deposits_{i,t}) = \sum_{k=1,k\neq 5}^{k=5} \sum_{j=-9,j\neq -1}^{j=+12} \beta_j^k \times Bin_k \cdot \mathbb{1}\{t=j\} + \theta_i + \theta_{z(i\in z),t} + \varepsilon_{i,t}$$

where, $LN(Deposits_{i,t})$ denotes the natural logarithm of total bank deposits of depositor $i$ (residing in ZIP code $z$) at time (month-year) $t$. $Bin_k$ is an indicator variable taking a value of one for depositors with pre-policy deposits within a certain range, and 0 otherwise. $\mathbb{1}\{t=j\}$ is the time indicator variable taking a value of one if the month is $j$ months before/after the month of February 2020. February 2020 is denoted by $j=0$. $\theta_i$ and $\theta_{z(i\in z),t}$ denote depositor and ZIP × time (month-year) fixed effects, respectively. We use the shorthand notation for numbers, i.e., 100 means ₹100,000. $Bin_1$ or $k=1$ refers to bunchers. Bunchers are defined as depositors with pre-policy deposits in the (70, 100] range and non-bunchers are depositors whose pre-policy deposits fall within (100, 500). Furthermore, we split non-bunchers into four groups of equal size of 100 or ₹100,000. $Non-Bunchers_1$ ($Bin_2$ or $k=2$) denotes non-bunchers with pre-policy deposits in the (100, 200] range. $Non-Bunchers_2$ ($Bin_3$ or $k=3$) denotes non-bunchers with pre-policy deposits in the (200, 300] range. $Non-Bunchers_3$ ($Bin_4$ or $k=4$) denotes non-bunchers with pre-policy deposits in the (300, 400] range. $Non-Bunchers_4$ ($Bin_5$ or $k=5$) denotes non-bunchers with pre-policy deposits in the (400, 500) range. $Non-Bunchers_4$ ($Bin_5$ or $k=5$) is the omitted variable in this regression. All continuous variables are winsorized at the 1% level. The 95% error bands are estimated by clustering the standard errors at the ZIP level.

**Figure 8:** Heterogeneous Response among Traders & Non-Traders



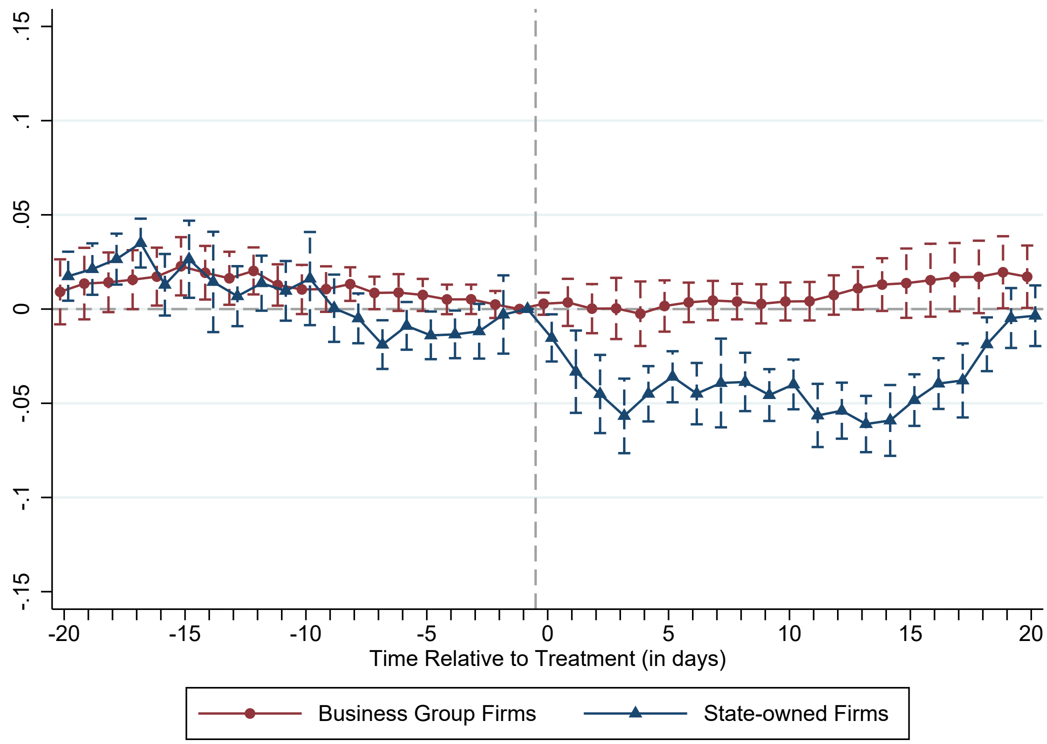

The figure plots the estimates of $\beta_j^{B,T}$, $\beta_j^{B,NT}$ and the associated 95% confidence intervals from the following regression equation:

$$LN(Deposits_{i,t}) = \sum_{j=-9, j\neq -1}^{j=+12} \beta_j^{B,T} \times Buncher_i \cdot Trader_i \cdot \mathbb{1}\{t = j\}$$

$$+ \sum_{j=-9, j\neq -1}^{j=+12} \beta_j^{B,NT} \times Buncher_i \cdot Non - Trader_i \cdot \mathbb{1}\{t = j\} + \theta_i + \theta_{z(i\in z),t} + \varepsilon_{i,t}$$

where, $LN(Deposits_{i,t})$ denotes the natural logarithm of total bank deposits of depositor $i$ (residing in ZIP code $z$) at time (month-year) $t$. $Trader_i$ is an indicator variable taking a value of one for depositors who trade in the stock market or mutual fund. $Non - Trader_i$ is an indicator variable taking a value of one for depositors who do not trade in the stock market or mutual fund. $\mathbb{1}\{t = j\}$ is the time indicator variable taking a value of one if the month is $j$ months before/after the month of February 2020. February 2020 is denoted by $j = 0$. $\theta_i$ and $\theta_{z(i\in z),t}$ denote depositor and ZIP × time (month-year) fixed effects, respectively. We use the shorthand notation for numbers, i.e., 100 means ₹100,000. Bunchers are defined as depositors with pre-policy deposits in the (70, 100] range and non-bunchers are depositors whose pre-policy deposits fall within (100, 200]. All bunchers are divided into two groups. $B, T$ refers to the group of depositors who are bunchers and traders. $B, NT$ refers to the group of depositors who are bunchers and non-traders. Non-bunchers are the omitted category in the specification. All continuous variables are winsorized at the 1% level. The 95% error bands are estimated by clustering the standard errors at the ZIP level.

**Figure 9:** Asset Pricing Implications of SOE Liquidation

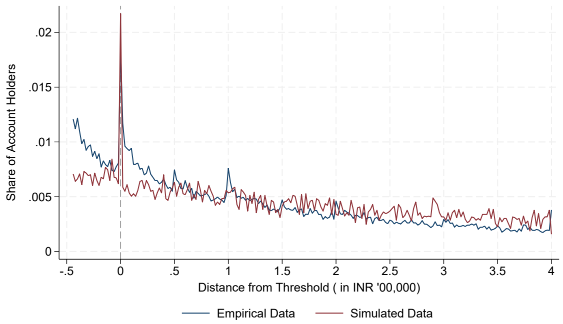



The figure compares the cumulative abnormal returns (CAR) for state-owned enterprises (SOE) with business group firms and other non-financial firms. Specifically, the figure plots the estimates of $\beta_j$ and $\gamma_j$ and the 95% confidence intervals from the following regression equation:

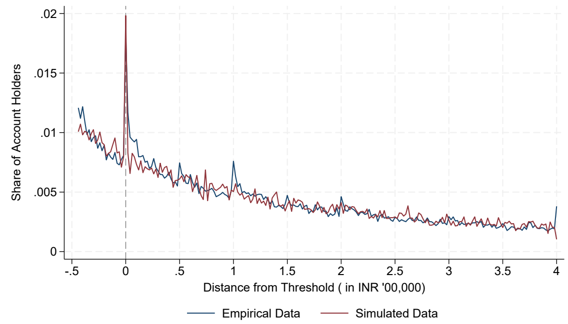
$$CAR_{i,t} = \sum_{j=-20, j\neq -1}^{j=+20} \beta_j \times SOE_i \cdot \mathbb{1}\{t=j\} + \sum_{j=-20, j\neq -1}^{j=+20} \gamma_j \times BG_i \cdot \mathbb{1}\{t=j\} + \theta_i + \theta_t + \varepsilon_{i,t}$$

where, $CAR_{i,t}$ denotes the cumulative abnormal returns for stock $i$ on trading day $t$. $SOE_i$ takes a value of one for SOE firms and zero otherwise. Similarly, $BG_i$ takes a value of one for business group firms and zero otherwise. $\mathbb{1}\{t = j\}$ is the time indicator variable taking a value of one if the date is $j$ days before or after the DI expansion date. February 1, 2020 is denoted by $j = 0$. $\theta_i$ and $\theta_t$ denote stock and trading day fixed effects, respectively. The 95% error bands are estimated by clustering the standard errors at the stock level.

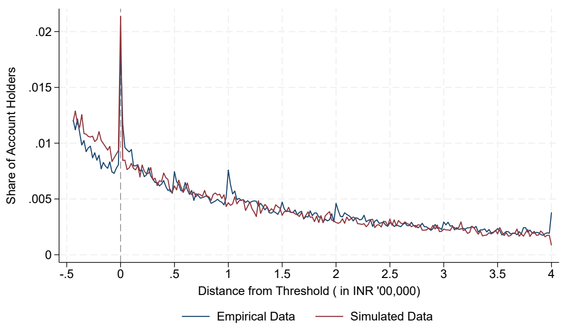
**Figure 10:** Model Fit & Depositor Implied Probability of Bank Failure



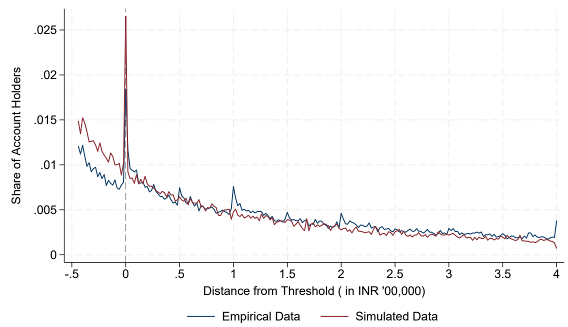

(a) $\gamma = 1$



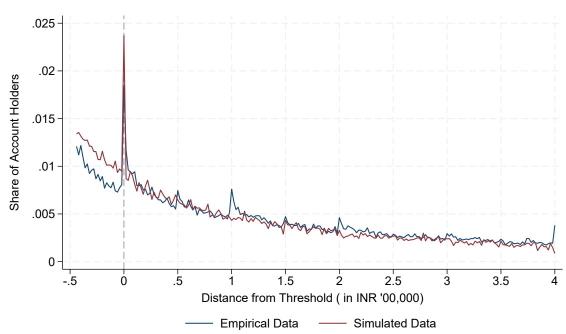

(b) $\gamma = 3$




(c) $\gamma = 5$




(d) $\gamma = 10$

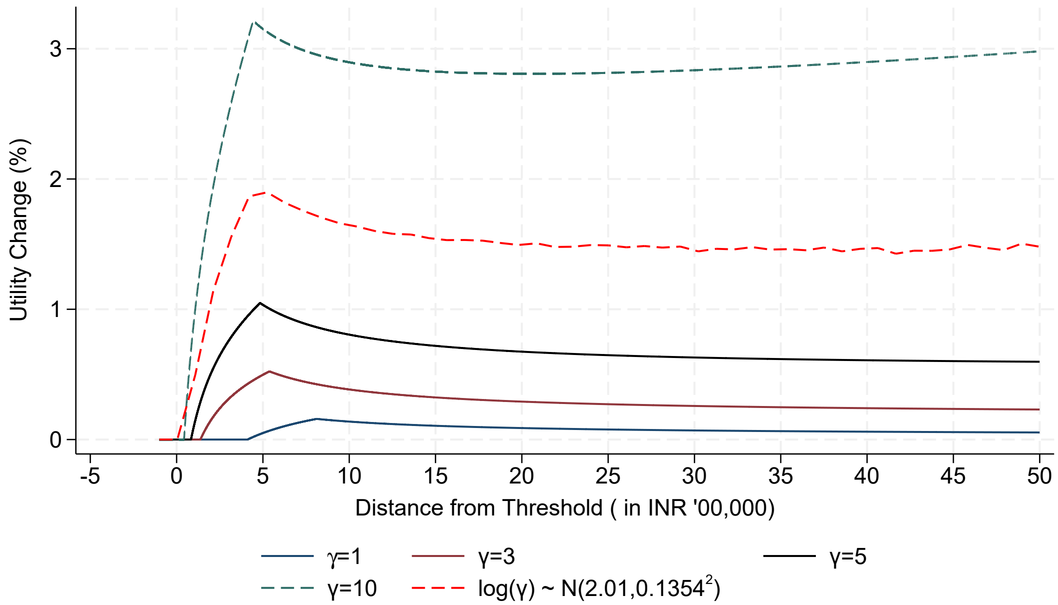



(e) $ln(\gamma) \sim \mathcal{N}(2.01, 0.134^2)$

| | $\gamma = 1$ | $\gamma = 3$ | $\gamma = 5$ | $\gamma = 10$ | $ln(\gamma) \sim \mathcal{N}(2.01, 0.134^2)$ |
|---|---|---|---|---|---|
| Estimated $\pi$ | 0.0026 | 0.0054 | 0.0084 | 0.0174 | 0.0128 |

The figure compares the distribution of depositors in the simulated data with the empirical distribution observed before the DI expansion. The X-axis plots the distance of the deposits from the initial DI limit. The Y-axis plots the fraction of account holders. Figures 10a, 10b, 10c, and 10d compare the empirical and the simulated distribution for various levels of risk-aversion: $\gamma = 1$, $\gamma = 3$, $\gamma = 5$, and $\gamma = 10$, respectively. Figure 10e compares the empirical and the simulated distribution in case of heterogeneous risk-aversion: $ln(\gamma) \sim \mathcal{N}(2.01, 0.1354^2)$. The table below the figure presents the estimated values of the probability of bank failure for each value of risk-aversion.

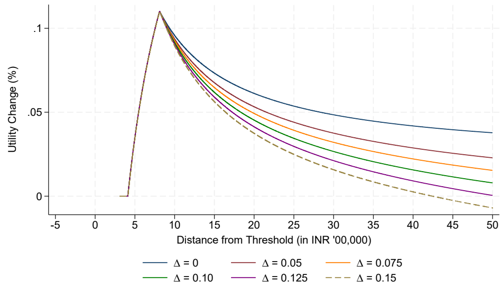
**Figure 11:** Distribution of Welfare Effects of DI Expansion



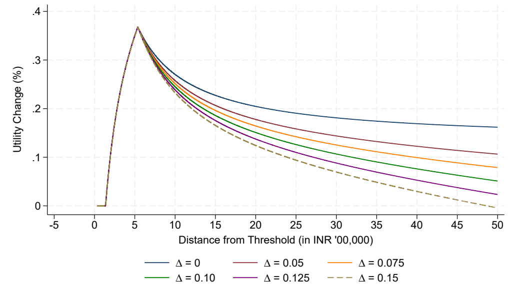

| | $\gamma = 1$ | $\gamma = 3$ | $\gamma = 5$ | $\gamma = 10$ | $ln(\gamma) \sim \mathcal{N}(2.01, 0.1354^2)$ |
|---|---|---|---|---|---|
| Welfare ($\sum_w \frac{\Delta U}{U}$) | 0.0433 | 0.0861 | 0.1158 | 0.1863 | 0.1534 |

The figure plots the distribution of the welfare effects of DI expansion. The X-axis plots the distance of the endowment from the initial Di limit. The Y-axis plots the percentage change in utility when the DI limit is increased by five times. The figure plots the welfare effects of DI expansion of various levels of risk-aversion: $\gamma = 1$, $\gamma = 3$, $\gamma = 5$, and $\gamma = 10$. The figure also plots the average welfare effect in case of heterogeneous risk-aversion: $ln(\gamma) \sim \mathcal{N}(2.01, 0.1354^2)$. The table below the figure presents the aggregate welfare effects for each value of risk-aversion.

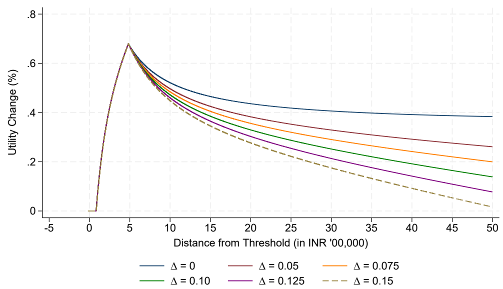
**Figure 12:** Distribution of Welfare Effects of DI Expansion in presence of Moral Hazard



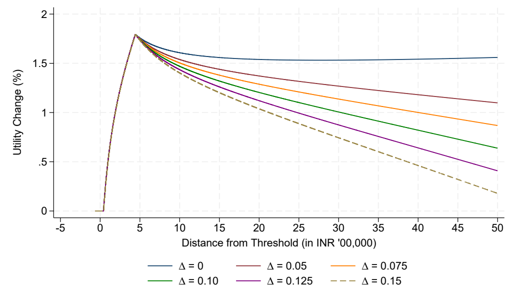

(a) $\gamma = 1$



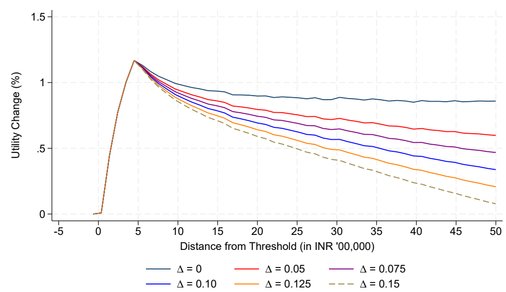

(b) $\gamma = 3$




(c) $\gamma = 5$




(d) $\gamma = 10$




(e) $ln(\gamma) \sim \mathcal{N}(2.01, 0.1354^2)$

| | Welfare in presence of Moral Hazard; $\pi^* = (1+\Delta)\pi$ | | | | | |
|---|---|---|---|---|---|---|
| | $\Delta = 0$ | $\Delta = 0.05$ | $\Delta = 0.075$ | $\Delta = 0.1$ | $\Delta = 0.125$ | $\Delta = 0.15$ |
| $\gamma = 1$ | 0.0433 | 0.0422 | 0.0417 | 0.0411 | 0.0406 | 0.0400 |
| $\gamma = 3$ | 0.0861 | 0.0852 | 0.0847 | 0.0843 | 0.0838 | 0.0833 |
| $\gamma = 5$ | 0.1158 | 0.1148 | 0.1143 | 0.1139 | 0.1134 | 0.1129 |
| $\gamma = 10$ | 0.1863 | 0.1850 | 0.1843 | 0.1837 | 0.1830 | 0.1824 |
| $ln(\gamma) \sim \mathcal{N}(2.01, 0.1354^2)$ | 0.1534 | 0.1523 | 0.1517 | 0.1511 | 0.1506 | 0.1500 |

The figure plots the distribution of the welfare effects of DI expansion in the presence of moral hazard. We simulate moral hazard by assuming that the DI expansion increases the expected probability of bank failure according to $\pi^* = (1+\Delta)\pi$. We estimate the moral hazard effects for five values: $\Delta = 5\%$, $\Delta = 7.5\%$, $\Delta = 10\%$, $\Delta = 12.5\%$, and $\Delta = 15\%$. We also plot welfare effects for $\Delta = 0\%$, the case of no moral hazard to benchmark the effects of moral hazard. The X-axis plots the distance of the endowment from the initial DI limit. The Y-axis plots the percentage change in utility when the DI limit is increased by five times for different values of $\Delta$. The figure plots the welfare effects of DI expansion of various levels of risk-aversion: $\gamma = 1$ (Panel a), $\gamma = 3$ (Panel b), $\gamma = 5$ (Panel c), and $\gamma = 10$ (Panel d). The figure also plots the average welfare effect in case of heterogeneous risk-aversion: $ln(\gamma) \sim \mathcal{N}(2.01, 0.1354^2)$ (Panel e). The table below the figure presents the aggregate welfare effects for each value of risk-aversion and moral hazard.

**Table 1:** Summary Statistics

| Panel A: Month End Balances (in ₹) | # Obs | p25 | p50 | p75 | Mean | SD |
|---|---|---|---|---|---|---|
| Banked Wealth | 7,933,335 | 8,635.48 | 102,486.00 | 598,410.80 | 1,037,256.00 | 3,072,891.00 |
| Total Deposits | 7,933,335 | 5,620.04 | 59,298.26 | 295,421.10 | 327,480.30 | 715,401.70 |
| Saving Deposits | 7,933,335 | 3,775.00 | 31,746.09 | 159,486.70 | 212,053.90 | 517,419.70 |
| Time Deposits | 7,933,335 | 0.00 | 0.00 | 17,647.00 | 96,485.48 | 291,267.10 |
| Recurring Deposits | 7,933,335 | 0.00 | 0.00 | 0.00 | 1,203.15 | 7,923.79 |
| Amount in Stock Market | 7,933,335 | 0.00 | 0.00 | 0.00 | 571,042.50 | 2,568,341.00 |
| Amount in Mutual Funds | 7,933,335 | 0.00 | 0.00 | 0.00 | 57,118.99 | 223,235.60 |
| Amount in PPF | 7,933,335 | 0.00 | 0.00 | 0.00 | 13,889.38 | 88,529.21 |

| Panel B: Individual-Level Holdings Data | # Obs | p25 | p50 | p75 | Mean | SD |
|---|---|---|---|---|---|---|
| # Shares for each ISIN, Total | 29,870,623 | 31.00 | 112.00 | 500.00 | 850.37 | 2,674.23 |
| Amount for each ISIN, Total | 29,870,623 | 4,695.00 | 23,550.00 | 98,875.00 | 160,388.75 | 447,389.89 |
| # Shares for each ISIN, Stocks | 29,153,308 | 32.00 | 110.00 | 499.00 | 816.23 | 2,608.13 |
| Amount for each ISIN, Stocks | 29,153,308 | 4,650.00 | 23,353.20 | 98,130.00 | 160,502.01 | 448,176.35 |
| # Shares for each ISIN, Mutual Fund | 717,315 | 23.00 | 211.00 | 2,100.00 | 2,237.91 | 4,401.16 |
| Amount for each ISIN, Mutual Fund | 717,315 | 6,218.10 | 33,146.50 | 126,258.80 | 155,785.49 | 414,138.37 |

| Panel C: Depositor Level Characteristics | # Obs | p25 | p50 | p75 | Mean | SD |
|---|---|---|---|---|---|---|
| Age (as of Feb, 2020) | 321,350 | 27.00 | 36.00 | 47.00 | 37.77 | 13.39 |
| Female (=1) | 320,608 | 0.00 | 0.00 | 1.00 | 0.44 | 0.50 |
| Imputed Monthly Income (in ₹) | 303,508 | 9,877.93 | 40,071.50 | 107,204.10 | 72,761.80 | 134,697.60 |
| Unscored (=1) | 321,350 | 0.00 | 0.00 | 1.00 | 0.49 | 0.50 |
| Credit Score | 164,116 | 744.00 | 776.00 | 794.00 | 759.81 | 49.49 |
| Self Employed (=1) | 313,759 | 0.00 | 0.00 | 1.00 | 0.34 | 0.47 |
| # HH members | 321,350 | 2.00 | 3.00 | 5.00 | 3.63 | 1.43 |
| Account Age (as of Feb, 2020) | 321,350 | 3.13 | 7.12 | 12.24 | 8.13 | 5.93 |
| Has Loan (=1) | 321,350 | 0.00 | 0.00 | 1.00 | 0.37 | 0.48 |
| Has Stock Market Inv (=1) | 321,350 | 0.00 | 0.00 | 0.00 | 0.23 | 0.42 |
| Has Mutual Fund Inv (=1) | 321,350 | 0.00 | 0.00 | 0.00 | 0.14 | 0.34 |
| Has PPF (=1) | 321,350 | 0.00 | 0.00 | 0.00 | 0.05 | 0.21 |

This table presents summary statistics for the key variables in a 4% random sample of depositors from a large private sector bank in India. The sample consists of 321,350 unique depositors, encompassing 7,933,335 observations across 8,034 ZIP codes from February 2019 to February 2021. The table shows the number of observations, as well as the 25th, 50th, and 75th percentile values, along with the mean and standard deviation. Panel A presents month-end balances. Banked wealth is defined as the sum of total deposits, stock market investments, mutual funds, and public provident funds (PPF). Total deposits refer to the combined balance of savings, time, and recurring deposits. Panel B presents depositor-level characteristics, including gender, imputed monthly income, credit score as of December 2019, number of household members, age, account age, and indicators for whether the depositor has a loan, stock market investment, mutual fund investment, or public provident fund (PPF). Panel C presents summary statistics for ISIN-level holdings for depositors with stock or mutual fund investments.

