Order Exposure in High Frequency Markets

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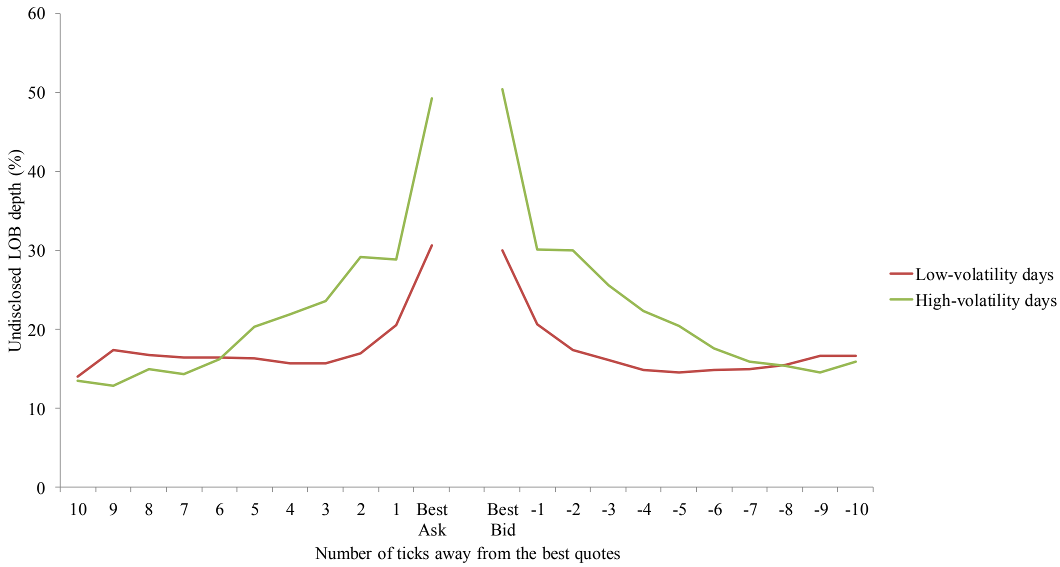
1. Introduction

Public stock exchanges are not fully transparent; opacity – the choice to hide orders – is on the rise. The SEC's market data show that hidden volume's contribution to trades increased from 15% to over 30% in the US between 2012 and 2017[2]; our own estimates (see Fig below) show that 30% (50%) of the Nasdaq order book near the best quotes is hidden on low (high) volatility days.[3]



A parallel trend during the last decades has been the rise of high frequency trading (HFT). According to the Tabb Group, while HFT accounted for 20% of U.S. equity volume in 2005, in

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[2] https://www.sec.gov/marketstructure/datavis/ma_exchange_hiddenvolume.html#.XM-0auhKg2w

[3] Opacity in financial markets come from orders that are fully or partly hidden (iceberg) in lit exchanges as well as venues known as dark pools that are completely opaque. In lit markets (the focus of this study), fully hidden orders are more prevalent in North American markets (e.g., US, Canada) while iceberg orders are widespread in Europe and the Asia-Pacific (e.g., Spain, France, India, Australia).

2016 it had reached 50%. While correlation is not causation, the outsized influence of HFT in modern financial markets raises the question: Do high-frequency traders (HFTs) contribute to opacity in public exchanges by hiding their trading interest? We develop testable propositions from theories of order exposure to address this question and use multi-country data that flag trader and order types to test these propositions. We find that HFTs extensively use hidden orders as part of their trading strategy. This finding is surprising because the logic of the extant theories of hidden order usage suggests that HFTs should have less incentives to hide limit orders.

2. Reasons to hide orders – Do they apply to HFTs?

Why should a trader choose to hide her trading interest? Extant theory models this choice depending on whether the trader is informed (Moinas, 2010; Boulatov and George, 2013) or uninformed (Buti and Rindi, 2013) which ignores differences in latency (speed), quotation frequency, or monitoring intensity among traders. Most empirical tests that address these theories are done in markets of the pre-HFT era (De Winne and D'Hondt, 2007; Bessembinder, Panayides and Venkataraman, 2009 (hereafter, BPV); Pardo and Pascual, 2012), where speed was not as important an issue as in modern markets. Therefore, there is a need to extrapolate the theoretical rationale for order non-exposure to markets populated by HFTs.

One strand of the literature we call the *free-option theory* (Buti and Rindi, 2013) focuses on an uninformed liquidity provider who, by displaying large order sizes, exposes herself to the risk of being picked off by faster traders, adversely selected by informed traders, or undercut by parasitic traders. In this framework, the uninformed trader hides her orders to mitigate their option value (Copeland and Galai, 1983). Should this narrative apply to HFTs? The literature shows that HFTs are a significant source of liquidity supply (Hagströmer and Nordén, 2013), but they use smaller order sizes (O'Hara, 2015), and monitor markets in near-continuous time (Hoffmann, 2014), resulting in high rates of ultra-fast cancellations (Hasbrouck and Saar, 2009). Their limit orders should therefore have a low option value. Moreover, hidden orders lose time priority per exchange rules, which increases their time to execution. Since the success of HFTs' trading strategies relies on speed (Baron, Brogaard, Hagströmer, and Kirilenko, 2018), they should be better off displaying their orders and quickly canceling or updating their quotes as market conditions necessitate.

A second branch of the literature models informed traders' motives for hiding orders. The *information-revelation theory* posits that informed traders may use hidden orders to obscure their trading intentions (Moinas, 2010), thereby reducing the expropriation of informational rents (Boulatov and George, 2013). Studies show that HFTs' trades (Brogaard, Hendershott, and Riordan, 2014) and orders (Chordia, Green, and Kottimukkalur, 2018) carry information, although Weller (2018) emphasizes that HFTs are not informed in the traditional sense of producing new information. Rather, they contribute to price discovery by rapidly incorporating signals gleaned from order flow (Hirschey, 2018; Korajczyk and Murphy, 2019) or public news (Chakrabarty, Moulton, and Wang, 2019). In this case we expect HFTs to use displayed orders since such information is short lived and, by losing time priority, hidden orders delay execution.

Thus, whether HFTs are informed or uninformed, given their trading technology and the unique features of hidden orders, extant theory suggests that HFTs should display their orders.

3. Data – How we identify HFTs and hidden versus displayed orders

To test if that, indeed, is the case, we need data that (a) flag HFT versus other traders, and (b) provide order level information including the display condition (hidden or not). Publicly available trade and quote data generally do not have either flag. We use proprietary data from two markets that provide such identifiers. Our primary data come from the National Stock Exchange of India (NSE), the fifth largest market in the world by number of trades.[4] The NSE data furnish rich details on trader accounts, using which we classify each order as coming from one of three mutually exclusive trader types: proprietary algorithmic traders (i.e., HFTs), other ("agency") algorithmic traders (AATs), and non-algorithmic traders (NATs). The NSE allows iceberg orders and we can identify both the displayed and the hidden portions of each order.

Our second data source is the Nasdaq exchange in the US which allows fully hidden orders. The Nasdaq data provide one-minute snapshots of the ten best bids and offers in the order book. For each snapshot, we see all standing limit orders, whether they are hidden or displayed, and whether they were placed by HFTs or non-HFTs. We use the term hidden limit orders (HLOs) for both fully hidden and iceberg orders, noting that the NSE HLOs are iceberg orders while the Nasdaq HLOs are fully hidden.

