# Informational Advantage of the Wealthy *

Sumit Agarwal† Longwei Cheng‡ Pulak Ghosh§ Poorya Kabir¶

July 2026

Preliminary draft; please do not circulate.

**Abstract**

Wealthier individuals earn systematically higher returns on their wealth, yet the channels driving this return gap remain unclear. Using a proprietary dataset of over 90,000 Indian retail investors, we document that average annual excess returns rise monotonically with financial wealth, driven almost entirely by higher risk-adjusted returns, not by differences in systematic risk. Exploiting India's 2015 amendment to its insider-trading regulations, which sharply increased the cost of trading on private information, we show that the risk-adjusted return gap between the top 1% and the rest shrinks by 68%. The top 1% trade disproportionately in stocks during proven insider-trading violation windows, and their pre-announcement buying of M&A target firms disappears after the reform. To examine how wealthier individuals obtain private information, we draw on information-network theory and use two complementary proxies for investor connections to show that wealthier individuals have better-informed connections. Overall, private information can generate substantial return inequality even in stock markets commonly viewed as level playing fields.

*We thank comments and helpful suggestions by Stijn van Nieuwerburgh, Abhiroop Mukherjee, and seminar participants at 2026 China International Conference in Finance, 2026 Five-Star Asia Pacific Workshop in Finance, NUS Finance, and NUS Economics. We thank Trong Nghia Phung for excellent research assistance.

†National University of Singapore; ushakri@yahoo.com

‡National University of Singapore; longwei.cheng@u.nus.edu

§Indian Institute of Management Bangalore; pulak.ghosh@iimb.ac.in

¶National University of Singapore; poorya.kabir@nus.edu.sg

## 1 Introduction

Wealth is concentrated among a small fraction of the population in many countries around the world (Piketty, 2014; Saez and Zucman, 2016; Kuhn et al., 2020; Chancel et al., 2022; Bharti et al., 2024). A growing literature documents that returns heterogeneity, that is, wealthier individuals earning higher returns on their wealth, plays a crucial role in explaining wealth inequality.[1] However, much less is known about *why* this return gap exists.

This return gap could arise from three channels: differential access to investment opportunities (Ebrahimian and Ljungqvist, 2025; Gocmen et al., 2025), differential exposure to systematic risk (Bach et al., 2020), or differential access to information (Kacperczyk and Pagnotta, 2019; Kacperczyk et al., 2019).

We pursue this question in India, the third-largest equity market in the world by market capitalization. Direct stock holdings account for approximately 20% of individual wealth, making the stock market a relevant domain to study return heterogeneity. A 2015 amendment to India's Prohibition of Insider Trading (PIT) regulations, which raised the cost of insider trading, provides a natural experiment to identify the role of access to private information.

We use a proprietary dataset from a large commercial bank in India, spanning 2012 to 2019. The dataset contains monthly equity holdings for over 90,000 individuals, together with detailed financial information (deposits, credit, debit spending, and cash withdrawals) and demographic characteristics. Our dataset offers two key advantages. First, the sample provides substantial coverage of the right tail of the wealth distribution, which is critical for studying wealth inequality and heterogeneity in returns (Bach et al., 2020; Balloch and Richers, 2023). For example, approximately 1,200 individuals in our sample have financial wealth that on its own places them in the top 0.1% of the In-

[1] See Benhabib et al. (2011, 2019); Gabaix et al. (2016); Kacperczyk et al. (2019); Azarmsa (2026) for theoretical arguments, and Bach et al. (2020); Fagereng et al. (2020); Hubmer et al. (2024) for empirical evidence.

dian wealth distribution, based on the estimates of Bharti et al. (2024). Second, we observe end-of-month stock-level holdings for each individual, which we use to examine whether informational advantages drive differential returns across the wealth distribution.

We begin by documenting that wealthier[2] individuals earn systematically higher returns. We define financial wealth as the sum of direct stock holdings and bank deposits. Average annual excess returns increase monotonically with financial wealth, rising by 7 percentage points from the 10th to the 90th percentile of the wealth distribution, and by 20 percentage points from the 10th percentile to the top 1%. The monotonic pattern is consistent with existing evidence (Bach et al., 2020; Fagereng et al., 2020). Direct equity accounts for roughly a fifth of individual wealth in India, so a gap of this magnitude contributes several percentage points to the dispersion in returns on total wealth.

Two of the three channels proposed earlier can be ruled out in our setting. First, differential access to investment opportunities is held fixed by construction, since all individuals in our sample face the same public-equity opportunity set. Second, unlike much of the existing literature, differential exposure to systematic risk does not explain the gap: the systematic component of returns, estimated using the Fama-French 3-factor model, is stable across the wealth distribution. Instead, the gap is almost entirely driven by higher risk-adjusted returns, consistent with the third channel.

The portfolio structure of wealthier individuals is also consistent with an information advantage. Models of portfolio choice with information acquisition predict that investors with an information advantage hold more concentrated portfolios (e.g., Van Nieuwerburgh and Veldkamp, 2010). Consistent with this prediction, individuals at the right tail of the wealth distribution hold significantly less diversified portfolios.

This third channel can take two forms: *private information*, access to information not reflected in prices, and *skill*, the ability to process public information more effectively

[2]Throughout the paper, we use *wealthier* to refer to the continuous wealth gradient and *higher-wealth* to refer to individuals in the top 1% of the financial wealth distribution; *lower-wealth* (or *the rest*) refers to the bottom 99%.

(Kacperczyk and Pagnotta, 2019). Our findings so far are consistent with a role for both. We next provide our primary evidence on the private-information channel by examining how raising the cost of trading on private information affects the risk-adjusted return gap.

Our identification comes from the 2015 amendment to India's PIT regulations. The Securities and Exchange Board of India (SEBI) announced the revised framework in January 2015, and it came into force in May 2015 (Varottil, 2016). The amendment substantially raised the cost of trading on private information, with the number of insider trading investigations quadrupling between the 2014/15 and 2016/17 fiscal years (SEBI, 2020; Bhattacharya and Daouk, 2002).

Following the amendment, the risk-adjusted return gap between higher-wealth individuals (top 1%) and the rest (bottom 99%) shrinks by 68%, indicating that private information is a key driver of return differences. The reduction is concentrated in the right tail of the risk-adjusted return distribution, where the excess mass for higher-wealth individuals largely disappears. This pattern is consistent with a decline in returns from large price movements, where private information is most valuable.

The reduced return gap following the amendment implies that higher-wealth individuals benefit disproportionately from private information. We test this implication using a hand-collected sample of all proven SEBI insider-trading cases: higher-wealth individuals trade more in these stocks during the documented violation windows. Our tightest specification includes individual-by-stock and individual-by-time fixed effects. The individual-by-stock fixed effects rule out that higher-wealth individuals systematically trade stocks more prone to violations; the individual-by-time fixed effects rule out that they simply trade more in all stocks during violation months.

The 2015 PIT amendment names specific categories of private information that investors are prohibited from trading on. We next focus on one of them: mergers, demergers, and acquisitions. M&A is also well-suited to detect such trading: the direction of informed positioning is unambiguous, since target shareholders earn large positive an-

nouncement returns (Jensen and Ruback, 1983; Andrade et al., 2001), and the public announcement provides a clean event date anchoring the test. If higher-wealth individuals have access to such information, they should accumulate target firm shares before M&A announcements. In the pre-PIT period, they do: higher-wealth individuals systematically buy target shares in the 12 months preceding the announcement, and this differential trading disappears following the amendment.

If the reform reduced the benefits of trading on private information for higher-wealth individuals, we would expect a decline in their net flows into equities (purchases minus sales). Consistent with this prediction, we find a reduction in net flows into equities for higher-wealth individuals relative to lower-wealth individuals. We also observe a modest increase in their spending, concentrated in discretionary categories, consistent with lower returns weakening the incentive to defer consumption in favor of investment.

Lastly, we ask how wealthier individuals obtain private information. Information-network theory predicts that more centrally positioned investors receive market-relevant information earlier than peripheral ones (Rossi et al., 2018; Ozsoylev and Walden, 2011; Walden, 2019). A natural possibility, then, is that wealthier individuals have better-informed connections, occupying more central positions in such networks. Because the true network is unobservable, we proxy it in two complementary ways, each capturing a different dimension of connection. The first is a communication network, built from call volumes between Indian pincodes (six-digit postal codes, analogous to U.S. ZIP codes) provided by a national telecommunications company, which measures how closely two areas are tied by direct contact. The second is an investor network inferred from trading behavior, in which two investors are linked when they trade the same stocks at similar times, following Rossi et al. (2018) and Ozsoylev et al. (2014). The two draw on entirely different data, one on communication and the other on trading, so their agreement is more telling than either measure alone. Under both, network centrality increases monotonically with financial wealth, and more central individuals earn higher risk-adjusted

returns. Furthermore, wealthier individuals' portfolios are markedly more similar to one another than to those of less wealthy individuals, pointing to a common rather than idiosyncratic information source.

Our results recast insider trading as a force in the distribution of wealth, not only a matter of market integrity. Because access to private information is concentrated at the top, the rents it generates widen the return gap that compounds into wealth inequality. The 2015 PIT amendment compressed the risk-adjusted return gap between higher- and lower-wealth individuals by roughly two-thirds, indicating that credible enforcement of insider-trading regulation is a lever on wealth concentration. This perspective bridges two literatures that have developed largely in isolation: returns heterogeneity and wealth inequality (Bach et al., 2020; Fagereng et al., 2020; Hubmer et al., 2024), which has documented the return gap but said relatively little about its origins, and insider trading (Bhattacharya and Daouk, 2002; Kacperczyk and Pagnotta, 2024), which has examined consequences for prices and market quality rather than for the distribution of wealth.

We mainly contribute to the literature on returns heterogeneity by providing *causal* evidence on the role of information. The literature has documented that heterogeneity in returns on wealth is an important factor in explaining wealth concentration at the top, both theoretically (Benhabib et al., 2011, 2019; Gabaix et al., 2016; Kacperczyk et al., 2019; Azarmsa, 2026) and empirically (Campbell et al., 2019; Bach et al., 2020; Fagereng et al., 2020; Hubmer et al., 2024). However, prior studies report mixed evidence on the role of information. Using Norwegian data, Fagereng et al. (2020) document significant individual fixed effects, suggesting a potential role for information, while Bach et al. (2020) find that returns heterogeneity in Sweden is almost entirely driven by differential risk exposures.

To the best of our knowledge, we provide the first *causal* evidence on the role of information in generating returns heterogeneity. We show that when access to private information is exogenously restricted, the return gap shrinks substantially. Our findings

provide empirical support for Lusardi et al.'s (2017) model, which argues that financial knowledge is a key determinant of wealth inequality. By linking individual returns to spending records, we also provide direct evidence for Daminato and Pistaferri's (2024) model, in which returns heterogeneity is a key factor explaining consumption inequality.

We also contribute to the literature on insider trading. An extensive empirical literature studies whether insider trading generates abnormal returns and carries information (e.g., Seyhun, 1986; Lakonishok and Lee, 2001; Cohen et al., 2012; Dai et al., 2026; Guest et al., 2026), how insiders execute trades (e.g., Collin-Dufresne and Fos, 2015; Kacperczyk and Pagnotta, 2019), what affects insider trading (Ravina and Sapienza, 2010; Ali and Hirshleifer, 2017), how private information flows (Ahern, 2017), and how to regulate insider trading (Bhattacharya and Daouk, 2002; Jagolinzer, 2009; Kacperczyk and Pagnotta, 2024). However, little attention has been paid to its implications for wealth inequality. We show that insider trading can have a significant impact on wealth accumulation, as wealthier individuals are more likely to be connected to insiders and trade on private information.

The remainder of the paper is organized as follows: We describe our data in the next section. In Section 3, we establish the returns heterogeneity and provide suggestive evidence that it is driven by information. In Section 4, we analyze the effect of the PIT regulations, and we discuss potential mechanisms in Section 4.4 and Section 5. Section 6 concludes.

## 2 Data and Variable Definitions

### 2.1 Account and Holdings Data

Our primary data is a proprietary dataset of the Dematerialized (Demat) accounts held by customers at one of India's top four banks by assets. A Demat account holds securities electronically and is required for securities trading in India. The data record each customer's stock holdings at the security level at the end of every month from January 2012 to December 2019.

For each individual, we also observe end-of-month balances in savings accounts, time deposits, and Public Provident Fund (PPF) accounts. We define *financial wealth* as the sum of direct stock holdings, savings, time deposits, and PPF. We further observe credit card, debit card, and ATM transactions, from which we measure spending, and demographics, including age, gender, and a credit score from a leading credit bureau. All monetary values are expressed in real 2019 INR, adjusted for inflation using the World Bank Consumer Price Index (CPI). For reference, the end-of-2019 exchange rate is 71.36 INR per USD (Reserve Bank of India).

Our sample is a random and representative draw of the bank's customers across nine major cities (Ahmedabad, Bangalore, Bhubaneshwar, Chennai, Delhi, Gurgaon, Kolkata, Mumbai, and Surat) in seven states with diverse geographic and economic characteristics. We apply two filters: following Andersen et al. (2024), we require account-month observations to have a minimum wealth of INR 1,000 (about $14 at the 2019 exchange rate) to screen out inactive accounts; and following Fagereng et al. (2020), we restrict the sample to individuals aged 16 to 85, so that they represent independent financial decision-makers. These filters yield a final sample of 91,555 individuals. We restrict the holdings data to publicly listed equities, which constitute over 93% of holdings value in our sample and let us study returns heterogeneity on a "level playing field" of an asset class in principle accessible to all individuals, leaving 4,243 distinct stocks.

Two features of the data make it well-suited to our question. First, because we observe each individual's holdings, deposits, and spending at the same time, we can construct a more precise measure of wealth than brokerage data alone. Spending, moreover, cannot be measured from brokerage data at all. Second, the sample oversamples the right tail of the wealth distribution, which is critical for studying wealth inequality and returns heterogeneity (Bach et al., 2020; Balloch and Richers, 2023). Roughly 1.3% of individuals in our data, nearly 1,200 people, would rank in the top 0.1% of India's 2022 wealth distribution on their financial wealth alone, based on Bharti et al.'s (2024) estimates. Our sample's

holdings represent 0.3% of total Indian market capitalization at the end of 2019, or 3.6% of the equity held by all individual investors in India, a coverage ratio comparable to the data used by Balloch and Richers (2023) and Gabaix et al. (2025).[3]

### 2.2 Measuring Returns

We obtain daily stock price and returns data from the Prowess database, maintained by the Centre for Monitoring Indian Economy (CMIE), which is the standard source for Indian market data (analogous to CRSP in the US).[4]

Individual $i$'portfolio return is measured as the value-weighted average of stock-level excess returns using beginning-of-month stock holdings, assuming a buy-and-hold portfolio over the month. Specifically, for stock $s$ during month $t$, we measure the dividend-adjusted returns $r_{s,t}$ by compounding daily returns. Excess returns, $\tilde{r}_{s,t}$, is then computed as the return in excess of the risk-free rate using the monthly yield on the 91-day T-bill (Agarwalla et al., 2014). Individual $i$'s portfolio excess return in month $t$ equals

$$\tilde{r}_{i,t} = \sum_{s=1}^{N} w_{i,s,t-1}\tilde{r}_{s,t}, \tag{1}$$

where $w_{i,s,t-1}$ is the value-weight of stock $s$ in individual $i$'s portfolio at the beginning of month $t$. Our return measure therefore applies to the equity portfolio alone, in the terminology of Bach et al. (2020), the *risky financial portfolio* rather than the *complete financial portfolio*, which also includes safe assets. Following Bach et al. (2020), excess returns can be decomposed into systematic return $r^s_{i,t}$, and risk-adjusted return, $\alpha_{i,t}$. Our decomposition procedure begins at the stock level. Specifically, for each stock $s$, we model the excess returns in month $t$ as

$$\tilde{r}_{s,t} = \alpha_s + \beta_s' f_t + \mu_{s,t}, \tag{2}$$

[3]Individual investors owned 8.4% of Indian market capitalization in December 2019 (NSE, 2020); domestic mutual funds owned 7.8%.

[4]See Fisman et al. (forthcoming) and Kabir et al. (2025) for example.

where $\alpha_s$ is a measure of risk-adjusted performance, $f_t$ is a column vector of pricing factors, $\beta_s$ is a column vector of factor loadings, and $\mu_{s,t}$ is a residual uncorrelated to the factors. For each stock $s$, we estimate equation (2) and obtain $\alpha_s$ and $\beta_s$ using OLS with all available historical returns from 2012 to 2019. We employ the Fama and French (1993) three factors as the components of $f_t$.[5] In our Internet Appendix, we show that the main results are robust to using the four-factor model of Carhart (1997).