**Table 2:** Effect of DI Expansion on Bank Deposits

| Panel A: Narrow Bandwidth | | | | |
|---|---|---|---|---|
| Dep Var: LN(Deposits) | (1) | (2) | (3) | (4) |
| *Bunchers* × Post | 0.0372** | 0.0372** | 0.0363** | 0.0417** |
| | (0.0161) | (0.0161) | (0.0157) | (0.0162) |
| *Bunchers* | -0.2196*** | -0.2196*** | | |
| | (0.0154) | (0.0154) | | |
| Post | 0.0044 | | | |
| | (0.0123) | | | |
| Time FE | | Yes | Yes | |
| Depositor FE | | | Yes | Yes |
| ZIP X Time FE | | | | Yes |
| # Obs | 604,592 | 604,592 | 604,592 | 604,592 |
| $R^2$ | 0.0031 | 0.0035 | 0.5158 | 0.5609 |

| Panel B: Baseline Bandwidth | | | | |
|---|---|---|---|---|
| Dep Var: LN(Deposits) | (1) | (2) | (3) | (4) |
| *Bunchers* × Post | 0.0484*** | 0.0483*** | 0.0366*** | 0.0517*** |
| | (0.0107) | (0.0107) | (0.0105) | (0.0106) |
| *Bunchers* | -1.0519*** | -1.0518*** | | |
| | (0.0108) | (0.0108) | | |
| Post | 0.0038 | | | |
| | (0.0055) | | | |
| Time FE | | Yes | Yes | |
| Depositor FE | | | Yes | Yes |
| ZIP X Time FE | | | | Yes |
| # Obs | 2,666,481 | 2,666,481 | 2,666,481 | 2,666,481 |
| $R^2$ | 0.0422 | 0.0423 | 0.5775 | 0.5972 |

This table presents the response of bank deposits among bunchers compared to non-bunchers following the expansion of deposit insurance (DI). The dependent variable is the natural logarithm of bank deposits for depositor $i$ in month $t$. Post is an indicator variable taking a value of one for months since February 2020, and zero otherwise. The data covers the period from February 2019 to February 2021. Depositors are classified as bunchers or non-bunchers based on their average monthly deposits in the 12 months prior to February 2020. Panel A compares depositors in the ₹25,000 (25) bandwidth around the ₹100,000 (100) threshold. Specifically, we compare the response of bunchers (with pre-policy deposits $\in (75, 100]$) with the non-bunchers (with pre-policy deposits $\in (100, 125]$). Panel B compares the response of bunchers with pre-policy deposits in the $(75, 100]$ range with the non-bunchers whose pre-policy deposits fall within $(100, 500)$. All continuous variables are winsorized at the 1% level. Standard errors, clustered at the ZIP code level, are shown in parentheses. Statistical significance is indicated by *, **, and ***, corresponding to the 10%, 5%, and 1% levels, respectively.

**Table 3:** Characteristics of Bunchers

| Dep Var: Buncher | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| LN(Age) | -0.0599*** | -0.0139 | -0.0139 | -0.0136 | -0.0116 | -0.0188 |
| | (0.0123) | (0.0129) | (0.0130) | (0.0131) | (0.0130) | (0.0239) |
| Female (=1) | -0.0098 | 0.0110 | 0.0099 | 0.0092 | 0.0098 | 0.0091 |
| | (0.0079) | (0.0081) | (0.0082) | (0.0084) | (0.0083) | (0.0140) |
| Married (=1) | 0.0042 | -0.0121 | -0.0107 | -0.0106 | -0.0098 | 0.0148 |
| | (0.0100) | (0.0102) | (0.0103) | (0.0103) | (0.0103) | (0.0188) |
| HH Head (=1) | -0.0046 | -0.0067 | -0.0063 | -0.0062 | -0.0087 | -0.0117 |
| | (0.0089) | (0.0089) | (0.0090) | (0.0090) | (0.0090) | (0.0137) |
| LN(# HH Members) | 0.0143 | 0.0031 | 0.003 | 0.0031 | 0.0054 | |
| | (0.0106) | (0.0107) | (0.0107) | (0.0107) | (0.0115) | |
| LN(Bank Relationship) | 0.0014 | 0.0292*** | 0.0294*** | 0.0294*** | 0.0301*** | -0.008 |
| | (0.0042) | (0.0044) | (0.0045) | (0.0045) | (0.0047) | (0.0106) |
| LN(Income) | | 0.0002 | 0.0003 | 0.0003 | 0.0002 | 0.0017 |
| | | (0.0010) | (0.0011) | (0.0011) | (0.0011) | (0.0021) |
| LN(Banked Wealth) | | -0.1363*** | -0.1373*** | -0.1373*** | -0.1486*** | -0.2117*** |
| | | (0.0054) | (0.0054) | (0.0054) | (0.0055) | (0.0111) |
| Sh. Stocks | | 0.4049*** | 0.4067*** | 0.4067*** | 0.4398*** | 0.6393*** |
| | | (0.0218) | (0.0220) | (0.0220) | (0.0223) | (0.0478) |
| Sh. Mututal Funds | | 0.3059*** | 0.3077*** | 0.3078*** | 0.3443*** | 0.4290*** |
| | | (0.0252) | (0.0253) | (0.0253) | (0.0252) | (0.0566) |
| Sh. PPF | | 0.3679*** | 0.3708*** | 0.3707*** | 0.3948*** | 0.5899*** |
| | | (0.0334) | (0.0336) | (0.0336) | (0.0332) | (0.0755) |
| Scored (=1) | | | -0.0557 | -0.0539 | -0.0365 | 0.0342 |
| | | | (0.0963) | (0.0963) | (0.1005) | (0.1744) |
| CIBIL Score X Scored | | | 0.0001 | 0.0001 | 0.0000 | 0.0000 |
| | | | (0.0001) | (0.0001) | (0.0001) | (0.0002) |
| CC Holder (=1) | | | 0.0053 | 0.0055 | 0.0016 | -0.0037 |
| | | | (0.0091) | (0.0091) | (0.0091) | (0.0164) |
| Mortgage (=1) | | | -0.0448 | -0.0445 | -0.0343 | -0.1218 |
| | | | (0.0290) | (0.0290) | (0.0296) | (0.1134) |
| Auto Loan (=1) | | | -0.052 | -0.0517 | -0.0924*** | -0.085 |
| | | | (0.0346) | (0.0346) | (0.0323) | (0.0873) |
| Personal Loan (=1) | | | -0.0202 | -0.0201 | -0.0285 | -0.1015** |
| | | | (0.0261) | (0.0261) | (0.0253) | (0.0499) |
| Self Employed (=1) | | | | -0.0029 | -0.0032 | 0.0126 |
| | | | | (0.0085) | (0.0087) | (0.0183) |
| ZIP FE | | | | | Yes | |
| Household FE | | | | | | Yes |
| # Obs | 102,497 | 102,497 | 102,497 | 102,497 | 102,497 | 61,423 |
| $R^2$ | 0.0022 | 0.0452 | 0.0456 | 0.0456 | 0.1658 | 0.8082 |

This table presents the comparison of bunchers and non-bunchers across several characteristics. Depositors are classified as bunchers or non-bunchers based on their average monthly deposits in the 12 months prior to February 2020. Specifically, we compare bunchers (with pre-policy deposits $\in (70, 100]$) with the non-bunchers (with pre-policy deposits $\in (100, 500)$). LN(Age) is the natural logarithm of the depositor's age as of Jan 2020. Female (=1) is a binary variable taking a value of 1 for female depositors and 0 otherwise. Married (1=) is a binary variable taking a value of 1 for married depositors and 0 otherwise. HH Head (=1) is a binary variable taking a value of 1 for the household head and zero otherwise. LN(# HH Members) is the natural logarithm of the number of individuals in the depositor's household. LN(Bank Relationship) is the natural logarithm of the years since the depositor has had a bank account. LN(Income) is the natural logarithm of imputed income. LN(Bank Wealth) is the natural logarithm of banked wealth. Sh. stocks, Mutual Funds and PPF are the fraction of wealth in stocks, mutual funds and PPF, respectively. All depositor-level continuous characteristics are defined as the average value of characteristics over the twelve months before the DI expansion. Scored (=1) is a binary variable taking a value of one if the depositor has a credit score and zero otherwise. CIBIL Score refers to the Transunion-CIBIL credit score of depositors. CC Holder (=1), Mortgage (=1), Auto Loan (=1), and Personal Loan (=1) are binary variables taking a value of one if the depositor has a credit card, mortgage loan, auto loan, and personal loan with our bank before the DI expansion, respectively. Self-employed (=1) is a binary variable taking a value of 1 for depositors that are self-employed and zero otherwise. The regressions are weighted by the distance of the depositor's pre-policy average deposits from ₹100,000. All continuous variables are winsorized at the 1% level. Standard errors, clustered at the ZIP code level, are shown in parentheses. Statistical significance is indicated by *, **, and ***, corresponding to the 10%, 5%, and 1% levels, respectively.

**Table 4:** Characteristics of Trading Bunchers

| Dep Var: Trader | (2) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| LN(Age) | 0.0835*** | -0.0297** | -0.0193 | -0.0183 | -0.0287* |
| | (0.0188) | (0.0150) | (0.0148) | (0.0149) | (0.0155) |
| Female (=1) | -0.0481*** | -0.0629*** | -0.0460*** | -0.0477*** | -0.0512*** |
| | (0.0114) | (0.0092) | (0.0094) | (0.0099) | (0.0100) |
| Married (=1) | -0.0059 | 0.0162 | 0.0081 | 0.0085 | 0.0167 |
| | (0.0145) | (0.0117) | (0.0116) | (0.0116) | (0.0116) |
| HH Head (=1) | 0.0204 | 0.0220** | 0.0142 | 0.0144 | 0.0186* |
| | (0.0131) | (0.0105) | (0.0105) | (0.0106) | (0.0107) |
| LN(# HH Members) | -0.0302* | -0.0092 | -0.0094 | -0.0092 | 0.0079 |
| | (0.0159) | (0.0132) | (0.0131) | (0.0131) | (0.0142) |
| LN(Bank Relationship) | 0.0848*** | -0.0160*** | -0.0216*** | -0.0218*** | -0.0274*** |
| | (0.0070) | (0.0061) | (0.0062) | (0.0062) | (0.0065) |
| LN(Income) | | 0.0039*** | 0.0026** | 0.0024** | 0.0001 |
| | | (0.0012) | (0.0012) | (0.0012) | (0.0012) |
| LN(Banked Wealth) | | 0.2209*** | 0.2218*** | 0.2216*** | 0.2181*** |
| | | (0.0035) | (0.0035) | (0.0036) | (0.0038) |
| Sh. PPF | | -0.4906*** | -0.5044*** | -0.5046*** | -0.5094*** |
| | | (0.0437) | (0.0437) | (0.0438) | (0.0425) |
| Scored (=1) | | | 0.0288 | 0.0339 | 0.1510 |
| | | | (0.0943) | (0.0950) | (0.0965) |
| CIBIL Score X Scored | | | 0.0000 | 0.0000 | -0.0002 |
| | | | (0.0001) | (0.0001) | (0.0001) |
| CC Holder (=1) | | | 0.0440*** | 0.0447*** | 0.0474*** |
| | | | (0.0109) | (0.0109) | (0.0109) |
| Mortgage (=1) | | | -0.0132 | -0.0123 | -0.0138 |
| | | | (0.0386) | (0.0386) | (0.0364) |
| Auto Loan (=1) | | | 0.0153 | 0.0161 | 0.0335 |
| | | | (0.0438) | (0.0438) | (0.0322) |
| Personal Loan (=1) | | | 0.0723** | 0.0725** | 0.0692** |
| | | | (0.0354) | (0.0353) | (0.0333) |
| Self Employed (1=) | | | | -0.0077 | -0.0025 |
| | | | | (0.0100) | (0.0102) |
| ZIP FE | | | | | Yes |
| # Obs | 13,071 | 13,071 | 13,071 | 13,071 | 13,071 |
| $R^2$ | 0.0566 | 0.403 | 0.4084 | 0.4085 | 0.5314 |

This table presents the comparison of trading bunchers and non-trading bunchers across several characteristics. Depositors are classified as bunchers based on their average monthly deposits in the 12 months prior to February 2020. A buncher is defined as a trader if they hold a stock market security or a mutual fund in their portfolio. LN(Age) is the natural logarithm of the depositor's age as of Jan 2020. Female (=1) is a binary variable taking a value of 1 for female depositors and 0 otherwise. Married (1=) is a binary variable taking a value of 1 for married depositors and 0 otherwise. HH Head (=1) is a binary variable taking a value of 1 for the household head and zero otherwise. LN(# HH Members) is the natural logarithm of the number of individuals in the depositor's household. LN(Bank Relationship) is the natural logarithm of the years since the depositor has had a bank account. LN(Income) is the natural logarithm of imputed income. LN(Bank Wealth) is the natural logarithm of banked wealth. All depositor-level continuous characteristics are defined as the average value of characteristics over the twelve months before the DI expansion. Scored (=1) is a binary variable taking a value of one if the depositor has a credit score and zero otherwise. CIBIL Score refers to the Transunion-CIBIL credit score of depositors. CC Holder (=1), Mortgage (=1), Auto Loan (=1), and Personal Loan (=1) are binary variables taking a value of one if the depositor has a credit card, mortgage loan, auto loan, and personal loan with our bank before the DI expansion, respectively. Self-employed (=1) is a binary variable taking a value of 1 for depositors that are self-employed and zero otherwise. The regressions are weighted by the distance of the depositor's pre-policy average deposits from ₹100,000. All continuous variables are winsorized at the 1% level. Standard errors, clustered at the ZIP code level, are shown in parentheses. Statistical significance is indicated by *, **, and ***, corresponding to the 10%, 5%, and 1% levels, respectively.

**Table 5:** Liquidation of Security Holdings & DI Expansion

| Panel A: Dep Var = LN(Amount of $Security_j$) | | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| Buncher X Post | -0.0171*** | -0.0174*** | -0.0132*** |
| | (0.0051) | (0.0040) | (0.0044) |
| Buncher | -0.1458*** | | |
| | (0.0093) | | |
| ISIN X Time FE | Yes | Yes | Yes |
| Depositor FE | | Yes | Yes |
| ZIP X Time FE | | | Yes |
| # Obs | 9,364,485 | 9,364,485 | 9,364,485 |
| $R^2$ | 0.5498 | 0.7369 | 0.7381 |

| Panel B: Dep Var = LN(#Shares of $Security_j$) | | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| Buncher X Post | -0.0171*** | -0.0162*** | -0.0116*** |
| | (0.0051) | (0.0040) | (0.0044) |
| Buncher | -0.1464*** | | |
| | (0.0094) | | |
| ISIN X Time FE | Yes | Yes | Yes |
| Depositor FE | | Yes | Yes |
| ZIP X Time FE | | | Yes |
| # Obs | 9,364,485 | 9,364,485 | 9,364,485 |
| $R^2$ | 0.3280 | 0.6065 | 0.6083 |

This table presents the response of security holdings among bunchers compared to non-bunchers following the expansion of deposit insurance (DI). In Panel A, the dependent variable is the natural logarithm of the total amount invested in security $j$ by the depositor $i$ in month $t$. In Panel B, the dependent variable is the natural logarithm of the total number of shares held of security $j$ by the depositor $i$ in month $t$. Post is an indicator variable taking a value of one for months since February 2020, and zero otherwise. The data covers the period from February 2019 to February 2021. Depositors are classified as bunchers or non-bunchers based on their average monthly deposits in the 12 months prior to February 2020. We compare the response of bunchers with pre-policy deposits in the $(75, 100]$ range with the non-bunchers whose pre-policy deposits fall within $(100, 500)$. ISIN refers to a unique identifier of security $j$. All continuous variables are winsorized at the 1% level. Standard errors, clustered at the ZIP code and ISIN level, are shown in parentheses. Statistical significance is indicated by *, **, and ***, corresponding to the 10%, 5%, and 1% levels, respectively.

**Table 6:** What Do Bunchers Liquidate?

| Dep Var: $Portfolio - Tilt^{c}_{i,t}$ | Coef | St Error | # Obs | $R^2$ |
|---|---|---|---|---|
| *Firm Owenrship* | | | | |
| State Owned | -0.0351** | (0.0140) | 507,265 | 0.8742 |
| Business Group Firm | 0.0010 | (0.0128) | 507,265 | 0.8773 |
| *Sector of Operations* | | | | |
| Manufacturing | 0.0140 | (0.0123) | 507,265 | 0.8846 |
| Financial | -0.0056 | (0.0125) | 507,265 | 0.8671 |
| Wholesale | 0.0064 | (0.0120) | 507,265 | 0.8645 |
| Diversified | -0.0008 | (0.0126) | 507,265 | 0.8829 |
| Construction | -0.0042 | (0.0130) | 507,265 | 0.8988 |
| Information & Communication | -0.0020 | (0.0118) | 507,265 | 0.9172 |
| Agriculture | -0.0082 | (0.0144) | 507,265 | 0.8517 |
| *Stock Market Characteristics* | | | | |
| Market Alpha | -0.0093 | (0.0121) | 496,230 | 0.8918 |
| Market Beta | -0.0024 | (0.0119) | 496,230 | 0.9099 |
| Realized Returns | -0.0078 | (0.0131) | 498,046 | 0.8810 |
| Realized Volatility | -0.0215 | (0.0131) | 498,044 | 0.9099 |
| Market Cap | 0.0096 | (0.0119) | 498,046 | 0.9134 |
| *Accounting Characteristics* | | | | |
| Dividend Payer | 0.0058 | (0.0133) | 503,668 | 0.8844 |
| Market to Book | 0.0100 | (0.0110) | 494,378 | 0.9044 |
| Age | 0.0059 | (0.0131) | 507,204 | 0.8757 |
| Size | -0.0012 | (0.0122) | 503,668 | 0.9064 |
| Leverage | -0.0187 | (0.0131) | 503,649 | 0.8796 |
| Interest Coverage Ratio | 0.0038 | (0.0127) | 494,746 | 0.8865 |
| Cash to Assets | 0.0168 | (0.0109) | 503,668 | 0.8813 |
| Operating Margin | 0.0006 | (0.0138) | 478,326 | 0.8757 |
| Tangibility | 0.0066 | (0.0133) | 503,668 | 0.8669 |

This table presents the change in portfolio tilts of bunchers relative to non-bunchers after DI expansion. We estimate the following regression of each depositor-stock characteristic separately and report the associated coefficients, standard errors, number of observations and model $R^2$:

$$Portfolio - Tilt^{c}_{i,t} = \beta^{c} \times Buncher_i \cdot Post_t + \theta_i + \theta_{z(i \in z),t} + \varepsilon_{i,t}$$

where, $Portfolio - Tilt^{c}_{i,t}$ refers to the portfolio tilt for characteristic $c$ for depositor $i$ at time $t$. For each depositor and each stock characteristic, we construct the monthly holdings-weighted characteristic of the household's portfolio using portfolio shares as holdings. For continuous variables, we first rank stocks by their characteristic values and use the demeaned rank as our stock-level characteristic measure. The characteristics we consider are (1) firm ownership: state-owned and business group ownership; (2) sector of operations: manufacturing, financial, wholesale, diversified, construction, information and communication, and agriculture; (3) market characteristics: market alpha, market beta, realized returns, realized volatility, and market capitalization; and (4) accounting characteristics: dividend payer, market to book value ratio (market capitalization to book equity), age (years since incorporation relative in 2020), size (total assets), leverage (total debt minus preferred shares divided by total net worth plus total debt minus preferred shares), interest coverage ratio (profits before interest, taxes, depreciation and amortization divided by interest expense plus interest capitalized plus Interest transferred to deferred revenue expenditure, cash to assets ratio, operating margin (profits before interest, taxes, depreciation and amortization divided by total sales), and tangibility (gross property and plant divided by total assets). We compute stock-level characteristics by taking their average value between 2017 and 2019. Standard errors, clustered at the ZIP code level, are shown in parentheses. Statistical significance is indicated by *, **, and ***, corresponding to the 10%, 5%, and 1% levels, respectively.

**Table 7:** Bunchers & Portfolio Tilt based on State Owned Enterprises (SOE)

| Dep Var: Portfolio Tilt based on SOE | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| *Bunchers* × Post | -0.0402** | -0.0367** | -0.0365** | -0.0355*** | -0.0351** | -0.0257*** |
| | (0.0163) | (0.0160) | (0.0160) | (0.0135) | (0.0140) | (0.0089) |
| *Bunchers* | 0.0745*** | 0.0620** | 0.0620** | | | |
| | (0.0266) | (0.0269) | (0.0269) | | | |
| Post | 0.0450*** | 0.0343*** | | | | |
| | (0.0064) | (0.0062) | | | | |
| Controls for Other Portfolio Titls | | | | | | Yes |
| ZIP FE | | Yes | Yes | | | |
| Time FE | | | Yes | Yes | | |
| Depositor FE | | | | Yes | Yes | Yes |
| ZIP X Time FE | | | | | Yes | Yes |
| # Obs | 507,265 | 507,265 | 507,265 | 507,265 | 507,265 | 462,608 |
| $R^2$ | 0.0007 | 0.1044 | 0.1052 | 0.8588 | 0.8742 | 0.9296 |

This table presents the change in portfolio tilt based on state-owned enterprises (SOE) of bunchers relative to non-bunchers after DI expansion. For each depositor and each stock characteristic, we construct the monthly holdings-weighted characteristic of the household's portfolio using portfolio shares as holdings. For continuous variables, we first rank stocks by their characteristic values and use the demeaned rank as our stock-level characteristic measure. The characteristics we consider are (1) firm ownership: state-owned and business group ownership; (2) sector of operations: manufacturing, financial, wholesale, diversified, construction, information and communication, and agriculture; (3) market characteristics: market alpha, market beta, realized returns, realized volatility, and market capitalization; and (4) accounting characteristics: dividend payer, age (years since incorporation relative in 2020), size (total assets), leverage (total debt minus preferred shares divided by total net worth plus total debt minus preferred shares), interest coverage ratio (profits before interest, taxes, depreciation and amortization divided by interest expense plus interest capitalized plus Interest transferred to deferred revenue expenditure, cash to assets ratio, operating margin (profits before interest, taxes, depreciation and amortization divided by total sales), and tangibility (gross property and plant divided by total assets). We compute stock-level characteristics by taking their average value between 2017 and 2019. The controls in Column 6 include portfolio tilts based on all other characteristics. Standard errors, clustered at the ZIP code level, are shown in parentheses. Statistical significance is indicated by *, **, and ***, corresponding to the 10%, 5%, and 1% levels, respectively.