4. The three questions we address

[4] In our sample period, HFTs contribute 33% of the total daily volume on the NSE. See https://www.nseindia.com/research/content/1314_BS6.pdf

We address three issues on HFTs' hidden order use – the "whether", the "how", and the "why."

4a. The whether question

In response to whether HFTs use hidden orders, we find that they make extensive use of HLOs. In the NSE, in large-cap firms 10.38% (9.83%) of all limit orders (share volume) submitted by HFTs are HLOs. Corresponding numbers for mid-cap and small-cap firms are 36.0% (34.42%) and 15.84% (15.23%), respectively. In the Nasdaq, HFTs hide 21.8% (15.25%) of all limit orders (share volume) in large-cap stocks, 23.17% (34.71%) for mid-cap stocks, and 31.65% (47.84%) for small-cap stocks.

Analyzing order placement in different layers of the book, for the NSE we find that HFTs place 46.03% (1.5%) of their hidden (displayed) orders in large stocks at or better than the best quotes. In fact, over 97.72% of HFT's HLOs in large stocks are placed within the first five ticks from the best quotes. In contrast, NATs place 39.12% of their HLOs away from the five best ticks. In small stocks, HFTs' HLOs are rarely placed away from the five best ticks while NATs place the bulk of their HLOs far away from the best quotes. The Nasdaq data corroborate that HFTs' HLOs are more aggressive than their displayed limit orders (DLOs) as well as the HLOs of non-HFTs.

4b. The how question

Results from both the NSE and the Nasdaq indicate that HFTs use HLOs. But how efficiently do they use these orders? We model this part of the investigation on BPV who find that HLOs have a lower probability of completion and take longer to execute compared to similar DLOs, although DLOs have a higher implementation cost. How do HFTs manage this cost-benefit trade-off vis-à-vis other traders? To test the effectiveness of HFTs' hidden order usage, we model the execution probabilities of HLOs placed by HFTs versus other traders. We find that HFTs' HLOs have the *highest* likelihood of execution. Although HLOs lose time priority, HFTs' hidden orders have a similar (higher) fill rate than their displayed orders for large (mid or small) caps, suggesting that HFTs strategically place HLOs in anticipation of short-term volatility increases, which increases the likelihood of execution. We also model the time to full execution of HLOs vis-à-vis other orders using survival analysis, as in Lo, MacKinlay, and Zhang (2002). This test is particularly relevant in our context, since iceberg orders may mechanically induce a protracted time to completion. Results show that although compared to DLOs, HLOs take longer to fully execute, HLOs placed by HFTs execute faster than those placed by other traders.

Clearly HFTs benefit from the increased likelihood of execution and reduced time to completion of their HLOs. But any benefit must be weighed against the cost incurred. To estimate the costs, we use the implementation shortfall metric (Perold, 1988). This metric has two components: effective cost (price impact), and the opportunity cost of non-execution (which measures forgone profits). We find that HFTs face higher effective cost for hidden orders, which is expected since HFTs use more aggressive HLOs. However, their opportunity cost of non-execution is lower, indicating less adverse price movements after their hidden order submissions. When combined, the lower opportunity costs either compensate for, or exceed, the higher execution costs and overall HFTs' HLOs have a lower implementation shortfall. These findings suggest that HFTs use HLOs more efficiently than non-HFTs.

4c. The why question

Our final set of tests address the why question. First we test the free-option theory which suggests that large limit orders are more likely to be hidden. Do HFTs hide (relatively) larger limit orders? Our results suggest that is not the case. In fact, HFTs use smaller share sizes for HLOs. In the NSE, HFTs' HLOs average 456.58 shares compared to 1139.59 shares for NATs. For displayed orders, the patterns reverse: HFTs use larger DLOs (1150.50 shares) than NATs (309.27 shares). 76.28% (5.11%) of HFTs' HLOs (DLOs) in large firms are placed in the under-50-shares category while for mid and small firms, this rises to 98.72% and 83.96%, respectively. We also estimate the probability of hiding a limit order conditional on order size and find that HFTs are more likely to hide smaller orders. These patterns are also present in the Nasdaq data. Thus, our results find no confirmation for the free-option theory when extended to the use of HLOs by HFTs.

To test the information-revelation theory, we examine whether HFTs' HLOs are informationally motivated using three complementary metrics. First, we measure the average information content of HLOs for each trader type. Second, we decompose the order-flow related component of the efficient price variance into proportions attributable to each trader-type (HFT, AAT, NAT) – order-type (hidden, displayed) combination. Third, we measure the information share (Hasbrouck, 1995) of each trader-type order-type combination. We find that HFTs' HLOs have an insignificant price impact once we account for order aggressiveness, they explain the smallest portion of order-flow related efficient price volatility, and they have the lowest information share of all trader-type order-type combinations. Overall, our findings are inconsistent with HFTs using HLOs to trade on time sensitive information and fail to confirm the information-revelation theory.

5. Testing two conjectures

Collectively, these results indicate that HFTs use HLOs neither to manage free-option risk nor to manage information revelation. Existing models, therefore, do not explain why HFTs should use hidden orders, which calls for new theory to explicitly model HFTs' order exposure choice. To that end, and as a first step, we empirically investigate two possible reasons why HFTs may use HLOs: (a) to undercut standing quotes and compete to supply liquidity,[5] and (b) in anticipation of peaks in short term volatility. We note here that this is not an exhaustive list of the possible reasons why HFTs use HLOs, but rather tests based on some characteristics of HFT strategies documented in contemporary studies.

HFTs' ultra-fast algorithms put them in a position to anticipate other traders' orders (Hirschey, 2018) or detect institutional investors' orders that use order-splitting algorithms (van Kervel and Menkveld, 2019). Using HLOs, HFTs could undercut standing orders without revealing their presence. Additionally, there could be some speed advantage to letting the exchange's engine (software) reveal each successive tranche of an iceberg order, rather than transmitting several small DLOs from the HFTs' server by monitoring market conditions. We define an undercutting order as a limit order that (i) is placed immediately after another submission on the same side of the market, (ii) comes in under 10 milliseconds of the previous order, and (iii) improves upon the previous price. We find that HFTs are more likely to use HLOs than DLOs to undercut existing orders at or near the best quotes using aggressively priced HLOs.

Foucault, Hombert and Roşu (2016) show that traders with speed advantages deploy anticipatory trading strategies, and evidence in Hirschey (2018) confirm that HFTs anticipate order flow. Extending this line of reasoning, we ask if HFTs also anticipate volatility and place non-aggressive HLOs in periods before volatility peaks, thereby improving their probability of

[5] Offering minimal price improvement to undercut standing quotes and move up in the order queue may enhance liquidity supply and narrow the bid-ask spread, or adversely impact other liquidity suppliers if such quotes are used to persistently jump ahead of standing orders. Since HFTs do not have any fiduciary obligation towards the traders whose quotes they undercut, our tests do not address the illegal practice of "front running," where the undercutting party has such obligation to the party whose orders are undercut.

execution (a result we documented earlier). Our empirical tests also confirm this conjecture about the use of HLOs by HFTs.

6. Conclusion and Discussion

This study sits at the cusp of two important issues facing investors and regulators – market opacity and high-speed trading. Research shows that when markets allow traders the facility to hide orders, they substitute non-displayed for displayed orders and change their trading aggressiveness (Bloomfield, O'Hara, and Saar, 2015). Meanwhile, improved (pre-trade) transparency can increase liquidity and the informational efficiency of prices (Boehmer, Saar, and Yu, 2005). Since transparency is a cornerstone of the SEC's investor protection function, current trends have regulators worried that opacity may be attractive to "bad-actors" (see SEC Chairman's speech).[6] The growth of HFT has also been accompanied by a frenzy of media commentaries on its inherent unfairness. Although studies find that HFT has both positive (Brogaard, Hendershott, and Riordan, 2014) and negative (Budish, Cramton, and Shim, 2015) effects, there has been no evidence to date linking HFTs to market opacity.