With these stock-level estimates, we then construct the systematic and risk-adjusted returns for individual $i$'s portfolio in month $t$. The portfolio's systematic return, $r^s_{i,t}$, and risk-adjusted return, $\alpha_{i,t}$, are value-weighted average of stock-level systematic and risk-adjusted returns:

$$r^s_{i,t} = \sum_{s=1}^{N} w_{i,s,t-1} \beta_s^{'} f_t \tag{3}$$

$$\alpha_{i,t} = \sum_{s=1}^{N} w_{i,s,t-1} (\tilde{r}_{s,t} - \beta_s^{'} f_t). \tag{4}$$

Systematic return $r^s_{i,t}$ captures the return the individual would have earned during month $t$ if she held a portfolio of only risk-factors with the same risk exposures as her portfolio. Risk-adjusted returns $\alpha_{i,t}$ is therefore the difference between returns generated by the actual portfolio and the counterfactual portfolio.

Because our analyses use data at both monthly and quarterly frequencies, we report all returns in annualized percentage points, multiplying monthly returns by twelve and quarterly returns by four, so that magnitudes are comparable across analyses. All returns are winsorized at the 1% level.

**SEBI enforcement data:** We hand-collect the orders that conclude SEBI's insider-trading investigations, each of which names the stock involved and the period over which the violation occurred. We retrieve them from SEBI's public order repository, searching

[5] Following Balasubramaniam et al. (2023), we use the regularly maintained data set provided by Agarwalla et al. (2014). The data are available at https://faculty.iima.ac.in/iffm/Indian-Fama-French-Momentum/.

the keyword "insider" over orders issued between January 2012 and January 2026. We extend the search six years beyond the end of our sample because SEBI typically issues an order several years after the conduct it concerns. We use `Gemini-3.0-Flash-Preview` to extract the stock and the violation window from each order, retaining only orders in which SEBI found a violation. This yields 496 stocks with a proven violation over our sample period. Appendix Section B details the collection procedure, including the types of order we retain and the accuracy of the extraction.

**M&A data:** We also obtain data on M&As between 2012 and 2019 from Prowess. Prowess reports detailed deal characteristics, including the deal type (such as a merger or an acquisition of shares) and identifiers for the acquirer and the target. Following the literature (LAGARAS, ????), we restrict attention to mergers and to acquisitions of a majority stake ($> 50\%$) in the target. Because target shareholders earn large positive announcement returns while acquirer shareholders typically do not (e.g., Jensen and Ruback, 1983; Andrade et al., 2001), we focus exclusively on trading in the target's stock around the announcement. Appendix Figure IA.2 confirms that target firms in our sample earn positive abnormal returns following the announcement. Merging these deals with our holdings data yields a final sample of 278 M&A events.

**Phone call data:** We obtain pincode-to-pincode call volumes from a national telecommunications company. For each pair of Indian pincodes (six-digit postal codes, analogous to U.S. ZIP codes), the data record the total minutes of calls between the two in each week from August to December 2019 (calendar weeks 32–52). We use these call volumes in Section 5.1 to construct a communication network that proxies for the flow of information across locations.

### 2.3 Summary Statistics

Table 1 reports summary statistics for our final sample; all continuous variables are winsorized at the 1% level. At the individual-stock-month level, the average position in a

single stock is 62,820 INR, with a standard deviation of 139,510 INR. The median holding is well below the mean, indicating a right-skewed distribution. The average net flow into a single stock is $-2{,}090$ INR, with a standard deviation of 9,100 INR.

On average, an individual earns a portfolio excess return of $-1.25\%$ and a risk-adjusted return of $-4.88\%$; both are widely dispersed, with a standard deviation of 71 percentage points for risk-adjusted returns and 96 for excess returns. Average financial wealth is 1.95 million INR, and, like individual holdings, it is highly right-skewed. In the next section, we document how returns vary with wealth, showing that wealthier individuals earn higher returns.

## 3 Returns Heterogeneity and the Role of Information

In this section, we study how portfolio returns vary with financial wealth. We group individuals by financial wealth and compare their average portfolio excess returns. We then decompose excess returns into systematic and risk-adjusted components and examine how each varies with financial wealth. Finally, we examine portfolio diversification across the wealth distribution, to assess whether concentration patterns are consistent with an information-based explanation.

We find that excess returns increase with financial wealth, particularly at the top of the distribution. This gradient is driven almost entirely by differences in risk-adjusted returns rather than systematic returns. Consistent with an information-based interpretation, wealthier individuals hold more concentrated portfolios. Taken together, these results suggest that differences in returns across the wealth distribution are closely linked to information advantages among higher-wealth individuals.

### 3.1 Returns Heterogeneity

We first document how portfolio excess returns vary across the financial wealth distribution.

At the beginning of each month, we sort individuals into percentiles of financial wealth, following prior work (e.g., Fagereng et al., 2020). For each individual and month, we measure portfolio excess returns as described in Section 2.2. Within each percentile-month, we average these excess returns across individuals, weighting by beginning-of-month financial wealth, and take the time-series average across months to obtain one excess return per percentile. We compute average financial wealth in each percentile the same way, and relate the two.

Figure 1 plots portfolio excess returns against financial wealth, measured on a log scale. Excess returns increase monotonically with financial wealth, rising by about 7 percentage points per year from the 10th percentile ($-4.08\%$) to the 90th (3.04%); the wealthiest 1% earn 16.22% annually, in line with this gradient.

A positive wealth–return gradient is well documented in developed economies (Bach et al., 2020; Fagereng et al., 2020; Balloch and Richers, 2023), though existing estimates are measured on broader baskets that blend high- and low-return assets. Bach et al. (2020) report a spread of 4.5 percentage points in historical excess returns on gross wealth—financial, real estate, private equity, and pension assets combined—between the 10–20th and 90–95th percentile groups in Sweden, and Fagereng et al. (2020) a spread of 1.6 percentage points in returns to financial wealth, which also includes safe assets, between the 10th and 90th percentiles in Norway. Measured on directly held equity alone, our gradient is steeper—and, as we show next, driven by risk-adjusted rather than systematic returns. We return in Section **??** to whether this gradient reflects scale dependence, type dependence, or both, in the sense of Gabaix et al. (2016).

### 3.2 Information or Risk Exposure?

Wealthier individuals' higher excess returns could reflect either a higher systematic return, the reward for greater exposure to systematic risk (higher beta), or a higher risk-adjusted return (higher alpha). To distinguish these, we decompose individual excess

returns into a systematic and a risk-adjusted component.

We estimate systematic and risk-adjusted returns at the individual-month level from equations (3) and (4), and average each component into wealth bins exactly as we did for excess returns (Figure 1).

Figure 2 decomposes excess returns into systematic (Panel A) and risk-adjusted (Panel B) components. Systematic returns are largely flat across the wealth distribution. Risk-adjusted returns, by contrast, closely track the excess-return gradient in Figure 1: moving from the 10th percentile to the top 1%, they rise by 21.5 percentage points per year, from $-7.51\%$ to 13.99%.

This composition differs from the benchmark evidence. Bach et al. (2020) find that the Swedish gradient is determined primarily by systematic returns, with risk-adjusted performance differing by only about half a percentage point per year between the median bracket and the top 0.01%. That returns rise with wealth is a common finding; that the rise is risk-adjusted is not.

Our results provide little support for a risk-based explanation: the systematic component is flat across the wealth distribution. And because every investor in our sample chooses from the same set of publicly listed stocks, the risk-adjusted gradient cannot reflect differential access to investment opportunities either. What remains is an information advantage: wealthier individuals earn higher returns on the same securities, at the same risk exposure.

### 3.3 Diversification

The portfolio structure of wealthier individuals is also consistent with an information advantage. Portfolio choice theory predicts that investors with an information advantage hold more concentrated portfolios (Van Nieuwerburgh and Veldkamp, 2010), allocating more to the stocks they are informed about and less to the rest. Under this interpretation, the wealthiest individuals should hold the least diversified portfolios.

We study how portfolio diversification varies with financial wealth, following the same construction as in Figures 1 and 2. For each individual-month, we measure diversification as one minus the Herfindahl–Hirschman Index of portfolio shares (1−HHI), following Dorn and Huberman (2010), where each share is the value of a stock relative to the individual's total stock holdings at the beginning of the month.

Figure 3 plots portfolio diversification against financial wealth. Diversification first increases with wealth, reaching a peak of 0.61 at the 80th percentile, then declines to 0.56 at the 90th and to 0.04 for the top 0.1%. For reference, a portfolio of $N$ equally weighted stocks has a diversification measure of 0.66 for $N = 3$, 0.5 for $N = 2$, and 0 for $N = 1$, so the top 0.1%, at 0.04, hold portfolios close to a single stock.

That diversification increases with wealth through most of the distribution is well understood: it is consistent with standard explanations for under-diversification (Polkovnichenko, 2005; Dimmock et al., 2021), such as a preference for skewness among less wealthy investors (Mitton and Vorkink, 2007; Kumar, 2009). Its reversal at the top—the decline in diversification among the wealthiest individuals—is not: standard accounts do not predict that those who can most easily diversify would hold the most concentrated portfolios. In Swedish data spanning all asset classes, the under-diversification of the wealthy is attributed largely to their ownership of private businesses (Bach et al., 2020), which are large, illiquid, and inherently hard to diversify. The public equity we study, by contrast, can easily be diversified, so the concentration we document reflects choice rather than a constraint. Together with the higher returns this concentration accompanies, it is consistent with an information advantage among the wealthiest individuals.

## 4 Trading on Private Information and the 2015 Reform

The evidence so far is consistent with wealthier individuals holding an information advantage over the rest of the market. This advantage can take two forms: *private information*, access to information not reflected in prices, or *skill*, the ability to process public in-

formation more effectively (Kacperczyk and Pagnotta, 2019).[6] Both would lead wealthier individuals to earn higher risk-adjusted returns, so the return data alone are consistent with either. We therefore exploit the 2015 amendment to the Securities and Exchange Board of India's (SEBI) Prohibition of Insider Trading regulations, which raised the cost of trading on private information while plausibly leaving the returns to skill largely unaffected. If private information drives the return gap, it should narrow after the reform. Subsection 4.1 describes the amendment's provisions in more detail.

We present five findings. First, following the amendment the risk-adjusted return gap between higher- and lower-wealth individuals compresses by roughly 68%, concentrated in the disappearance of the largest positive returns among higher-wealth individuals (Section 4.2). Second, higher-wealth individuals increase their trading in a given stock precisely during the windows SEBI later flags for insider-trading violations (Section 4.3). Third, they accumulate shares in M&A targets in the months before deals are announced, and this positioning disappears after the amendment (Section 4.4). Fourth, their net equity flows fall, consistent with a lower expected return on equity (Section 4.5). Fifth, their spending rises, concentrated in discretionary categories (Section 4.6). Taken together, this evidence points to private information, rather than skill, as an important driver of higher-wealth individuals' return advantage, and traces the erosion of that advantage into their consumption decisions.

### 4.1 The 2015 Amendment and Its Enforcement

SEBI's Prohibition of Insider Trading framework, in place since 1992, was widely regarded as poorly enforced (Varottil, 2016), resting on a narrow definition of who counted as an insider and a standard of proof that produced almost no convictions over two decades. The 2015 amendment, announced in January 2015 and brought into effect that

[6] Our use of *skill* is narrower than in the wealth-returns literature, where the term often denotes risk-adjusted performance as a whole; Bach et al. (2020), for instance, describe the portfolio alpha as a measure of investment skill. We reserve *skill* for the public-information component and use *risk-adjusted returns* for the sum throughout.

May, redefined the regime along three dimensions.

First, it made the definition of an "insider" possession-based rather than position-based: any person in possession of, or with access to, unpublished price-sensitive information is an insider, regardless of how the information was obtained, and not only those holding a formal connection to the firm. Second, it broadened the category of "connected person" (Regulation 2(1)(d)) to deem relatives, bankers, intermediaries, and others who could reasonably be expected to have access to such information as connected, extending the regime well beyond corporate officers. Third, it prohibited trading by anyone in possession of such information, in place of the 1992 standard that required showing a trade was made on the basis of it, and placed the onus on the insider to demonstrate that the trade was not so motivated. The amendment also codified the categories of unpublished price-sensitive information, expressly naming mergers, de-mergers, and acquisitions among them. Together, these changes widened who is covered, lowered the evidentiary bar for establishing a violation, and shifted the burden of proof onto the trader. This breadth makes the amendment a relevant shock for the individuals we study, who need not be corporate insiders to fall within its reach.

These changes did not remain on paper. The amendment was widely noticed: Google search interest rose sharply around the announcement (Appendix Figure IA.1, Panel A). Enforcement also became markedly more active over the following years, with investigations rising from 70 in fiscal 2014/15 to 245 by 2016/17 (Panel B) (SEBI, 2020).[7] This rise is consistent with the amendment carrying a credible threat of sanction, which prior work identifies as the binding deterrent to trading on private information (Bhattacharya and Daouk, 2002).

[7] A fiscal year in India runs from 1 April to 31 March of the following year.

### 4.2 The Effect on the Return Gap

To test the effect of the 2015 amendment, we compare the risk-adjusted returns of higher- and lower-wealth individuals around its announcement. We classify individuals as higher-wealth (top 1%) or lower-wealth (bottom 99%) by their position in the financial wealth distribution at the end of December 2014, immediately before the announcement, and hold this classification fixed throughout the sample. This ensures that group membership is not itself affected by the amendment.

We use the top 1% as the cutoff to capture the extreme right tail while retaining a sufficient sample size (around 900 individuals).[8] We sum each individual's monthly risk-adjusted returns within a quarter to reduce the influence of month-to-month variation, and use a five-year window around the announcement, comprising the two years before and the three years after.[9]

Figure 4 plots kernel density estimates of quarterly risk-adjusted returns, annualized, pooled across all individual-quarter observations, for the two wealth groups before (Panel A) and after (Panel B) the amendment; vertical lines mark group means.

In the pre-amendment period (Panel A), higher-wealth individuals earn a higher average risk-adjusted return than lower-wealth individuals, as the group means (vertical lines) show. The gap reflects a higher incidence of large positive risk-adjusted returns among higher-wealth individuals, visible as a distinct hump in the upper right tail of their distribution, centered near 90%.

In the post-amendment period (Panel B), higher-wealth individuals still earn a higher average risk-adjusted return than lower-wealth individuals, but the gap is smaller than before. The hump in the upper right tail largely disappears, so the compression is driven by a lower incidence of large positive risk-adjusted returns among higher-wealth individ-

[8] Results are robust to using the top 5% instead (Appendix Table IA.1).

[9] We use a five-year window to isolate the 2015 amendment from neighboring changes to the insider-trading regime: SEBI last amended the 1992 framework in August 2011, when it extended disclosure obligations to promoters, and first amended the 2015 regulations in December 2018 outside our window.

uals.

The concentration of this effect in the right tail is what we would expect if private information drives the gap. An investor with private information trades on it only when the advantage is large, because the stock's own volatility can easily swamp the gain from a small one. Trading on private information therefore leaves its mark in the right tail rather than as a uniform shift in returns. By raising the cost of trading on private information, the amendment should thin the right tail, which is what Panel B shows.

We next estimate the change in the return gap with the following difference-in-differences specification:

$$\alpha_{i,t} = \beta_1 \times \mathbb{1}(\text{Top } 1\%)_i + \beta_2 \times \mathbb{1}(\text{Top } 1\%)_i \times \text{Post}_t + \gamma \mathbf{X}_{i,t} + \eta_t + \epsilon_{i,t}, \tag{5}$$

where $\alpha_{i,t}$ is individual $i$'s risk-adjusted return in quarter $t$, computed as the sum of the monthly risk-adjusted returns from equation (4) and annualized. $\mathbb{1}(\text{Top } 1\%)_i$ equals one for higher-wealth individuals, and $\text{Post}_t$ equals one from the amendment's announcement quarter onward. $\beta_1$ captures the pre-amendment return gap, and $\beta_2$, our coefficient of interest, captures its change following the amendment. The controls $\mathbf{X}_{i,t}$ include portfolio diversification[10], which could affect returns (Campbell et al., 2019), along with individual age, gender, and credit score. Time fixed effects ($\eta_t$) absorb shocks common to all individuals in a quarter, and we cluster standard errors at the individual level.

Table 2 reports estimates of equation (5). Column 1 includes time fixed effects and no controls: the pre-amendment gap is 17.4 percentage points and the interaction is $-11.0$ percentage points. Column 2 adds the controls: the pre-amendment gap is 17.1 percentage points and the interaction is $-11.7$ percentage points (significant at the 1% level), so the gap shrinks by roughly 68% following the amendment. Columns 3 and 4 add individual fixed effects, with and without controls, which absorb the time-invariant $\mathbb{1}(\text{Top } 1\%)_i$

[10]Because portfolio diversification may itself respond to the amendment, we report estimates with and without it.

term and identify the interaction from within-individual variation. The interaction is unchanged in both, though the pre-amendment gap is no longer estimated. Because the amendment raised the cost of trading on private information, the reduction in the return gap is consistent with private information being an important driver of higher-wealth individuals' return advantage.