*Internet Appendix for:*

**"Household Portfolio and Deposit Insurance: Implications for the Supply of Safe Asset"**

# Contents

# Appendix A Institutional Details

## A.1 Deposit Insurance in India

Deposit Insurance and Credit Guarantee Corporation (DICGC) is a wholly-owned subsidiary of the Reserve Bank of India (RBI). It provides deposit insurance that works as a protection cover for bank deposit holders when the bank fails to pay its depositors. The agency's operations are performed as per The Deposit Insurance and Credit Guarantee Corporation Act, 1961 and The Deposit Insurance and Credit Guarantee Corporation General Regulations, 1961, framed by RBI under the provisions of sub-section (3) of Section 50 of the act.

### A.1.1 What does the insurance cover?

The agency insures all kinds of bank deposit accounts, such as savings, current, recurring, and fixed deposits up to a limit of ₹500,000 per account holder per bank. In case an individual's deposit amount exceeds ₹500,000 in a single bank, only ₹500,000, including the principal and interest, will be paid by DICGC if the bank becomes bankrupt. The deposits kept in different branches of a bank are aggregated for insurance coverage and a maximum amount of up to ₹500,000 is paid. DICGC protects depositors' money kept in all commercial and foreign banks located in India; central, state, and urban co-operative banks; regional rural banks; and local banks, provided that the bank has opted for DICGC cover.

However, DICGC does not cover – deposits of state or central governments, deposits from foreign governments, state land development banks depositing with the state co-operative bank, inter-bank deposits, funds that are due on account of India and deposits received outside India, and certain funds exempted by the corporation with the previous approval from RBI.

### A.1.2 DICGC accreditation

The deposit insurance scheme is mandatory for all commercial and foreign banks located in India; central, state, and urban cooperative banks; and regional rural banks. When banks register with DICGC, the agency grants a printed certificate to the bank that displays information regarding the protection offered by DICGC to depositors of the insured bank. Customers are entitled to enquire with the bank officials about the DICGC certification.

All DICGC-accredited banks must pay a premium to DICGC no later than the last day of May and November each year. They have to pay an annual premium of ₹0.12 per ₹100 of assessable deposits. This amount was revised from ₹0.1 per ₹100 on 1 April 2020. Failure to pay the premium can result in a financial penalty as well as cancellation of registration. The premium is absorbed by the bank and depositors do not need to pay the premium.

Moreover, the Corporation is empowered (vide Section 35 of the DICGC Act) to have free access to the records of any insured bank. DICGC can direct the RBI to investigate any insured bank.

### A.1.3 Changes in deposit insurance limit over time

The insurance limit has experienced a series of adjustments over the decades. Appendix Table A.1 presents the timeline of these changes. Initially set at ₹5,000 on January 1, 1968, it was raised to ₹10,000 on April 1, 1970, and further increased to ₹20,000 on January 1, 1976. The limit was then elevated to ₹30,000 on July 1, 1980. A significant increase occurred on May 1, 1993, when the insurance limit was raised to ₹100,000. Following this adjustment, the limit remained largely stagnant for nearly three decades. However, in 2020, it was dramatically raised to ₹500,000, representing a five-fold increase and substantially enhancing the coverage offered to depositors.

**Table A.1:** Timeline of changes in deposit insurance limit

| Effective Date | Amount Insured | |
|---|---|---|
| | (in INR) | (in USD) |
| 1 January, 1968 | ₹5,000 | $ 67.5 |
| 1 April, 1970 | ₹10,000 | $ 135 |
| 1 January, 1976 | ₹20,000 | $ 270 |
| 1 July, 1980 | ₹30,000 | $ 405 |
| 1 May, 1993 | ₹100,000 | $ 1,350 |
| 4 February, 2020 | ₹500,000 | $ 6,750 |

This table presents the timeline of changes in the deposit insurance limit in India since the inception of the deposit insurance program.

### A.1.4 Other changes to deposit insurance after 2020

Deposit Insurance & Credit Guarantee Corporation (Amendment) Bill 2021 provides an insurance amount of up to ₹500,000 to an account holder within 90 days in the event of a bank coming under the moratorium imposed by the RBI. Earlier, account holders had to wait for a substantial time till the liquidation or restructuring of a distressed lender to get their deposits that are insured against default.

### A.1.5 A brief history of DICGC

Deposit insurance, as a formalized policy, was introduced in India in 1962, making it the second country globally to adopt such a system, following the United States. The roots of deposit insurance in India can be traced back to the banking crisis of 1938, marked by the failure of the Travancore National and Quilon Bank, the largest bank in the Travancore region. This incident prompted the Indian government to prioritize banking legislation and reform, especially focusing on the need for depositors' protection.

The significance of deposit insurance recurred during the banking crisis in Bengal between 1946 and 1948. During this turbulent period, the necessity for a structured deposit insurance scheme was acknowledged; however, it was decided to defer implementation until the Banking Companies Act of 1949 was enacted. The aim was to ensure sufficient oversight and regulation of banking institutions, facilitated by the Reserve Bank of India. The eventual catalyst for the establishment of a formal deposit insurance scheme came in 1960, following the failures of Laxmi Bank and Palai Central Bank. These incidents highlighted the vulnerability of depositors and the banking sector, leading to the introduction of the Deposit Insurance Corporation (DIC) Bill in Parliament on August 21, 1961. The bill received presidential assent on December 7, 1961, and the DIC commenced its operations on January 1, 1962.

Initially intended for commercial banks, the Deposit Insurance Scheme aimed to protect depositors, particularly small account holders, from the risk of bank failures. By assuring depositor safety, the scheme sought to prevent mass withdrawals—often rooted in panic—thereby promoting stability and growth within the banking system. Additionally, enhancing depositor confidence was deemed crucial for facilitating the mobilization of savings necessary for broader economic development.

In its early years, the DIC saw a considerable registration of banks. At the start, 287 banks were insured under the scheme; however, due to the Reserve Bank of India's policies aimed at restructuring the banking sector, this number dwindled to 100 by the end of 1967. These policies focused on the amalgamation of smaller, financially weak banks to strengthen the banking framework in India.

An important development occurred in 1968 when the DIC was empowered to extend deposit insurance to eligible cooperative banks. This move significantly broadened the institution's scope, as the number of cooperative banks far exceeded that of commercial banks, with over 1,000 cooperative banks compared to 83 commercial banks at that time. Consequently, this expansion necessitated a considerable enhancement of DIC's operational capabilities.

Further evolution took place with the founding of the Credit Guarantee Corporation of India Ltd. (CGCI) in 1971. While the DIC primarily focused on deposit insurance to safeguard depositors, the CGCI aimed to address the credit needs of underrepresented sectors and promote inclusive banking practices. In 1978, a pivotal change occurred when the DIC and CGCI were merged to form the Deposit Insurance and Credit Guarantee Corporation (DICGC). This merger not only integrated the functions of deposit insurance and credit guarantees but also redefined the focus of the newly formed entity, shifting towards enhanced credit guarantees in light of the banking sector's nationalization. However, as India underwent financial sector reforms in the 1990s, the landscape of banking and credit guarantees shifted dramatically. Consequently, the DICGC began to gradually phase out credit guarantees, returning its focus to its core mission of deposit insurance.

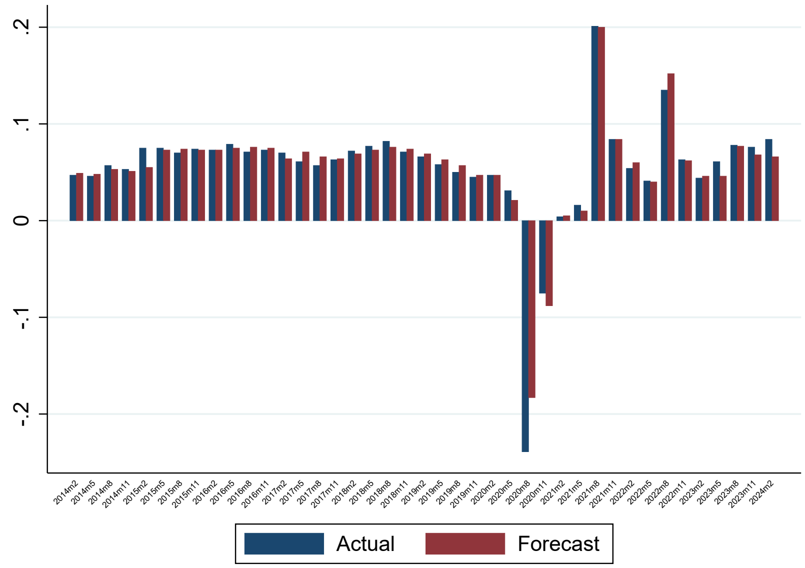
## A.2 Indian Economy at Large

**Table A.2:** Deposit insurance to per capita income ratio across the world

| Country | Deposit Insurance | GDP per capita, | Deposit to per capita Income |
|---|---|---|---|
| Brazil | $ 48,950 | $ 6,923 | 7.07 |
| Russia | $ 19,460 | $ 10,194 | 1.91 |
| India | $ 1,350 | $ 1,913 | 0.71 |
| China | $ 72,500 | $ 10,408 | 6.97 |
| South Africa | $ 6,110 | $ 5,753 | 1.06 |
| | | | |
| US | $ 250,000 | $ 63,528 | 3.94 |
| UK | $ 109,114 | $ 40,217 | 2.71 |
| Canada | $ 74,620 | $ 43,562 | 1.71 |

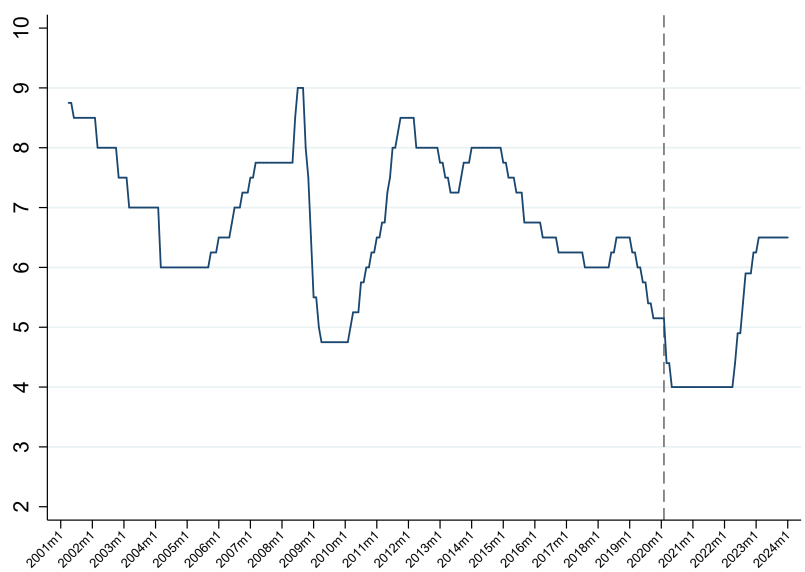
This table presents the deposit insurance to per capita income ratio across the BRICS (Brazil, Russia, India, China, and South Africa) nations and the United States, United Kingdom and Canada. The raw numbers come from World Bank statistics.

**Figure A.1:** Indian GDP growth rate over time




This figure plots the actual and forecasted quarterly GDP (gross domestic product) growth rate from February 2014 until February 2024. The figure is plotted by the authors based on raw numbers from the Reserve Bank of India.

**Figure A.2:** Repo rate over time




This figure plots the repo rate – the key monetary policy tool employed by the Reserve Bank of India – from January 2001 until January 2021. The repo rate is equivalent to the Fed funds rate in the US. The figure is plotted by the authors based on raw numbers from the Reserve Bank of India.

## A.3 Deposit Rate Schedule

**Table A.3:** Deposit rate schedule

| Deposit Amount (in INR million) | Interest rate (per annum) on 26 Apr 2019 | | | |
|---|---|---|---|---|
| | State Owned Bank (A) | State Owned Bank (B) | Comparable Private Bank | Our Bank |
| Upto 5 mn | 3.50% | 3.50% | 3.50% | 3.50% |
| Above 5 mn & Upto 10 mn | 3.50% | 3.50% | 4.00% | 4.00% |
| Above 10 mn | 4.00% | 4.00% | 4.00% | 4.00% |

This table presents the deposit rate schedule for four key banks in India as of April 2019. Columns 1 and 2 present deposit rates for the two large state-owned banks in India. Column 3 presents the deposit rate schedule for a large private sector bank in India that is comparable to our data provider. Column 4 presents the deposit rate schedule of our data provider.

## A.4 Mutual Funds Landscape in India

This section presents an overview of the mutual funds landscape in India, with specific emphasis on the trends in fund types, investor categories, and their respective contributions to assets under management (AUM). Mutual funds are professionally managed investment vehicles that pool money from multiple investors to purchase a diversified portfolio of stocks, bonds, or other securities. The analysis herein explores the different types of mutual funds and investors, summarizing their share in the mutual fund landscape.

### A.4.1 Mutual Funds Classification in India

Mutual funds in India are classified into several categories based on their investment strategies. Equity funds primarily invest in stocks and aim for long-term capital appreciation. Debt funds, in contrast, focus on fixed-income securities like bonds. Hybrid funds provide a mix of equity and debt instruments. Money market funds in India specialize in short-term, low-risk instruments that are highly liquid. They primarily invest in treasury bills, certificates of deposits, commercial papers, repos, and call money. Gilt funds primarily invest in debt instruments issued by the federal and state governments in India. Exchange-Traded Funds (ETFs) are designed to track indices or sectors and trade on stock exchanges like individual stocks. Lastly, foreign funds provide exposure to international markets, allowing diversification across global assets.

### A.4.2 Types of Investors in Indian Mutual Funds

The investor base for mutual funds in India is diverse, encompassing several distinct categories. First, retail investors who typically invest smaller amounts, often utilizing systematic investment plans (SIPs) to construct their portfolios. In contrast, there are high-net-worth individuals (HNIs), who possess significant wealth and generally qualify for exclusive investment opportunities and specialized financial services. HNIs typically have a minimum investment threshold of ₹50 million (approximately $650,000) in mutual funds, distinguishing them from the broader retail investor segment.

Foreign investors also play a crucial role in the Indian mutual fund landscape. This category includes individuals and entities based outside of India, categorized according to regulatory frameworks. Among them are foreign portfolio investors (FPIs), who are entities or individuals registered with the

Securities and Exchange Board of India (SEBI). These investors can access the Indian securities markets, including mutual funds, and they often consist of institutional investors such as pension funds, endowments, and hedge funds. Additionally, some foreign investors can adhere to guidelines set by SEBI and the Reserve Bank of India (RBI) to become qualified foreign investors (QFIs), granting them the ability to invest directly in Indian mutual funds. There are also non-resident Indians (NRIs), who are Indian citizens residing abroad, who qualify as foreign investors and are permitted to invest in mutual funds as well.

Beyond these groups, corporates and financial institutions, including banks and insurance companies, actively participate in mutual fund investments.

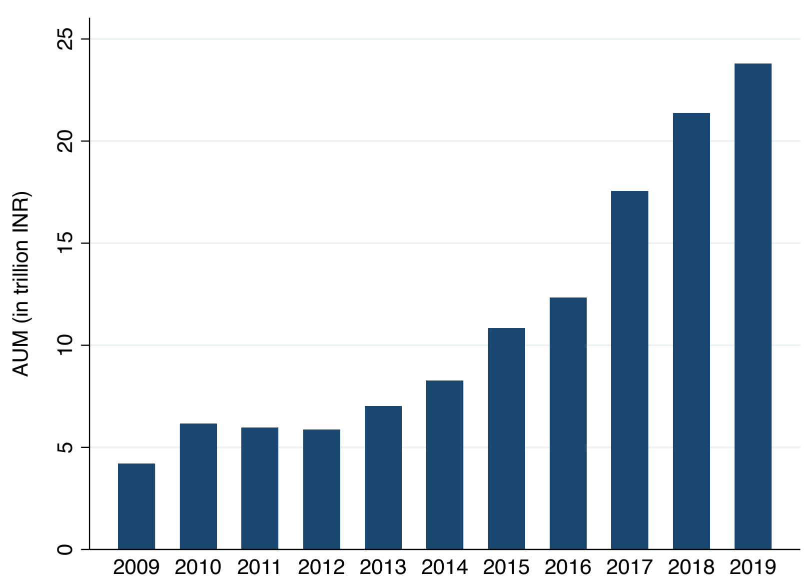
### A.4.3 Data

The data utilized in this analysis is sourced from the Association of Mutual Funds in India (AMFI), a non-profit organization that serves as a representative body for all mutual funds registered with the Securities and Exchange Board of India (SEBI). The specific dataset employed, titled *AUM-Category / Age Wise and Folio Data*, is accessible on AMFI's official website and can be found here. This dataset provides detailed quarterly information on assets under management (AUM) across various fund categories and investor types. We use the data as on the quarter ending in March (the end of the fiscal year) for our description of the mutual fund landscape in India.

### A.4.4 Assets Under Management (AUM)

Figure A.3 illustrates the total assets under management (AUM) in the Indian mutual fund industry from 2009 to 2019. The AUM demonstrates consistent growth, starting from below ₹5 trillion in 2009 and surpassing ₹25 trillion by 2019 indicating an exponential growth of 400% over the period.

**Figure A.3:** Total Assets Under Management (AUM)




This figure plots the total Assets Under Management (AUM) in the Indian mutual fund industry from 2009 to 2019. The figure is plotted by the authors using the end of the fiscal year data on AUM from Association of Mutual Funds in India (AMFI).

### A.4.5 Mutual Fund AUM by Fund Type

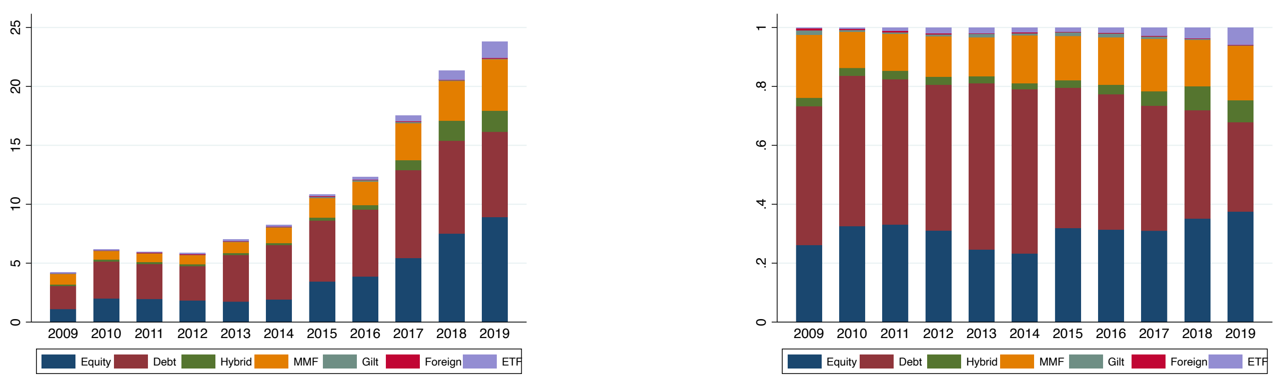
Figure A.4 illustrates the contributions of various fund types to the overall Assets Under Management (AUM). In particular, Figure A.4a details the absolute contributions from each fund type, while Figure A.4b highlights their relative contributions.

The Indian mutual fund landscape is predominantly shaped by equity and debt funds, which collectively accounted for 68% of the total Assets Under Management (AUM) in 2019. Within this framework, debt funds contributed 30% to the overall AUM. Over the past decade, the significance of equity funds has notably increased, rising from 26% in 2009 to 38% in 2019. In contrast, the share of debt funds has decreased from 47% in 2009.

Hybrid funds, which blend debt and equity instruments, have also gained prominence, increasing their share from 2.8% in 2009 to 7.6% in 2019. Meanwhile, Money Market Funds have seen a 6 percentage point increase in their contribution to total AUM, rising from 12% in 2010 to over 18% in 2019. Exchange-Traded Funds (ETFs) have also experienced substantial growth, accounting for 6% of total AUM in 2019, a significant rise from just 0.4% in 2009. In contrast, both gilt and foreign funds represent a modest fraction of the total AUM, each comprising less than 1% throughout this period.

While equity funds hold a significant position in the Indian mutual fund landscape, similar to patterns observed in developed economies like the United States, Exchange-Traded Funds (ETFs) tend to have a much larger presence in the U.S. fund market compared to India.

**Figure A.4:** Mutual Fund AUM by Fund Type



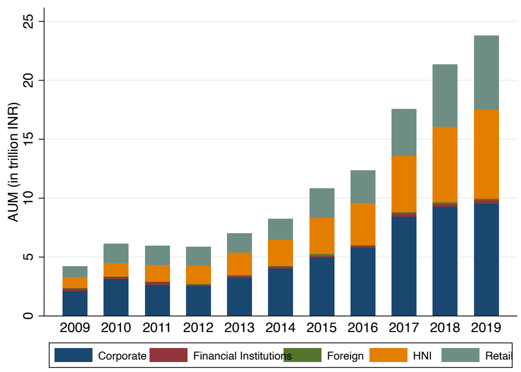

(a) Absolute Contributions (b) Proportional Contributions

These figures show the absolute and proportional contributions of different fund types to total Assets Under Management (AUM) from 2009 to 2019. The left panel displays absolute contributions, while the right panel shows proportional contributions. Fund types include Equity, Debt, Hybrid, MMF (Money Market Fund), Gilt, Foreign, and ETF (Exchange-Traded Fund). The figures are plotted by the authors using quarterly AUM reports from the Association of Mutual Funds in India (AMFI).

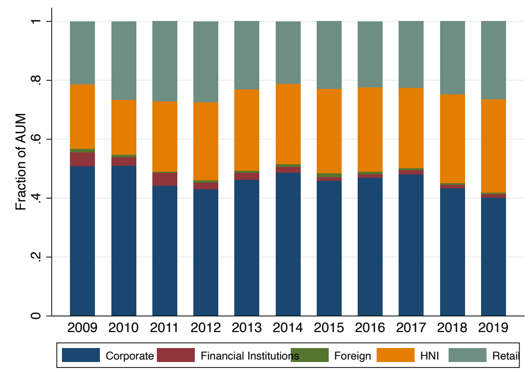
### A.4.6 Mutual Fund Investment by Investor Type

Figure A.5 presents the distribution of mutual fund investment by different types of investors. Non-financial corporate investors have consistently emerged as the largest investors in Indian mutual funds, accounting for more than 40% of total investments throughout the period. Following them are high-net-worth individuals, who represent the second-largest segment of investors. Retail investors are the third largest investors in this market, contributing at least 20% of total investments during this period. In contrast, financial institutions and foreign investors have made relatively limited contributions to the Indian mutual fund industry.

**Figure A.5:** Mutual Fund Investment by Investor Type




(a) Absolute Distribution




(b) Proportional Distribution

The figures display absolute and proportional AUM distribution across investor categories, including corporates, financial institutions, foreign investors, HNIs, and retail investors, from 2009 to 2019.