To our knowledge this is the first study to document that HFTs make extensive use of HLOs in lit markets. These orders are different in characteristics (e.g., size, aggressiveness), information content (e.g., contribution to price variance), and usage (e.g., liquidity supply, undercutting) than the HLOs of non-HFTs, and do not fit the logic of order exposure modeled in extant theory. These results are robust in that they hold for both consolidated (NSE) and fragmented (US) markets, and for iceberg as well as fully hidden orders, allowing us to rule out market design or the choice between partial versus full non-exposure as explanatory factors.

[6] https://www.sec.gov/news/speech/speech-clayton-2017-11-08

**On the Interconnectedness of Financial Institutions:
Emerging Market Experience**

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1. Introduction

The financial crisis of 2008 highlighted the absence of metrics for measuring, decomposing, managing, and predicting *systemic* risk. Systemic risk is interpreted as a risk that has (a) large impact, (b) is widespread, i.e., affects a large number of entities or institutions, and (c) has a ripple effect that endangers the existence of the financial system. The global financial crisis of 2008 had all these three characteristics. On the other hand, the U.S. market crash of 1987 impacted only a small set of assets (i.e. equities), and did not endanger the financial system. The 1987 crisis was an example of systematic risk, i.e., a common factor driving asset correlations, and was large in effect, unlike the 2008 crisis which adversely affected the wider financial system.

The role of systemic risks in emerging markets has become prominent in the last decade. Starting in 2007, emerging economies accumulated significant external debt as non-financial corporations from emerging markets increased their external borrowing significantly through the offshore issuance of debt securities.[2] Although greater leverage can facilitate higher corporate investment and perhaps stimulate growth, it can also increase corporate vulnerability. Since emerging market credit is dominated by bank loans, high corporate vulnerability can lead to increased systemic risks for banks. Further, if the high leverage through foreign debt is not adequately hedged by emerging market firms in the face of commodity and currency market shocks, and global monetary policy developments (e.g. Quantitative Easing (QE) induced taper-tantrum of year 2013), such shocks can further exacerbate the systemic risks of domestic banks.

2. Research Issue

In this paper, we undertake a large-scale empirical examination of systemic risk among major financial institutions in the emerging markets. There is limited prior research on systemic risks in

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[2] For example, emerging market corporate loans and debt rose from 73% of GDP at the end of 2007 to 107% of GDP by the end of 2014 (Source: Economist, Nov 14, 2015).

emerging markets.[3] We therefore undertake a large-scale empirical examination of systemic risk among major financial institutions in the emerging markets, and evaluate relative systemic risks across firms and over time. We provide comparative analysis and new insights into policies for measuring, managing and regulating systemic risk in the emerging market context.

We model systemic risk by modeling a network among banks in a country (Das, 2016). The network provides the mechanism for transmission of risk, and is the driving force of contagion. The interconnectedness of banks described by a network is augmented with information on the credit quality of banks. Network risk is measured using several network metrics, while credit quality is proxied by probability of default. We combine network and credit information into a single measure of systemic risk for the entire financial system.

3. Data Sample

Our sample of emerging countries is obtained by combining the IMF's and MSCI's lists of emerging countries with the firm-level data from two different sources: (1) stock return, financial and balance sheet data are extracted from Datastream, (2) Probability of default data sourced from the Credit Risk Initiative (CRI), National University of Singapore (NUS). We employ active financial firms trading in a primary exchange in the local market, by matching the industry classification based on Compustat Global Database. We exclude financial subsidiaries of non-financial corporations and specialized investment vehicles such as funds, REITs, and securitized assets. Our final quarterly data sample consists of 1048 firms comprised of 539 Banks, 389 Broker-Dealers and 120 Insurers from 23 emerging market countries for the period 2004-2016. Our sample of 23 countries is clustered into five geographical regions: East Asia (China, Indonesia, Malaysia, Philippines, South Korea, Taiwan, Thailand), South Asia (India), Eastern Europe (Bulgaria, Czech, Hungary, Poland, Russia, Ukraine), Southern Europe and Africa (Egypt, Greece, South Africa, Turkey) and South America (Argentina, Brazil, Chile, Columbia, Mexico). Table 1 below summarizes the sample decomposition across countries and firm types.

[3] For e.g. Sensoya (2017) using Turkish data finds evidence supporting the hypothesis that institutional ownership leads to enhanced systematic liquidity risk by increasing the commonality in liquidity. Borri (2017) estimates the vulnerability of individual countries to systemic risk in the market for local currency government debt.

Table 1: Sample of emerging market firms by each country

Country	Bank	Broker-Dealer	Insurer	Total	Valid PD
Argentina	8	1	0	9	6
Brazil	7	4	6	17	15
Bulgaria	4	5	3	12	9
Chile	8	5	3	16	13
China	26	29	7	62	61
Columbia	8	3	0	11	11
Czech	2	0	0	2	2
Egypt	11	8	2	21	21
Greece	8	3	2	13	12
Hungary	2	3	1	6	5
India	193	191	3	387	356
Indonesia	58	14	14	86	82
Malaysia	15	7	9	31	31
Mexico	9	7	4	20	17
Philippines	28	5	1	34	31
Poland	27	28	5	60	47
Russia	19	2	1	22	16
South Africa	12	12	9	33	32
South Korea	16	24	13	53	52
Taiwan	23	15	12	50	34
Thailand	24	14	17	55	52
Turkey	22	9	6	37	37
Ukraine	9	0	2	11	6
	539	389	120	1,048	948

4. Findings

We provide five key results on the systemic risk evolution in emerging markets.

A) We find that the global financial crisis period of 2007-09 witnessed severe spikes in systemic risks across all emerging markets (Figures 1 and 2). Interestingly, Indian firms were unaffected during the 2002 crisis, but experienced high systemic risks during the Taper-tantrum period of 2013, when the U.S. reversed its QE policy. Financial sector firms from India and Southern Europe and Africa also witnessed high systemic risks following the 2015-16 currency crisis, led by steep commodity price drops and capital outflows. Figure 2, further shows that Indian firms behave differently compared to Asian firms with respect to the evolution of underlying systemic risks.

B) Examining the correlations among systemic risks across different geographic regions, we find that information in systemic risks is quickly transmitted within the same quarter across emerging markets. Interestingly, India is relatively isolated from other country groups as its systemic risks are weakly correlated across other regions. Further univariate analysis shows that lead and lag effects in systemic risks are usually very short-term, at a quarterly level, and long-term effects fade out. Often the highest correlation in systemic risks across markets is contemporaneous, implying that markets co-move with respect to underlying systemic risks. Granger Causality tests show that the systemic risks have strong momentum within each market, while the spillover effects of systemic risks across markets is weak. Vector Auto Regression analysis confirms the earlier evidence that contemporaneous dependence of systemic risk across markets matters far more than lagged effects.