Figure 5 plots estimates from a dynamic version of equation (5), each giving the difference in risk-adjusted returns between higher- and lower-wealth individuals in a given quarter, relative to the quarter preceding the announcement. Before the announcement the estimates display no trend. After the announcement the estimates shift downward, and the gap remains compressed on average through the end of the window, consistent with the average effect in Table 2.

Higher-wealth individuals are few and hold concentrated portfolios, and both the value of private information and the frequency with which it arrives likely vary over time. The return gap therefore fluctuates from quarter to quarter in both the pre- and post-amendment periods, even absent any policy change. This fluctuation has two implications. First, in the pre-period, identification requires only the absence of a differential trend between higher- and lower-wealth individuals, not the absence of fluctuations; Figure 5 shows no such trend. Second, in the post-period, we should not expect the effect to be monotone, so we read the post-period estimates as a shift in the average gap rather than the trajectory traced quarter by quarter.

Appendix Table IA.1 reports alternative specifications. The estimated change in the gap is similar when risk-adjusted returns are constructed with the Carhart four-factor model, and when higher-wealth individuals are defined as the top 5% rather than the top 1%.

### 4.3 Trading in Stocks with Insider-Trading Violations

The reduced return gap following the amendment implies that higher-wealth individuals benefit disproportionately from trading on private information. We test this implication by examining whether they trade more in a stock during its proven insider-trading violation windows. A proven violation window is a period in which material private information about a stock both existed and was traded on. If higher-wealth individuals also trade on private information, their trading should concentrate in exactly these windows.

We test this prediction at the individual-stock-month level:

$$\text{abs}(\text{Net Flow}_{i,s,t}) = \beta \times \mathbb{1}(\text{SEBI})_{s,t} \times \mathbb{1}(\text{Top 1\%})_{i,t} + \eta_{i,t} + \eta_{s,t} + \eta_{i,s} + \epsilon_{i,s,t}, \qquad (6)$$

where $\text{abs}(\text{Net Flow}_{i,s,t})$ is the absolute value of the change in individual $i$'s holdings of stock $s$ from the end of month $t-1$ to the end of month $t$, valued at the end-of-$(t-1)$ price, in thousands of INR. The absolute value captures the magnitude of the position change, regardless of whether the private information was positive, inducing net buying, or negative, inducing net selling. $\mathbb{1}(\text{SEBI})_{s,t}$ equals one if month $t$ falls within a proven insider-trading violation window for stock $s$, and $\mathbb{1}(\text{Top 1\%})_{i,t}$ equals one if individual $i$ is in the top 1% of the wealth distribution at the start of month $t$. The coefficient of interest, $\beta$, is the additional trading by higher-wealth individuals in a stock during its violation window, relative to lower-wealth individuals in the same stock and month. Standard errors are clustered at the individual level.

Our tightest specification is fully saturated, with each set of fixed effects ruling out a distinct alternative. Individual-by-stock fixed effects ($\eta_{i,s}$) identify $\beta$ from within-individual-stock variation over time, ruling out that higher-wealth individuals systematically trade stocks more prone to violations. Individual-by-time fixed effects ($\eta_{i,t}$) identify $\beta$ by comparing an individual's trading in the stock during its violation window with her trading in every other stock that same month, ruling out that she simply trades more across

all stocks during violation months. Stock-by-time fixed effects ($\eta_{s,t}$) identify $\beta$ relative to lower-wealth individuals holding the same stock in the same month, ruling out that violation-window stocks simply draw more trading from all investors through changing fundamentals or investor attention.

Table 3 reports estimates of equation (6). Column 1 includes stock, individual, and time fixed effects: higher-wealth individuals trade 3,151 INR more in a stock during its violation window than lower-wealth individuals do. Column 2 replaces the individual and time fixed effects with individual-by-time fixed effects, and Column 3 further replaces the stock fixed effect with stock-by-time fixed effects; the interaction is unchanged in both. Column 4 adds individual-by-stock fixed effects to reach the fully saturated specification. The interaction falls to 535 INR and remains highly significant.

To interpret this magnitude, we scale it by the size of a typical position: 535 INR is 3.8% of the median individual-stock-month holding (14,010 INR) and 0.9% of the mean (62,820 INR). The estimated magnitude should not be read as a quantitative measure of how much higher-wealth individuals trade on private information, for two reasons. First, the violation window identified by the regulator is likely narrower than the true period over which informed trading occurs, so some informed trading also occurs in the comparison months. This bears most on our fully saturated specification, which compares window and non-window months within an individual-stock pair: informed trading outside the flagged window narrows that comparison and understates the effect. Second, the regulator detects only a fraction of insider trading, so the coefficient reflects the detected episodes alone. The test is best read as evidence that higher-wealth individuals trade more in a stock precisely when private information about it is being traded on, not as a measure of how much.

### 4.4 Buying M&A Target Shares Before Announcement

We now test whether higher-wealth individuals trade on a category of private information whose use the amendment prohibits. The amendment names several such categories, and we focus on one: mergers, de-mergers, and acquisitions, which Regulation 2(1)(n) enumerates as unpublished price-sensitive information.[11] M&A is also the category in which insider trading is most often found: among prosecuted U.S. cases, mergers and acquisitions account for 51% of the events on which insiders traded, the largest share of any category (Ahern, 2017).[12]

Two features of these deals make informed trading in them testable in holdings data. First, the direction of an informed trade is known in advance: a target's shares jump when a deal is announced, so an investor with advance knowledge buys the target ahead of the news.[13] Prosecuted U.S. cases bear this out: insiders traded the target rather than the acquirer in 99% of acquisition events, almost all of them positive-news events in which they took long or call positions (Ahern, 2017). The predicted trade is therefore signed, net accumulation of the target, without reference to the market's prior expectations. Second, the announcement provides a discrete date against which pre-announcement positioning can be measured. If higher-wealth individuals have access to this private information, they should accumulate shares in target firms in the months before the announcement.

We test this prediction using a stacked event-study design on net flows into target stocks at the individual-stock-month level:

$$\begin{aligned}\text{Net Flow}_{i,s,t} = \beta \times \mathbb{1}(\text{Pre-Announce})_{s(e),t} \times \mathbb{1}(\text{Top 1\%})_{i,e} \\ + \gamma \mathbf{X}_{s,t-1} + \eta_t + \eta_{s(e),pre} + \eta_{i,s} + \epsilon_{i,s,t}.\end{aligned} \tag{7}$$

[11] Regulation 2(1)(n) also lists financial results, dividends, changes in capital structure, and changes in key managerial personnel.

[12] The other categories in Ahern (2017) are clinical trials and drug regulation, earnings, operations, sales of securities, and a residual "other" category.

[13] Target shareholders earn large positive announcement returns (Jensen and Ruback, 1983; Andrade et al., 2001), and targets in our sample earn an average cumulative abnormal return of approximately 10% over the $[-21, 63]$ day event window (Appendix Figure IA.2).

Net Flow$_{i,s,t}$ is the change in individual $i$'s holdings of stock $s$ from the end of month $t-1$ to the end of month $t$, valued at the end-of-$(t-1)$ price, in thousands of INR. $\mathbb{1}(\text{Pre-Announce})_{s(e),t}$ equals one for the target stock of M&A event $e$ during the $[-12,-1]$ pre-announcement window, and $\mathbb{1}(\text{Top 1\%})_{i,e}$ equals one if individual $i$ is in the top 1% of the wealth distribution at the start of the announcement month for event $e$. The coefficient of interest, $\beta$, is the additional monthly net flow of higher-wealth individuals into a target during the pre-announcement window, relative to lower-wealth individuals in the same target and relative to their own flows outside that window. Standard errors are clustered at the individual level.

The specification includes individual-by-stock fixed effects ($\eta_{i,s}$), which absorb the time-invariant component of an individual's net flow into a particular stock. Higher-wealth individuals may, for instance, buy stocks whose characteristics also make them more likely to become M&A targets. Because such tendencies are absorbed, $\beta$ is identified from within-individual-stock variation: whether a given individual buys more of a target during its pre-announcement window than she does after the announcement. We also include a fixed effect for each event's target stock over its pre-announcement window ($\eta_{s(e),\text{pre}}$). This gives every deal its own pre-announcement intercept, absorbing the run-up in net flow into the target that is common to all investors and identifying $\beta$ relative to lower-wealth holders of the same target. A year-month fixed effect ($\eta_t$) absorbs market-wide conditions. The controls $\mathbf{X}_{s,t-1}$ are two lagged stock characteristics that could drive net flows independent of any information: the stock's return in month $t-1$, $r_{s,t-1}$, computed by compounding its daily returns over that month, and the volatility of its daily returns over month $t-1$, $\sigma_{s,t-1}$.

To capture net flows along both the extensive and intensive margins, we construct a balanced individual-stock-month panel. For each stock an individual ever holds, we fill the months without a holding with zero quantity and hence zero value. We further restrict the post-announcement sample to the four months following the announcement,

to avoid the confounding effect of delisting, which mechanically induces outflow for all investors.[14]

Table 4 reports estimates of equation (7). Column 1 covers deals announced before the amendment and includes no controls: during the 12-month pre-announcement window, higher-wealth individuals buy 1,388 INR more of the target per month than lower-wealth individuals do (significant at the 1% level). Cumulated over the window, this amounts to roughly 16,700 INR, about a quarter of the mean individual-stock holding (62,820 INR) and roughly 1.2 times the median (14,010 INR). Column 2 adds the controls and yields a similar estimate. If this accumulation reflects access to private information, raising the cost of trading on it should curtail it. Column 3 turns to deals announced after the amendment: the additional buying falls to 191 INR per month and is statistically indistinguishable from zero.[15] Column 4 adds the controls and again finds no effect.

Figure 6 plots the gap in net flows into M&A targets between higher- and lower-wealth individuals across the event window, separately for deals announced before and after the amendment, from a dynamic version of equation (7). For deals before the amendment, the gap is positive and significant throughout the 12-month pre-announcement window. For deals after the amendment, the gap is no longer significantly positive. The dynamics mirror the average effects in Table 4.

Taken together, these results provide evidence that higher-wealth individuals trade on private information. They trade more heavily in a stock during the windows in which SEBI later proved an insider-trading violation. They also systematically accumulate target shares in the year before a deal becomes public. This positioning disappears after the amendment, which raised the cost of trading on private information. The disappearance distinguishes private information from skill: an investor forecasting takeovers from public signals would have no reason to stop after the amendment, whereas one trading on

[14] No M&A target in our sample delisted within the first four months after the announcement.

[15] We restrict the post-amendment sample to deals announced after May 2016, so that the full 12-month pre-announcement window falls under the new regime.

private information would. Their return advantage therefore rests, at least in part, on private information of the kind the regulation names, and not on skill in processing public information alone.

### 4.5 The Effect on Net Equity Flows

In standard portfolio choice, a lower expected return on equity reduces an investor's optimal allocation to it. Because the amendment lowered the return higher-wealth individuals earn on equity, their equity investment should fall. We test this by estimating equation (5) with an individual's quarterly net equity flow as the dependent variable, measured as the value of net share purchases across all stocks in her portfolio.

Table 5 reports the estimates. Column 1 includes time fixed effects and no controls: following the amendment, higher-wealth individuals reduce their quarterly net equity flows by 48,442 INR relative to lower-wealth individuals. Column 2 adds the controls, and Columns 3 and 4 add individual fixed effects, without and with controls. The estimate is stable across all four specifications, between 42,000 and 49,000 INR per quarter.

This finding is consistent with higher-wealth individuals perceiving the lower return they earn on equity after the amendment, complementing the reduction in the return gap documented in Section 4.2: higher-wealth individuals reduced their equity investment as though the return had fallen, corroborating that result through their portfolio choices.

### 4.6 The Effect on Consumption

We next examine the amendment's effect on higher-wealth individuals' spending. Because the amendment lowered the return they could expect on their wealth, the effect on current consumption is theoretically ambiguous: lower expected future wealth reduces it through an income effect, while the lower return raises it through a substitution effect (Daminato and Pistaferri, 2024).

We measure spending as the sum of debit card, credit card, and ATM transactions,

following Agarwal and Qian (2014) and Ganong and Noel (2019). The advantage of this transaction-based measure is its precision: unlike consumption proxies derived from tax registries, it records spending as it occurs and is free of imputation error (Baker et al., 2022). Because we observe only transactions made through this bank, we restrict the spending sample to individuals who use it as a spending account. Using merchant category codes (MCCs), we classify card transactions as discretionary or non-discretionary, following Agarwal and Qian (2014); ATM withdrawals are excluded from this classification, as cash carries no merchant category.

Table 6 reports the estimates. Column 1, for total spending, shows that higher-wealth individuals increase spending by 6,004 INR per quarter relative to lower-wealth individuals after the amendment. The positive sign implies that the substitution effect dominates: a lower return on wealth reduces the incentive to defer consumption. Columns 2 and 3 decompose card spending into discretionary and non-discretionary categories. The increase is concentrated in discretionary spending, at 4,006 INR, or two-thirds of the total, against 1,238 INR for non-discretionary spending.[16]

Figure 7 plots event-study estimates of the spending gap between higher- and lower-wealth individuals, separately for discretionary and non-discretionary spending, relative to the quarter preceding the announcement. Before the announcement, the estimates show no trend in either category. After it, the discretionary gap opens and remains positive, while the non-discretionary gap shifts up only slightly.

Taken together with the reduction in equity flows documented in Section 4.5, this increase in consumption, concentrated in discretionary categories, is consistent with higher-wealth individuals responding to a lower expected return on their wealth by investing less and consuming more.

[16]The two categories do not sum to total spending, which also includes ATM withdrawals.

## 5 Networks and the Source of Private Information

The preceding section showed that higher-wealth individuals trade on private information. A natural question is *how* they come to possess it. We consider the role of information networks: theory predicts that investors in more central network positions receive price-relevant information earlier than peripheral ones (Rossi et al., 2018; Ozsoylev and Walden, 2011; Walden, 2019). If wealthier individuals occupy more central positions, they would have this information while it is not yet reflected in prices, which would help explain the return advantage documented in Section 3.

The information network is not directly observable, so we proxy it in two complementary ways, each capturing a different dimension of connection. The first is a communication network, built from pincode-to-pincode call volumes: two areas are more closely tied the more their residents call one another. Call volumes proxy for the social ties along which private information travels: tips flow predominantly through family, business, and personal relationships, and over short distances (Ahern, 2017). The second is an investor network, in which two investors are linked when they trade several of the same stocks in the same direction and month, following Ozsoylev et al. (2014). In each, we summarize a node's position by its eigenvector centrality, so that a node is more central when connected to others that are themselves central. The two networks draw on entirely different data, one on communication and the other on trading, so their agreement is more telling than either measure alone. We find that centrality increases monotonically with financial wealth under both measures, and that more central individuals earn higher risk-adjusted returns. We also find that portfolios are more alike among wealthier individuals than among less wealthy ones, consistent with a common source of information among the wealthier.

### 5.1 Network Centrality and Wealth

We construct two networks that differ in how a link between two nodes is defined; in each, higher eigenvector centrality marks a node positioned earlier in the diffusion of information.

In the communication network, each pincode is a node and the call volume between two pincodes is the strength of the tie between them. The underlying assumption is that price-relevant information travels along the same channels as ordinary communication, so that the volume of calls between two pincodes proxies the intensity of information flow between them. We compute the eigenvector centrality of every pincode in each week and average them across the weeks of call data to obtain a single centrality per pincode (the weekly centralities are highly persistent). Because the network is defined over locations rather than individuals, centrality varies across pincodes but not within them, and measures how centrally connected an individual's place of residence is.

In the investor network, each investor is a node, and two investors are linked in a given month if they make at least five matching trades that month, where a match is a trade in the same stock and the same direction, following Ozsoylev et al. (2014). The premise is that investors acting on the same information trade the same stocks at the same time and in the same direction, so overlapping trades reveal an informational tie. Ozsoylev et al. (2014) show that more central investors trade earlier around information events, confirming that centrality captures early access to information rather than trading activity alone. We compute each investor's eigenvector centrality within that month's network; unlike the communication measure, this centrality varies over time.

Figures 8 and 9 present the results for the communication and investor networks. In each, Panel A plots centrality against financial wealth and Panel B plots risk-adjusted returns against centrality. Both panels are binned scatter plots, constructed as in Figure 1: we sort individuals into bins and plot the average of each variable within a bin. Under both networks, centrality rises monotonically with financial wealth, and more central

individuals earn higher risk-adjusted returns.

Table 7 reports the corresponding regressions. Panel A uses the communication network, at the pincode level: Column 1 regresses a pincode's centrality on the log average financial wealth of its residents, and Column 3 regresses residents' average risk-adjusted returns on that centrality. Panel B uses the investor network, at the individual-month level: Column 1 regresses an individual's centrality on an indicator for the top 1% of the wealth distribution, and Column 3 regresses her risk-adjusted returns on that centrality. Columns 2 and 4 add controls in each panel. Both relationships hold in both networks and survive the controls, so the conclusion does not depend on how connections are defined.