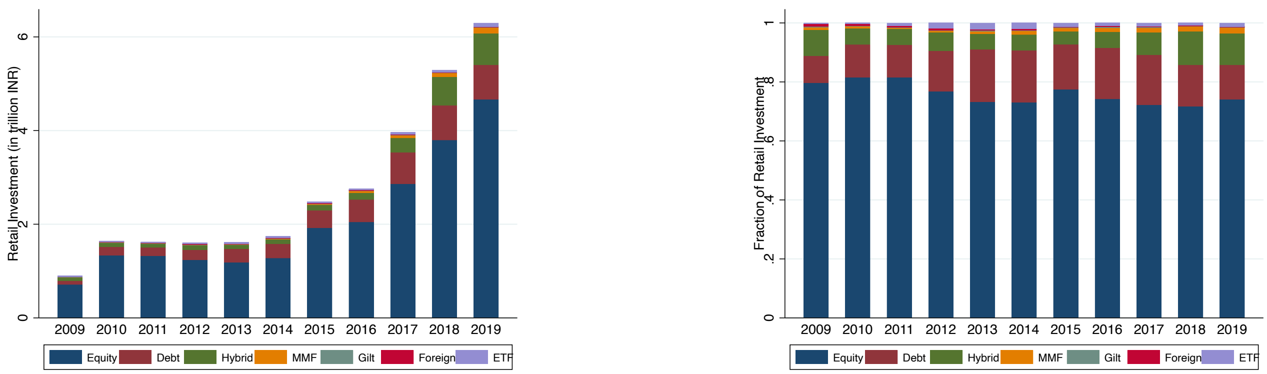
This contrasts sharply with the U.S. mutual fund market, where retail investors represent a significant portion of mutual fund investments. Financial institutions also play a crucial role. Additionally, foreign investors are more actively engaged in the U.S. mutual fund market.

### A.4.7 What type of Funds Do Retail Investors Invest In?

Figure A.6 presents the distribution of retail investment in Indian mutual funds by fund type. Retail investors predominantly favor equity funds, which account for over 70% of their total investments during the sample period. Debt funds follow as the second most popular choice, representing 12% of retail investments in 2019, while hybrid funds account for 11%. Money market funds make up approximately 2% of retail investments in 2019, up from 0.8% in 2009.

In contrast, non-retail investors show a preference for debt funds and money market funds, as shown in Figure A.7. This highlights a clear segmentation in demand within India's mutual fund industry: smaller retail investors invest more in equity funds, while larger non-retail investors predominantly invest in debt and money market funds.

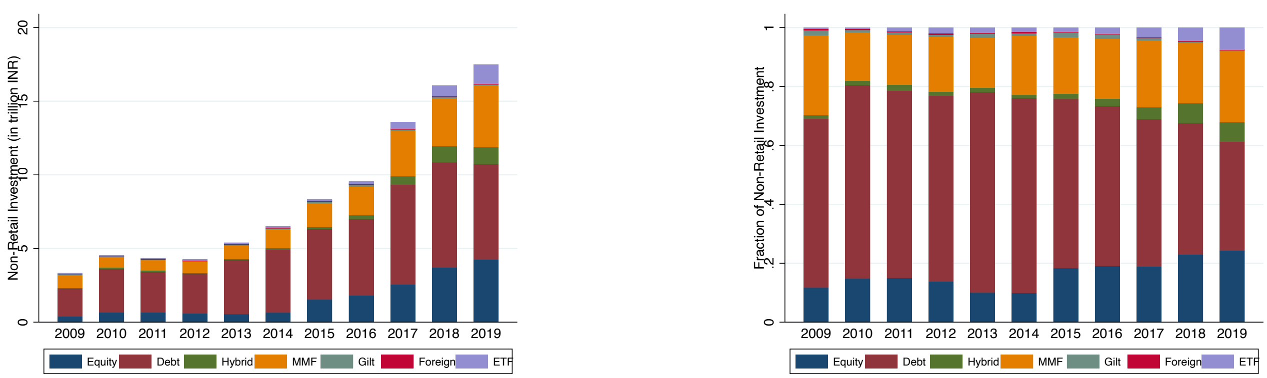
**Figure A.6:** Retail Investments Across Fund Types




(a) Absolute retail investments (b) Proportional retail investments

The figures present absolute and proportional retail investments across various fund types from 2009 to 2019. Fund categories include Equity, Debt, Hybrid, MMF(Money Market Fund), Gilt, Foreign, and ETFs (Exchange-Traded Funds).

**Figure A.7:** Non-retail Investments Across Fund Types




(a) Absolute non-retail investments (b) Proportional non-retail investments

The figures present absolute and proportional non-retail investments across various fund types from 2009 to 2019. Fund categories include Equity, Debt, Hybrid, MMF (Money Market Fund), Gilt, Foreign, and ETFs (Exchange-Traded Funds).

# Appendix B Theoretical Framework

We characterize the setting through a quadratic utility function with risk aversion coefficient $\gamma$, $U(E,\sigma) = E - \gamma\sigma^2$, considering that the endowment is placed in stocks $M$ and deposits $D$, $Y = M + D$, and defining the expected returns from stocks as $\rho = E(\widetilde{R}_M) > 1$. Let $\sigma_M^2$ be the variance of the risky asset's returns. By the definition of $\tilde{R}_D$, $\sigma_D^2 D^2 = \pi(1-\pi)(D-\delta)^2 \mathbb{I}(D \geq \delta)$.

Due to the discontinuity of the deposit's payoff and risk structure, a consumer chooses his optimal $D^* \geq \delta$ if $U(D^*|D^* \geq \delta) \geq U(D^*|D^* < \delta)$ and vice versa. This means that a consumer will first decide whether to invest $D \geq \delta$ and then chooses his optimal $D^*$.

Conditional on $D < \delta$, the problem is as simple as:

$$\begin{aligned} &\max_D \rho(Y-D) + D - \gamma\left[\sigma_M^2 (Y-D)^2\right] \\ =&\max_D -\gamma\sigma_M^2 D^2 + (2\gamma\sigma_M^2 Y + 1 - \rho)D + (\rho Y - \gamma\sigma_M^2 Y^2) \end{aligned}$$

This hyperbola is maximized at $D = Y - \frac{\rho-1}{2\gamma\sigma_M^2}$ but it may very much be the case that $Y - \frac{\rho-1}{2\gamma\sigma_M^2} > \delta$. Considering that the function is increasing up to $Y - \frac{\rho-1}{2\gamma\sigma_M^2}$, consumer's optimal $D^*$ conditional $D < \delta$ is $\min\left[Y - \frac{\rho-1}{2\gamma\sigma_M^2}, \delta\right]$.

The utility of a consumer conditional on $D < \delta$, is then:

$$U = \begin{cases} U_1 = & \frac{(\gamma\sigma_M^2 Y + \frac{1-\rho}{2})^2}{\gamma\sigma_M^2} + (\rho Y - \gamma\sigma_M^2 Y^2) \\ & \text{if } Y - \frac{\rho-1}{2\gamma\sigma_M^2} < \delta \\ U_2 = & -\gamma\sigma_M^2\delta^2 + (2\gamma\sigma_M^2 Y + 1 - \rho)\delta + (\rho Y - \gamma\sigma_M^2 Y^2) \\ & \text{if } Y - \frac{\rho-1}{2\gamma\sigma_M^2} \geq \delta \end{cases} \tag{B.1}$$

Conditional on $D \geq \delta$, the problem is:

$$\begin{aligned} &\max_D \rho(Y-D) + E(\widetilde{R}_D D) - \gamma\left[\sigma_M^2(Y-D)^2 + \sigma_D^2 D^2\right] \\ =&\max_D \rho(Y-D) + \pi\delta + (1-\pi)D - \gamma\left[\sigma_M^2(Y-D)^2 + \pi(1-\pi)(D-\delta)^2\right] \\ =&\max_D -[\gamma\sigma_M^2 + \gamma\pi(1-\pi)]D^2 + [2\gamma\sigma_M^2 Y + 2\pi\gamma(1-\pi)\delta + 1 - \pi - \rho]D - \gamma\pi(1-\pi)\delta^2 - \gamma\sigma_M^2 Y^2 + \\ &+ \rho Y + \pi\delta \end{aligned}$$

We start by expressing the given function as a function of $D$:

$$f(D) = -[\gamma\sigma_M^2 + \gamma\pi(1-\pi)]D^2 + \left[2\gamma\sigma_M^2 Y + 2\pi\gamma(1-\pi)\delta + 1 - \pi - \rho\right]D - \gamma\pi(1-\pi)\delta^2 - \gamma\sigma_M^2 Y^2 + \rho Y + \pi\delta.$$

Next, we take the derivative of $f(D)$ with respect to $D$ and solve for $D$, yielding:

$$D = \frac{1-\pi-\rho+2\gamma\sigma_M^2 Y+2\gamma\pi(1-\pi)\delta}{2\gamma[\sigma_M^2+\pi(1-\pi)]}.$$

Adding and subtracting $Y$, we can rewrite $D$ to express the optimal level of deposits as:

$$D = Y + \frac{2\gamma\pi(1-\pi)(\delta-Y)+(1-\pi-\rho)}{2\gamma[\sigma_M^2+\pi(1-\pi)]}.$$

that can be rewritten as:

$$D = Y - \frac{2\gamma\pi(1-\pi)(Y-\delta)-(1-\pi-\rho)}{2\gamma[\sigma_M^2+\pi(1-\pi)]}.$$

However, it is possible that $Y - \frac{2\gamma\pi(1-\pi)(Y-\delta)-(1-\pi-\rho)}{2\gamma[\sigma_M^2+\pi(1-\pi)]} < \delta$. In this case, the optimal deposit level $D^*$ is given by $D^* = \max\left[Y - \frac{2\gamma\pi(1-\pi)(Y-\delta)-(1-\pi-\rho)}{2\gamma[\sigma_M^2+\pi(1-\pi)]}, \delta\right]$.

The utility of a consumer conditional on $D \geq \delta$, is then:

$$U = \begin{cases} U_3 = & \frac{[2\gamma\sigma_M^2 Y+2\gamma\pi(1-\pi)\delta+(1-\pi-\rho)]^2}{4\gamma[\sigma_M^2+\pi(1-\pi)]} - \gamma\pi(1-\pi)\delta^2 - \gamma\sigma_M^2 Y^2 + \rho Y + \pi\delta \\ & \text{if } Y - \frac{2\gamma\pi(1-\pi)(Y-\delta)-(1-\pi-\rho)}{2\gamma[\sigma_M^2+\pi(1-\pi)]} \geq \delta \\ U_4 = & -\gamma\sigma_M^2\delta^2 + (2\gamma\sigma_M^2 Y + 1 - \rho)\delta + (\rho Y - \gamma\sigma_M^2 Y^2) \\ & \text{if } Y - \frac{2\gamma\pi(1-\pi)(Y-\delta)-(1-\pi-\rho)}{2\gamma[\sigma_M^2+\pi(1-\pi)]} < \delta \end{cases} \tag{B.2}$$

It is valuable to characterize the relationship between

$$\frac{\rho-1}{2\gamma\sigma_M^2} \quad \text{and} \quad \frac{2\gamma\pi(1-\pi)(Y-\delta)-(1-\pi-\rho)}{2\gamma\left[\sigma_M^2+\pi(1-\pi)\right]},$$

and determine the value of $\rho$ such that:

$$\frac{2\gamma\pi(1-\pi)(Y-\delta)-(1-\pi-\rho)}{2\gamma\left[\sigma_M^2+\pi(1-\pi)\right]} \geq \frac{\rho-1}{2\gamma\sigma_M^2}.$$

To simplify, we multiply both sides of the inequality by $(\sigma_M^2+\pi(1-\pi))\sigma_M^2 2\gamma$, yielding:

$$[2\gamma\pi(1-\pi)(Y-\delta)-(1-\pi-\rho)]\cdot\sigma_M^2 \geq (\rho-1)\cdot\left[\sigma_M^2+\pi(1-\pi)\right].$$

Expanding both sides results in:

$$2\gamma\pi(1-\pi)(Y-\delta)\sigma_M^2 - \sigma_M^2(1-\pi-\rho) \geq \rho\cdot\sigma_M^2 - \sigma_M^2 + \pi(1-\pi)(\rho-1).$$

Simplifying further, we obtain:

$$2\gamma\pi(1-\pi)(Y-\delta)\sigma_M^2 + \sigma_M^2\pi \geq \pi(1-\pi)\rho - \pi(1-\pi).$$

This leads to the inequality:

$$\rho \leq \bar{\rho} = 1 + \frac{\sigma_M^2}{1-\pi} + 2\gamma\sigma_M^2(Y-\delta),$$

which implies that $\bar{\rho} \geq 1$ if

$$\delta \leq \bar{\delta} = Y + \frac{1}{2\gamma(1-\pi)}.$$

Thus, for all values of $\rho \in [1, \bar{\rho}]$, consumers can be categorized into the following four types:

- High endowment: $\bar{\delta} > Y - \frac{\rho-1}{2\gamma\sigma_M^2} > Y - \frac{2\gamma\pi(1-\pi)(Y-\delta)-(1-\pi-\rho)}{2\gamma[\sigma_M^2+\pi(1-\pi)]} \geq \delta$
- Moderate endowment: $\bar{\delta} > Y - \frac{\rho-1}{2\gamma\sigma_M^2} \geq \delta > Y - \frac{2\gamma\pi(1-\pi)(Y-\delta)-(1-\pi-\rho)}{2\gamma[\sigma_M^2+\pi(1-\pi)]}$
- Low endowment: $\bar{\delta} > \delta > Y - \frac{\rho-1}{2\gamma\sigma_M^2} > Y - \frac{2\gamma\pi(1-\pi)(Y-\delta)-(1-\pi-\rho)}{2\gamma[\sigma_M^2+\pi(1-\pi)]}$
- Lowest endowment: $\bar{\delta} > \delta > Y$

## For High Endowment consumers:

Let us now analyze the case of a high-endowment individual. This occurs when

$$Y - \frac{\rho-1}{2\gamma\sigma_M^2} > \delta \quad \text{and} \quad Y - \frac{2\gamma\pi(1-\pi)(Y-\delta)-(1-\pi-\rho)}{2\gamma[\sigma_M^2+\pi(1-\pi)]} \geq \delta.$$

Conditional on $D < \delta$: The optimal deposit amount is as previously derived:

$$D^* = \min\left[Y - \frac{\rho-1}{2\gamma\sigma_M^2}, \delta\right].$$

Conditional on $D \geq \delta$: The optimal deposit amount is:

$$D^* = \max\left[Y - \frac{2\gamma\pi(1-\pi)(Y-\delta)-(1-\pi-\rho)}{2\gamma[\sigma_M^2+\pi(1-\pi)]}, \delta\right].$$

In these cases, the individual would choose $D^* = \delta$ when $D < \delta$ and

$$D^* = Y - \frac{2\gamma\pi(1-\pi)(Y-\delta) - (1-\pi-\rho)}{2\gamma[\sigma_M^2 + \pi(1-\pi)]} \quad \text{when } D \geq \delta.$$

A rational individual would then compare the utility associated with each of these optimal deposit levels and select the unconditional optimal amount. In other words, they would compare the utilities $U_2$ and $U_3$.

We aim to find a value of $\rho$ such that the following inequality holds:

$$\frac{[2\gamma\sigma_M^2 Y + 2\gamma\pi(1-\pi)\delta + (1-\pi-\rho)]^2}{4\gamma[\sigma_M^2 + \pi(1-\pi)]} - \gamma\pi(1-\pi)\delta^2 + \pi\delta \geq -\gamma\sigma_M^2\delta^2 + (2\gamma\sigma_M^2 Y + 1 - \rho)\delta$$

Given the complexity of these calculations, we simplify the problem by introducing variable substitutions. Let us define:

$$A = 2\gamma\sigma_M^2 Y + 2\gamma\pi(1-\pi)\delta + (1-\pi-\rho), \quad B = 2\gamma\sigma_M^2 Y + 1, \quad D = \sigma_M^2 + \pi(1-\pi)$$

With these substitutions, the inequality becomes:

$$\frac{A^2}{4\gamma D} - \gamma\pi(1-\pi)\delta^2 + \pi\delta + \gamma\sigma_M^2\delta^2 - \delta(B-\rho) \geq 0$$

Simplifying further, we rewrite this as:

$$\frac{A^2}{4\gamma D} + \gamma\delta^2(\sigma_M^2 - \pi(1-\pi)) + \delta(\pi - B) + \rho\delta \geq 0$$

Next, let us introduce $C = 2\gamma\sigma_M^2 Y + 2\gamma\pi(1-\pi)\delta + 1 - \pi$, so that $A = C - \rho$. Substituting this into the inequality gives:

$$\frac{C^2}{4\gamma D} + \frac{\rho^2}{4\gamma D} - \frac{C\rho}{2\gamma D} + \gamma\delta^2(\sigma_M^2 - \pi(1-\pi)) + \delta(\pi - B) + \rho\delta \geq 0$$

Reorganizing terms, we obtain:

$$\rho^2 + \rho\Big(4\gamma D\delta - 2C\Big) + C^2 + 4\gamma^2 D\delta^2(\sigma_M^2 - \pi(1-\pi)) + 4\gamma D(\pi - B)\delta \geq 0$$

Now that we have a quadratic inequality in $\rho$, we compute the discriminant, $\Delta$:

$$\Delta = (4\gamma D\delta - 2C)^2 - 4\Big(C^2 + 4\gamma^2 D\delta^2(\sigma_M^2 - \pi(1-\pi)) + 4\gamma D(\pi - B)\delta\Big)$$

Expanding the terms yields:

$$\Delta = 16\gamma^2 D^2\delta^2 - 16\gamma D\delta C - 16\gamma^2 D\delta^2\sigma_M^2 + 16\gamma^2 D\delta^2\pi(1-\pi) - 16\gamma D(\pi - B)\delta$$

Simplifying further:

$$\Delta = 16\gamma^2 D^2\delta^2 - 16\gamma^2 D\delta^2(\sigma_M^2 - \pi(1-\pi)) - 16\gamma D(\pi - B)\delta - 16\gamma D\delta C$$

Grouping terms gives:

$$\Delta = 16\gamma^2 D\delta^2[D - (\sigma_M^2 - \pi(1-\pi))] - 16\gamma D(C + \pi - B)\delta$$

Noting that:

$$D - (\sigma_M^2 - \pi(1-\pi)) = \sigma_M^2 + \pi(1-\pi) - \sigma_M^2 + \pi(1-\pi) = 2\pi(1-\pi)$$

$$C + \pi - B = 2\gamma(\pi(1-\pi))\delta,$$

we substitute these values to obtain:

$$\Delta = 32\gamma^2 D\delta^2\pi(1-\pi) - 32\gamma^2 D\delta^2\pi(1-\pi) = 0$$

Thus, the discriminant is zero, confirming the condition for $\rho$. This implies that high endowment consumers would always choose $D^* = Y - \frac{2\gamma\pi(1-\pi)(Y-\delta)-(1-\pi-\rho)}{2\gamma[\sigma_M^2+\pi(1-\pi)]}$.

## For Moderate-Endowment Consumers:

The case of a moderate-endowment individual arises when:

$$Y - \frac{\rho - 1}{2\gamma\sigma_M^2} > \delta \quad \text{and} \quad \delta \geq Y - \frac{2\gamma\pi(1-\pi)(Y-\delta) - (1-\pi-\rho)}{2\gamma[\sigma_M^2 + \pi(1-\pi)]}.$$

In this case, the individual chooses $D^* = \delta$ both conditional on $D < \delta$ and $D \geq \delta$. This leads to bunching behavior for moderate-endowment individuals.

## For Low-Endowment Consumers:

This case arises when the following inequality holds:

$$\delta > Y - \frac{\rho - 1}{2\gamma\sigma_M^2} > Y - \frac{2\gamma\pi(1-\pi)(Y-\delta) - (1-\pi-\rho)}{2\gamma[\sigma_M^2 + \pi(1-\pi)]}.$$

When $D < \delta$:

$$D^* = \min\left[Y - \frac{\rho - 1}{2\gamma\sigma_M^2}, \delta\right] = Y - \frac{\rho - 1}{2\gamma\sigma_M^2}.$$

When $D \geq \delta$:

$$D^* = \max\left[Y - \frac{2\gamma\pi(1-\pi)(Y-\delta) - (1-\pi-\rho)}{2\gamma[\sigma_M^2 + \pi(1-\pi)]}, \delta\right] = \delta.$$

In this scenario, the individual compares the utility levels $U_1$ and $U_4$. To evaluate whether $U_1 \leq U_4$, $U_1 \geq U_4$, or $U_1 = U_4$, we reformulate the comparison as follows:

$$-\gamma\sigma_M^2\delta^2 + (2\gamma\sigma_M^2 Y + 1 - \rho)\delta + (\rho Y - \gamma\sigma_M^2 Y^2) \leq \frac{\left(\gamma\sigma_M^2 Y + \frac{1-\rho}{2}\right)^2}{\gamma\sigma_M^2} + \left(\rho Y - \gamma\sigma_M^2 Y^2\right).$$

Rewriting, we obtain:

$$\gamma\sigma_M^2(2Y\delta - \delta^2 - Y^2) + \delta(1-\rho) - Y(1-\rho) \leq \frac{(1-\rho)^2}{4\gamma\sigma_M^2}$$

Finally, this simplifies to:

$$-\gamma\sigma_M^2(\delta - Y)^2 + (1-\rho)(\delta - Y) - \frac{(1-\rho)^2}{4\gamma\sigma_M^2} \leq 0.$$

Changing the sign of the inequality, we rewrite it as:

$$\gamma\sigma_M^2\left((\delta - Y) - \frac{(1-\rho)}{2\gamma\sigma_M^2}\right)^2 \geq 0.$$

This inequality holds for all values of $\delta - Y$ as long as $\gamma \geq 0$, which implies that:

$$U_4 \leq U_1.$$

Given that $U_4 \leq U_1$, the individual chooses:

$$D^* = Y - \frac{\rho - 1}{2\gamma\sigma_M^2}.$$

## B.1 Proof of Proposition 2:

We begin by rewriting the problem of a consumer:

$$\max_D \rho(Y-D)+\pi\delta+(1-\pi)D-\gamma\left[\sigma_M^2(Y-D)^2+\pi(1-\pi)(D-\delta)^2\right].$$

Solving this optimization problem, the optimal deposit allocation is given by:

$$D=\frac{1-\pi-\rho+2\gamma\sigma_M^2 Y+2\gamma\pi(1-\pi)\delta}{2\gamma[\sigma_M^2+\pi(1-\pi)]}.$$

Next, we analyze the portfolio allocation in greater detail and examine how it changes as insurance increases from $\delta_1$ to $\delta_2$. Specifically, we demonstrate that individuals with endowment $Y^{MB}$, who are marginal bunchers at $\delta_1$, respond by increasing their deposits more than individuals with a higher endowment, $Y^{NB} > Y^{MB}$, who were not bunching at $\delta_1$.