C) We next conduct Principal Component (PC) Analysis of the systemic risks across five regions. The prime PC explains 52% of variance, while the first three PCs explain 92% of variance. This implies that there is a factor structure or a commonality in the systemic risk evolution across emerging markets. Figure 3 below shows that 1st PC correlates highly with the default risk during the financial crisis. The 2nd PC spikes in the post-financial crisis period (associated with Dodd-Frank regulation), reflecting possible policy uncertainty shock; and again during the foreign exchange crisis event of 2015-16. The 3rd PC seems to capture the taper tantrum of 2013 and the 2015-16 foreign exchange crisis, episodes both associated with capital outlows from emerging markets to US. Further analysis shows that the 1st PC is significantly related to the US default factor. The 2nd PC is weakly influenced by the contemporaneous funding (TED) and lagged risk aversion (VIX) factors at 5% level. The 3rd PC is significantly affected by the contemporaneous funding cost (TED) factor.

D) Using time series and panel data regressions, we examine to what extent emerging market systemic risks across geographic regions can be explained by different risks. We find that credit and network risks together explain the majority of the variation in systemic risks i.e. between 88% - 94% of the time-series variation, and 70%-80% across firms and over time. Firm-specific attributes (such as leverage, profitability, loans to assets, loans to deposits, and market to book ratios) add an additional 5% - 20% explanatory power in panel data regressions.

E) Finally, we examine the information content of systemic risk in an out-of- sample setting. For all five geographic regions, we see that lagged changes in systemic risk are highly predictive of aggregate default risk (PD) in the following period. This suggests that our network measure of systemic risk provides explanatory power over and above the measure of credit risk levels in the economy.

5. Discussion

Systemic risk implies quick propagation of illiquidity and insolvency risks, and financial losses across the financial system as a whole, impacting the connections and interactions among financial stakeholders (Billio, et al., 2012). In this project, we undertake a large-scale empirical examination of systemic risk among major financial institutions in the emerging markets. We extend the literature on network models by incorporating credit quality information in order to compute a single systemic risk score that summarizes the level of systemic risk across all emerging market financial entities. We provide computations of the dynamics of systemic risk evolution across emerging markets, and study the cross-sectional and time series determinants of systemic risk. Taken together, our findings show that systemic risks for emerging market financial firms, determined jointly by underlying network and credit risks, are quickly transmitted across markets contemporaneously within the same quarter. This implies that regulators may perhaps have to initiate quick policy actions to manage and stabilize financial markets facing possible systemic risk events. The policy measures should target lowering network and default risks, perhaps through financial easing and short-term liquidity provision measures. Moreover, we find a factor structure among systemic risks across markets, where the first three principal components explain over 90% of the variance, and each factor is sensitive to a different type of systemic risk event. Accordingly, regulators could design specific strategies to control systemic risks based on which type of PC dominates that event. Moreover, our network measure of systemic risk can be used to predict financial sector credit quality changes in emerging markets.

6. Conclusion

Systemic risk captures the conditional failure of the system at large, conditional on the failure of key financial institutions in an economy. Overall, in this project we undertake a large-scale study of systemic risk involving emerging market financial institutions in many countries and provide insights into policies for measuring, managing and regulating systemic risk. Our findings can be useful to academics, regulators, and financial practitioners.

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Figure 1. Systemic risks over time for each geographic region