These findings are what we would expect if wealthier individuals receive price-relevant information earlier than others. This early access to private information would help explain their return advantage.

### 5.2 Shared versus Idiosyncratic Information Across Individuals

We now ask what kind of information the advantage rests on: a common source, shared among wealthier individuals, or signals specific to each of them. Portfolio similarity distinguishes the two. If wealthier individuals draw on a common source, their portfolios should resemble one another. If instead each acts on her own signal, their portfolios should be no more alike than those of the less wealthy are among themselves.

We measure portfolio similarity by cosine similarity between two individuals' holdings. For individuals $i$ and $j$ with holding vectors $h_i$ and $h_j$,

$$\text{Cosine Similarity}_{i,j} = \frac{h_i \cdot h_j}{\|h_i\| \, \|h_j\|}, \tag{8}$$

where $h_i = (h_{i1}, \ldots, h_{iK})$ and $h_{ik}$ is the value of stock $k$ held by individual $i$ as a share of the total value of her portfolio, and $\|h_i\| = \left(\sum_{k=1}^{K} h_{ik}^2\right)^{1/2}$ is the Euclidean norm. The measure ranges from zero, when two individuals hold no stock in common, to one, when

they hold the same stocks in the same proportions. Because the vectors are normalized, it compares the composition of two portfolios rather than their size.

Computing similarity for every pair of individuals would require billions of comparisons in each month. We instead obtain the average similarity within and between wealth groups exactly, from aggregated portfolio vectors alone, without computing any individual pair (Appendix Section C).

Figure 10 plots the group-wise similarities, with darker cells indicating greater similarity. The dark region concentrates in the high-wealth corner and fades toward the less wealthy groups, a pattern with two parts. First, along the diagonal (each group compared with itself), within-group similarity rises monotonically with wealth.[17] Second, at the top the darkness spreads off the diagonal: different high-wealth groups resemble one another, not only themselves. What wealthier individuals act on is therefore common among them, rather than specific to each. The less wealthy groups, by contrast, are light throughout. Their portfolios have little in common with the wealthy's, or with one another's.

Taken together, the evidence in this section points to an information advantage that operates through networks. Wealthier individuals are more central in both networks, consistent with earlier access to information, and their portfolios resemble one another far more than those of the less wealthy, pointing to a common source rather than signals specific to each.

## 6 Conclusion

This paper provides causal evidence that access to private information is a primary driver of return heterogeneity across the wealth distribution. Using administrative data from a

[17] Portfolio concentration does not drive this pattern. Because cosine similarity is mechanically higher for diversified portfolios, a concentration artifact would peak in the middle of the wealth distribution, where diversification peaks; instead similarity rises monotonically to the top. The least and most wealthy both hold concentrated portfolios, yet only the wealthiest resemble one another. What distinguishes them is which stocks they hold, not how many.

large Indian bank, we document a sharp monotonic relationship between financial wealth and portfolio returns: average annual excess returns rise by 7 percentage points from the 10th to the 90th percentile of the wealth distribution, and by 20 percentage points from the 10th percentile to the top 1%. This gradient is not explained by differential risk exposure: the systematic return is flat across the distribution, and the gradient instead reflects differences in risk-adjusted returns.

Exploiting the 2015 amendment to India's Prohibition of Insider Trading regulation, which raised the cost of trading on private information, we show that the risk-adjusted return gap between higher- and lower-wealth individuals shrinks by 68% following the reform. The reduction is concentrated in the right tail of the return distribution, where private information is most valuable. Consistent with the loss of return on wealth, higher-wealth individuals reduce their net flows into equities and modestly increase discretionary spending after the reform.

Two further pieces of evidence support the private-information channel. Higher-wealth individuals systematically accumulate shares of M&A target firms in the months before announcements — a category of price-sensitive information the regulation explicitly enumerates — and this differential trading disappears following the reform. They are also more centrally positioned in an information network inferred from pincode-to-pincode cellular call volumes, and hold portfolios that are increasingly similar to one another, consistent with drawing on a common rather than idiosyncratic information source.

These findings arise in publicly traded equity markets, where all individuals in our sample have access to the same set of securities and, in principle, compete on a level playing field. In contrast to settings such as private equity or venture capital, where unequal access to investment opportunities can mechanically generate return differences, public equity markets are commonly viewed as environments without such access constraints. Our results show that even in this setting, informational frictions alone — independent of differential access to investment opportunities — can generate substantial and persistent

return inequality, and contribute to wealth concentration.

Our results also recast insider trading as a force in the distribution of wealth, not only a matter of market integrity. Because access to private information is concentrated at the top, the rents it generates widen the return gap that compounds into wealth inequality. Enforcement of insider-trading regulation is therefore a lever on wealth concentration: the 2015 reform compressed the risk-adjusted return gap by roughly two-thirds, suggesting that credible enforcement can slow the rate at which wealth accumulates at the top.

**References**


Agarwal, S., Qian, W., 2014. Consumption and debt response to unanticipated income shocks: Evidence from a natural experiment in singapore. American Economic Review 104, 4205–4230.

Agarwalla, S. K., Jacob, J., Varma, J. R., 2014. Four factor model in indian equities market. Working Paper, Indian Institute of Management Ahmedabad .

Ahern, K. R., 2017. Information networks: Evidence from illegal insider trading tips. Journal of Financial Economics 125, 26–47.

Ali, U., Hirshleifer, D., 2017. Opportunism as a firm and managerial trait: Predicting insider trading profits and misconduct. Journal of Financial Economics 126, 490–515.

Andersen, A. L., Johannesen, N., Sheridan, A., 2024. Dynamic spending responses to wealth shocks: Evidence from quasi lotteries on the stock market. American Economic Review: Insights 6, 434–452.

Andrade, G., Mitchell, M., Stafford, E., 2001. New evidence and perspectives on mergers. Journal of Economic Perspectives 15, 103–120.

Azarmsa, E., 2026. Investment sophistication and wealth inequality. Journal of Economic Theory p. 106206.

Bach, L., Calvet, L. E., Sodini, P., 2020. Rich pickings? Risk, return, and skill in household wealth. American Economic Review 110, 2703–2747.

Baker, S. R., Kueng, L., Meyer, S., Pagel, M., 2022. Consumption imputation errors in administrative data. Review of Financial Studies 35, 3021–3059.

Balasubramaniam, V., Campbell, J. Y., Ramadorai, T., Ranish, B., 2023. Who owns what? A factor model for direct stockholding. Journal of Finance 78, 1545–1591.

Balloch, C., Richers, J., 2023. Asset allocation and returns in the portfolios of the wealthy. Working paper, LSE .

Benhabib, J., Bisin, A., Luo, M., 2019. Wealth distribution and social mobility in the US: A quantitative approach. American Economic Review 109, 1623–1647.

Benhabib, J., Bisin, A., Zhu, S., 2011. The distribution of wealth and fiscal policy in economies with finitely lived agents. Econometrica 79, 123–157.

Bharti, N. K., Chancel, L., Piketty, T., Somanchi, A., 2024. Income and wealth inequality in India, 1922-2023: The rise of the Billionaire Raj. Working paper, New York University, Abu Dhabi .

Bhattacharya, U., Daouk, H., 2002. The world price of insider trading. Journal of Finance 57, 75–108.

Campbell, J. Y., Ramadorai, T., Ranish, B., 2019. Do the rich get richer in the stock market? Evidence from India. American Economic Review: Insights 1, 225–240.

Carhart, M. M., 1997. On persistence in mutual fund performance. Journal of Finance 52, 57–82.

Chancel, L., Piketty, T., Saez, E., Zucman, G., 2022. World inequality report 2022. Harvard University Press.

Cohen, L., Malloy, C., Pomorski, L., 2012. Decoding inside information. Journal of Finance 67, 1009–1043.

Collin-Dufresne, P., Fos, V., 2015. Do prices reveal the presence of informed trading? Journal of Finance 70, 1555–1582.

Dai, J., Tseng, K., Zeng, J. J., Zuo, L., 2026. The effect of insider trading law on firms' innovation disclosures. Available at SSRN .

Daminato, C., Pistaferri, L., 2024. Returns heterogeneity and consumption inequality over the life cycle. Working paper, Lund University .

Dimmock, S. G., Kouwenberg, R., Mitchell, O. S., Peijnenburg, K., 2021. Household portfolio underdiversification and probability weighting: Evidence from the field. Review of Financial Studies 34, 4524–4563.

Dorn, D., Huberman, G., 2010. Preferred risk habitat of individual investors. Journal of Financial Economics 97, 155–173.

Ebrahimian, M., Ljungqvist, A., 2025. Private innovation and wealth inequality. Available at SSRN 5957735 .

Fagereng, A., Guiso, L., Malacrino, D., Pistaferri, L., 2020. Heterogeneity and persistence in returns to wealth. Econometrica 88, 115–170.

Fama, E. F., French, K. R., 1993. Common risk factors in the returns on stocks and bonds. Journal of Financial Economics 33, 3–56.

Fisman, R., Ghosh, P., Sarkar, A., Zhang, J., forthcoming. Dirty air and green investments: The impact of pollution information on portfolio allocations. Journal of Financial Economics .

Gabaix, X., Koijen, R. S., Mainardi, F., Oh, S., Yogo, M., 2025. Asset demand of US households. Working paper, Harvard University .

Gabaix, X., Lasry, J.-M., Lions, P.-L., Moll, B., 2016. The dynamics of inequality. Econometrica 84, 2071–2111.

Ganong, P., Noel, P., 2019. Consumer spending during unemployment: Positive and normative implications. American Economic Review 109, 2383–2424.

Gocmen, A., Martinez-Toledano, C., Mittal, V., 2025. Private capital markets and inequality. Available at SSRN 5166981 .

Guest, N., Zeng, J. J., Zuo, L., 2026. Corporate innovation and insider trading. Available at SSRN 6737198 .

Hubmer, J., Halvorsen, E., Salgado, S., Ozkan, S., 2024. Why are the wealthiest so wealthy? New longitudinal empirical evidence and implications for theories of wealth inequality. Working paper, University of Pennsylvania .

Jagolinzer, A. D., 2009. SEC rule 10b5-1 and insiders' strategic trade. Management Science 55, 224–239.

Jensen, M. C., Ruback, R. S., 1983. The market for corporate control: The scientific evidence. Journal of Financial Economics 11, 5–50.

Kabir, P., Tan, E., Vardishvili, I., 2025. Quantifying the allocative efficiency of capital: The role of capital utilization. Journal of Monetary Economics p. 103822.

Kacperczyk, M., Nosal, J., Stevens, L., 2019. Investor sophistication and capital income inequality. Journal of Monetary Economics 107, 18–31.

Kacperczyk, M., Pagnotta, E. S., 2019. Chasing private information. Review of Financial Studies 32, 4997–5047.

Kacperczyk, M., Pagnotta, E. S., 2024. Legal risk and insider trading. Journal of Finance 79, 305–355.

Kuhn, M., Schularick, M., Steins, U. I., 2020. Income and wealth inequality in America, 1949–2016. Journal of Political Economy 128, 3469–3519.

Kumar, A., 2009. Who gambles in the stock market? Journal of Finance 64, 1889–1933.

LAGARAS, S., ???? M&as, employee costs, and labor reallocation. The Journal of Finance n/a.

Lakonishok, J., Lee, I., 2001. Are insider trades informative? Review of Financial Studies 14, 79–111.

Lusardi, A., Michaud, P.-C., Mitchell, O. S., 2017. Optimal financial knowledge and wealth inequality. Journal of Political Economy 125, 431–477.

Mitton, T., Vorkink, K., 2007. Equilibrium underdiversification and the preference for skewness. Review of Financial Studies 20, 1255–1288.

NSE, 2020. Market pulse, volume 2, issue 3 .

Ozsoylev, H. N., Walden, J., 2011. Asset pricing in large information networks. Journal of Economic Theory 146, 2252–2280.

Ozsoylev, H. N., Walden, J., Yavuz, M. D., Bildik, R., 2014. Investor networks in the stock market. Review of Financial Studies 27, 1323–1366.

Piketty, T., 2014. Capital in the twenty-first century. Harvard University Press.

Polkovnichenko, V., 2005. Household portfolio diversification: A case for rank-dependent preferences. Review of Financial Studies 18, 1467–1502.

Ravina, E., Sapienza, P., 2010. What do independent directors know? Evidence from their trading. Review of Financial Studies 23, 962–1003.

Rossi, A. G., Blake, D., Timmermann, A., Tonks, I., Wermers, R., 2018. Network centrality and delegated investment performance. Journal of Financial Economics 128, 183–206.

Saez, E., Zucman, G., 2016. Wealth inequality in the united states since 1913: Evidence from capitalized income tax data. Quarterly Journal of Economics 131, 519–578.

SEBI, 2020. Handbook of statistics 2019 .

Seyhun, H. N., 1986. Insiders' profits, costs of trading, and market efficiency. Journal of Financial Economics 16, 189–212.

Van Nieuwerburgh, S., Veldkamp, L., 2010. Information acquisition and under-diversification. Review of Economic Studies 77, 779–805.

Varottil, U., 2016. The long and short of insider trading regulation in India. Quarterly Briefing, NSE Centre for Excellence in Corporate Governance .

Walden, J., 2019. Trading, profits, and volatility in a dynamic information network model. Review of Economic Studies 86, 2248–2283.

Figure 1: **Excess returns across the wealth distribution**

This figure plots the relationship between average monthly excess returns on direct equity holdings and financial wealth percentiles. Financial wealth is defined as the sum of direct equity holdings and bank deposits, measured at the beginning of the month and adjusted for inflation (in Dec 2019 real INR). For each individual and month, portfolio excess returns are constructed as the value-weighted average of stock-level excess returns using beginning-of-month stock holdings, assuming a buy-and-hold portfolio over the month. Within each percentile and month, individual excess returns are aggregated to obtain a percentile-month excess return, and the plotted excess return is the time-series average of these percentile-month returns. Average financial wealth within each percentile is computed analogously. The y-axis reports annualized returns. The x-axis reports average financial wealth on a logarithmic scale. The exchange rate at the end of 2019 is 1 USD = 71.36 INR.