Consider an individual who is not bunching at $\delta_1$, meaning their endowment satisfies $Y^{NB} > Y^{MB}$. The optimal level of deposits for this non-buncher at $\delta_1$ is denoted by $D_1^{*NB}$, while the corresponding level at $\delta_2$ is $D_2^{*NB}$. The increase in deposits for this non-buncher induced by higher insurance is therefore:

$$\Delta D^{*NB}=D_2^{*NB}-D_1^{*NB}.$$

Substituting the expressions for $D_1^{*NB}$ and $D_2^{*NB}$, we obtain:

$$\Delta D^{*NB}=\frac{1-\pi-\rho+2\gamma\sigma_M^2 Y^{NB}+2\gamma\pi(1-\pi)\delta_2}{2\gamma[\sigma_M^2+\pi(1-\pi)]}-\frac{1-\pi-\rho+2\gamma\sigma_M^2 Y^{NB}+2\gamma\pi(1-\pi)\delta_1}{2\gamma[\sigma_M^2+\pi(1-\pi)]}.$$

Simplifying, we find:

$$\Delta D^{*NB}=\frac{\pi(1-\pi)(\delta_2-\delta_1)}{\sigma_M^2+\pi(1-\pi)}.$$

Consider now a marginal buncher with income $Y^{MB}$. Her optimal deposit at the old threshold corresponds to the deposit insurance threshold. This represents the optimal deposit level of an individual who is kink-insensitive (as depicted in the left panel of Figure 1) and has income $Y^{KI} < Y^{MB}$. Consequently, the optimal deposits are:

$$D_1^{*MB}=\delta_1=\frac{1-\pi-\rho+2\gamma\sigma_M^2 Y^{KI}+2\gamma\pi(1-\pi)\delta_1}{2\gamma[\sigma_M^2+\pi(1-\pi)]},$$

$$D_2^{*MB} = \frac{1 - \pi - \rho + 2\gamma\sigma_M^2 Y^{MB} + 2\gamma\pi(1-\pi)\delta_2}{2\gamma[\sigma_M^2 + \pi(1-\pi)]},$$

where $Y^{MB} = Y^{KI} + \Delta Y^{MB}$. Substituting this relationship into $D_2^{*MB}$, we obtain:

$$D_2^{*MB} = \frac{1 - \pi - \rho + 2\gamma\sigma_M^2 (Y^{KI} + \Delta Y^{MB}) + 2\gamma\pi(1-\pi)\delta_2}{2\gamma[\sigma_M^2 + \pi(1-\pi)]}.$$

The increase in the optimal deposit for a marginal buncher is thus given by:

$$D_2^{*MB} - D_1^{*MB} =$$

$$\frac{1 - \pi - \rho + 2\gamma\sigma_M^2 (Y^{KI} + \Delta Y^{MB}) + 2\gamma\pi(1-\pi)\delta_2}{2\gamma[\sigma_M^2 + \pi(1-\pi)]} - \frac{1 - \pi - \rho + 2\gamma\sigma_M^2 Y^{KI} + 2\gamma\pi(1-\pi)\delta_1}{2\gamma[\sigma_M^2 + \pi(1-\pi)]}.$$

Simplifying, this results in:

$$D_2^{*MB} - D_1^{*MB} = \frac{\sigma_M^2 \Delta Y^{MB} + \pi(1-\pi)(\delta_2 - \delta_1)}{\sigma_M^2 + \pi(1-\pi)}.$$

We can show that $\Delta D^{*MB}$ is always higher than $\Delta D^{*NB}$:

$$\frac{\sigma_M^2 \Delta Y^{MB} + \pi(1-\pi)(\delta_2 - \delta_1)}{\sigma_M^2 + \pi(1-\pi)} > \frac{\pi(1-\pi)(\delta_2 - \delta_1)}{\sigma_M^2 + \pi(1-\pi)}$$

$$\sigma_M^2 \Delta Y^{MB} > 0$$

which is always true. This implies that a change in deposit insurance produces heterogeneous effects on depositors: those who used to bunch and were holding an endowment $Y^{MB}$ respond more than those who were not with endowment $Y^{NB}$.

## B.2 Derivation of $U_3$

$$\begin{aligned} U_3 = &- [\gamma\sigma_M^2 + \gamma\pi(1-\pi)]\left[Y - \frac{2\gamma\pi(1-\pi)(Y-\delta) - (1-\pi-\rho)}{2\gamma[\sigma_M^2 + \pi(1-\pi)]}\right]^2 \\ &+ [2\gamma\sigma_M^2 Y + 2\pi\gamma(1-\pi)\delta + 1 - \pi - \rho]\left[Y - \frac{2\gamma\pi(1-\pi)(Y-\delta) - (1-\pi-\rho)}{2\gamma[\sigma_M^2 + \pi(1-\pi)]}\right] \\ &- \gamma\pi(1-\pi)\delta^2 - \gamma\sigma_M^2 Y^2 + \rho Y + \pi\delta \end{aligned}$$

Given the complexity of these calculations, we simplify the problem by introducing variable substitutions. Let us define: $D = \sigma_M^2 + \pi(1-\pi)$ , $A = \frac{2\gamma\pi(1-\pi)(Y-\delta)-(1-\pi-\rho)}{2\gamma D}$ and $C = 2\gamma\sigma_M^2 Y + 2\gamma\pi(1-\pi)\delta + 1 - \pi - \rho$. The expression becomes:

$$-\gamma D(Y-A)^2 + C(Y-A) - \gamma\pi(1-\pi)\delta^2 + \pi\delta - \gamma\sigma_M^2 Y^2 + \rho Y$$

Before proceeding to expand and simplify this expression, it is important to note that:

$$\begin{aligned}
Y - A =& Y - \frac{2\gamma\pi(1-\pi)(Y-\delta) - (1-\pi-\rho)}{2\gamma D} \\
=& Y + \frac{2\gamma\pi(1-\pi)(\delta - Y) + (1-\pi-\rho)}{2\gamma D} \\
=& \frac{2\gamma DY + 2\gamma\pi(1-\pi)(\delta - Y) + (1-\pi-\rho)}{2\gamma D} \\
=& \frac{2\gamma DY + 2\gamma\pi(1-\pi)\delta - 2\gamma\pi(1-\pi)Y + (1-\pi-\rho)}{2\gamma D} \\
=& \frac{2\gamma Y[D - \pi(1-\pi)] + 2\gamma\pi(1-\pi)\delta + (1-\pi-\rho)}{2\gamma D}
\end{aligned}$$

Since $D - \pi(1-\pi) = \sigma_M^2$, we can re write the above equation as:

$$\begin{aligned}
Y - A =& \frac{2\gamma Y\sigma_M^2 + 2\gamma\pi(1-\pi)\delta + (1-\pi-\rho)}{2\gamma D} \\
=& \frac{C}{2\gamma D}
\end{aligned}$$

the previous expression can be re written as:

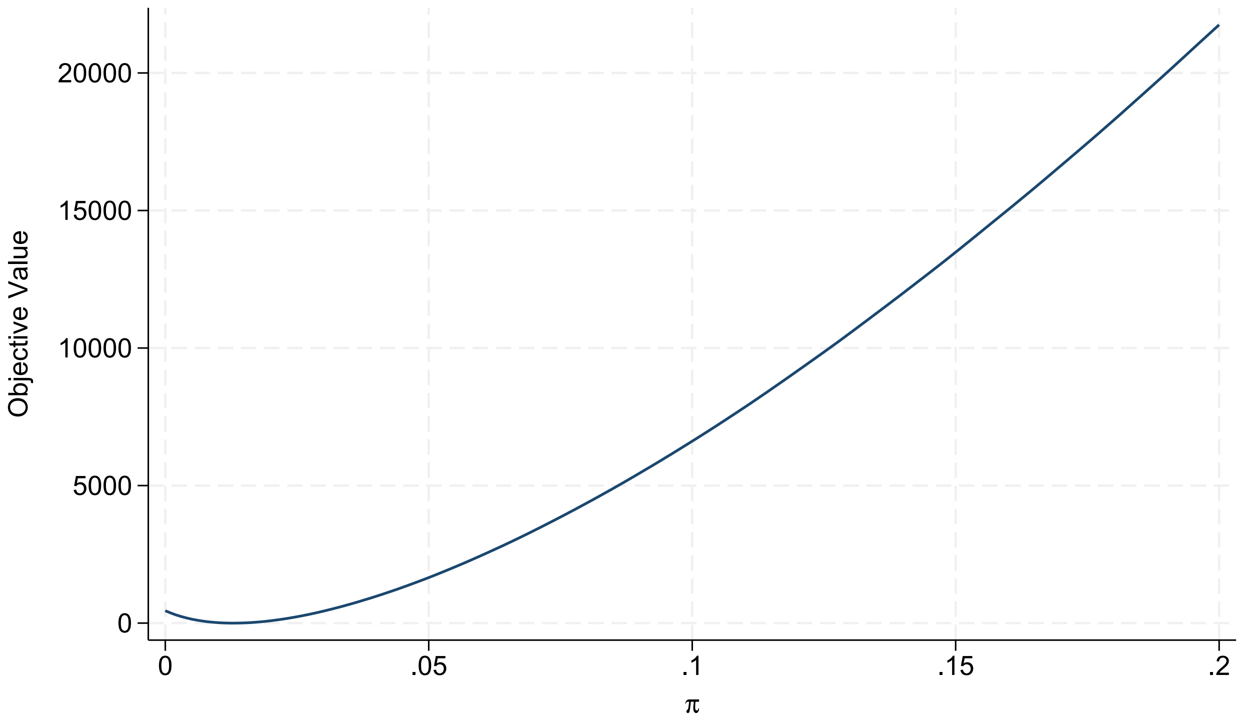
$$\begin{aligned}
U_3 =& -\gamma D\left(\frac{C}{2\gamma D}\right)^2 + C\left(\frac{C}{2\gamma D}\right) - \gamma\pi(1-\pi)\delta^2 + \pi\delta - \gamma\sigma_M^2 Y^2 + \rho Y \\
=& \frac{C^2}{4\gamma D} - \gamma\pi(1-\pi)\delta^2 + \pi\delta - \gamma\sigma_M^2 Y^2 + \rho Y \\
=& \frac{[2\gamma\sigma_M^2 Y + 2\gamma\pi(1-\pi)\delta + 1 - \pi - \rho]^2}{4\gamma[\sigma_M^2 + \pi(1-\pi)]} - \gamma\pi(1-\pi)\delta^2 + \pi\delta - \gamma\sigma_M^2 Y^2 + \rho Y
\end{aligned}$$

## B.3 Model Estimation

**Table B.1:** Calibration

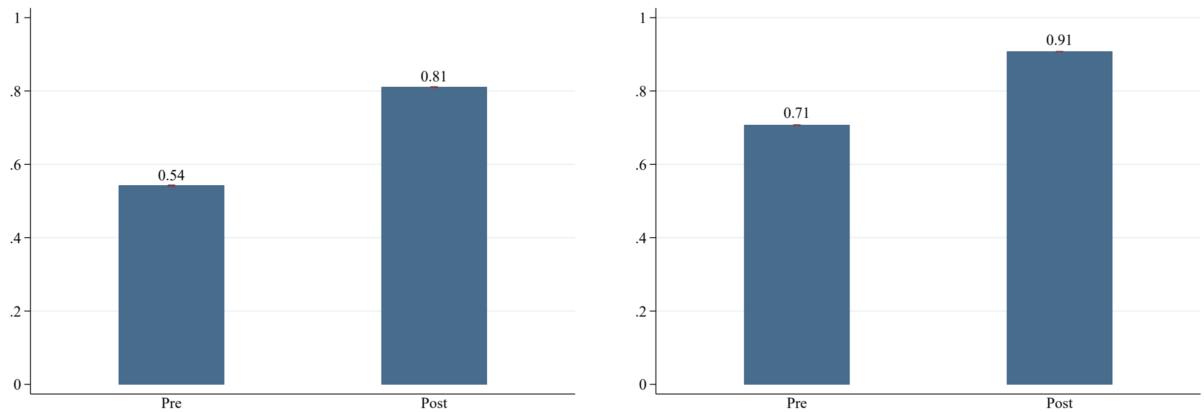
| Parameter | $\rho$ | $\sigma^2_M$ | $\delta_{initial}$ | $\delta_{new}$ |
|---|---|---|---|---|
| Calibrated Value | 1.3434 | 4.1964 | 100000 | 500000 |

**Figure B.1:** Identification: Objective Value as Function of $\pi$



# Appendix C Data

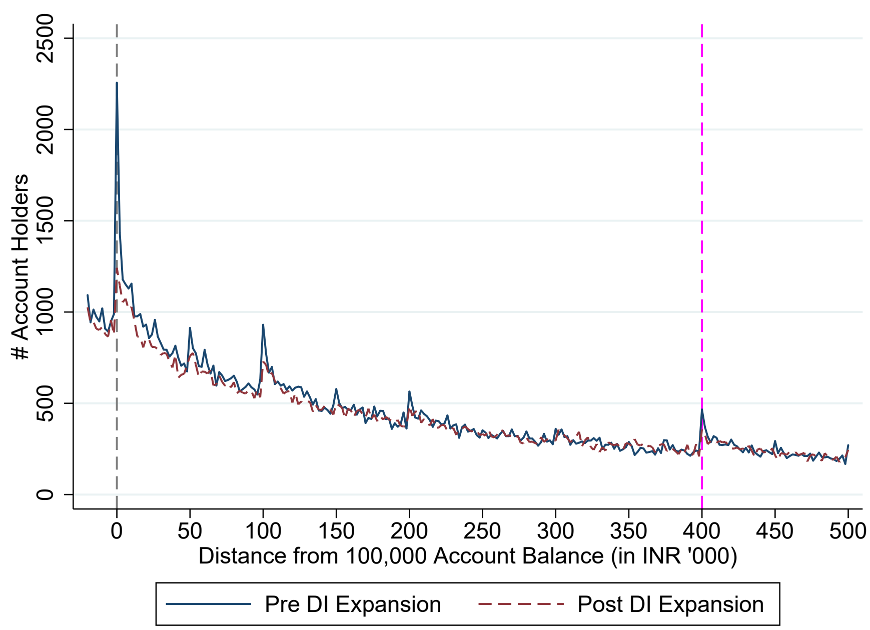
**Figure C.1:** Aggregate Analysis: Insured deposits and DI Limit Expansion




(a) Frac. of Accounts Completely Insured (b) Sh. Deposits Insured

This figure presents the association between deposits and DI limit expansion. Figure C.1a presents the fraction of accounts completely insured in the pre- and the post-period. Figure C.1b presents the share of deposits insured in the pre- and the post-period. February 2020 is defined as the delimiter for the pre and the post DI limit expansion periods. The sample includes 321,350 unique depositors, with 7,933,335 observations spread across 8,034 ZIP codes, covering the period from February 2019 to February 2021. Total deposits are defined as the sum of savings, time and recurring deposits.

**Figure C.2:** Depositor Distribution & Deposit Insurance Threshold




This figure presents the distribution of depositors in our sample around the deposit insurance thresholds. The figure compares the density plot of depositors based on their average month-end balances twelve months before and after February 2020. The solid blue line denotes the pre-policy distribution and the dashed maroon line denotes the post-policy distribution. The vertical dashed grey line denotes the ₹100,000 threshold which is standardized to ₹0. The vertical dashed pink line denotes the post February 2020 new deposit insurance threshold of ₹500,000. Amounts are reported in ’000 ₹(or INR).

## C.1 Summary of the Regression Sample

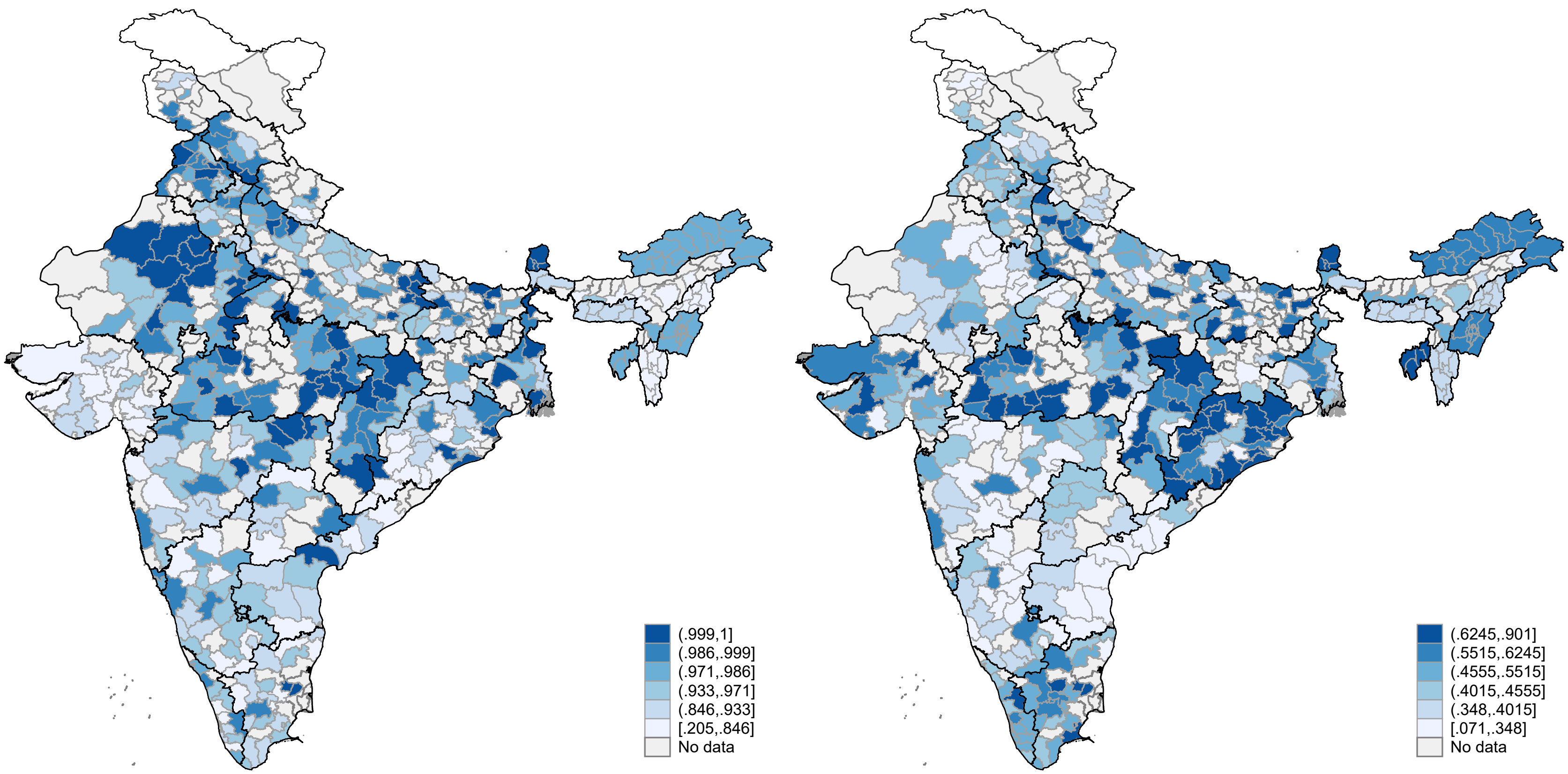
**Table C.1:** Summary Statistics for the Baseline Regression Sample

| | # Obs | p25 | p50 | p75 | Mean | SD |
|---|---|---|---|---|---|---|
| **Panel A: Month End Balances (in ₹)** | | | | | | |
| Banked Wealth | 2,666,481 | 51,315.25 | 140,850.90 | 343,847.00 | 567,145.50 | 1,610,610.00 |
| Total Deposits | 2,666,481 | 34,142.93 | 99,537.75 | 200,610.40 | 146,943.40 | 174,875.60 |
| Saving Deposits | 2,666,481 | 15,012.72 | 56,771.00 | 134,500.50 | 104,495.30 | 146,325.60 |
| Time Deposits | 2,666,481 | 0.00 | 0.00 | 31,624.50 | 37,842.66 | 81,462.47 |
| Recurring Deposits | 2,666,481 | 0.00 | 0.00 | 0.00 | 1,476.53 | 8,442.59 |
| Amount in Stock Market | 2,666,481 | 0.00 | 0.00 | 0.00 | 350,057.10 | 1,522,468.00 |
| Amount in Mutual Funds | 2,666,481 | 0.00 | 0.00 | 0.00 | 33,006.27 | 137,258.70 |
| Amount in PPF | 2,666,481 | 0.00 | 0.00 | 0.00 | 14,583.56 | 87,133.13 |
| **Panel B: Individual-Level Holdings Data** | | | | | | |
| | # Obs | p25 | p50 | p75 | Mean | SD |
| # Shares for each ISIN, Total | 9,364,485 | 26.00 | 100.00 | 375.00 | 633.97 | 1,909.38 |
| Amount for each ISIN, Total | 9,364,485 | 3,638.95 | 17,600.00 | 63,473.70 | 98,712.85 | 266,356.10 |
| # Shares for each ISIN, Stocks | 9,143,267 | 27.00 | 100.00 | 355.00 | 614.16 | 1,875.42 |
| Amount for each ISIN, Stocks | 9,143,267 | 3,605.00 | 17,510.00 | 62,960.00 | 99,033.37 | 267,702.30 |
| # Shares for each ISIN, Mutual Fund | 221,218 | 17.00 | 142.00 | 1,390.00 | 1,453.02 | 2,875.82 |
| Amount for each ISIN, Mutual Fund | 221,218 | 5,003.15 | 21,916.80 | 84,620.11 | 85,465.29 | 202,611.80 |
| **Panel C: Depositor Level Characteristics** | | | | | | |
| | # Obs | p25 | p50 | p75 | Mean | SD |
| Age (as of Feb, 2020) | 108,916 | 27.00 | 35.00 | 47.00 | 37.54 | 13.39 |
| Female (=1) | 108,636 | 0.00 | 0.00 | 1.00 | 0.46 | 0.50 |
| Imputed Monthly Income (in ₹) | 107,672 | 14,733.29 | 44,573.13 | 98,424.07 | 64,188.28 | 91,282.37 |
| Unscored (=1) | 108,916 | 0.00 | 0.00 | 1.00 | 0.49 | 0.50 |
| Credit Score | 55,620 | 750.00 | 777.00 | 794.00 | 763.78 | 44.31 |
| Self Employed (=1) | 106,421 | 0.00 | 0.00 | 1.00 | 0.33 | 0.47 |
| # HH members | 108,916 | 2.00 | 3.00 | 5.00 | 3.62 | 1.40 |
| Account Age (as of Feb, 2020) | 108,916 | 2.96 | 6.81 | 12.37 | 8.04 | 6.00 |
| Has Loan (=1) | 108,916 | 0.00 | 0.00 | 1.00 | 0.41 | 0.49 |
| Has Stock Market Inv (=1) | 108,916 | 0.00 | 0.00 | 0.00 | 0.24 | 0.43 |
| Has Mutual Fund Inv (=1) | 108,916 | 0.00 | 0.00 | 0.00 | 0.12 | 0.33 |
| Has PPF (=1) | 108,916 | 0.00 | 0.00 | 0.00 | 0.06 | 0.23 |

This table presents summary statistics for the key variables in the baseline regression sample drawn from the 4% random sample of depositors from a large private sector bank in India. The sample consists of 108,916 unique depositors, encompassing 2,666,481 observations across 3,538 ZIP codes from February 2019 to February 2021. The table shows the number of observations, as well as the 25th, 50th, and 75th percentile values, along with the mean and standard deviation. Panel A presents month-end balances. Banked wealth is defined as the sum of total deposits, stock market investments, mutual funds, and public provident funds (PPF). Total deposits refer to the combined balance of savings, time, and recurring deposits. Panel B presents depositor-level characteristics, including gender, imputed monthly income, credit score as of December 2019, number of household members, age, account age, and indicators for whether the depositor has a loan, stock market investment, mutual fund investment, or public provident fund (PPF). Panel C presents summary statistics for ISIN-level holdings for depositors with stock or mutual fund investments.