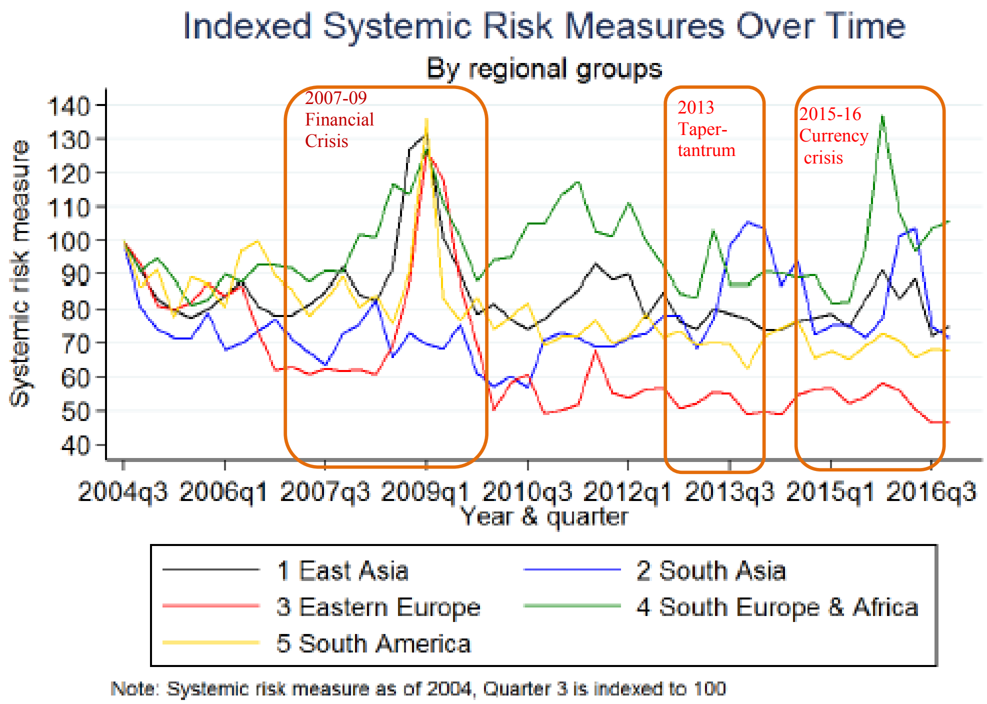


Figure 2. Systemic risks comparing Indian versus rest of Asian firms

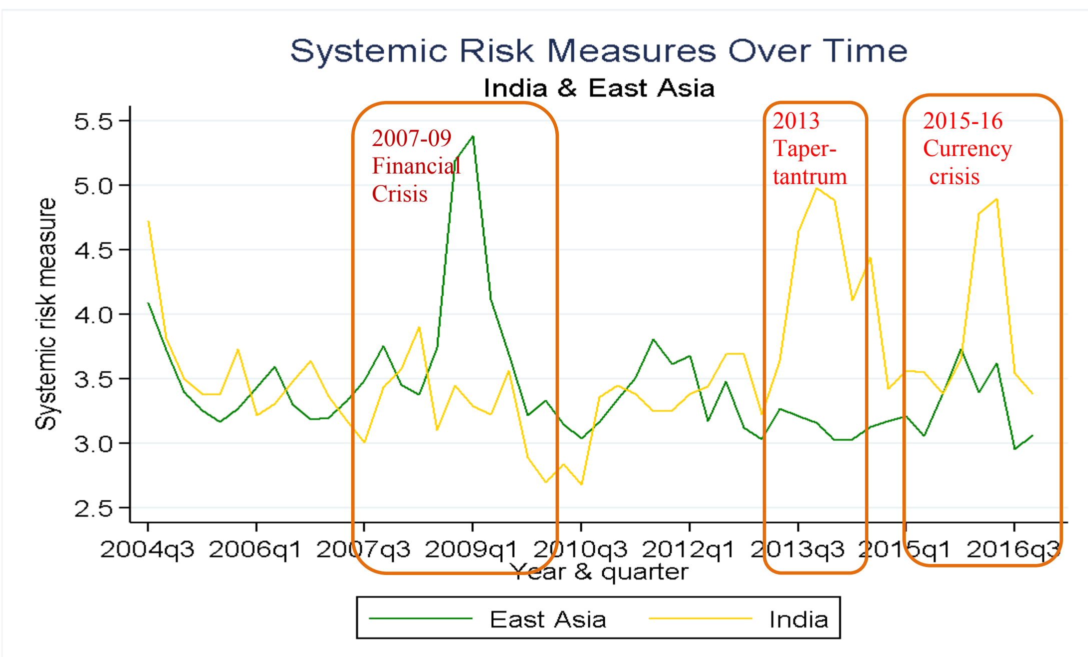
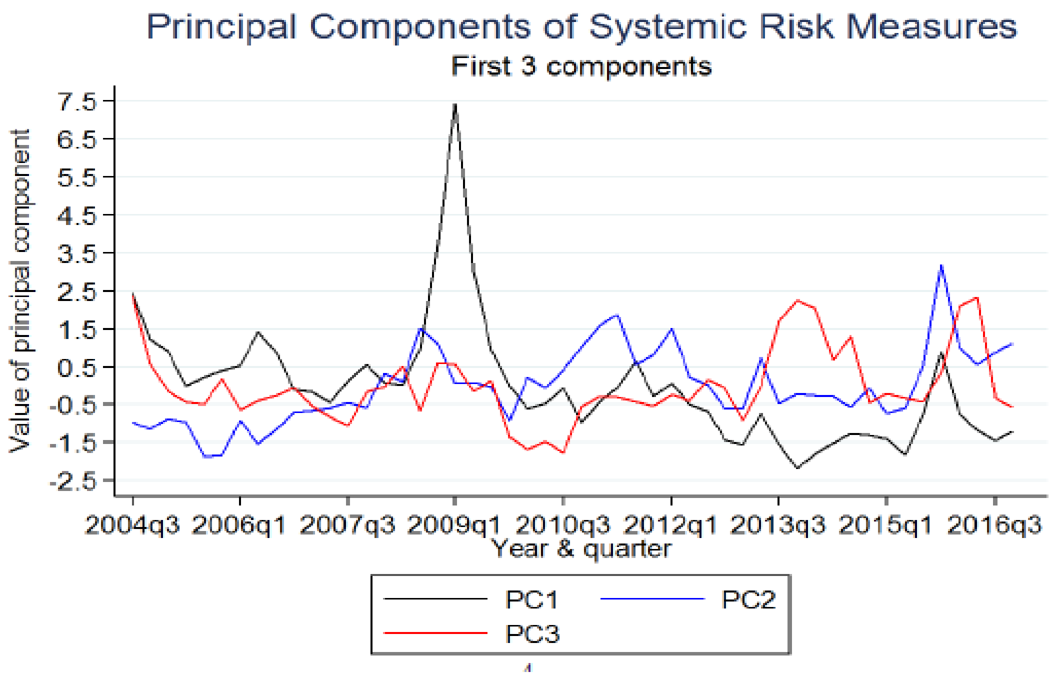


Figure 3. Principal Component (PC) Analysis of Systemic risks across emerging markets



Informativeness of Orders in Electronic Limit Order Book Markets: A Revealed Preference Framework

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1 Introduction

The vast majority of securities are now traded in electronic limit order book markets, particularly equities. Electronic limit order book markets are much more transparent than the dealer or non-electronic-order-matching markets they have replaced, and provide the opportunity to market participants to observe significantly greater information through the trading process. Since information is the primary driver of asset values, and is incorporated into prices through the trading activity of informed traders, it is important to estimate and analyze the relative informativeness of different orders and traders as manifested in the distribution of market and limit orders. In this study we develop an empirical measure of informativeness based on the preferences revealed through the market and limit orders posted by different categories of traders (hereafter the IPRO measure), and utilize the IPRO measure to empirically investigate several important issues and hypotheses of widespread interest to academics, regulators and market participants.

2 Our Informativeness Measure: IPRO

The basic assumption behind our informativeness measure is that a trader should arguably have acted in his best interest based on his information at the time of submitting an order. In this context, if a trader has submitted a limit buy order, then the expected profitability from submitting such order based on his information must dominate that of submitting any other type(s) of order(s) like limit sell, market buy or market sell. If a trader has more information than what is revealed in the current traded price, he would take positions accordingly. Thus if he believes that price is going to go up in a particular interval of time then he would submit a buy order, and if he believes that prices are going to go down then he would submit a sell order. Furthermore, his notional profit from his information in a particular interval may be measured as the difference between the mid quote at the end of the interval relative to the current mid quote. The principle behind the informativeness measure is that higher informativeness should lead to a higher notional profit.

Using this revealed preference of order choice at the time of submitting one's order, we recover the informativeness of the trader based on how his ex-ante information compares to that of the ex-post market value of the stock. The order choice will establish a ranking of different order types (buy/sell, limit/market) conditional on the perceived ex-ante value of the stock for the trader weighted by the probability of his order being executed. The concurrent state of the order book helps us get an estimate of this ex-ante value for each trader.

Our definition of informativesness assumes that if the trader is more informed, then his ex-ante value and the ex-post value of the stock (realized in the future) must be related 'more' to each other, relative to someone who is relatively less informed. Intuitively, based on our informativeness measure, if a more informed trader has a higher ex-ante value, it is more likely that the ex-post value of the stock will be higher. The strength of the relationship between these ex-ante and ex-post values is therefore the basis for our informativeness measure.

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We estimate the strength of the relationship between the ex-ante and ex-post values based on the monotone likelihood ratio property (MLRP) between two random variables. Intuitively, if a trader has relatively higher informativeness, then he should receive a correspondingly higher (lower) ex-ante value signal when the ex-post value is higher (lower) relative to a trader who has lower informativeness. We characterize this notion in terms of the conditional distribution of ex-post values in terms of the ex-ante values. Equivalently, conditional on a higher value drawn from a more informed trader's distribution, the conditional probability distribution of the ex-post value (conditional on the ex ante value) will be more likely. We use the semi-parametric copula-based techniques, as used in the statistics literature, to characterize the relationship between the ex-post and ex-ante values – and hence the informativeness – based on the properties of the Archimedean family of copulas.

3 Data and Sample Description

We use data on the limit order book of the National Stock Exchange of India (NSE) to estimate our measure of informativeness. Our sample consist of all the 50 stocks in Standard & Poor's CNX Nifty index, which represents about 60% of the market capitalization on the NSE and covers 21 sectors of the economy. The sample period is from April 1 through June 30, 2006, covering 56 trading days.

Insert Table1 about here

The dataset provides complete information of trades and orders that enables the reconstruction of the order book to obtain best quotes' and depth information. Further, the data also provides identification codes and classifications of traders for all the orders and trades in the dataset. We aggregate the 14 trader classifications flagged in the dataset into 4 broad categories: Individuals, Financial Institutions, Dealers, and Other Institutions. Table 2 presents descriptions of the four trader categories. More importantly, the dataset also provides identification codes of traders for all the orders and trades in the dataset, thereby enabling us to accurately estimate trader profitability over time and across stocks.

Insert Table2 about here

4 Results

4.1 Trading Profitability and Informativeness Across Trader Categories

Our IPRO measure is estimated for each trader-stock combination, using data sampled at 30-minute intervals and reported in Table 3. As seen from the table, the median trader loses money over this specific sample period as median profitability and relative profitability ratio are both negative. Clearly, there is significant variation in trader profitability and informativeness. Informativeness of all the trader-stock combinations are plotted in Figure 1. Informativeness ranges between -0.12 and 0.19.