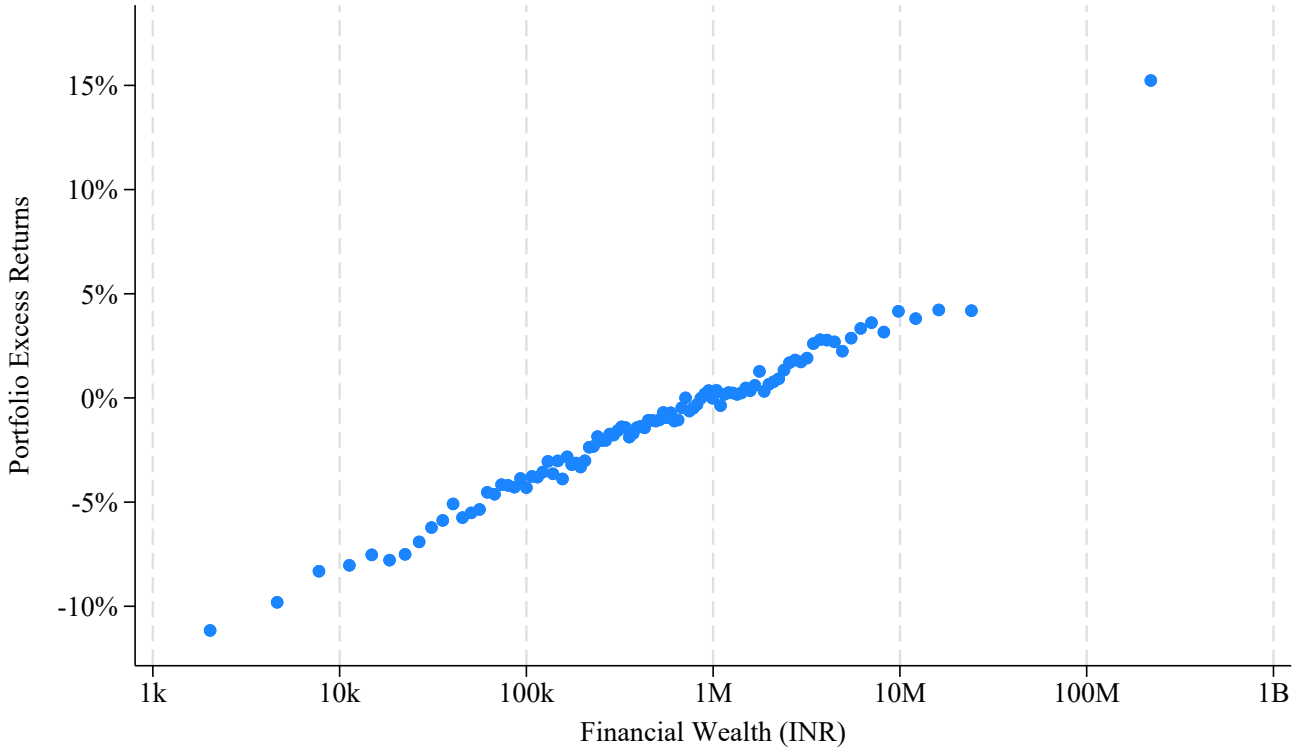
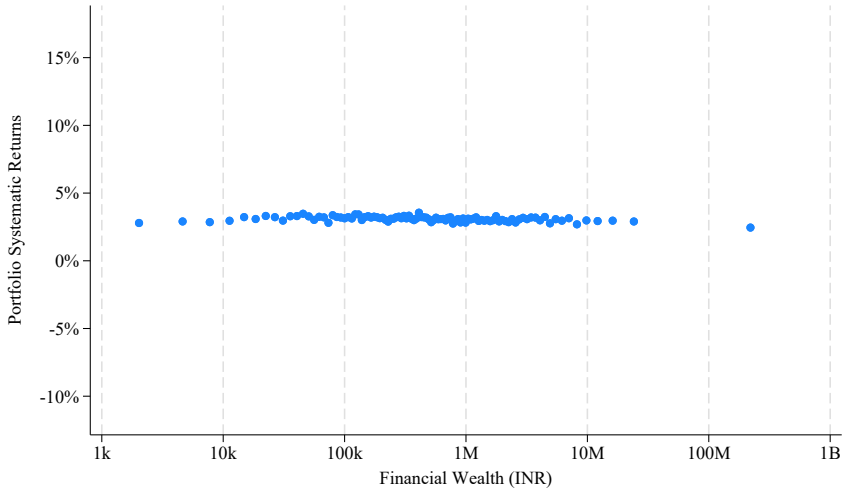
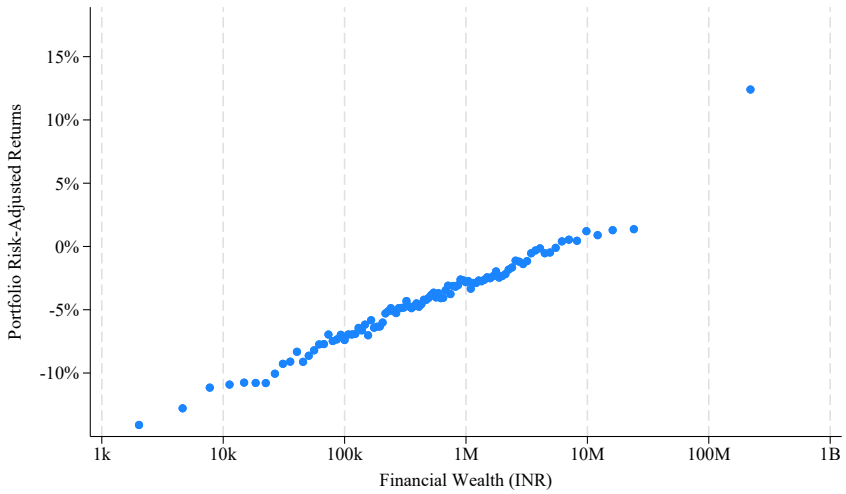


Figure 2: **Systematic and risk-adjusted returns across the wealth distribution**

This figure plots the relationship between average monthly systematic returns (Panel A) and risk-adjusted returns (Panel B) on direct equity holdings and financial wealth percentiles. Financial wealth is defined as the sum of direct equity holdings and bank deposits, measured at the beginning of the month and adjusted for inflation (in Dec 2019 real INR). For each individual and month, we first construct the portfolio excess return as the value-weighted average of stock-level excess returns using beginning-of-month stock holdings, assuming a buy-and-hold portfolio over the month. We then decompose this portfolio excess return into a systematic return component, $r^s_{i,t}$, computed using equation (3), and a risk-adjusted return, $\alpha_{i,t}$, computed using equation (4). Within each percentile and month, $r^s_{i,t}$ (Panel A) and $\alpha_{i,t}$ (Panel B) are aggregated across individuals to obtain percentile-month averages, and the plotted series report the time-series average of these percentile-month values. Average financial wealth within each percentile is computed analogously. The y-axis reports annualized returns. The x-axis reports average financial wealth on a logarithmic scale. The exchange rate at the end of 2019 is 1 USD = 71.36 INR.




Panel A: Systematic returns




Panel B: Risk-adjusted returns

Figure 3: **Diversification across the wealth distribution**

This figure plots the relationship between average monthly portfolio diversification and financial wealth percentiles. Financial wealth is defined as the sum of direct equity holdings and bank deposits, measured at the beginning of the month and adjusted for inflation (in Dec 2019 real INR). For each individual and month, diversification is measured as one minus the HHI, where portfolio shares are defined as the value of each stock divided by the total value of the individual's equity portfolio, computed using beginning-of-month stock holdings. Within each percentile and month, individual diversification measures are aggregated to obtain a percentile-month average, and the plotted diversification measure is the time-series average of these percentile-month values. Average financial wealth within each percentile is computed analogously. The x-axis reports average financial wealth on a logarithmic scale. The exchange rate at the end of 2019 is 1 USD = 71.36 INR.

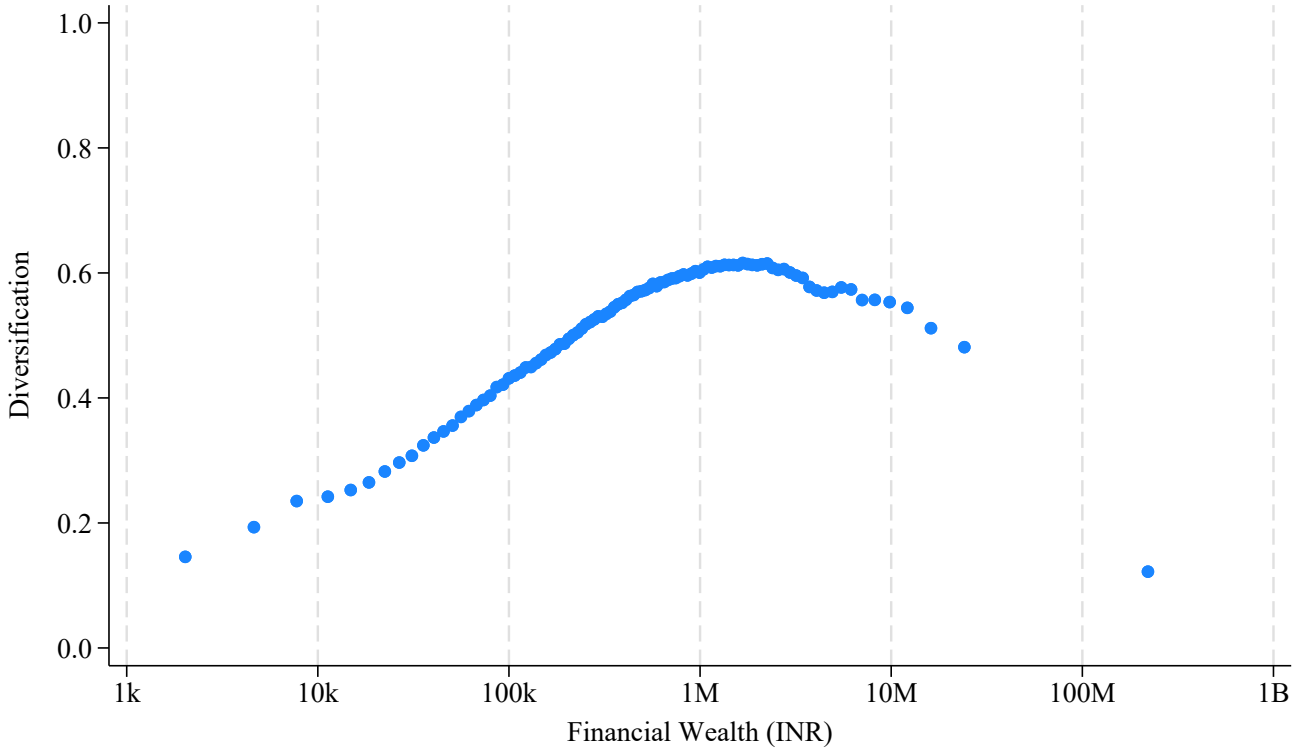


Figure 4: **Distributions of risk-adjusted returns by wealth group before and after PIT**

This figure plots kernel density estimates of quarterly risk-adjusted returns for higher-wealth individuals (top 1% of the financial wealth distribution) and lower-wealth individuals (bottom 99%). Returns are annualized for ease of interpretation. Panel A shows the distribution in quarters before the 2015 PIT amendment announcement, and Panel B shows the distribution in quarters after the announcement. Vertical lines denote mean risk-adjusted returns for each wealth group within each period.




Panel A: Before PIT announcement




Panel B: After PIT announcement

Figure 5: **The effect of the PIT on the risk-adjusted return gap by wealth**

This figure plots event-study estimates of the effect of the PIT on the wealth-based annualized risk-adjusted return gap between higher-wealth individuals (top 1% of the financial wealth distribution) and lower-wealth individuals (bottom 99%). The dependent variable, $\alpha_{i,t}$, is the individual-quarter (annualized) risk-adjusted return. The coefficients are obtained from the following specification:

$$\alpha_{i,t} = \sum_{k \neq -1} \beta_k \left( \mathbb{1}(Top\ 1\%)_i \times \mathbb{1}_{t=k} \right) + \gamma \mathbf{X}_{i,t} + \eta_t + \eta_i + \epsilon_{i,t},$$

where $\mathbb{1}_{t=k}$ are indicator variables for quarters relative to the PIT announcement quarter ($k = 0$), $X_{i,t}$ denotes time-varying individual controls, and $\eta_t$ and $\eta_i$ are time and individual fixed effects. Standard error bars denote 95% confidence intervals, with standard errors clustered at the individual level.

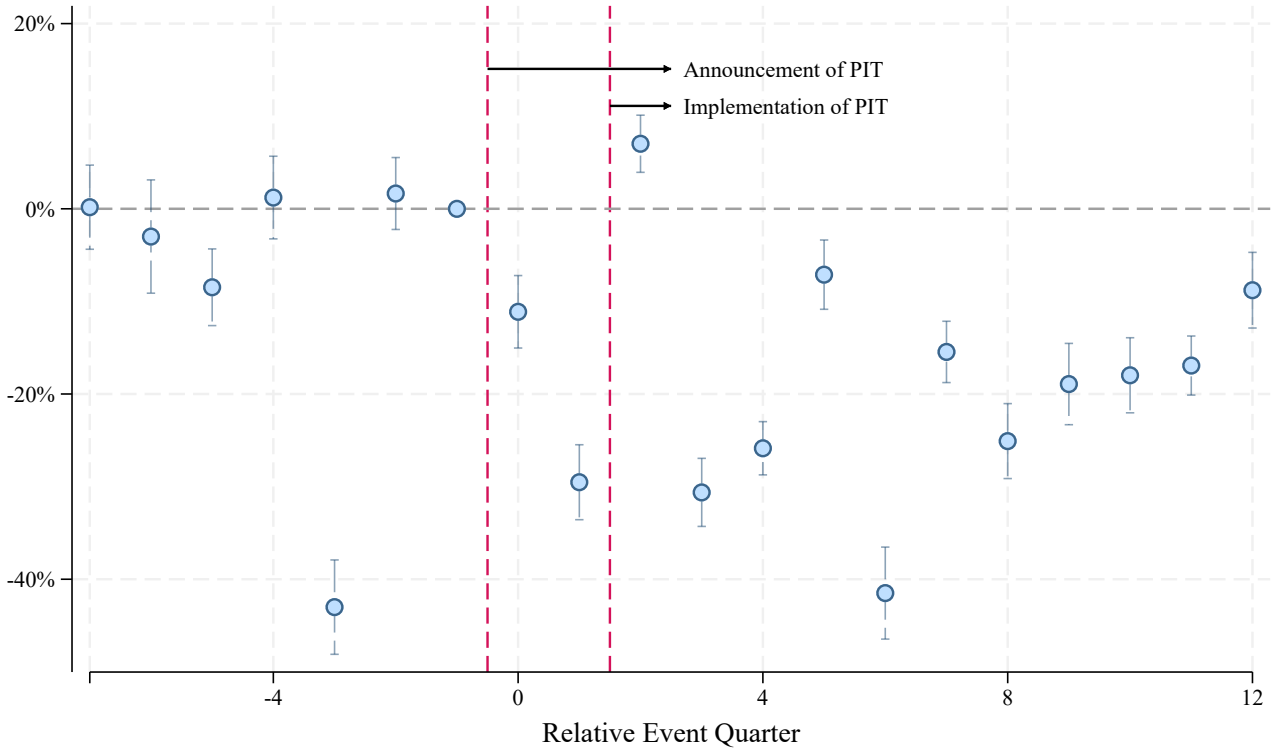


Figure 6: **Net flows into M&A target firms by higher- versus lower-wealth individuals**

This figure plots event-study estimates of the net flow gap in M&A targets between higher-wealth individuals (top 1% of the financial wealth distribution) and lower-wealth individuals (bottom 99%). The dependent variable is individual-stock-month net flow in thousand INR, measured as the change in holding quantity multiplied by end-of-period price. The exchange rate at the end of 2019 is 1 USD = 71.36 INR. The coefficients are obtained from the following specification:

$$\text{Net Flow}_{i,s,t} = \sum_{k \neq 0} \beta_k \left( \mathbb{1}(\text{Top } 1\%)_{i,e} \times \mathbb{1}_{s(e),t=k} \right) + \gamma \mathbf{X}_{s,t-1} + \eta_t + \eta_{e,pre} + \eta_{i,s} + \epsilon_{i,s,t},$$

where $\mathbb{1}_{s(e),t=k}$ are indicator variables for months relative to the M&A announcement ($k = 0$), $\mathbb{1}(\text{Top } 1\%)_{i,e}$ is an indicator equal to one if individual $i$ is in the top 1% of the financial wealth distribution at the start of the announcement month for M&A event $e$, and $\eta_t$, $\eta_{e,pre}$ and $\eta_{i,s}$ are time fixed effects, event fixed effects separately for the pre- and post-announcement periods, and individual-by-stock fixed effects. Estimates are obtained from separate regressions for the M&A announcements made during the pre-PIT (before the PIT announcement) and post-PIT (after May 2016 to allow for a full pre-announcement window) periods. Standard error bars denote 95% confidence intervals, with standard errors clustered at the individual level.

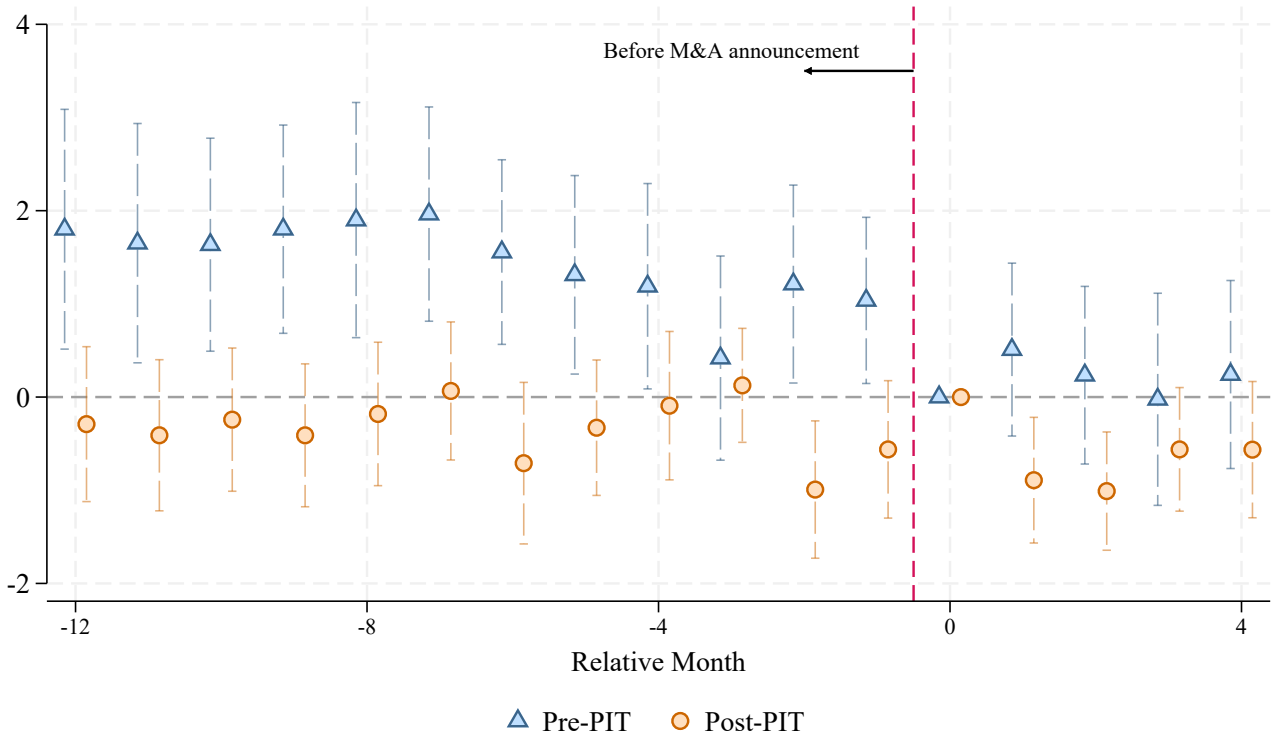


Figure 7: **The effect of the PIT on the spending gap by wealth**

This figure plots event-study estimates of the effect of the PIT on the wealth-based spending gap between higher-wealth individuals (top 1% of the financial wealth distribution) and lower-wealth individuals (bottom 99%). The dependent variable is individual-quarter spending in thousand INR, measured as the sum of credit card and debit card transactions, and cash withdrawals and utility bill payments via ATM. The exchange rate at the end of 2019 is 1 USD = 71.36 INR. We decompose total spending (excluding ATM transactions) into discretionary and non-discretionary categories, following Agarwal and Qian (2014). The coefficients are obtained from the following specification:

$$\text{Spending}_{i,t} = \sum_{k \neq -1} \beta_k \left( \mathbb{1}(\text{Top } 1\%)_i \times \mathbb{1}_{t=k} \right) + \gamma \mathbf{X}_{i,t} + \eta_t + \eta_i + \epsilon_{i,t},$$

where $\mathbb{1}_{t=k}$ are indicator variables for quarters relative to the PIT announcement quarter ($k = 0$), $X_{i,t}$ denotes time-varying individual controls, and $\eta_t$ and $\eta_i$ are time and individual fixed effects. Estimates for discretionary and non-discretionary spending are obtained from separate regressions. Standard error bars denote 95% confidence intervals, with standard errors clustered at the individual level.