## C.2 Trust Measures

**Figure C.3:** Spatial Distribution of Trust in Banks & Government

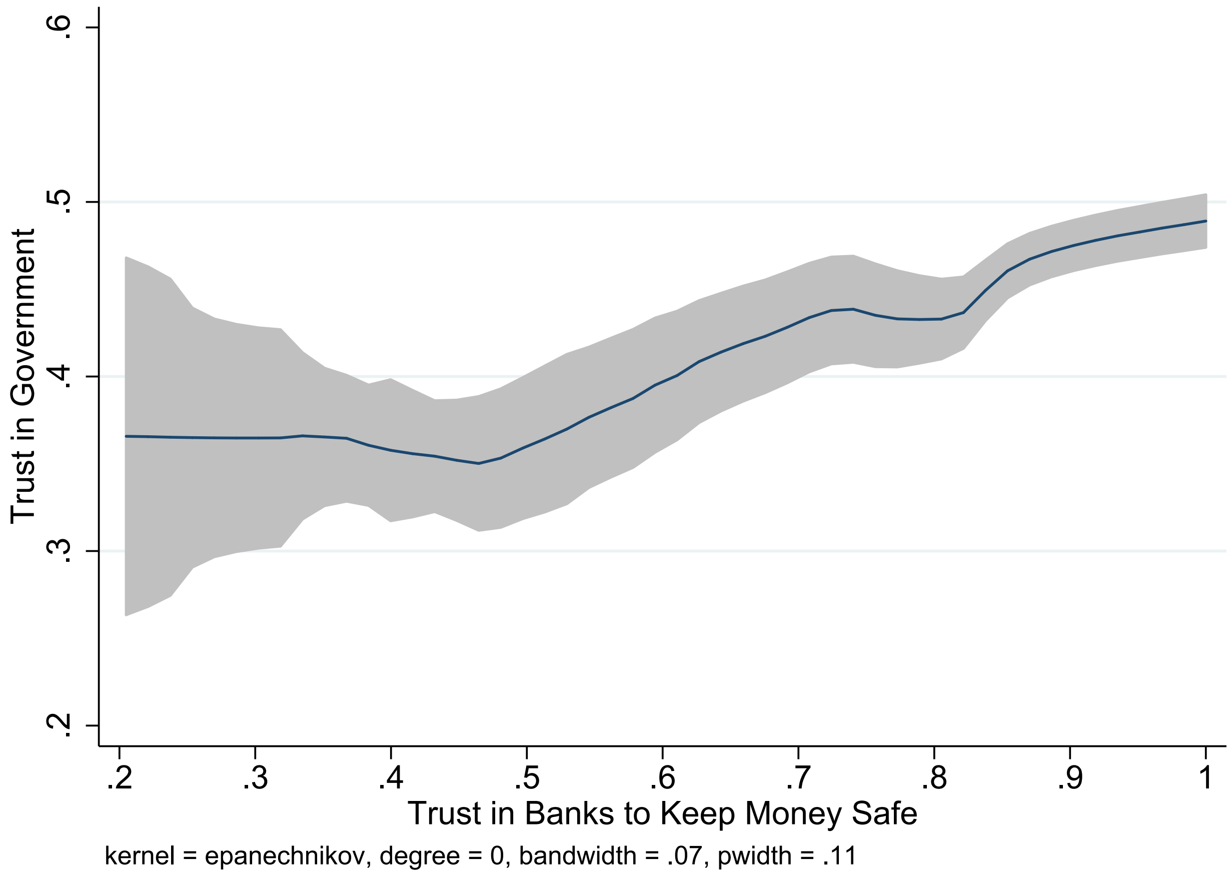



(a) Trust in Banks to Keep Money Safe

(b) Trust in Government

This figure presents the spatial distribution of the trust in banks (Panel C.3a) and the government (Panel C.3b). The distribution is constructed based on India Human Development Survey (IHDS), 2012 data. We use the responses to two questions where the respondents are asked about – (1) their confidence in the banks to keep their money safe, and (2) their confidence in the government to look after people. For both questions the respondent chooses one of the three options: (1) A great deal of confidence, (2) Only some confidence, and (3) Hardly any confidence at all. We code the choice of option (1) as 1 and that of option (3) as zero. Lastly, we code the choice of option (2) as 0.33 to account for the fact that the respondent chooses from within 3 options and the middle option appears to be shifted towards a negative rather than a positive tone. We collapse the respondent-level data by taking the average of all respondents within a district. We use survey weights while taking the average. The above figure plots the spatial distribution of these average confidence measures. A higher value of the trust measure indicates a higher level of trust.

**Figure C.4:** Relationship between Trust Measures




| Summary Statistics of Trust Measures | | | |
|---|---|---|---|
| | p50 | Mean | SD |
| Trust in Banks to Keep Money Safe | 0.971 | 0.921 | 0.120 |
| Trust in Government | 0.454 | 0.473 | 0.146 |

This figure presents the relationship between the trust in banks and the government with the blue line presenting the kernel-weighted local polynomial and the grey shaded zone representing the 95% confidence interval. The measures are constructed based on India Human Development Survey (IHDS), 2012 data. We use the responses to two questions where the respondents are asked about – (1) their confidence in the banks to keep their money safe, and (2) their confidence in the government to look after people. For both questions the respondent chooses one of the three options: (1) A great deal of confidence, (2) Only some confidence, and (3) Hardly any confidence at all. We code the choice of option (1) as 1 and that of option (3) as zero. Lastly, we code the choice of option (2) as 0.33 to account for the fact that the respondent chooses from within 3 options and the middle option appears to be shifted towards a negative rather than a positive tone. We collapse the respondent-level data by taking the average of all respondents within a district. We use survey weights while taking the average. A higher value of the trust measure indicates a higher level of trust.

## C.3 Construction of UPI Index

In addition to the credit bureau and local weather shocks datasets, we employ several other data sources to assess the role of technology in the comparative advantage of shadow banks. Specifically, we utilize the data on the Unified Payment Interface (UPI). Launched in 2016 and funded by the National Payments Corporation of India (NPCI), UPI is a no-cost, instant payment system that facilitates transactions between bank accounts.

We employ a UPI Index, designed to predict UPI adoption while mitigating endogeneity issues associated with directly using UPI transactions. This index is based on the argument first presented in Dubey and Purnanandam (2023) to construct such an index at the district level and more recently employed in Cramer et al. (2024) to construct a similar index at the ZIP level.

The index exploits two key sources of variation: the timing of banks' participation in the UPI platform and its impact on consumer adoption of digital payments across different ZIP codes. First, to fully utilize the UPI system, customers must link their bank accounts to a UPI application, making their bank's participation crucial for enabling digital transactions. Different banks joined the UPI platform at varying times, leading to disparities in customer access. Second, banks cater to distinct geographic areas, meaning that the timing of a dominant bank's UPI adoption can create regional differences in usage among its customers. Specifically, when a leading deposit-supplying bank adopts UPI early, it increases the likelihood of widespread and persistent adoption in that area, both directly through early engagement of their depositors and indirectly through network effects among larger population.

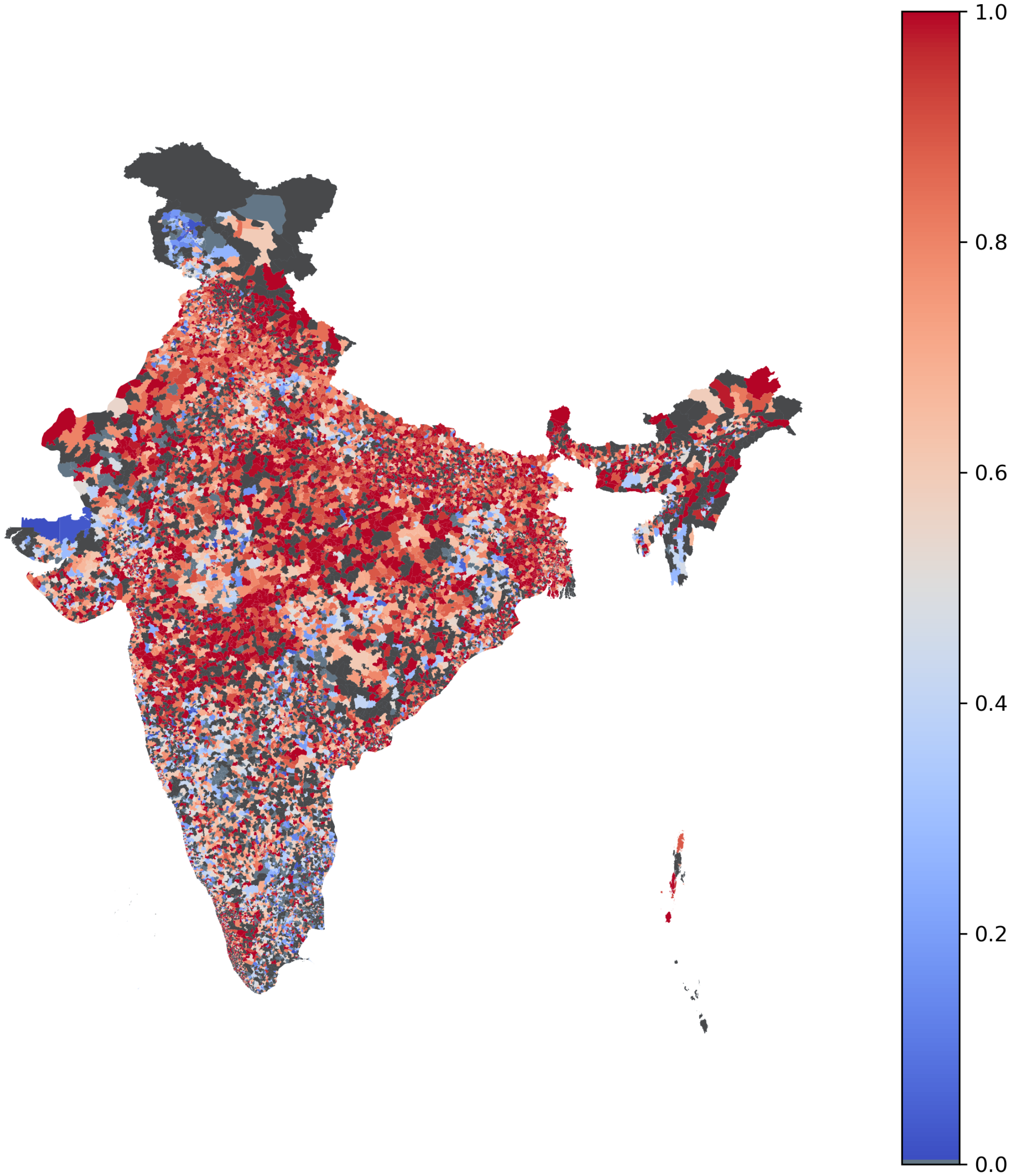
The UPI index for a ZIP code $z$ is defined as the share of total deposits of early adopter banks over total deposits of all banks. By construction, it thus ranges from zero to one and is a cross-sectional measure. The empirical strategy exploits the staggered adoption of UPI by banks. Following Dubey and Purnanandam (2023), we define early adopters as banks that were providing UPI services as of November 2016. November 2016 is an important date in the history of digital transaction adoption in India due to the demonetization of old notes.[22] Data on deposits is from the Basic Statistical Returns (BSR) database maintained by the RBI. The BSR is a comprehensive statistical database of branch-level data on deposits recorded at the end of every fiscal year. The UPI index is defined for ZIP codes with at least one bank branch, which corresponds to 13,313 ZIP codes. We use deposits measured as of March 2016 and create a deposit-weighted index of early adopter banks:

$$\text{UPI Index}_z = \frac{\text{Total Deposits of Early Adopter Banks}_z}{\text{Total Deposit of all Banks}_z} \tag{C.1}$$

Appendix Figure C.5 presents the geographic distribution of the UPI Index at the ZIP level.

[22]The adoption dates of UPI by banks are public information and can be accessed here.

**Figure C.5:** Spatial Distribution of UPI Index




This figure presents the spatial distribution of the UPI Index, reproduced based on data provided by Cramer et al. (2024). The UPI index for a ZIP code $z$ is defined as the share of total deposits of early adopter banks over total deposits of all banks. By construction, it thus ranges from zero to one and is a cross-sectional measure. Following Dubey and Purnanandam (2023), we define early adopters as banks that were providing UPI services as of November 2016. The adoption dates of UPI by banks are public information and can be accessed here. Data on deposits is from the Basic Statistical Returns (BSR) database maintained by the Reserve Bank of India (RBI). The BSR is a comprehensive statistical database of branch-level data on deposits recorded at the end of every fiscal year. The UPI index is defined for ZIP codes with at least one bank branch, which corresponds to 13,313 ZIP codes. We use deposits measured as of March 2016 and create a deposit-weighted index of early adopter banks:

$$\text{UPI Index}_z = \frac{\text{Total Deposits of Early Adopter Banks}_z}{\text{Total Deposit of all Banks}_z}$$

# Appendix D Effect on Deposits

## D.1 Heterogeneous Response of Non-Bunchers

**Table D.1:** Heterogeneous Response of Non-Bunchers

| Dep Var: LN(Deposits) | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| $Bunchers \times$ Post | 0.0722*** | 0.0720*** | 0.0524*** | 0.0815*** |
| | (0.0143) | (0.0143) | (0.0138) | (0.0140) |
| $Non-Bunchers_1$ (100-200] × Post | 0.0483*** | 0.0482*** | 0.0336*** | 0.0556*** |
| | (0.0110) | (0.0110) | (0.0109) | (0.0110) |
| $Non-Bunchers_2$ (200-300] × Post | 0.0257** | 0.0257** | 0.0151 | 0.0290** |
| | (0.0121) | (0.0121) | (0.0120) | (0.0121) |
| $Non-Bunchers_3$ (300-400] × Post | -0.0041 | -0.0041 | -0.0109 | -0.0054 |
| | (0.0130) | (0.0130) | (0.0131) | (0.0133) |
| $Bunchers$ | -1.7422*** | -1.7421*** | | |
| | (0.0141) | (0.0141) | | |
| $Non-Bunchers_1$ (100-200] | -1.1853*** | -1.1852*** | | |
| | (0.0111) | (0.0111) | | |
| $Non-Bunchers_2$ (200-300] | -0.6081*** | -0.6081*** | | |
| | (0.0120) | (0.0120) | | |
| $Non-Bunchers_3$ (300-400] | -0.2277*** | -0.2277*** | | |
| | (0.0125) | (0.0125) | | |
| Post | -0.0200* | | | |
| | (0.0104) | | | |
| Time FE | | Yes | Yes | |
| Depositor FE | | | Yes | Yes |
| ZIP X Time FE | | | | Yes |
| # Obs | 2,666,481 | 2,666,481 | 2,666,481 | 2,666,481 |
| $R^2$ | 0.0997 | 0.0999 | 0.5775 | 0.5973 |

f-stats for equality of coefficients

| | | | | |
|---|---|---|---|---|
| All double interaction terms | 14.16*** | 14.10*** | 9.94*** | 18.49*** |
| $Bunchers \times Post = Non-Bunchers_1 \times Post$ | 4.28** | 4.26** | 2.79* | 5.22** |
| $Non-Bunchers_1 \times Post = Non-Bunchers_2 \times Post$ | 6.09** | 6.06** | 4.20** | 8.82*** |
| $Non-Bunchers_2 \times Post = Non-Bunchers_3 \times Post$ | 7.06*** | 7.05*** | 5.39** | 9.27*** |

This table presents the response of bank deposits among bunchers compared to non-bunchers following the expansion of deposit insurance (DI). The dependent variable is the natural logarithm of bank deposits for depositor $i$ in month $t$. Post is an indicator variable taking a value of one for months since February 2020, and zero otherwise. The data covers the period from February 2019 to February 2021. Depositors are classified as bunchers or non-bunchers based on their average monthly deposits in the 12 months prior to February 2020. Specifically, we compare the response of bunchers (with pre-policy deposits $\in (70, 100]$) with the non-bunchers (with pre-policy deposits $\in (100, 500)$). Furthermore, we split non-bunchers into four groups of equal size of 100 or ₹100,000. $Non-Bunchers_1$ denotes non-bunchers with pre-policy deposits in the $(100, 200]$ range. $Non-Bunchers_2$ denotes non-bunchers with pre-policy deposits in the $(200, 300]$ range. $Non-Bunchers_3$ denotes non-bunchers with pre-policy deposits in the $(300, 400]$ range. $Non-Bunchers_4$ denotes non-bunchers with pre-policy deposits in the $(400, 500)$ range. $Non-Bunchers_4$ is the omitted variable in this regression. All continuous variables are winsorized at the 1% level. Standard errors, clustered at the ZIP code level, are shown in parentheses. Statistical significance is indicated by *, **, and ***, corresponding to the 10%, 5%, and 1% levels, respectively.

## D.2 Discussion of Magnitude

**Table D.2:** Estimates of the elasticity of deposits to deposit insurance

| Dep Var: $\Delta LN(Deposits)$ | (1) | (2) |
|---|---|---|
| $\Delta Coverage_i$ | 0.0206*** | 0.0300*** |
| | (0.0026) | (0.0026) |
| ZIP FE | | Yes |
| # Obs | 108,621 | 108,621 |
| $R^2$ | 0.0006 | 0.0667 |

This table reports estimates of the elasticity of deposits to deposit insurance for the baseline sample depositors. The dependent variables are at the depositor $i$ level. The key dependent variable is $\Delta LN(Deposits)$. $\Delta LN(Deposits)$ is the difference between the log of average deposits during the twelve months before and after the DI expansion in February 2020. The key independent variable is $\Delta Coverage_i$, defined as the ratio between the increment in deposit insurance, ₹400,000, and the average level of deposits in the pre-period. All continuous variables are winsorized at the 1% level. Standard errors, clustered at the ZIP code level, are shown in parentheses. Statistical significance is indicated by *, **, and ***, corresponding to the 10%, 5%, and 1% levels, respectively.

## D.3 Robustness

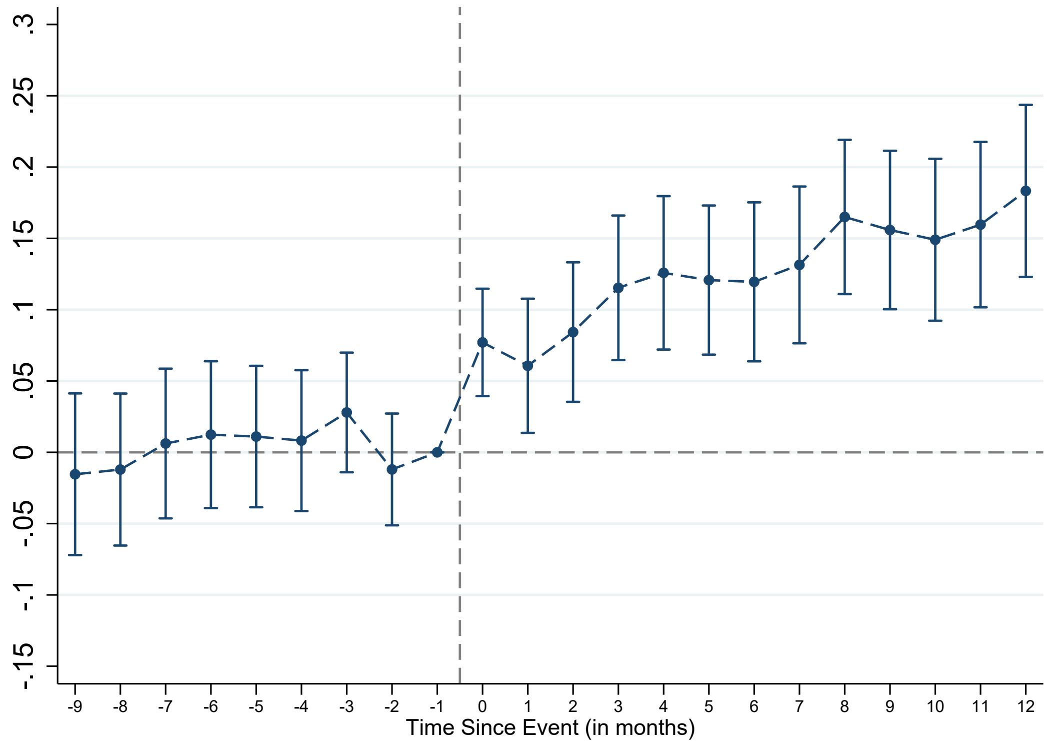
### D.3.1 Within Family Estimation

**Table D.3:** Within Family Estimation: Effect of DI Expansion on Deposits

| Dep Var: LN(Deposits) | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Buncher X Post | 0.0768*** | 0.1185*** | 0.1185*** | 0.1185*** |
| | (0.0147) | (0.0230) | (0.0230) | (0.0175) |
| Depositor FE | Yes | Yes | Yes | Yes |
| ZIP X Time FE | Yes | Yes | Yes | |
| Household ID X Time FE | | Yes | Yes | |
| Household ID X ZIP FE | | | Yes | |
| Household ID X ZIP X Time FE | | | | Yes |
| # Obs | 1,450,568 | 1,450,568 | 1,450,568 | 1,450,568 |
| $R^2$ | 0.6069 | 0.8097 | 0.8097 | 0.8097 |

This table presents the response of bank deposits among bunchers compared to non-bunchers following the expansion of deposit insurance (DI). The sample includes all depositors in our baseline sample where there is a buncher as well as a non-buncher within the same household. The dependent variable is the natural logarithm of bank deposits for depositor $i$ in month $t$. Post is an indicator variable taking a value of one for months since February 2020, and zero otherwise. The data covers the period from February 2019 to February 2021. Depositors are classified as bunchers or non-bunchers based on their average monthly deposits in the 12 months prior to February 2020. Specifically, we compare the response of bunchers with pre-policy deposits in the $(75, 100]$ range with the non-bunchers whose pre-policy deposits fall within $(100, 500)$. Household ID refers to the unique identifier for depositors belonging to the same family. All continuous variables are winsorized at the 1% level. Standard errors, clustered at the ZIP code level, are shown in parentheses. Statistical significance is indicated by *, **, and ***, corresponding to the 10%, 5%, and 1% levels, respectively.

**Figure D.1:** Within Family Estimation: Assessment of Pre-Trends




The figure plots the estimates of $\beta_j$ and the 95% confidence intervals from the following regression equation:

$$LN(Deposits_{i,t}) = \sum_{j=-9, j\neq -1}^{j=+12} \beta_j \times Buncher_i \cdot \mathbb{1}\{t=j\} + \theta_i + \theta_{f,z(i\in z),t} + \varepsilon_{i,t}$$

where, $LN(Deposits_{i,t})$ denotes the natural logarithm of total bank deposits of depositor $i$ (residing in ZIP code $z$) at time (month-year) $t$. $\mathbb{1}\{t = j\}$ is the time indicator variable taking a value of one if the month is $j$ months before/after the month of February 2020. February 2020 is denoted by $j = 0$. $\theta_i$ and $\theta_{f,z(i\in z),t}$ denote depositor and Household ID × ZIP × time (month-year) fixed effects, respectively. Household ID refers to the unique identifier for depositors belonging to the same family. We use the shorthand notation for numbers, i.e., 100 means ₹100,000. Bunchers are defined as depositors with pre-policy deposits in the $(70, 100]$ range and non-bunchers are depositors whose pre-policy deposits fall within $(100, 500)$. All continuous variables are winsorized at the 1% level. The 95% error bands are estimated by clustering the standard errors at the ZIP level.