Insert Table3 about here

Table 3, Panel A describes the relationship of trader ex-post profitability with ex-ante informativeness. Exchange members appear to be the most informed, followed by financial institutions, other institutions, and, finally, individuals. Moreover, Exchange Members are also the most positively skewed of all trader categories, followed by financial institutions, individuals and other institutions. Interestingly, comparisons of trader profitability ($Total\_PL$ and $Total\_PL\_Ratio$) also yield similar results. Again, exchange members are the most profitable followed by financial institutions.

IPRO distributions of different trader categories are presented in Figure 1, and a formal comparison of IPRO distributions of all trader categories are presented in Table 3, Panel B. We find that IPRO distribution of Individuals continues to be significantly different from those of exchange members and financial institutions, financial institutions and exchange members have statistically similar IPRO distributions.

Insert Figure1 about here

4.2 Portfolio Sorts

In order to validate our measure of informativeness, we examine how it relates to trader profitability. First, we form portfolios based on deciles of Total_PL_Ratio and analyze how informativeness varies across these portfolios. The results of this analysis are presented in Figure2. Results show a clear positive relation between trader profitability and the copula based measure of informativeness - greater trader profitability is associated with higher measures of informativeness. For example, when the average profitability (Total_PL_Ratio) is -1.16%, average informativeness is -0.0027; and when average profitability is 0.82%, average informativeness is 0.0007. Further, the relation between the two is almost monotonic. Also, the relation is similarly strong when measured through mean or median values.

Insert Figure2 about here

4.3 Informativeness and Macroeconomic Shocks

We found an interesting relationship between order choice with that of a major macro economic shock. On May 18th 2006, Indian stock market had the largest ever intra-day drop in their histories so far with Sensex losing 826 points. Analysts speculated that the reason for this drop was that the US CPI number which was released the day before, was much above expectations. This, coupled with the weakness observed in the London Metal Exchange, led to losses in emerging markets like India, Mexico and Brazil. We found that in the event of such a large macro shock, informed traders become even more aggressive in their order choice. Specifically, for one standard deviation change in informativeness, the likelihood of submitting a market order goes up by about 2.2% after the macro event (on top of the 2.8% figure mentioned above). Interestingly, it appears that informed traders could anticipate the shocks earlier as their net positions turned negative prior to the event, while the uninformed traders had a positive net position.

Insert Figure3 about here

4.4 Informativeness and Order Choice

Whether an informed trader uses a limit order or a market order is an important policy question. We find that it is more likely that a trader submits a market order if he is more informed. The effect is also economically significant; a one standard deviation increase in informativeness makes it 2.8% more likely to submit a market order. However we find that the relationship between order choice and informativeness is more nuanced depending on the type of the information event or time of the day. For example, in the first hour of the day the likelihood of submitting a market order by a more informed trader goes up by about 2.9%. However during the post earnings announcement period, the likelihood goes down by about 1.4%.

We next study the role of informativeness on the choice of hidden orders. If a trader is more informed it is likely that he/she may prefer to hide his information behind the veil of hidden orders. We find that the likelihood of submitting a hidden order is positively related to informativeness. A one standard deviation increase in informativeness increases the likelihood of submitting a hidden order by about 3.6%. The choice of hidden order is also nuanced depending on the time of the day or type of information event. During the first hour of trading, for one standard deviation increase in informativeness, the likelihood of submitting a hidden order goes up by 6.6%. During the last hour of trading, for a one standard deviation increase in informativeness, the likelihood of submitting a hidden order goes up by 3%. During a global macro shock, like the event on May 18th, for a one standard deviation increase in informativeness, the likelihood of submitting a hidden order goes up by 3%. While during the post earnings announcements period, for a one standard deviation increase in informativeness, the likelihood of submitting a hidden order goes down by 3.5%.

4.5 Informativeness and Trader Type: Algo vs. Non-Algo

Algorithmic trading was allowed in India since 2008. Our dataset for the period 2012 has a flag based on whether the trader is an algorithmic trader or not, besides trader categories (institutional, exchange members etc.). In table 4, we compare the informativeness of various trader categories (institutional, individual, exchange members).We find that within every category (institutional, individual and exchange members), algorithmic traders are more informed than non-algo traders, on average.

Insert Tables4 about here

4.6 Heterogeneity of Trader Beliefs

One of the by-products of our measure of informativeness is the bound on the ex-ante value perceived by the trader while submitting their order. We use this as a proxy for the ex-ante belief about the value of the stock as perceived by the trader while submitting their order. Heterogenous beliefs and its impact on speculation and trading in the financial market is an important policy question. It is argued in the extant literature that if agents have heterogenous beliefs about an asset's fundamental value, and short sales are not allowed, equilibrium prices would reflect the opinion of the more optimistic investor.

We use the inter-quintile range of the ex-ante values $\{(75thQuintile - 25thQuintile)/75thQuintile\}$ computed for every 30-minute interval as a measure of heterogeneity of beliefs. This is plotted in figure 4. One interesting point to note from this graph is that the heterogeneity of beliefs goes up significantly around the global macro event period (in the middle region of the graph). In Panel A of figure 4, we plot the intra-day pattern of this heterogeneity. The graph has an interesting U-shaped pattern, signifying higher heterogeneity of beliefs toward the opening and close of the day.

Insert Figure4 about here

We also investigate the link between profits of momentum strategies and the heterogeneity of beliefs of traders. In particular, we do "Fama-Macbeth" predictive cross-sectional regressions, the dependent variable being the mid-quote based return over a thirty-minute interval, and the independent variable being the inter-quintile based measure of trader heterogeneity of beliefs. The coefficient of trader heterogeneity of beliefs is positive and statistically significant, suggesting that greater trader heterogeneity of beliefs is associated with significantly greater momentum profits.

5 Conclusion

In this paper, we have proposed a new measure of ex-ante informativeness of a trader based on his order submission behavior. Using the revealed preference of order choice of a trader at the time of submitting the order, we recover the informativeness of the trader based on how his ex-ante information compares to that of the ex-post market value of the stock. We apply our measure to the limit order book from the National Stock Exchange (NSE) of India. Our measure performs significantly better out of sample than extant measures of informativeness.

We document several interesting results. We find that informed traders can better anticipate macroeconomic shocks. We find a strong relationship between the informativeness of a trader and the order choice made by that trader. For example, it is more likely that a trader submits a market order if he is more informed; and the likelihood of submitting a hidden order is positively related to informativeness. We also find that within every category (institutional, individual and exchange members), algorithmic traders are more informed than non-algorithmic traders, on average. Finally, we use heterogeneity of beliefs as a by-product of our measure and test various hypothesis related to momentum profits and heterogeneity of beliefs.

Figure 1: IPRO across Trader Categories

This figure presents the distribution of trader informativeness across different trader categories (defined in Table 2). *IPRO* is the copula-based measure of informativeness estimated for each trader-stock combination using data on the 50 stocks that make up the Standard & Poor's CNS Nifty index at the National Stock Exchange (NSE), India, during our sample period, April to June, 2006.