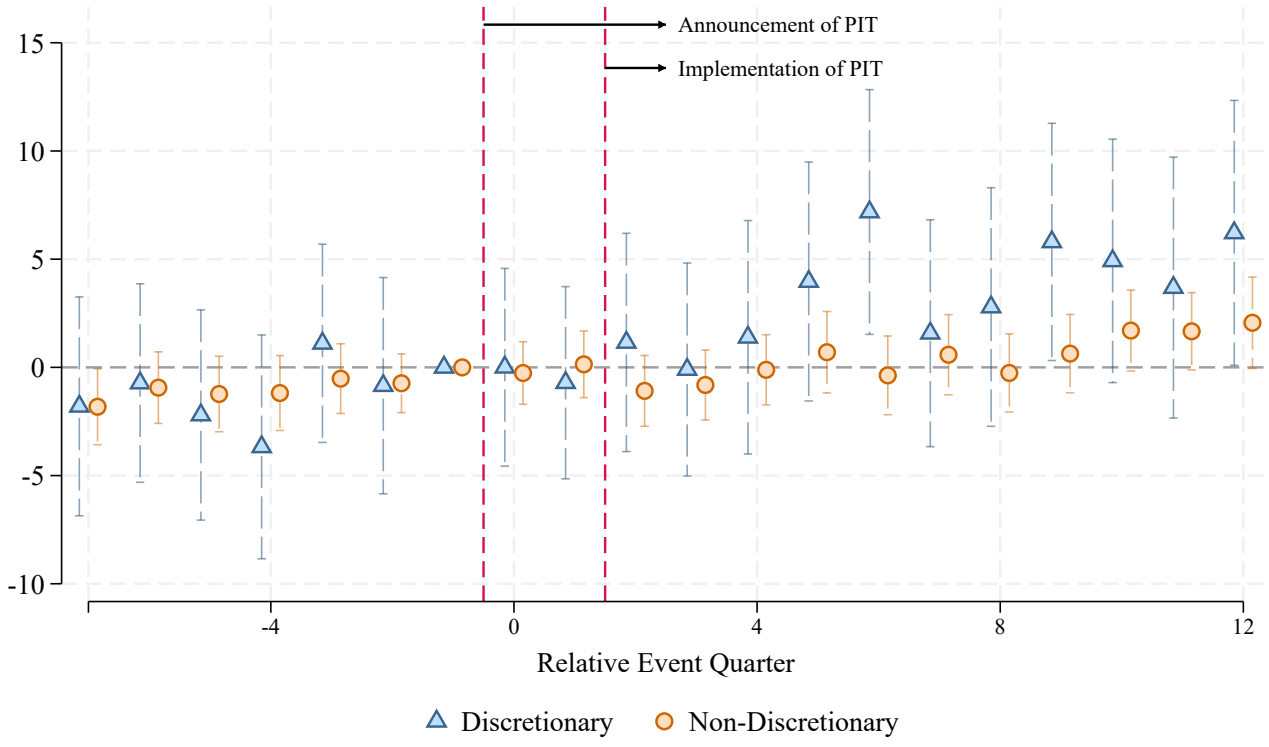
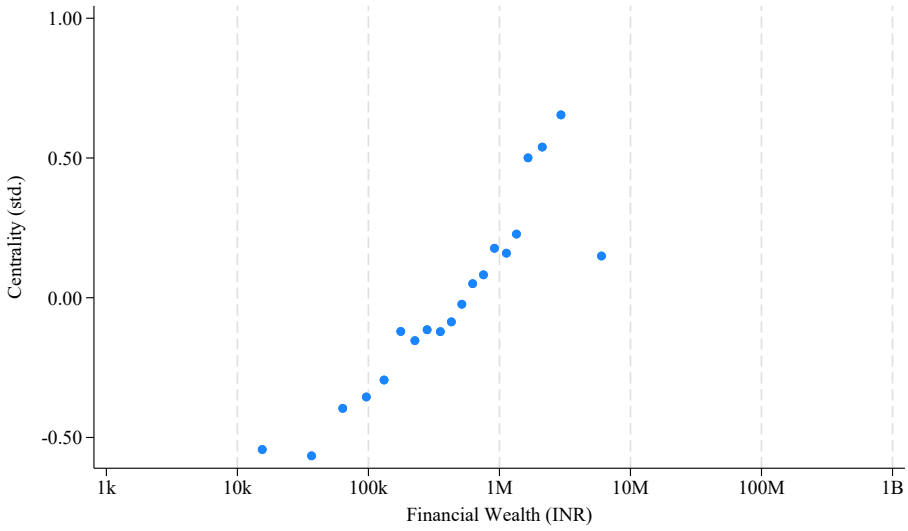
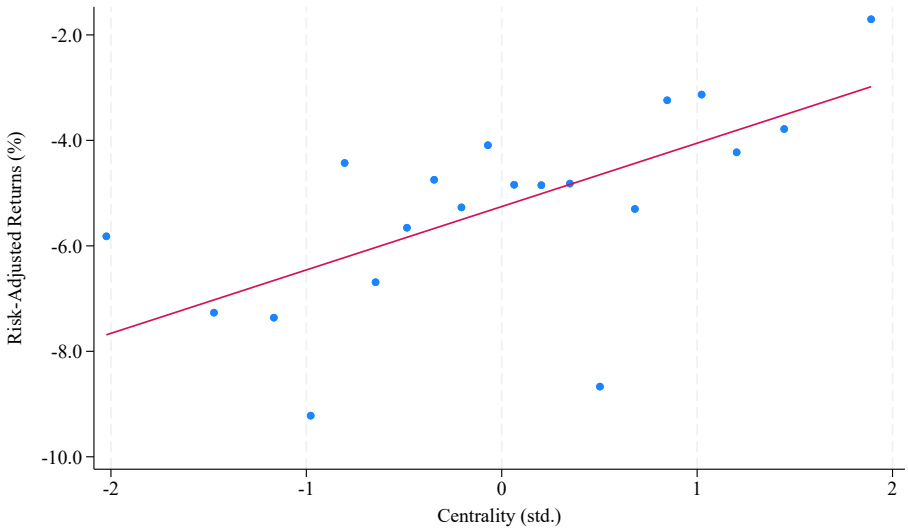


Figure 8: **Communication Network**

This figure plots network centrality against wealth in Panel A and annualized risk-adjusted returns against centrality in Panel B, at the PIN code level. Centrality is each PIN code's eigenvector centrality, inferred from PIN code-to-PIN code weekly phone call volumes (August–December 2019, averaged across weeks) and standardized for ease of interpretation. Financial wealth is the sum of direct equity holdings and bank deposits, measured at the beginning of the month and inflation-adjusted (Dec 2019 real INR); portfolio risk-adjusted returns are the value-weighted average of stock-level risk-adjusted returns on beginning-of-month holdings, held over the month. Both are aggregated to a PIN code-month average and then averaged over time. In Panel A, PIN codes are binned by average financial wealth; the x-axis reports average financial wealth on a logarithmic scale and the y-axis average centrality. Panel B is a binscatter of average annualized risk-adjusted returns (percentage points) against centrality. The exchange rate at end-2019 is 1 USD = 71.36 INR.



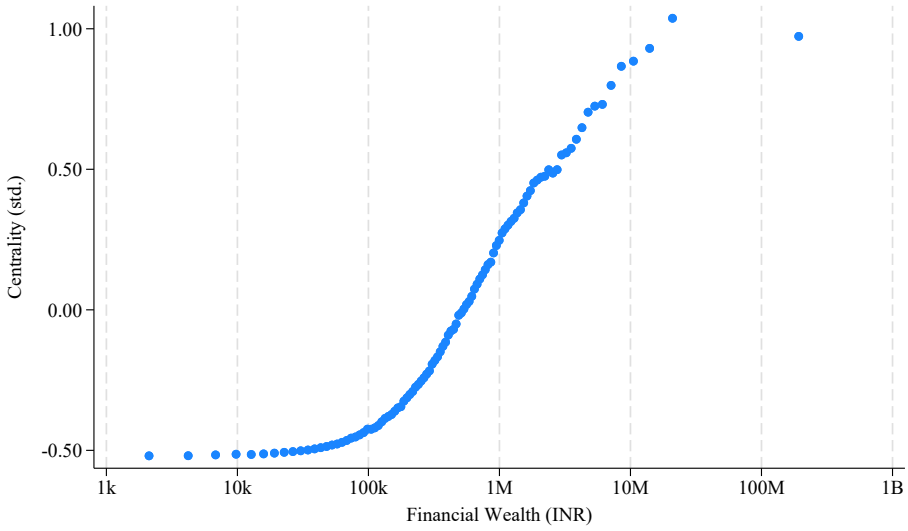

Panel A: Wealth and centrality



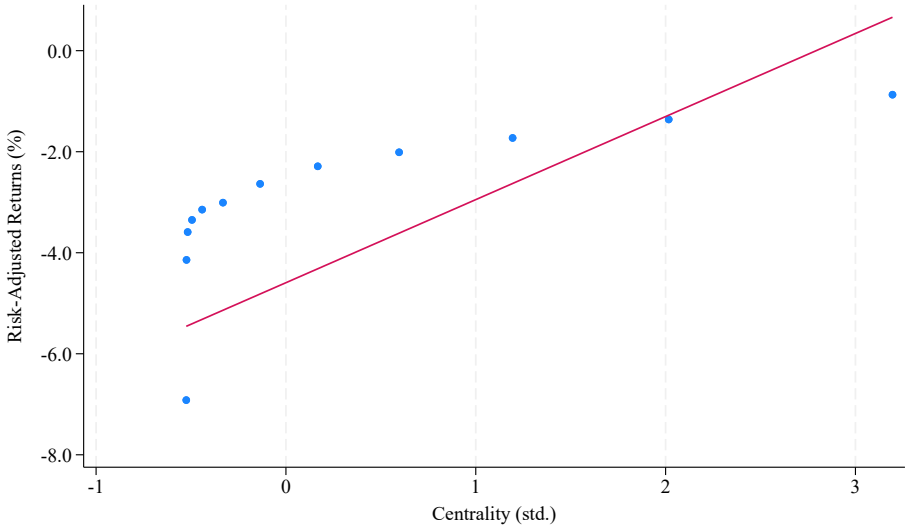

Panel B: Centrality and return

Figure 9: **Investor Network**

This figure plots network centrality against wealth in Panel A and annualized risk-adjusted returns against centrality in Panel B, at the individual-month level. Centrality is each individual's eigenvector centrality, inferred from trading behavior following Ozsoylev et al. (2014) and standardized for ease of interpretation. Financial wealth is the sum of direct equity holdings and bank deposits, measured at the beginning of the month and inflation-adjusted (Dec 2019 real INR); portfolio risk-adjusted returns are the value-weighted average of stock-level risk-adjusted returns on beginning-of-month holdings, held over the month. In Panel A, individuals are grouped into wealth bins within each month, centrality is averaged within each bin-month, and the plotted value is the time-series average across months; the x-axis reports average financial wealth on a logarithmic scale and the y-axis average centrality. Panel B is a binscatter of annualized risk-adjusted returns (percentage points) against centrality and an OLS fitted line. The exchange rate at end-2019 is 1 USD = 71.36 INR.




Panel A: Wealth and centrality




Panel B: Centrality and return

Figure 10: **Holding similarity within and between wealth groups**

This figure plots average pairwise portfolio holding similarity across the financial wealth percentiles. Financial wealth is defined as the sum of direct equity holdings and bank deposits, measured at the beginning of the month and adjusted for inflation (in Dec 2019 real INR). For each month and for each pair of individuals, portfolio similarity is computed using the cosine similarity of their portfolio holding vectors, using equation (8). Within each month, similarity is averaged across all individual pairs belonging to a given pair of wealth percentiles to obtain a percentile pair–month similarity measure. The plotted values report the time-series average of these percentile pair–month similarities. Cells along the diagonal represent within-percentile similarity, while off-diagonal cells represent between-percentile similarity. Darker colors indicate higher portfolio similarity.