### D.3.2 Addressing Optimization Error

**Table D.4:** Addressing Optimization Error: Effect of DI Expansion on Deposits

| Dep Var: LN(Deposits) | (1) | (2) |
|---|---|---|
| Buncher X Post | 0.0517*** | 0.0532*** |
| | (0.0106) | (0.0102) |
| Depositor FE | Yes | Yes |
| ZIP X Time FE | Yes | Yes |
| # Obs | 2,666,481 | 2,666,481 |
| $R^2$ | 0.5972 | 0.5972 |
| Sample | Baseline | Bunchers include depositors between (100,104] |

This table presents the response of bank deposits among bunchers compared to non-bunchers following the expansion of deposit insurance (DI). The dependent variable is the natural logarithm of bank deposits for depositor $i$ in month $t$. Post is an indicator variable taking a value of one for months since February 2020, and zero otherwise. The data covers the period from February 2019 to February 2021. Depositors are classified as bunchers or non-bunchers based on their average monthly deposits in the 12 months prior to February 2020. Column 1 compares the response of bunchers with pre-policy deposits in the $(75, 100]$ range with the non-bunchers whose pre-policy deposits fall within $(100, 500)$. Column 2 compares the response of bunchers with pre-policy deposits in the $(75, 104]$ range with the non-bunchers whose pre-policy deposits fall within $(104, 500)$. All continuous variables are winsorized at the 1% level. Standard errors, clustered at the ZIP code level, are shown in parentheses. Statistical significance is indicated by *, **, and ***, corresponding to the 10%, 5%, and 1% levels, respectively.

### D.3.3 Poisson Estimator

**Table D.5:** Poisson Estimator: Effect of DI Expansion on Deposits

| Dep Var: Deposits | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Buncher X Post | 0.2600*** | 0.2602*** | 0.2452*** | 0.2574*** |
| | (0.0111) | (0.0111) | (0.0109) | (0.0106) |
| Buncher | -1.0988*** | -1.0989*** | | |
| | (0.0052) | (0.0052) | | |
| Post | 0.2804*** | | | |
| | (0.0044) | | | |
| Time FE | | Yes | Yes | |
| Depositor FE | | | Yes | Yes |
| ZIP X Time FE | | | | Yes |
| # Obs | 2,666,481 | 2,666,481 | 2,666,481 | 2,666,481 |
| Pseudo $R^2$ | 0.0837 | 0.091 | 0.574 | 0.5965 |

This table presents the response of bank deposits among bunchers compared to non-bunchers following the expansion of deposit insurance (DI) using Poisson pseudo-likelihood regression. The dependent variable is the level of bank deposits for depositor $i$ in month $t$. Post is an indicator variable taking a value of one for months since February 2020, and zero otherwise. The data covers the period from February 2019 to February 2021. Depositors are classified as bunchers or non-bunchers based on their average monthly deposits in the 12 months prior to February 2020. We compare the response of bunchers with pre-policy deposits in the $(75, 100]$ range with the non-bunchers whose pre-policy deposits fall within $(100, 500)$. All continuous variables are winsorized at the 1% level. Standard errors, clustered at the ZIP code level, are shown in parentheses. Statistical significance is indicated by *, **, and ***, corresponding to the 10%, 5%, and 1% levels, respectively.

### D.3.4 Alternative Transformation of the Dependent Variable

**Table D.6:** Alternative Transformation of the Dependent Variable: Effect of DI Expansion on Deposits

| Dep Var: $\Delta LN(Deposits)$ | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Buncher X Post | 0.0185*** | 0.0184*** | 0.0182*** | 0.0180*** |
| | (0.0024) | (0.0024) | (0.0025) | (0.0025) |
| Buncher | -0.0153*** | -0.0153*** | | |
| | (0.0017) | (0.0017) | | |
| Post | 0.0050*** | | | |
| | (0.0009) | | | |
| Time FE | | Yes | Yes | |
| Depositor FE | | | Yes | Yes |
| ZIP X Time FE | | | | Yes |
| # Obs | 2,552,189 | 2,552,189 | 2,552,189 | 2,552,189 |
| $R^2$ | 0.0000 | 0.0008 | 0.0118 | 0.0514 |

This table presents the response of bank deposits among bunchers compared to non-bunchers following the expansion of deposit insurance (DI). The dependent variable is the monthly difference of the natural logarithm of bank deposits for depositor $i$ in month $t$. Specifically, $\Delta LN(Deposits_t) = LN(Deposits_t) - LN(Deposits_{t-1})$ Post is an indicator variable taking a value of one for months since February 2020, and zero otherwise. The data covers the period from February 2019 to February 2021. Depositors are classified as bunchers or non-bunchers based on their average monthly deposits in the 12 months prior to February 2020. We compare the response of bunchers with pre-policy deposits in the $(75, 100]$ range with the non-bunchers whose pre-policy deposits fall within $(100, 500)$. All continuous variables are winsorized at the 1% level. Standard errors, clustered at the ZIP code level, are shown in parentheses. Statistical significance is indicated by *, **, and ***, corresponding to the 10%, 5%, and 1% levels, respectively.

### D.3.5 Alternative Exposure Variable

**Table D.7:** Alternative Exposure Variable: Effect of DI Expansion on Deposits

| Dep Var: $LN(Deposits)$ | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| LN($\frac{\Delta Coverage}{Pre-Deposits}$) X Post | 0.0431*** | 0.0430*** | 0.0318*** | 0.0502*** |
| | (0.0063) | (0.0063) | (0.0062) | (0.0062) |
| LN($\frac{\Delta Coverage}{Pre-Deposits}$) | -1.0747*** | -1.0746*** | | |
| | (0.0066) | (0.0066) | | |
| Post | -0.0178*** | | | |
| | (0.0066) | | | |
| Time FE | | Yes | Yes | |
| Depositor FE | | | Yes | Yes |
| ZIP X Time FE | | | | Yes |
| # Obs | 2,666,481 | 2,666,481 | 2,666,481 | 2,666,481 |
| $R^2$ | 0.1123 | 0.1124 | 0.5775 | 0.5973 |

This table presents the response of bank deposits among bunchers compared to non-bunchers following the expansion of deposit insurance (DI). The dependent variable is the natural logarithm of bank deposits for depositor $i$ in month $t$. Post is an indicator variable taking a value of one for months since February 2020, and zero otherwise. LN($\frac{\Delta Coverage}{Pre-Deposits}$) denotes the change in coverage divided by the pre-policy deposits for each depositor $i$. Change in coverage is fixed to ₹400,000 for all depositors. Pre-policy deposits are calculated as the average deposits of each depositor during the twelve months before the DI expansion. The data covers the period from February 2019 to February 2021. All continuous variables are winsorized at the 1% level. Standard errors, clustered at the ZIP code level, are shown in parentheses. Statistical significance is indicated by *, **, and ***, corresponding to the 10%, 5%, and 1% levels, respectively.

### D.3.6 Alternative Clustering

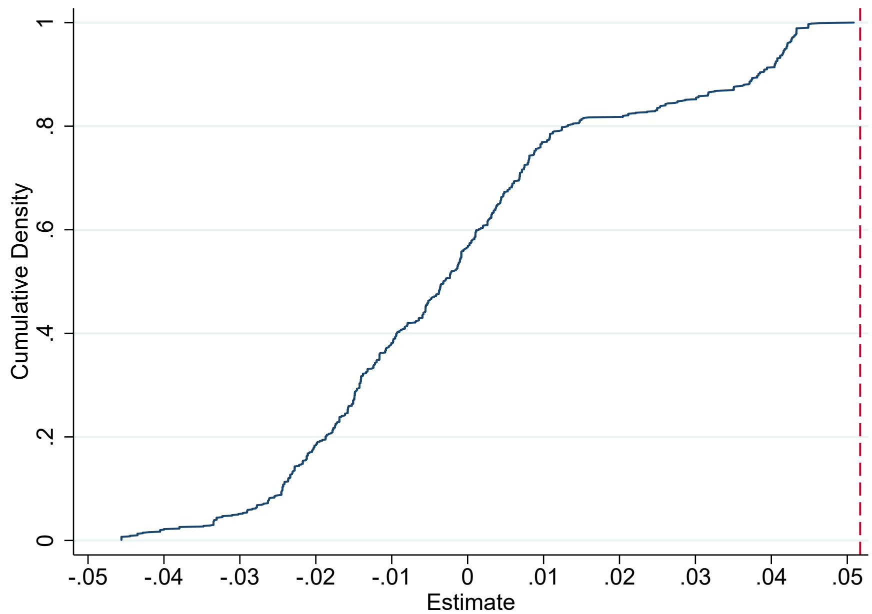
**Table D.8:** Alternative Clustering: Effect of DI Expansion on Deposits

| Dep Var: LN(Deposits) | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| Buncher X Post | 0.0517*** | 0.0517*** | 0.0517*** | 0.0517*** | 0.0517*** | 0.0517*** |
| | (0.0106) | (0.0145) | (0.0105) | (0.0144) | (0.0106) | (0.0145) |
| Depositor FE | Yes | Yes | Yes | Yes | Yes | Yes |
| ZIP X Time FE | Yes | Yes | Yes | Yes | Yes | Yes |
| # Obs | 2,666,481 | 2,666,481 | 2,666,481 | 2,666,481 | 2,666,481 | 2,666,481 |
| $R^2$ | 0.5972 | 0.5972 | 0.5972 | 0.5972 | 0.5972 | 0.5972 |
| Cluster | ZIP | ZIP, Month | Depositor | Depositor, Month | Depositor, ZIP | Depositor, ZIP, Month |

This table presents the response of bank deposits among bunchers compared to non-bunchers following the expansion of deposit insurance (DI). The dependent variable is the natural logarithm of bank deposits for depositor $i$ in month $t$. Post is an indicator variable taking a value of one for months since February 2020, and zero otherwise. The data covers the period from February 2019 to February 2021. Depositors are classified as bunchers or non-bunchers based on their average monthly deposits in the 12 months prior to February 2020. We compare the response of bunchers with pre-policy deposits in the $(75, 100]$ range with the non-bunchers whose pre-policy deposits fall within $(100, 500)$. All continuous variables are winsorized at the 1% level. Standard errors, clustered at the level reported in the last row of the table, are shown in parentheses. Column 1 clusters at ZIP level, column 2 conducts two-way clustering at ZIP and month level, column 3 clusters at the depositor level, column 4 conducts two-way clustering at the depositor and month level, column 5 conducts two-way clustering at ZIP and depositor level, and column 6 conducts multi-way clustering at ZIP, depositor and month level, Statistical significance is indicated by *, **, and ***, corresponding to the 10%, 5%, and 1% levels, respectively.

### D.3.7 Placebo Test

**Figure D.2:** Placebo Test




| # Sims | Summary Statistics of the placebo estimates | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| | Min | p10 | p25 | p50 | p75 | p90 | Max | Mean | SD |
| 1,000 | -0.0456 | -0.0244 | -0.0158 | -0.0031 | 0.0088 | 0.0383 | 0.0509 | -0.0005 | 0.0217 |

The figure plots the cumulative density of the point estimates of the $Plaebo - Buchner \times Post$ obtained from the 1,000 Monte Carlo simulations. We randomly select a DI threshold between ₹231,000 and ₹600,000 from a uniform distribution. The random threshold thus generated is used to classify depositors into bunchers and non-bunchers. Specifically, the depositors with pre-policy deposits less than or equal to the random threshold and greater than or equal to the threshold minus ₹30,000 are defined as placebo bunchers and all other depositors are defined as non-bunchers. We do not include depositors with pre-policy deposits less than ₹200,000 in our placebo sample. We estimate the coefficient of $Placebo - Buncher \times Post$ in the baseline specification and repeat this exercise 1,000 times. The distribution of $\beta$ is centered around 0, with a standard deviation of 0.0216. The red dashed line denotes the location of the coefficient of the interaction term from column 4 of Table 2 with none of the estimates, among the 1,000 simulated placebo $\beta$, lying to the right of the red dashed line.

## D.4 Effect across different Types of Deposits

**Table D.9:** Effect of DI Expansion on Different Types of Deposits

| | (1) Total Deposits | (2) Saving Deposits | (3) Time Deposits | (4) Recurring Deposits |
|---|---|---|---|---|
| Buncher X Post | 0.2574*** | 0.2356*** | 0.0744 | 0.3420*** |
| | (0.0106) | (0.0107) | (0.0503) | (0.0250) |
| Depositor FE | Yes | Yes | Yes | Yes |
| ZIP X Time FE | Yes | Yes | Yes | Yes |
| # Obs | 2,666,481 | 2,666,479 | 239,710 | 1,082,684 |
| Pseudo $R^2$ | 0.5965 | 0.5644 | 0.656 | 0.6451 |

This table presents the response of different types of deposits among bunchers compared to non-bunchers following the expansion of deposit insurance (DI). Post is an indicator variable taking a value of one for months since February 2020, and zero otherwise. The data covers the period from February 2019 to February 2021. Depositors are classified as bunchers or non-bunchers based on their average monthly deposits in the 12 months prior to February 2020. We compare the response of bunchers with pre-policy deposits in the $(75, 100]$ range with the non-bunchers whose pre-policy deposits fall within $(100, 500)$. Column 1 reports the results for total deposits. Column 2 reports the results for saving deposits. Column 3 reports the results for time deposits. Column 4 reports the results for recurring deposits. We estimate the coefficients using Poisson pseudo-likelihood regression to account for the presence of zeroes in some deposit types as suggested by Cohn, Liu, and Wardlaw (2022) and Chen and Roth (2024). All continuous variables are winsorized at the 1% level. Standard errors, clustered at the ZIP code level, are shown in parentheses. Statistical significance is indicated by *, **, and ***, corresponding to the 10%, 5%, and 1% levels, respectively.

## D.5 Response of Depositors at the New Boundary

**Table D.10:** Response of Depositors at the New Boundary

| Dep Var: LN(Deposits) | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| $Bunchers \times$ Post | 0.0687*** | 0.0686*** | 0.0522*** | 0.0831*** |
| | (0.0142) | (0.0142) | (0.0138) | (0.0140) |
| $Non-Bunchers_1$ (100-200] $\times$ Post | 0.0456*** | 0.0455*** | 0.0338*** | 0.0570*** |
| | (0.0111) | (0.0111) | (0.0110) | (0.0110) |
| $Non-Bunchers_2$ (200-300] $\times$ Post | 0.0235* | 0.0235* | 0.0158 | 0.0310** |
| | (0.0121) | (0.0121) | (0.0120) | (0.0121) |
| $Non-Bunchers_3$ (300-400] $\times$ Post | -0.0056 | -0.0056 | -0.0095 | -0.0033 |
| | (0.0130) | (0.0130) | (0.0131) | (0.0133) |
| $Non-Bunchers_5$ [500-600] $\times$ Post | -0.0235 | -0.0236 | -0.0177 | -0.0133 |
| | (0.0146) | (0.0146) | (0.0143) | (0.0144) |
| $Bunchers$ | -1.7505*** | -1.7504*** | | |
| | (0.0140) | (0.0140) | | |
| $Non-Bunchers_1$ (100-200] | -1.1941*** | -1.1940*** | | |
| | (0.0111) | (0.0111) | | |
| $Non-Bunchers_2$ (200-300] | -0.6181*** | -0.6181*** | | |
| | (0.0120) | (0.0120) | | |
| $Non-Bunchers_3$ (300-400] | -0.2370*** | -0.2370*** | | |
| | (0.0124) | (0.0124) | | |
| $Non-Bunchers_5$ [500-600] | 0.1159*** | 0.1160*** | | |
| | (0.0152) | (0.0152) | | |
| Post | -0.0172* | | | |
| | (0.0103) | | | |
| Time FE | | Yes | Yes | |
| Depositor FE | | | Yes | Yes |
| ZIP X Time FE | | | | Yes |
| # Obs | 2,958,175 | 2,958,175 | 2,958,175 | 2,958,175 |
| $R^2$ | 0.1149 | 0.115 | 0.5868 | 0.6054 |

This table presents the response of bank deposits among bunchers compared to non-bunchers following the expansion of deposit insurance (DI). The dependent variable is the natural logarithm of bank deposits for depositor $i$ in month $t$. Post is an indicator variable taking a value of one for months since February 2020, and zero otherwise. The data covers the period from February 2019 to February 2021. Depositors are classified as bunchers or non-bunchers based on their average monthly deposits in the 12 months prior to February 2020. Specifically, we compare the response of bunchers (with pre-policy deposits $\in (70, 100]$) with the non-bunchers (with pre-policy deposits $\in (100, 600]$). Furthermore, we split non-bunchers into four groups of equal size of 100 or ₹100,000. $Non-Bunchers_1$ denotes non-bunchers with pre-policy deposits in the $(100, 200]$ range. $Non-Bunchers_2$ denotes non-bunchers with pre-policy deposits in the $(200, 300]$ range. $Non-Bunchers_3$ denotes non-bunchers with pre-policy deposits in the $(300, 400]$ range. $Non-Bunchers_4$ denotes non-bunchers with pre-policy deposits in the $(400, 500)$ range. $Non-Bunchers_5$ denotes non-bunchers with pre-policy deposits in the $[500, 600]$ range. $Non-Bunchers_4$ is the omitted variable in this regression. All continuous variables are winsorized at the 1% level. Standard errors, clustered at the ZIP code level, are shown in parentheses. Statistical significance is indicated by *, **, and ***, corresponding to the 10%, 5%, and 1% levels, respectively.

## D.6 Heterogeneity by Depositor Characteristics

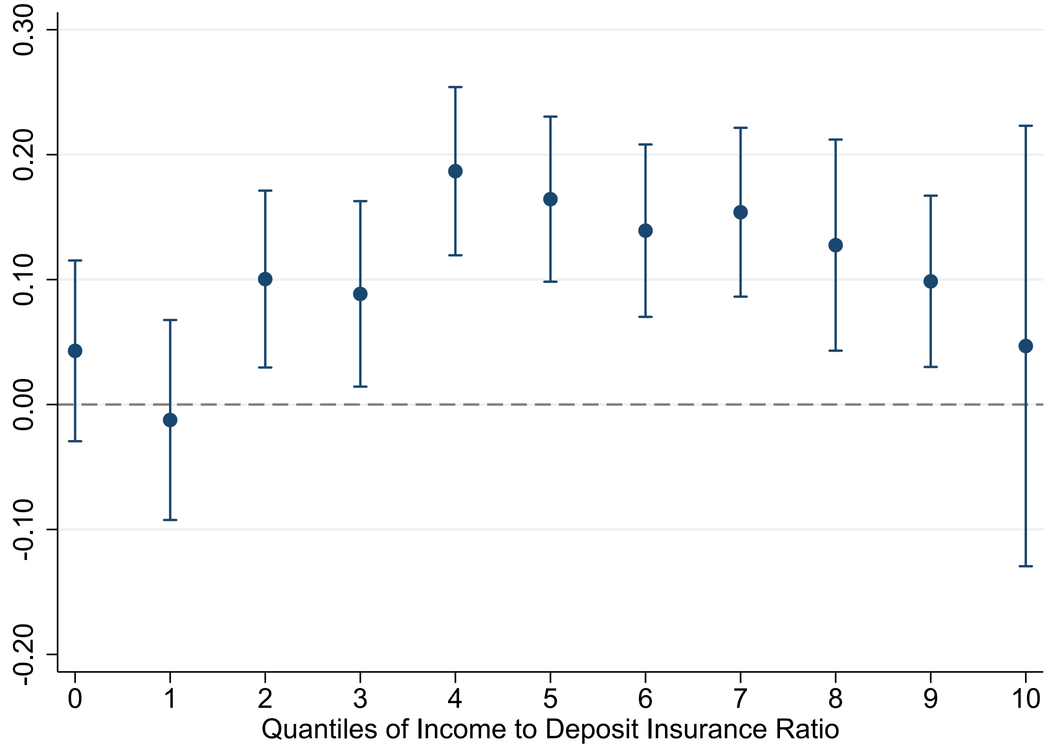
**Table D.11:** Heterogeneity by Depositor Characteristics: Effect of DI Expansion on Deposits

| Dep Var: LN(Deposits) | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
|---|---|---|---|---|---|---|---|---|
| | Baseline | Demographic Characteristics | | | Relationship Characteristics | | | |
| | | Female | Age | Family Size | Acct Age | Oth Savings Products | Loans | PPF |
| Buncher X Post | 0.0517*** | 0.0435*** | 0.0497*** | 0.0409* | 0.0660*** | 0.0617*** | 0.0489*** | 0.0521*** |
| | (0.0106) | (0.0147) | (0.0150) | (0.0211) | (0.0149) | (0.0130) | (0.0124) | (0.0109) |
| Post X $H_i$ | | 0.0119* | 0.0049 | 0.0206** | 0.1699*** | 0.0179** | -0.0215*** | 0.0646*** |
| | | (0.0067) | (0.0074) | (0.0093) | (0.0084) | (0.0077) | (0.0082) | (0.0154) |
| Buncher X Post X $H_i$ | | 0.0155 | 0.0046 | 0.0138 | -0.0055 | -0.0289 | 0.0077 | -0.0005 |
| | | (0.0205) | (0.0211) | (0.0244) | (0.0208) | (0.0220) | (0.0232) | (0.0434) |
| Depositor FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| ZIP X Time FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| # Obs | 2,666,481 | 2,659,503 | 2,666,481 | 2,666,481 | 2,666,481 | 2,666,481 | 2,666,481 | 2,666,481 |
| $R^2$ | 0.5973 | 0.5973 | 0.5973 | 0.5973 | 0.5978 | 0.5973 | 0.5973 | 0.5973 |

This table presents the response of bank deposits among bunchers compared to non-bunchers following the expansion of deposit insurance (DI). The dependent variable is the natural logarithm of bank deposits for depositor $i$ in month $t$. Post is an indicator variable taking a value of one for months since February 2020, and zero otherwise. The data covers the period from February 2019 to February 2021. Depositors are classified as bunchers or non-bunchers based on their average monthly deposits in the 12 months prior to February 2020. We compare the response of bunchers with pre-policy deposits in the $(75, 100]$ range with the non-bunchers whose pre-policy deposits fall within $(100, 500)$. Column 1 presents the baseline results and columns 2-10 present results that interact our baseline coefficient with a depositor-level characteristic. The depositor level characteristic $H_i$ is a binary variable taking a value of 1 if the depositor is a female in column 2, has other savings products such as recurring deposits and time deposits with the bank in column 6, has taken out a loan from the bank in column 7, and has a PPF account with the bank in column 8. The depositor level characteristic $H_i$ is a binary variable taking a value of 1 if the depositor's age, family size, and account age or years since in relationship with the bank in columns 3, 4, and 5 is greater than the sample median value. All continuous variables are winsorized at the 1% level. Standard errors, clustered at the ZIP code level, are shown in parentheses. Statistical significance is indicated by *, **, and ***, corresponding to the 10%, 5%, and 1% levels, respectively.

## D.7 Heterogeneity by Depositor Income

**Figure D.3:** Heterogeneous Response across the Income to DI Threshold Ratio Distribution




| Mean & Median Values of Monthly Income to DI Threshold Ratio | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Group # | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 |
| Mean | 0.000 | 0.029 | 0.143 | 0.261 | 0.358 | 0.472 | 0.624 | 0.820 | 1.067 | 1.409 | 2.391 |
| Median | 0.000 | 0.023 | 0.144 | 0.262 | 0.358 | 0.473 | 0.622 | 0.817 | 1.069 | 1.500 | 2.257 |

The figure plots the point estimate of the baseline regression estimated separately for each of the eleven groups across the income to the DI threshold ratio distribution. We divide all the depositors in our baseline sample into ten deciles based on their income to DI threshold ratio calculated by dividing their pre-policy (monthly) income by ₹100,000. Furthermore, we classify the depositors with zero income into a separate group, resulting in a total of eleven groups. The table below the figure reports the mean and median values of monthly income to DI threshold ratio for each of the groups. We then estimate the baseline regression 5 for each of the samples. Depositors in the baseline regression are classified as bunchers or non-bunchers based on their average monthly deposits in the 12 months prior to February 2020. We compare the response of bunchers with pre-policy deposits in the $(75, 100]$ range with the non-bunchers whose pre-policy deposits fall within $(100, 500)$. All continuous variables are winsorized at the 1% level. The 95% error bands are estimated by clustering the standard errors at the ZIP level.