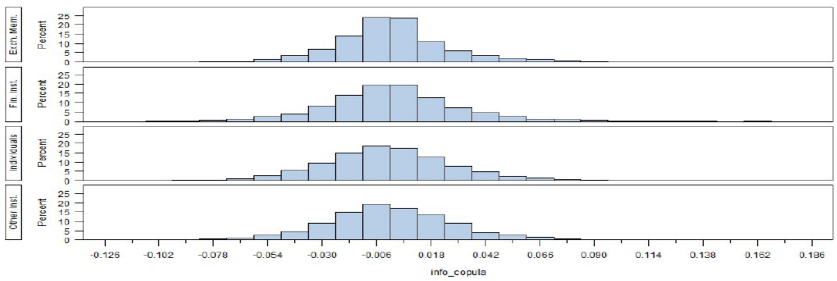


Figure 2:

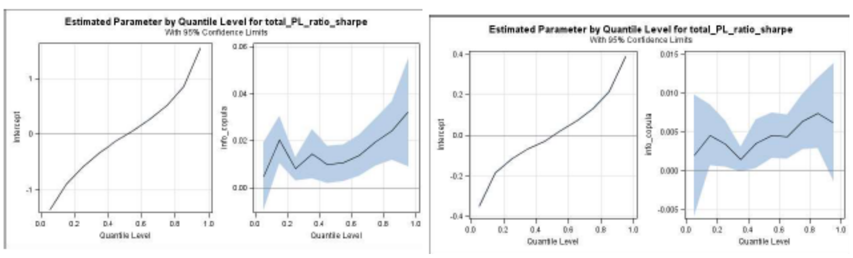


Figure 3:

This figure compares the cumulative trading volume of informed and uninformed traders around the Forex event. The analysis is conducted using data on the 50 stocks that make up the Standard & Poor's CNS Nifty index at the National Stock Exchange (NSE), India, during the entire sample period, April to June, 2006. *IPRO* is the copula-based measure of informativeness calculated for each trader-stock combination. Traders in the top quartile of IPRO are identified as informed and those in the bottom quartile are identified as the uninformed.

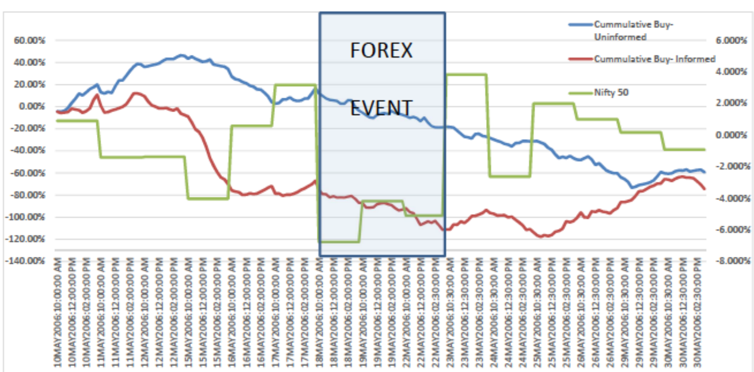
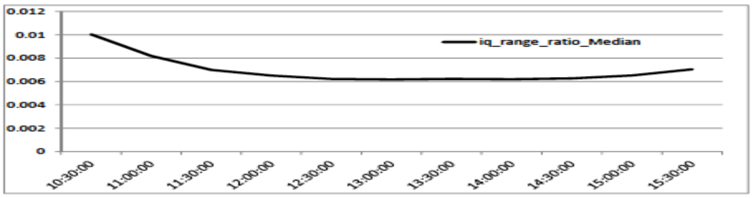


Figure 4: Informativeness and Heterogeneity of Beliefs

Panel A: Intraday Variation



Panel B: Variation over the Sample Period

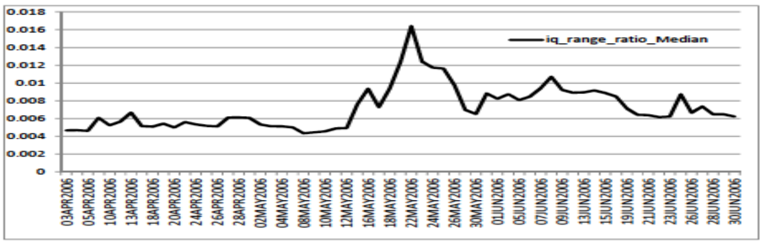


Table 1: Sample Descriptive Statistics

This table presents descriptive statistics of characteristics of 50 stocks that make up the Standard & Poor's CNS Nifty index at the National Stock Exchange (NSE), India, during our sample period, April to June, 2006. *Panel A* presents descriptive statistics of stock characteristics. *Number of Trades* is the average number of trades in a stock in the sample; it is first calculated over 30 minute intervals for each stock and then averaged across the 50 stocks in the sample. *Volume of Trades*, *Number of Orders* and *Volume of Orders* are calculated analogously. *Buy Depth* and *Sell Depth* are the total volume of the ten most aggressive limit orders on the buy side and sell side of the book respectively. *BidAsk Spread* (estimated from the order book, expressed as a ratio of the mid-quote), *Return* (total stock return) and *Volatility* (standard deviation of *Return*) are first calculated over 30 minute intervals for each stock and then averaged across the 50 stocks in the sample.

	Mean	Median	Std. Dev.
Market Capitalization (USD Billions)	7	4	3
Number of Trades	1303	910	1165
Volume of Trades	121343	48294	174902
Number of Orders	1678	1150	1450
Volume of Orders	469357	207827	608518
Bid-Ask Spread	0.03%	0.02%	0.03%
Volatility	0.43%	0.42%	0.07%
Return	-0.02%	-0.02%	0.02%

Table 2 –Trader Categories

This table describes the different trader categories identified in the data. Their share of total limit order volume submitted in the sample, and the proportions of their limit order volume that are cancelled, modified and revised (cancelled or modified) are also presented. The proprietary data from the NSE identifies 14 different trader clienteles, which are further classified into 4 broader categories: Individuals, Financial Institutions, Dealers and Other Institutions.

Trader Category	Description	Number of Traders	Percentage of Total Limit Order Volume Submitted
Individuals	Individual Non-Residential Indians HUF (Families)	1,070,125	32.18%
Financial Institutions	Mutual Fund Bank Insurance Other Domestic Financial Institutions Foreign Financial Institutions	5,771	16.45%
Exchange Members	Dealers	509	40.68%
Others Institutions	Public and Private companies Partnership Firms Trusts and Societies Other Corporate Bodies Statutory Bodies	153,894	10.69%

Table 3:

This table presents descriptive statistics of trader profitability, trader profitability ratio, and trader informativeness estimated using data on the 50 stocks that make up the Standard & Poor's CNS Nifty index at the National Stock Exchange (NSE), India, during our sample period, April to June, 2006. *Total_PL* is the average hourly profit/loss (sum of change in market value of inventory and profit/loss from round-trip transactions during the one-hour interval) estimated for each trader-stock combination. *Total_PL_Ratio* is the average of the ratio of hourly profit/loss and the capital) employed (absolute value of inventory by the trader in the stock during the one-hour interval. *IPRO* is the copula-based measure of informativeness calculated for each trader-stock combination. Panel A presents overall descriptive statistics for the three measures over the entire sample; Panel B presents the descriptive statistics for the three measures across different trader categories defined in Table 2; and Panel C presents pairwise two-sided comparison of informativeness across different trader categories, along with Wilcoxon and DSCF test values.