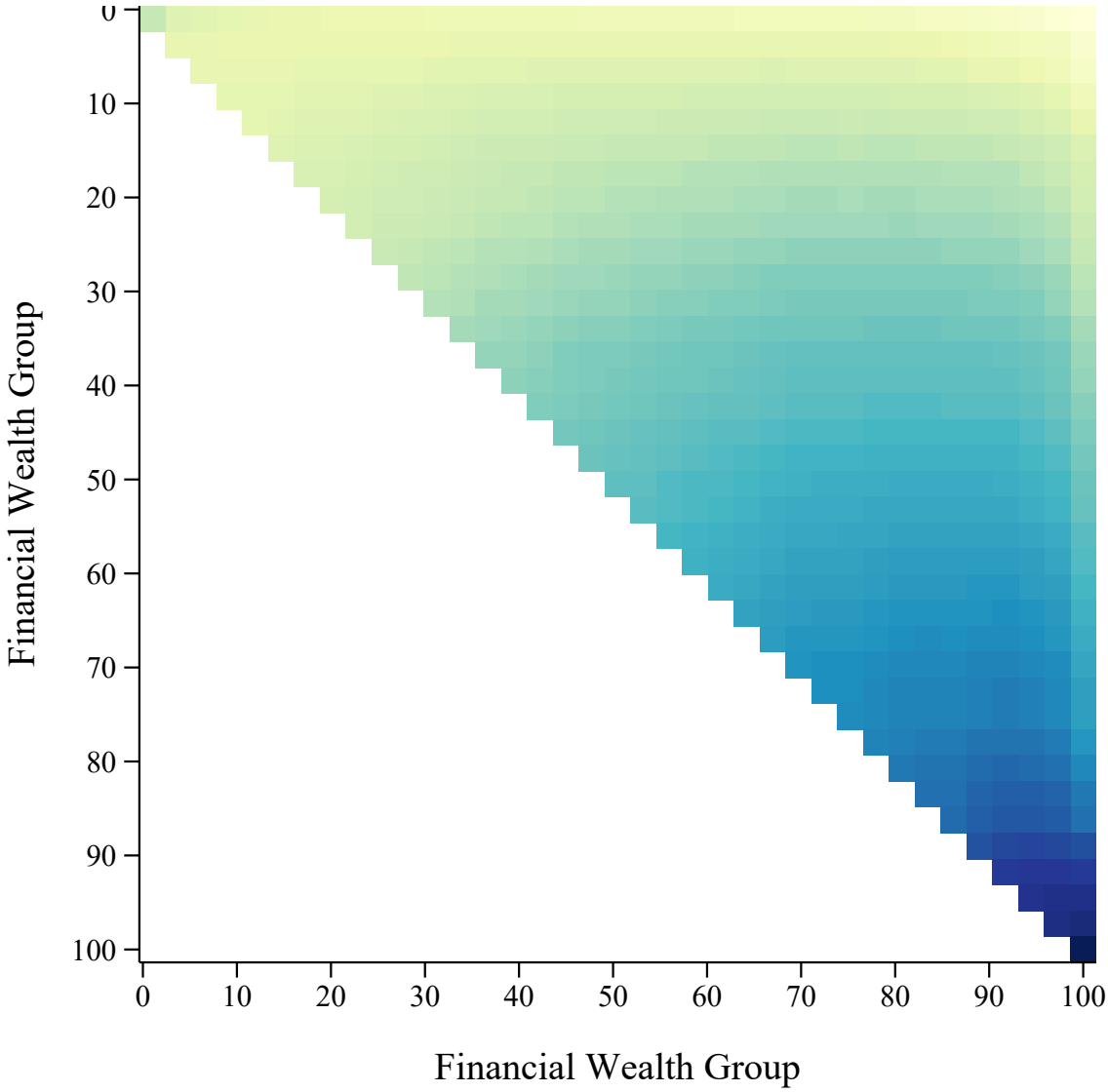


Table 1: **Summary statistics**

This table reports summary statistics for the main variables used in the analysis. The main sample covers the period from February 2012 to December 2019. The top panel reports statistics at the individual-stock-month level, where $\text{Value}_{i,s,t}$ and $\text{Quantity}_{i,s,t}$ denote the INR value and number of shares of a specific stock in an individual's portfolio in a month, respectively. $\text{Net Flow}_{i,s,t}$ is the net flow to a stock, measured as the change in holding quantity multiplied by end-of-month price. The middle panel reports statistics at the individual-month level. $\text{Financial Wealth}_{i,t}$ is the sum of direct equity holdings and bank deposits, measured at the beginning of the month. $\text{Diversification}_{i,t}$ is measured by one minus the HHI. $\text{Excess Returns}_{i,t}$ is the portfolio annualized excess returns calculated using equation (1). $\text{Risk-Adjusted Returns}_{i,t}$ is the portfolio annualized risk-adjusted returns computed using equation (4). $\text{Spending}_{i,t}$ is measured as the sum of credit card and debit card transactions, and cash withdrawals and utility bill payments via ATM. $\text{Discretionary}_{i,t}$ and $\text{Non-Discretionary}_{i,t}$ measure spending on discretionary and non-discretionary categories following Agarwal and Qian (2014). $\text{Net Flow}_{i,t}$ is the net flow into direct equity calculated as the aggregate value of net flows across all stocks in the portfolio. $\text{Age}_{i,t}$ is the age of an individual in a given month. The bottom panel reports time-invariant individual characteristics. $\mathbb{1}(\text{Female})_i$ is an indicator for whether an individual is female at the time of register. $\text{Credit Score}_i$ ranges from 300 to 900. All continuous variables are winsorized at the 1% level. Monetary values are adjusted for inflation (in Dec 2019 real INR). The exchange rate at the end of 2019 is 1 USD = 71.36 INR.

| | Obs. | Mean | Std. Dev. | 25% | 50% | 75% |
|---|---|---|---|---|---|---|
| *Individual-stock-month level:* | | | | | | |
| $\text{Value}_{i,s,t}$ (INR 000s) | 75,054,901 | 62.82 | 139.51 | 3.53 | 14.01 | 47.64 |
| $\text{Quantity}_{i,s,t}$ | 75,054,901 | 430.24 | 954.12 | 30.00 | 100.00 | 300.00 |
| $\text{Net Flow}_{i,s,t}$ (INR 000s) | 76,494,901 | -2.09 | 9.10 | -1.23 | -0.19 | 0.00 |
| *Individual-month level:* | | | | | | |
| $\text{Financial Wealth}_{i,t}$ (INR 000,000s) | 6,533,832 | 1.95 | 4.49 | 0.13 | 0.47 | 1.58 |
| $\text{Diversification}_{i,t}$ | 6,533,832 | 0.51 | 0.34 | 0.14 | 0.60 | 0.81 |
| $\text{Excess Returns}_{i,t}$ (%) | 6,533,832 | -1.25 | 95.57 | -56.11 | -2.64 | 51.29 |
| $\text{Risk-Adjusted Returns}_{i,t}$ (%) | 6,533,832 | -4.88 | 71.03 | -40.92 | -4.75 | 30.18 |
| $\text{Spending}_{i,t}$ (INR 000s) | 4,542,248 | 29.32 | 42.23 | 0.00 | 12.99 | 40.68 |
| $\text{Discretionary}_{i,t}$ | 4,542,248 | 9.69 | 21.44 | 0.00 | 0.13 | 8.92 |
| $\text{Non-Discretionary}_{i,t}$ | 4,542,248 | 3.76 | 9.35 | 0.00 | 0.00 | 2.78 |
| $\text{Net Flow}_{i,t}$ (INR 000s) | 6,533,832 | 4.02 | 69.27 | 0.00 | 0.00 | 0.00 |
| $\text{Age}_{i,t}$ | 6,533,832 | 58.56 | 11.47 | 51.00 | 58.00 | 66.00 |
| *Individual level:* | | | | | | |
| $\mathbb{1}(\text{Female})_i$ | 91,555 | 0.22 | 0.41 | 0.00 | 0.00 | 0.00 |
| $\text{Credit score}_i$ | 74,959 | 770.50 | 42.96 | 758.00 | 786.00 | 799.00 |

Table 2: **The effect of the PIT on the risk-adjusted return gap by wealth**

This table reports the estimated effect of the PIT amendment on the annualized risk-adjusted return gap between higher-wealth individuals (top 1% of the financial wealth distribution) and lower-wealth individuals (bottom 99%). The dependent variable is the individual-quarter (annualized) risk-adjusted return. $\text{Post}_t$ is an indicator variable equal to one from the PIT announcement quarter onward. $\mathbb{1}(\text{Top } 1\%)_i$ is an indicator variable equal to one if the individual belongs to the top 1% of the wealth distribution prior to the PIT announcement. Column 2 adds control variables. Column 3 and 4 include individual fixed effects, which absorb the time-invariant $\mathbb{1}(\text{Top } 1\%)_i$ term. All columns include time fixed effects. Control variables include $\text{Diversification}_{i,t-1}$, $\text{Age}_{i,t}$, $\mathbb{1}(\text{Female})_i$, and $\text{Credit Score}_i$. Column 1 reports the baseline estimates. Standard errors are clustered at the individual level. *t*-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

| *Dependent Variable* = | Risk-Adjusted $\text{Returns}_{i,t}$ (%) | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| $\text{Post}_t \times \mathbb{1}(\text{Top } 1\%)_i$ | -10.991*** | -11.717*** | -11.005*** | -11.270*** |
| | (-19.76) | (-18.27) | (-19.81) | (-20.21) |
| $\mathbb{1}(\text{Top } 1\%)_i$ | 17.381*** | 17.090*** | | |
| | (26.83) | (22.58) | | |
| Controls | | ✓ | | ✓ |
| Time FEs | ✓ | ✓ | ✓ | ✓ |
| Individual FEs | | | ✓ | ✓ |
| #Individual | 66,955 | 54,473 | 66,937 | 66,917 |
| Observations | 1,275,402 | 1,035,223 | 1,275,384 | 1,271,416 |
| Adj R-squared | 0.033 | 0.035 | 0.079 | 0.079 |

Table 3: **Average trading in stocks with insider trading violations by wealth**

This table reports estimates of the difference in trading stocks with insider trading violations proven by SEBI between higher-wealth individuals (top 1% of the financial wealth distribution) and lower-wealth individuals (bottom 99%). The dependent variable is individual-stock-month trading values in thousand INR, measured as the absolute value of the change in holding quantity multiplied by the end-of-period price. The exchange rate at the end of 2019 is 1 USD = 71.36 INR. $\mathbb{1}(\text{SEBI})_{s,t}$ is an indicator variable equal to one if month $t$ falls within the period of insider trading for stock $s$ found by SEBI. $\mathbb{1}(\text{Top 1\%})_{i,t}$ is an indicator equal to one if the individual $i$ is in the top 1% of the wealth distribution at the start of month $t$. Column 1 includes stock, individual, and time fixed effects, Column 2 includes stock and individual-by-time fixed effects, Column 3 includes stock-by-time and individual-by-time fixed effects, and Column 4 adds individual-by-stock fixed effects. Standard errors are clustered at the individual level. $t$-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

| *Dependent Variable* = | abs(Net Flow$_{i,s,t}$) ('000) | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| $\mathbb{1}(\text{SEBI})_{s,t} \times \mathbb{1}(\text{Top 1\%})_{i,t}$ | 3.151*** | 3.098*** | 3.148*** | 0.535*** |
| | (14.83) | (14.35) | (14.53) | (5.53) |
| $\mathbb{1}(\text{Top 1\%})_{i,t}$ | 1.714*** | | | |
| | (11.18) | | | |
| $\mathbb{1}(\text{SEBI})_{s,t}$ | 0.104*** | 0.087*** | | |
| | (12.81) | (10.71) | | |
| Stock FEs | ✓ | ✓ | | |
| Individual FEs | ✓ | | | |
| Time FEs | ✓ | | | |
| Individual-Time FEs | | ✓ | ✓ | ✓ |
| Stock-Time FEs | | | ✓ | ✓ |
| Individual-Stock FEs | | | | ✓ |
| #Individual | 91,555 | 91,555 | 91,555 | 91,555 |
| Observations | 167,352,767 | 167,352,767 | 167,352,767 | 167,352,767 |
| Adj R-squared | 0.128 | 0.162 | 0.184 | 0.446 |

Table 4: **Average net flows into M&A target firms by higher- versus lower-wealth individuals**

This table reports estimates of the net flow difference in M&A targets between higher-wealth individuals (top 1% of the financial wealth distribution) and lower-wealth individuals (bottom 99%). The dependent variable is individual-stock-month net flow in thousand INR, measured as the change in holding quantity multiplied by end-of-period price. The exchange rate at the end of 2019 is 1 USD = 71.36 INR. $\mathbb{1}(\text{Pre Announce})_{s(e),t}$ is an indicator variable equal to one for the target stock of M&A event $e$ during the $[-12, -1]$ pre-announcement window. $\mathbb{1}(\text{Top 1\%})_{i,e}$ is an indicator equal to one if the individual $i$ is in the top 1% of the wealth distribution at the start of the announcement month for M&A event $e$. Column 1 and 2 report results for M&A announcements made before the PIT announcement. Column 3 and 4 report results for M&A announcements made after May 2016, 12 months after the PIT implementation (to allow for a full pre-announcement window). Control variables include lagged stock returns, $r_{s,t-1}$, and lagged stock volatility, $\sigma_{s,t-1}$. Odd-numbered columns report the baseline estimates and even-numbered columns add control variables. All columns include time fixed effects, event fixed effects separately for the pre- and post-announcement periods, and individual-by-stock fixed effects. Standard errors are clustered at the individual level. $t$-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

| *Dependent Variable* = | Net Flow$_{i,s,t}$ ('000 INR) | | | |
|---|---|---|---|---|
| *M&As Period* = | Pre-PIT | | Post-PIT | |
| | (1) | (2) | (3) | (4) |
| $\mathbb{1}(\text{Pre-Announce})_{s(e),t}$ | 1.388*** | 1.386*** | 0.191 | 0.196 |
| $\times \mathbb{1}(\text{Top 1\%})_{i,e}$ | (5.85) | (5.84) | (1.14) | (1.16) |
| Controls | | ✓ | | ✓ |
| Time FEs | ✓ | ✓ | ✓ | ✓ |
| Event × Pre FEs | ✓ | ✓ | ✓ | ✓ |
| Individual × Stock FEs | ✓ | ✓ | ✓ | ✓ |
| #Individual | 91,447 | 91,445 | 91,489 | 91,487 |
| Observations | 160,225,345 | 160,196,629 | 160,477,469 | 160,448,753 |
| Adj R-squared | 0.381 | 0.381 | 0.381 | 0.382 |

Table 5: **The effect of the PIT on the net equity flow gap by wealth**

This table reports the estimated effect of the PIT on the wealth-based net equity flow gap between higher-wealth individuals (top 1% of the financial wealth distribution) and lower-wealth individuals (bottom 99%). The dependent variable is the individual-quarter net flow into direct equity in thousand INR, calculated as the aggregate value of net share purchases (i.e., change in quantity multiplied by end-of-period price) across all stocks in the portfolio. The exchange rate at the end of 2019 is 1 USD = 71.36 INR. $\text{Post}_t$ is an indicator variable equal to one from the PIT announcement quarter onward. $\mathbb{1}(\text{Top 1\%})_i$ is an indicator variable equal to one if the individual belongs to the top 1% of the wealth distribution prior to the PIT announcement. Control variables include $\text{Diversification}_{i,t-1}$, $\text{Age}_{i,t}$, $\mathbb{1}(\text{Female})_i$, and $\text{Credit Score}_i$. Column 1 reports the baseline estimates. Column 2 adds control variables. Column 3 and 4 include individual fixed effects, which absorb the time-invariant $\mathbb{1}(\text{Top 1\%})_i$ term. All columns include time fixed effects. Standard errors are clustered at the individual level. *t*-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

| *Dependent Variable* = | $\text{Net Flow}_{i,t}$ ('000 INR) | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| $\text{Post}_t \times \mathbb{1}(\text{Top 1\%})_i$ | -48.442*** | -41.523*** | -49.032*** | -46.471*** |
| | (-4.30) | (-3.41) | (-4.33) | (-4.12) |
| $\mathbb{1}(\text{Top 1\%})_i$ | 23.434** | 10.494 | | |
| | (2.06) | (0.85) | | |
| Controls | | ✓ | | ✓ |
| Time FEs | ✓ | ✓ | ✓ | ✓ |
| Individual FEs | | | ✓ | ✓ |
| #Individual | 66,955 | 54,473 | 66,937 | 66,917 |
| Observations | 1,275,402 | 1,035,223 | 1,275,384 | 1,271,416 |
| Adj R-squared | 0.006 | 0.009 | 0.077 | 0.077 |

Table 6: **The effect of the PIT on the spending gap by wealth**

This table reports the estimated effect of the PIT on the wealth-based spending gap between higher-wealth individuals (top 1% of the financial wealth distribution) and lower-wealth individuals (bottom 99%). The dependent variable in Column 1 is the individual-quarter spending in thousand INR, measured as the sum of credit card and debit card transactions, and cash withdrawals and utility bill payments via ATM. The exchange rate at the end of 2019 is 1 USD = 71.36 INR. Total spending (excluding ATM transactions) is decomposed into discretionary and non-discretionary categories, following Agarwal and Qian (2014), in Column 2 and 3. $\text{Post}_t$ is an indicator variable equal to one from the PIT announcement quarter onward. $\mathbb{1}(\text{Top } 1\%)_i$ is an indicator variable equal to one if the individual belongs to the top 1% of the wealth distribution prior to the PIT announcement. Control variables include $\text{Diversification}_{i,t-1}$, $\text{Age}_{i,t}$, $\mathbb{1}(\text{Female})_i$, and $\text{Credit Score}_i$. All columns include time and individual fixed effects. Standard errors are clustered at the individual level. *t*-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

| *Dependent Variable* = | $\text{Spending}_{i,t}$ ('000 INR) | | |
|---|---|---|---|
| | Total | Discretionary | Non-Discretionary |
| | (1) | (2) | (3) |
| $\text{Post}_t \times \mathbb{1}(\text{Top } 1\%)_i$ | 6.004** | 4.006*** | 1.238** |
| | (2.21) | (2.71) | (2.50) |
| Controls | ✓ | ✓ | ✓ |
| Time FEs | ✓ | ✓ | ✓ |
| Individual FEs | ✓ | ✓ | ✓ |
| #Individual | 66,917 | 66,917 | 66,917 |
| Observations | 1,271,416 | 1,271,416 | 1,271,416 |
| Adj R-squared | 0.668 | 0.592 | 0.496 |

Table 7: **Network centrality, wealth, and returns**

This table examines the relationship between network centrality and wealth in Columns 1–2 and between (annualized) risk-adjusted returns and centrality in Columns 3–4, for two information-network proxies. In Panel A, $\text{Centrality}_p$ is inferred from pairwise PIN code-level phone call data and the panel is a PIN code cross-section; in Panel B, $\text{Centrality}_{i,t}$ is inferred from trading behavior following Ozsoylev et al. (2014) at the individual-month level. Centrality is standardized for the ease of interpretation. The dependent variable is Centrality in Columns 1 and 2, which is regressed on the wealth measure ($\log(\text{Average Finwealth})_p$ in Panel A and $\mathbb{1}(\text{Top 1\%})_{i,t}$ in Panel B) and Risk-Adjusted Returns (%) in Columns 3 and 4, which is regressed on centrality. Control variables are diversification, age, female, and credit score, measured as PIN code averages in Panel A and at the individual level in Panel B. Odd-numbered columns report baseline estimates and even-numbered columns add control variables. Panel A, being a cross-section, includes no fixed effects and reports heteroskedasticity-robust standard errors; Panel B includes time fixed effects and clusters standard errors at the individual level. *t*-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

*Panel A: Communication Network*

| *Dependent Variable* = | $\text{Centrality}_p$ | | $\text{Risk-Adjusted Returns}_p$ (%) | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| $\log(\text{Average Finwealth})_p$ | 0.201*** | 0.201*** | | |
| | (14.06) | (11.31) | | |
| $\text{Centrality}_p$ | | | 1.202*** | 0.760** |
| | | | (3.49) | (2.12) |
| Controls | | ✓ | | ✓ |
| Observations | 2,110 | 1,989 | 2,110 | 1,989 |
| Adj R-squared | 0.088 | 0.092 | 0.006 | 0.031 |

*Panel B: Investor Network*

| *Dependent Variable* = | $\text{Centrality}_{i,t}$ | | $\text{Risk-Adjusted Returns}_{i,t}$ (%) | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| $\mathbb{1}(\text{Top 1\%})_{i,t}$ | 0.988*** | 0.997*** | | |
| | (20.78) | (21.81) | | |
| $\text{Centrality}_{i,t}$ | | | 1.551*** | 1.041*** |
| | | | (64.34) | (34.47) |
| Controls | | ✓ | | ✓ |
| Time FEs | ✓ | ✓ | ✓ | ✓ |
| Observations | 6,533,832 | 5,346,561 | 6,533,832 | 5,346,561 |
| #Individual | 91,555 | 74,959 | 91,555 | 74,959 |
| Adj R-squared | 0.011 | 0.256 | 0.051 | 0.052 |

# Internet Appendix

## Informational Advantage of the Wealthy

This Internet Appendix contains supplementary material.