## D.8 Role of Trust

**Table D.12:** Role of Trust: Effect of DI Expansion on Deposits

| Dep Var: LN(Deposits) | (1) | (2) | (3) |
|---|---|---|---|
| *Bunchers* × Post | 0.0503*** | | |
| | (0.0109) | | |
| Low Bank Trust × *Bunchers* × Post | | 0.0659*** | |
| | | (0.0168) | |
| Medium Bank Trust × *Bunchers* × Post | | 0.0494*** | |
| | | (0.0163) | |
| High Bank Trust × *Bunchers* × Post | | 0.0077 | |
| | | (0.0287) | |
| Low Gvt Trust × *Bunchers* × Post | | | 0.0153 |
| | | | (0.0204) |
| Medium Gvt Trust × *Bunchers* × Post | | | 0.0743*** |
| | | | (0.0182) |
| High Gvt Trust × *Bunchers* × Post | | | 0.0602*** |
| | | | (0.0176) |
| Depositor FE | Yes | Yes | Yes |
| ZIP X Time FE | Yes | Yes | Yes |
| # Obs | 2,498,598 | 2,498,598 | 2,498,598 |
| $R^2$ | 0.5951 | 0.5951 | 0.5951 |
| f-stat for equality: | | | |
| $High-Trust \times Bunchers \times Post =$ | | 3.06* | 2.78* |
| $Low-Trust \times Buncher \times Post$ | | | |

This table presents the heterogeneity in the response of bank deposits among bunchers compared to non-bunchers following the expansion of deposit insurance (DI) based on trust in banks and government. The dependent variable is the natural logarithm of bank deposits for depositor $i$ in month $t$. Post is an indicator variable taking a value of one for months since February 2020, and zero otherwise. The data covers the period from February 2019 to February 2021. Depositors are classified as bunchers or non-bunchers based on their average monthly deposits in the 12 months prior to February 2020. We compare the response of bunchers with pre-policy deposits in the $(75, 100]$ range with the non-bunchers whose pre-policy deposits fall within $(100, 500)$. We use the 2012 India Human Development Survey (IHDS) responses to questions on confidence in banks to keep money safe and confidence in government to look after people to create district-level measures of trust in banks and government. Appendix Figure C.3 discusses the construction of the two trust measures. We map this data to our depositor-level data after hand-matching district identifiers in both datasets. We divide the districts into three equally sized groups based on the trust measure and define districts as having low, medium and high trust values for banks and government based on the group they fall into. All continuous variables are winsorized at the 1% level. Standard errors, clustered at the ZIP code level, are shown in parentheses. Statistical significance is indicated by *, **, and ***, corresponding to the 10%, 5%, and 1% levels, respectively.

# Appendix E Effect on Security Holdings

## E.1 Effect by Security Type

**Table E.1:** Liquidation of Security Holdings & DI Expansion: Effect by Security Type

| | (1) | (2) |
|---|---|---|
| | LN(Amount) | LN(# Shares) |
| BuncherX Post X Stocks | -0.0126*** | -0.0108** |
| | (0.0043) | (0.0043) |
| BuncherX Post X Mutual Funds | -0.0460* | -0.0466* |
| | (0.0273) | (0.0271) |
| ISIN X Time FE | Yes | Yes |
| Depositor X Security Type FE | Yes | Yes |
| ZIP X Time FE | Yes | Yes |
| # Obs | 9,364,138 | 9,364,138 |
| $R^2$ | 0.7447 | 0.6175 |

This table presents the response of security holdings among bunchers compared to non-bunchers following the expansion of deposit insurance (DI). In column 1, the dependent variable is the natural logarithm of the total amount invested in security $j$ by the depositor $i$ in month $t$. In column 2, the dependent variable is the natural logarithm of the total number of shares held of security $j$ by the depositor $i$ in month $t$. Post is an indicator variable taking a value of one for months since February 2020, and zero otherwise. The data covers the period from February 2019 to February 2021. Depositors are classified as bunchers or non-bunchers based on their average monthly deposits in the 12 months prior to February 2020. We compare the response of bunchers with pre-policy deposits in the $(75, 100]$ range with the non-bunchers whose pre-policy deposits fall within $(100, 500)$. ISIN refers to a unique identifier of security $j$. All continuous variables are winsorized at the 1% level. Standard errors, clustered at the ZIP code and ISIN level, are shown in parentheses. Statistical significance is indicated by *, **, and ***, corresponding to the 10%, 5%, and 1% levels, respectively.

## E.2 Heterogeneous Response of Non-Bunchers

**Table E.2:** Heterogeneous Response of Non-Bunchers: Liquidation of Security Holdings & DI Expansion

| | (1) | (2) |
|---|---|---|
| | LN(Amount) | LN(# Shares) |
| $Bunchers$ × Post | -0.0244*** | -0.0225*** |
| | (0.0055) | (0.0055) |
| $Non - Bunchers_1$ (100-200] × Post | -0.0146*** | -0.0146*** |
| | (0.0044) | (0.0044) |
| $Non - Bunchers_2$ (200-300] × Post | -0.0177*** | -0.0172*** |
| | (0.0046) | (0.0046) |
| $Non - Bunchers_3$ (300-400] × Post | -0.0061 | -0.0054 |
| | (0.0048) | (0.0048) |
| ISIN X Time FE | Yes | Yes |
| Depositor X Security Type FE | Yes | Yes |
| ZIP X Time FE | Yes | Yes |
| # Obs | 9,364,510 | 9,364,485 |
| $R^2$ | 0.6083 | 0.7381 |
| f-stat (All) | 4.82*** | 4.46*** |
| f-stat ($Bunchers \times Post = Non - Bunchers_1 \times Post$) | 4.13** | 2.69 |
| f-stat ($Non - Bunchers_1 \times Post = Non - Bunchers_2 \times Post$) | 0.69 | 0.46 |
| f-stat ($Non - Bunchers_2 \times Post = Non - Bunchers_3 \times Post$) | 7.78*** | 8.00*** |

This table presents the response of security holdings among bunchers compared to non-bunchers following the expansion of deposit insurance (DI). In column 1, the dependent variable is the natural logarithm of the total amount invested in security $j$ by the depositor $i$ in month $t$. In column 2, the dependent variable is the natural logarithm of the total number of shares held of security $j$ by the depositor $i$ in month $t$. Post is an indicator variable taking a value of one for months since February 2020, and zero otherwise. The data covers the period from February 2019 to February 2021. Depositors are classified as bunchers or non-bunchers based on their average monthly deposits in the 12 months prior to February 2020. Specifically, we compare the response of bunchers (with pre-policy deposits $\in (70, 100]$) with the non-bunchers (with pre-policy deposits $\in (100, 500)$). Furthermore, we split non-bunchers into four groups of equal size of 100 or ₹100,000. $Non - Bunchers_1$ denotes non-bunchers with pre-policy deposits in the $(100, 200]$ range. $Non - Bunchers_2$ denotes non-bunchers with pre-policy deposits in the $(200, 300]$ range. $Non - Bunchers_3$ denotes non-bunchers with pre-policy deposits in the $(300, 400]$ range. $Non - Bunchers_4$ denotes non-bunchers with pre-policy deposits in the $(400, 500)$ range. $Non - Bunchers_4$ is the omitted variable in this regression. All continuous variables are winsorized at the 1% level. Standard errors, clustered at the ZIP code and ISIN level, are shown in parentheses. Statistical significance is indicated by *, **, and ***, corresponding to the 10%, 5%, and 1% levels, respectively.

## E.3 Robustness: Alternative Bandwidth

**Table E.3:** Alternative Bandwidth: Liquidation of Security Holdings & DI Expansion

| Panel A: Dep Var = LN(Amount of $Security_j$) | | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| Buncher X Post | -0.0134* | -0.0252*** | -0.0139* |
| | (0.0081) | (0.0063) | (0.0079) |
| Buncher | -0.0976*** | | |
| | (0.0142) | | |
| ISIN X Time FE | Yes | Yes | Yes |
| Depositor FE | | Yes | Yes |
| ZIP X Time FE | | | Yes |
| # Obs | 1,542,773 | 1,542,773 | 1,542,773 |
| $R^2$ | 0.5665 | 0.7539 | 0.7571 |

| Panel B: Dep Var = LN(#Shares of $Security_j$) | | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| Buncher X Post | -0.0147* | -0.0251*** | -0.0132* |
| | (0.0081) | (0.0063) | (0.0080) |
| Buncher | -0.0956*** | | |
| | (0.0144) | | |
| ISIN X Time FE | Yes | Yes | Yes |
| Depositor FE | | Yes | Yes |
| ZIP X Time FE | | | Yes |
| # Obs | 1,542,773 | 1,542,773 | 1,542,773 |
| $R^2$ | 0.3505 | 0.6312 | 0.636 |

This table presents the response of security holdings among bunchers compared to non-bunchers following the expansion of deposit insurance (DI). In Panel A, the dependent variable is the natural logarithm of the total amount invested in security $j$ by the depositor $i$ in month $t$. In Panel B, the dependent variable is the natural logarithm of the total number of shares held of security $j$ by the depositor $i$ in month $t$. Post is an indicator variable taking a value of one for months since February 2020, and zero otherwise. The data covers the period from February 2019 to February 2021. Depositors are classified as bunchers or non-bunchers based on their average monthly deposits in the 12 months prior to February 2020. We compare the response of bunchers with pre-policy deposits in the $(75, 100]$ range with the non-bunchers whose pre-policy deposits fall within $(100, 125]$. ISIN refers to a unique identifier of security $j$. All continuous variables are winsorized at the 1% level. Standard errors, clustered at the ZIP code and ISIN level, are shown in parentheses. Statistical significance is indicated by *, **, and ***, corresponding to the 10%, 5%, and 1% levels, respectively.

## E.4 Robustness: Alternative Specification

**Table E.4:** Alternative Specification: Liquidation of Security Holdings & DI Expansion

| | (1) | (2) |
|---|---|---|
| | LN(Amount) | LN(# Shares) |
| BuncherX Post | -0.0131*** | -0.0116*** |
| | (0.0040) | (0.0040) |
| ISIN X Time FE | Yes | Yes |
| Depositor | Yes | Yes |
| ZIP X Time FE | Yes | Yes |
| Buncher X ISIN FE | Yes | Yes |
| # Obs | 9,364,430 | 9,364,430 |
| $R^2$ | 0.7405 | 0.6118 |

This table presents the response of security holdings among bunchers compared to non-bunchers following the expansion of deposit insurance (DI). In column 1, the dependent variable is the natural logarithm of the total amount invested in security $j$ by the depositor $i$ in month $t$. In column 2, the dependent variable is the natural logarithm of the total number of shares held of security $j$ by the depositor $i$ in month $t$. Post is an indicator variable taking a value of one for months since February 2020, and zero otherwise. The data covers the period from February 2019 to February 2021. Depositors are classified as bunchers or non-bunchers based on their average monthly deposits in the 12 months prior to February 2020. We compare the response of bunchers with pre-policy deposits in the $(75, 100]$ range with the non-bunchers whose pre-policy deposits fall within $(100, 500)$. ISIN refers to a unique identifier of security $j$. All continuous variables are winsorized at the 1% level. Standard errors, clustered at the ZIP code and ISIN level, are shown in parentheses. Statistical significance is indicated by *, **, and ***, corresponding to the 10%, 5%, and 1% levels, respectively.

# Appendix F Alternative Sources of Deposit Growth

## F.1 Role of Cash-in-hand in Explaining Deposit Growth

**Table F.1:** Role of Cash-in-hand in Explaining Deposit Growth

| Dep Var: LN(Deposits) | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Buncher X Post | 0.0519*** | 0.0603*** | 0.0471*** | 0.0786*** |
| | (0.0109) | (0.0161) | (0.0129) | (0.0231) |
| Buncher X Post X High UPI Exposure | | -0.0158 | | |
| | | (0.0218) | | |
| Buncher X Post X Self Employed | | | 0.0154 | |
| | | | (0.0226) | |
| Buncher X Post X High Cash | | | | -0.0173 |
| | | | | (0.0311) |
| Self Employed X Post | | | -0.0448*** | |
| | | | (0.0080) | |
| High Cash X Post | | | | -0.0795*** |
| | | | | (0.0108) |
| Depositor FE | Yes | Yes | Yes | Yes |
| ZIP X Time FE | Yes | Yes | Yes | Yes |
| # Obs | 2,573,655 | 2,573,655 | 2,573,655 | 1,491,345 |
| $R^2$ | 0.5968 | 0.5968 | 0.5968 | 0.5906 |

This table presents the role of cash-in-hand in explaining the deposit growth among bunchers following the expansion of deposit insurance (DI). The dependent variable is the natural logarithm of bank deposits for depositor $i$ in month $t$. Post is an indicator variable taking a value of one for months since February 2020, and zero otherwise. The data covers the period from February 2019 to February 2021. Depositors are classified as bunchers or non-bunchers based on their average monthly deposits in the 12 months prior to February 2020. We compare the response of bunchers with pre-policy deposits in the $(75, 100]$ range with the non-bunchers whose pre-policy deposits fall within $(100, 500)$. High UPI Exposure is a binary variable taking a value of one for depositors in ZIP codes with above median value of UPI Exposure Index. UPI Exposure Index value comes from Cramer et al. (2024). Self-Employed is a binary variable taking a value of one for depositors who are self-employed and a value of zero for salaried depositors. High Cash Usage is a binary variable taking a value of one for depositors whose share of spending with cash during the twelve months before the policy is greater than the median value. All continuous variables are winsorized at the 1% level. Standard errors, clustered at the ZIP code level, are shown in parentheses. Statistical significance is indicated by *, **, and ***, corresponding to the 10%, 5%, and 1% levels, respectively.

## F.2 Role of Reallocation Across Banks in Explaining Deposit Growth

**Table F.2:** Role of Reallocation Across Banks in Explaining Deposit Growth

| Dep Var: LN(Deposits) | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| $Bunchers \times$ Post | 0.0515*** | 0.0509*** | 0.0511*** | 0.0514*** | 0.0504*** | 0.0505*** | 0.0515*** |
| | (0.0106) | (0.0152) | (0.0121) | (0.0111) | (0.0108) | (0.0107) | (0.0106) |
| $Bunchers \times$ Post $\times$ Dominant(>p50) | | 0.0011 | | | | | |
| | | (0.0212) | | | | | |
| $Bunchers \times$ Post $\times$ Dominant(>p75) | | | 0.0014 | | | | |
| | | | (0.0252) | | | | |
| $Bunchers \times$ Post $\times$ Dominant(>p90) | | | | 0.0010 | | | |
| | | | | (0.0368) | | | |
| $Bunchers \times$ Post $\times$ Dominant(>p95) | | | | | 0.0226 | | |
| | | | | | (0.0559) | | |
| $Bunchers \times$ Post $\times$ Dominant(>p99) | | | | | | 0.0874 | |
| | | | | | | (0.0853) | |
| $Bunchers \times$ Post $\times$ Only Bank | | | | | | | -0.0919 |
| | | | | | | | (0.2496) |
| Depositor FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| ZIP X Time FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| # Obs | 2,649,780 | 2,649,780 | 2,649,780 | 2,649,780 | 2,649,780 | 2,649,780 | 2,649,780 |
| $R^2$ | 0.5966 | 0.5966 | 0.5966 | 0.5966 | 0.5966 | 0.5966 | 0.5966 |

This table presents the response of bank deposits among bunchers compared to non-bunchers following the expansion of deposit insurance (DI). The dependent variable is the natural logarithm of bank deposits for depositor $i$ in month $t$. Post is an indicator variable taking a value of one for months since February 2020, and zero otherwise. The data covers the period from February 2019 to February 2021. Depositors are classified as bunchers or non-bunchers based on their average monthly deposits in the 12 months prior to February 2020. We compare the response of bunchers with pre-policy deposits in the $(75, 100]$ range with the non-bunchers whose pre-policy deposits fall within $(100, 500)$. We classify all ZIP codes as being dominant or non-dominant with respect to our data provider bank. For each ZIP code we calculate the share of branches that belong to our bank. We then classify ZIP codes as dominant if the share value is greater than or equal to the 50th (column 2), 75th (column 3), 90th (column 4), 95th (column 5), and 99th (column 6) percentile value. Column 7 uses the binary variable Only Bank that takes a value of one if our bank is the only bank in that ZIP and zero otherwise. All continuous variables are winsorized at the 1% level. Standard errors, clustered at the ZIP code level, are shown in parentheses. Statistical significance is indicated by *, **, and ***, corresponding to the 10%, 5%, and 1% levels, respectively.

**Table F.3:** Role of Reallocation Across Banks: Effect on # of Transactions

| Dep Var: # of Transactions | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| Buncher X Post | -0.0051 | -0.0048 | 0.0026 | 0.0018 |
| | (0.0088) | (0.0088) | (0.0080) | (0.0082) |
| Buncher | 0.0315** | 0.0308** | | |
| | (0.0143) | (0.0143) | | |
| Post | 0.0755*** | | | |
| | (0.0035) | | | |
| Time FE | | Yes | Yes | |
| Depositor FE | | | Yes | Yes |
| ZIP X Time FE | | | | Yes |
| # Obs | 1,755,563 | 1,755,563 | 1,755,563 | 1,755,563 |
| Pseudo $R^2$ | 0.0009 | 0.0091 | 0.6031 | 0.6155 |

This table presents the response of the number of transactions among bunchers compared to non-bunchers following the expansion of deposit insurance (DI) using Poisson pseudo-likelihood regression. The dependent variable is the number of transactions conducted by depositor $i$ in month $t$. Post is an indicator variable taking a value of one for months since February 2020, and zero otherwise. The data covers the period from February 2019 to February 2021. Depositors are classified as bunchers or non-bunchers based on their average monthly deposits in the 12 months prior to February 2020. We compare the response of bunchers with pre-policy deposits in the $(75, 100]$ range with the non-bunchers whose pre-policy deposits fall within $(100, 500)$. All continuous variables are winsorized at the 1% level. Standard errors, clustered at the ZIP code level, are shown in parentheses. Statistical significance is indicated by *, **, and ***, corresponding to the 10%, 5%, and 1% levels, respectively.

## F.3 Role of Spending in Explaining Deposit Growth

**Table F.4:** Role of Spending in Explaining Deposit Growth

| Dep Var: Spending (in '000) | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| *Bunchers* × Post | 2.2383 | 2.1218 | 1.6110 | 2.1228 |
| | (1.5398) | (1.5367) | (1.4460) | (1.4622) |
| *Bunchers* | -44.6326*** | -44.6144*** | | |
| | (1.4929) | (1.4930) | | |
| Post | 22.5630*** | | | |
| | (0.6795) | | | |
| Time FE | | Yes | Yes | |
| Depositor FE | | | Yes | Yes |
| ZIP X Time FE | | | | Yes |
| # Obs | 1,755,563 | 1,755,563 | 1,755,563 | 1,755,563 |
| $R^2$ | 0.0041 | 0.0102 | 0.3583 | 0.3855 |

This table presents the response of spending among bunchers compared to non-bunchers following the expansion of deposit insurance (DI). The dependent variable is the total spending for depositor $i$ in month $t$ in '000 rupees. We follow Ganong and Noel (2020) and use spending in its level form as the dependent variable, as this best corresponds to macroeconomic models of consumption. Post is an indicator variable taking a value of one for months since February 2020, and zero otherwise. The data covers the period from February 2019 to February 2021. Depositors are classified as bunchers or non-bunchers based on their average monthly deposits in the 12 months prior to February 2020. We compare the response of bunchers with pre-policy deposits in the $(75, 100]$ range with the non-bunchers whose pre-policy deposits fall within $(100, 500)$. All continuous variables are winsorized at the 1% level. Standard errors, clustered at the ZIP code level, are shown in parentheses. Statistical significance is indicated by *, **, and ***, corresponding to the 10%, 5%, and 1% levels, respectively.

## F.4 Role of Reallocation Within Household in Explaining Deposit Growth

**Table F.5:** Role of Reallocation Within Household in Explaining Deposit Growth

| Dep Var: LN(Deposits) | (1) | (2) |
|---|---|---|
| Buncher X Post | 0.0521*** | 0.0344*** |
| | (0.0106) | (0.0114) |
| Buncher X Post X Sh Dep | | -0.0569*** |
| | | (0.0045) |
| Sh Dep X Post | | -0.0019 |
| | | (0.0127) |
| Depositor FE | Yes | Yes |
| ZIP X Time FE | Yes | Yes |
| # Obs | 2,652,035 | 2,652,035 |
| $R^2$ | 0.5973 | 0.5975 |

This table presents the response of bank deposits among bunchers compared to non-bunchers following the expansion of deposit insurance (DI). The dependent variable is the natural logarithm of bank deposits for depositor $i$ in month $t$. Post is an indicator variable taking a value of one for months since February 2020, and zero otherwise. The data covers the period from February 2019 to February 2021. Depositors are classified as bunchers or non-bunchers based on their average monthly deposits in the 12 months prior to February 2020. We compare the response of bunchers with pre-policy deposits in the $(75,100]$ range with the non-bunchers whose pre-policy deposits fall within $(100,500)$. Sh Dep is a continuous variable ranging from zero to one, representing the share of depositor $i$'s pre-policy deposits relative to the total pre-policy deposits of their entire household. All continuous variables are winsorized at the 1% level. Standard errors, clustered at the ZIP code level, are shown in parentheses. Statistical significance is indicated by *, **, and ***, corresponding to the 10%, 5%, and 1% levels, respectively.

## F.5 Are Bunchers More Likely to Get Loans?

**Table F.6:** Are Bunchers More Likely to Get Loans?

| Dep Var: Loan (=1)*100 | (1) All | (2) Personal | (3) Auto | (4) Home | (5) Others |
|---|---|---|---|---|---|
| $Bunchers \times$ Post | 0.0241 | 0.0011 | 0.0203* | 0.0010 | 0.0041 |
| | (0.0234) | (0.0141) | (0.0108) | (0.0155) | (0.0048) |
| Depositor FE | Yes | Yes | Yes | Yes | Yes |
| ZIP X Time FE | Yes | Yes | Yes | Yes | Yes |
| # Obs | 2,666,481 | 2,666,481 | 2,666,481 | 2,666,481 | 2,666,481 |
| $R^2$ | 0.1056 | 0.1113 | 0.1001 | 0.0899 | 0.0935 |

This table presents the response of bank lending among bunchers compared to non-bunchers following the expansion of deposit insurance (DI). The dependent variable is a binary variable taking a value of one if depositor $i$ was given a new loan at time $t$. Column 1 uses all loans, column 2 uses personal loans, column 3 uses auto or vehicle loans that are used to purchase vehicles, column 4 uses home loans or mortgages, and column 5 uses all other loan types as the dependent variable. Post is an indicator variable taking a value of one for months since February 2020, and zero otherwise. The data covers the period from February 2019 to February 2021. Depositors are classified as bunchers or non-bunchers based on their average monthly deposits in the 12 months prior to February 2020. We compare the response of bunchers with pre-policy deposits in the $(75, 100]$ range with the non-bunchers whose pre-policy deposits fall within $(100, 500)$. All continuous variables are winsorized at the 1% level. Standard errors, clustered at the ZIP code level, are shown in parentheses. Statistical significance is indicated by *, **, and ***, corresponding to the 10%, 5%, and 1% levels, respectively.