### A Sample construction

Our account and holdings data is a random and representative sample of the Bank's customers in Ahmedabad, Bangalore, Bhubaneshwar, Chennai, Delhi, Gurgaon, Kolkata, Mumbai and Surat. They represent states (i.e., Haryana, Delhi, Gujarat, Maharashtra, Odisha, Karnataka and Tamil Nadu) from different parts of India and with differing levels of GDP.

The raw data contains over 250,000 individuals. Of these, approximately 120,000 have Demat accounts, which form the starting universe for our filtering procedure. From this, we apply several filters to construct our final analysis sample. First, following Andersen et al. (2024), we require account-month observations to have a minimum financial wealth of ₹1,000 (in 2012 Rupees) to screen out inactive or trivial accounts. Second, we restrict the sample to individuals between the ages of 16 and 85 to ensure our observations represent independent financial decision-makers. These filters yield our final sample of 91,555 unique individuals.

On the securities side, we identify a security by International Securities Identification Number (ISIN). The raw data contains 10,677 unique ISINs, spanning equities, bonds, and mutual funds. We restrict our analysis to equities of publicly listed firms for two primary reasons. First, they constitute the vast majority (>93%) of the total value of holdings in our sample. Second, focusing on listed equities allows us to study return heterogeneity on a "level playing field" of assets theoretically accessible to all investors. This results in a final sample of 4,243 distinct listed stocks.

We observe security-level holdings at a month-end frequency from January 2012 to December 2019. Because our analyses require a lagged measure of financial wealth, our final sample period begins in February 2012. The resulting panel dataset consists of 74,985,942 individual-stock-month observations.

## B SEBI Enforcement Orders

## C Group-wise Portfolio Similarity

This section provides a formal derivation of the computationally efficient within-group and between-group similarity measures presented in the main text.

The standard pairwise cosine similarity between the portfolio holding vectors of two individuals, $i$ and $j$, is:

$$\text{Cosine Similarity}_{i,j} = Sim(h_i, h_j) = \frac{h_i \cdot h_j}{\|h_i\| \|h_j\|} = \hat{h}_i \cdot \hat{h}_j,$$

where $\hat{h}_i = h_i / \|h_i\|$ is the L2-normalized portfolio vector for individual $i$.

### C.1 Within-Group Similarity

The brute-force calculation for the average within-group similarity for a group A with $N_A$ members is the sum of all unique pairwise similarities divided by the number of pairs:

$$\text{Avg within-group similarity}_A = \frac{\sum_{i,j \in A, i<j} \hat{h}_i \cdot \hat{h}j}{N_A(N_A-1)/2}. \tag{IA.1}$$

To compute this efficiently, we consider the sum of normalized vectors $S_A = \sum_{i \in A} \hat{h}_i$:

$$\|S_A\|^2 = S_A \cdot S_A = \sum_{i \in A} \hat{h}_i \cdot \sum_{j \in A} \hat{h}_j \tag{IA.2}$$

$$= \sum_{i \in A} \sum_{j \in A} (\hat{h}_i \cdot \hat{h}_j) \quad \text{(by the distributive property of the dot product)} \tag{IA.3}$$

$$= \sum_{i \in A} \hat{h}_i \cdot \hat{h}_i + \sum_{i,j \in A, i \neq j} \hat{h}_i \cdot \hat{h}_j \tag{IA.4}$$

$$= \sum_{i \in A} \|\hat{h}_i\|^2 + 2 \sum_{i,j \in A, i<j} \hat{h}_i \cdot \hat{h}_j \tag{IA.5}$$

$$= N_A + 2 \sum_{i,j \in A, i<j} \hat{h}_i \cdot \hat{h}_j. \tag{IA.6}$$

By rearranging equation (IA.6), we can solve for the sum of pairwise similarities:

$$2 \sum_{i,j \in A, i<j} \hat{h}_i \cdot \hat{h}_j = \|S_A\|^2 - N_A.$$

Substituting this back into equation (IA.1) yields our efficient estimator:

$$\text{Avg within-group similarity}_A = \frac{\|S_A\|^2 - N_A}{N_A(N_A - 1)}. \tag{IA.7}$$

### C.2 Between-Group Similarity

The average between-group similarity for groups A and B is:

$$\text{Avg between-group similarity}_{A,B} = \frac{\sum_{i \in A, j \in B} \hat{h}_i \cdot \hat{h}_j}{N_A N_B}, \tag{IA.8}$$

The numerator can be efficiently calculated by considering the dot product of the aggregate vectors $S_A$ and $S_B$:

$$S_A \cdot S_B = \sum_{i \in A} \hat{h}_i \cdot \sum_{j \in B} \hat{h}_j \tag{IA.9}$$

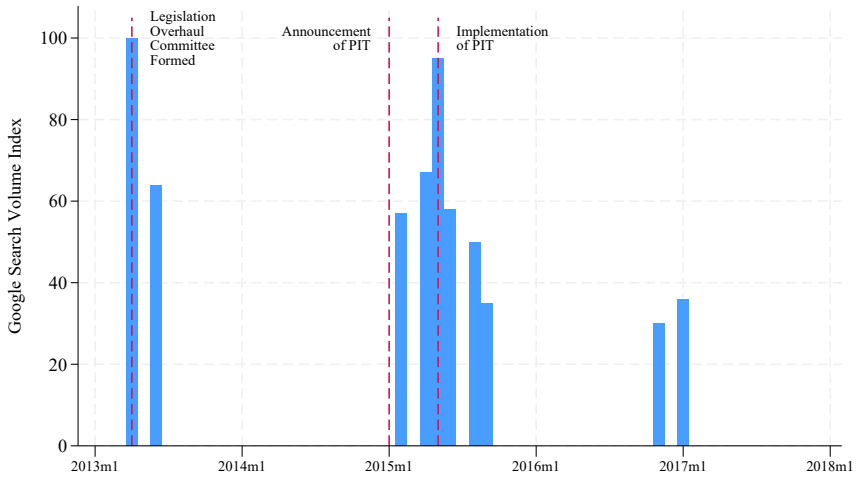
$$= \sum_{i \in A} \sum_{j \in B} (\hat{h}_i \cdot \hat{h}_j). \tag{IA.10}$$

Substituting this into equation (IA.8) gives the final estimator:

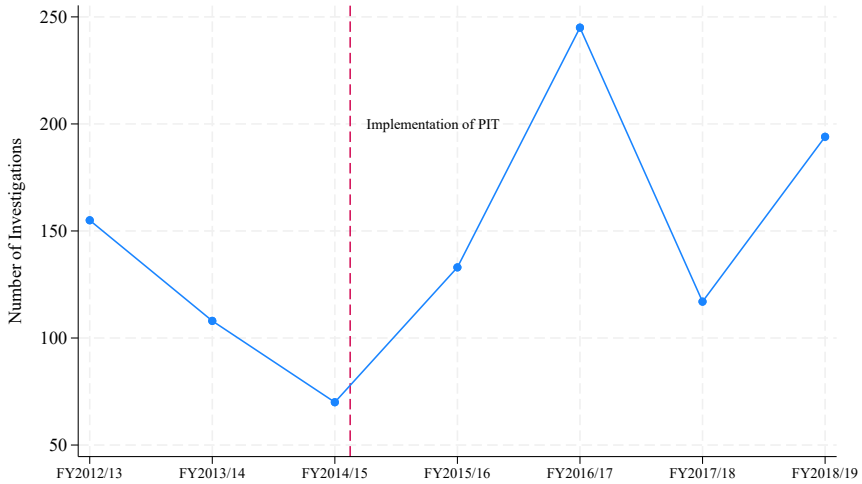
$$\text{Avg between-group similarity}_{A,B} = \frac{S_A \cdot S_B}{N_A N_B}. \tag{IA.11}$$

Figure IA.1: **Enforcement and attention around the PIT**

Panel A shows the monthly Google search volume index of the keyword "Prohibition of Insider Trading Regulations" in India from 2013 to 2017. Panel B shows the number of investigations taken up by SEBI that are related to insider trading in each fiscal year. Insider trading related investigations include investigations regarding market manipulation and price rigging, issue related manipulation, and insider trading. Data are obtained from SEBI (2020). A fiscal year starts from April 1 and ends on March 31 in India.




Panel A: Google search index of "Prohibition of Insider Trading Regulations"




Panel B: Number of insider trading related investigations

Figure IA.2: **Abnormal returns for M&A target firms**

This figure plots cumulative abnormal returns of target firms averaged across 278 M&A events in the $[-21, 63]$ event window. Abnormal returns are estimated using CAPM in a $[-220, -31]$ estimation window.

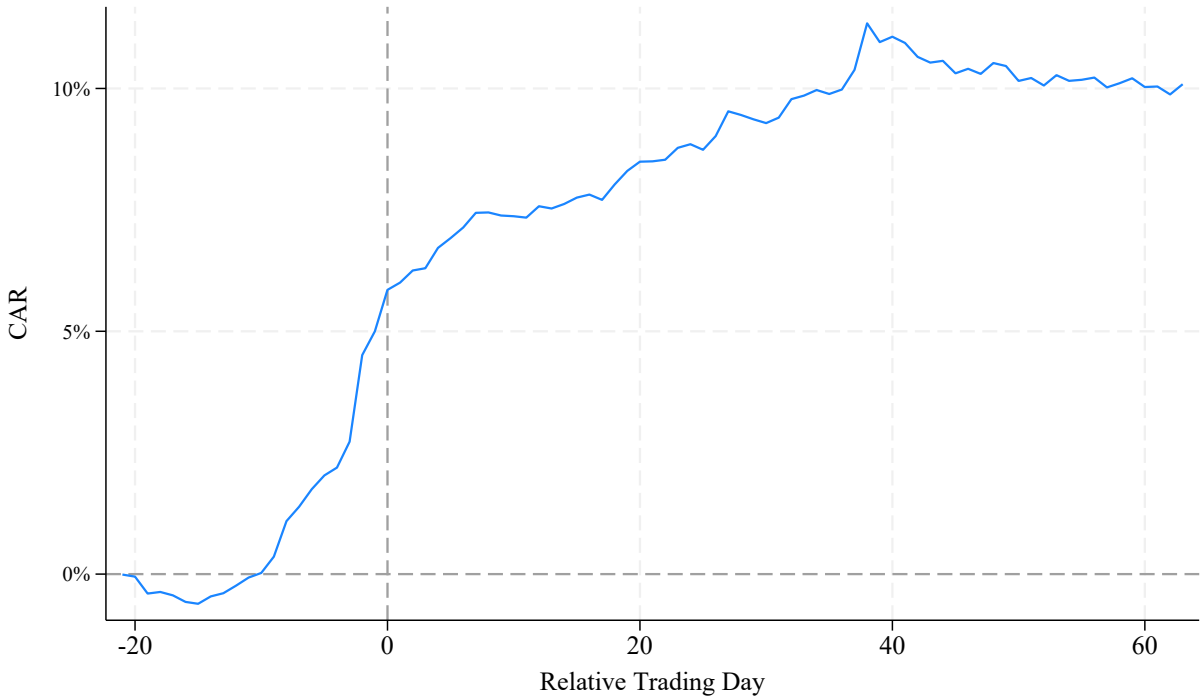


Table IA.1: **Robustness checks of the effect of the PIT on the risk-adjusted return gap by wealth**

This table reports robustness checks of the estimated effect of PIT on the wealth-based annualized risk-adjusted return gap between higher-wealth individuals (top 1% of the financial wealth distribution) and lower-wealth individuals (bottom 99%). The dependent variable is the individual-quarter (annualized) risk-adjusted return. $\text{Post}_t$ is an indicator variable equal to one from the PIT announcement quarter onward. $\mathbb{1}(\text{Top } 1\%)_i$ ($\mathbb{1}(\text{Top } 5\%)_i$) is an indicator variable equal to one if the individual belongs to the top 1% (5%) of the wealth distribution prior to the PIT announcement. Column 1 reports results using alternative individual-quarter risk-adjusted return estimated using the Carhart four-factor model. Columns 2 and 3 report results using alternative cutoff (top 5% and bottom 95%) to define higher-wealth and lower-wealth individuals. Control variables include $\text{Diversification}_{i,t-1}$ and $\text{Age}_{i,t}$. Standard errors are clustered at the individual level. *t*-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

| *Dependent Variable* = | Risk-Adjusted Returns $(C4)_{i,t}$ (%) | Risk-Adjusted $\text{Returns}_{i,t}$ (%) | Risk-Adjusted Returns $(C4)_{i,t}$ (%) |
|---|---|---|---|
| | (1) | (2) | (3) |
| $\text{Post}_t \times \mathbb{1}(\text{Top } 1\%)_i$ | -10.619*** | | |
| | (-19.42) | | |
| $\text{Post}_t \times \mathbb{1}(\text{Top } 5\%)_i$ | | -9.304*** | -8.674*** |
| | | (-35.95) | (-34.21) |
| Controls | ✓ | ✓ | ✓ |
| Time FEs | ✓ | ✓ | ✓ |
| Individual FEs | ✓ | ✓ | ✓ |
| #Individual | 66,917 | 66,917 | 66,917 |
| Observations | 1,271,416 | 1,271,416 | 1,271,416 |
| Adj R-squared | 0.042 | 0.080 | 0.042 |

Table IA.2: **Decompose the effect of PIT on the risk-adjusted return gap by connectedness**

This table reports the estimated effect of PIT on the wealth-based annualized risk-adjusted return gap between higher-wealth individuals (top 1% of the financial wealth distribution) and lower-wealth individuals (bottom 99%) separately for unconnected stocks and connected stocks. We define an individual is connected to a stock if the individual shares the last name with at least one board member of the stock. The dependent variable is the individual-quarter (annualized) risk-adjusted return. $\text{Post}_t$ is an indicator variable equal to one from the PIT announcement quarter onward. $\mathbb{1}(\text{Top 1\%})_i$ is an indicator variable equal to one if the individual belongs to the top 1% of the wealth distribution prior to the PIT announcement. Column 1 reports the result using individual-quarter (annualized) risk-adjusted return for all stocks in the portfolio, analogous to Column 4 of Table 2. Columns 2 and 3 report results using individual-quarter (annualized) risk-adjusted return for unconnected stocks and connected stocks, respectively. Sample in this table is restricted to individuals with reported last names. Control variables include $\text{Diversification}_{i,t-1}$ and $\text{Age}_{i,t}$. Standard errors are clustered at the individual level. *t*-statistics are reported in parentheses. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

| *Dependent Variable* = | Risk-Adjusted Returns$_{i,t}$ (%) | | |
|---|---|---|---|
| | Total | Unconnected | Connected |
| | (1) | (2) | (3) |
| $\text{Post}_t \times \mathbb{1}(\text{Top 1\%})_i$ | -11.396*** | -10.326*** | -0.208*** |
| | (-19.60) | (-19.04) | (-2.89) |
| Controls | ✓ | ✓ | ✓ |
| Time FEs | ✓ | ✓ | ✓ |
| Individual FEs | ✓ | ✓ | ✓ |
| #Individual | 63,879 | 63,879 | 63,879 |
| Observations | 1,213,656 | 1,213,656 | 1,213,656 |
| Adj R-squared | 0.080 | 0.079 | 0.063 |