Panel A: Overall

	Total_PL	*Total_PL_Ratio*	*IPRO*
Minimum	-42,381,387	-13.03%	-0.121
P5	-73,144	-0.77%	-0.046
Mean	81	-0.07%	-0.001
Std. Deviation	3,281	0.00%	0.000
Median	-588	-0.02%	-0.002
P95	72,291	0.49%	0.048
Maximum	75,614,331	12.56%	0.185

Panel B: Trader Profitability and Informativeness across Trader Categories

	Total_PL				*Total_PL_Ratio*				*IPRO*			
Trader Category	Median	Skewness	Mean	t-value	Median	Skewness	Mean	t-value	Median	Skewness	Mean	t-value
Exch. Mem.	2403.25	0.08	30994.13	0.84	0.01	1.48	0.02	1.32	-0.02	0.62	0.12	2.97
Fin. Inst.	-10.55	21.54	31352.41	0.87	0.00	1.87	0.02	0.89	-0.01	0.45	0.08	1.50
Individuals	-655.35	1.12	-3764.49	-5.45	-0.03	-2.65	-0.08	-27.93	-0.18	0.29	-0.09	-6.94
Other Inst.	-700.75	-31.37	-11156.01	-3.93	-0.05	-3.35	-0.14	-11.43	-0.10	0.19	0.00	-0.09

Table 4: Informativeness and Algorithmic Traders

This table presents descriptive statistics of trader informativeness estimated using data on the 50 stocks that make up the Standard & Poor's CNS Nifty index at the National Stock Exchange (NSE), India, during our sample period, May, 2012. *IPRO* is the copula-based measure of informativeness calculated for each trader category-stock combination.

Trader Type	Median	Mean	t-Value
Institutional Algo	0.34	0.19	1.34
Institutional Non-Algo	-0.17	-0.03	-0.16
Exchange Members Algo	-0.10	0.01	0.13
Exchange Members Non-Algo	-0.16	-0.09	-0.85
Individual Algo	-0.03	0.08	0.78
Individual Non-Algo	-0.20	-0.16	-1.14

Does Judicial Efficiency affect Corporate Investment?

Nishant Vats[1]

1. Introduction

In this paper, I study the role played by de facto enforcement of the law in India, an environment where enforcement issues are first order. As background, I note that India, like many countries, is attempting to rewrite bankruptcy law because enforcement is regarded as weak and essential. India's bankruptcy law has been amended about every decade in an effort to obtain time-bound enforcement. These efforts have met with little success, and even legally prescribed timelines for resolution are not met. The culmination of these efforts is India's 2016 bankruptcy law that essentially sidesteps the current legal system to create a parallel process.

Judicial inefficiency can significantly impede corporate investment. Honouring of a contractual obligation is conditional on the efficiency of the state to enforce the contract. Slow courts reduce the incentives for the counter-party and lower the punishment value. I provide an empirical analysis of the effects of the divergence of de facto implementation from the de jure law as they relate to firms' investment policies. Specifically, I identify the asymmetric impact of judicial delays on corporate investment.

2. Study

Using state-level data on civil cases under consideration by local courts, I construct a new measure of court enforcement. My measure is relatively straightforward: it is the ratio of cases pending at the start of the year to the cases cleared during the year. I call this measure as duration. It is a forward-looking measure, indicating the number of years courts will take to clear their backlog if they continue operating at the same efficiency. Figure 1 shows the average value of duration (in years) between 2002 and 2015.

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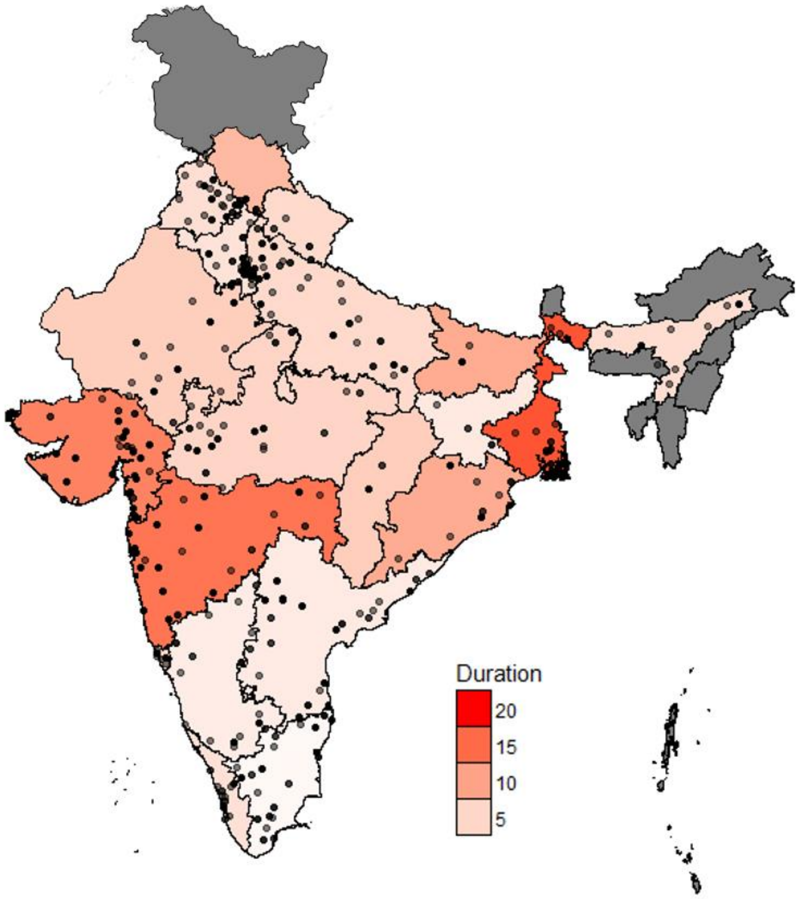

Figure 1: Average Value of duration (in years). The color of Indian states indicate the average value of duration in the states between 2002 and 2015. The black dots denote the location of firm headquarters. The map has been developed using open source software and used only for presentation purposes. The actual geographical boundaries are not confirmed.

Combining the state-wise measure of judicial enforcement with the data on firm-level outcomes, I show that firms that experience financial constraints cut back investment less when the judicial efficiency is high. I use Kaplan-Zingales Index (henceforth, KZ Index) as a measure of financial constraint for each firm-year. I define a firm to be financially constrained if the value of KZ Index for the firm is above the median value of KZ Index of the industry-year to which the firm belongs, else I code the firm-year as financially unconstrained. I define a region to have a high degree of judicial inefficiency if the value of duration in the state is higher than the median value of duration in that year. The firms are thus classified as either financially constrained or not, and further based on location if they are located in judicial efficient or inefficient regions.

Table 1 compares the key financial metrics of firms in the two-by-two set up described above. Panel A describes the metrics for financially constrained firms, and panel B illustrates the same for unconstrained firms. Prima-facie evidence suggests that financially constrained firms located in judicially inefficient regions have lower investment level as against financially constrained firms in areas with high judicial efficiency. However, the difference in investment for unconstrained firms located in efficient and inefficient regions is relatively small. Financially constrained firms in regions with high judicial inefficiency have marginally smaller size as against their peers in judicially efficient regions, with similar levels of profitability (RoA), firm age (LN(Age)), sales growth and Tobin's Q.

Table 1: Comparison of Key Metrics

This table reports the summary statistics (number of observations, median and mean) for the variables in the analysis. The sample period is 2002 to 2015, comprising of all listed manufacturing firms. Panel A compares the key variables for financially constrained firms located in regions with and low judicial inefficiency. Panel B compares similar statistics for financially unconstrained firms.

Panel A: Financially Constrained Firms						
	High Judicial Inefficiency			Low Judicial Inefficiency		
	# Obs	Median	Mean	# Obs	Median	Mean
LN (1+CapEx)	5,602	2.621	2.863	3,331	3.082	3.159
LN(Assets)	5,614	7.018	7.109	3,331	7.285	7.290
LN(Age)	5,614	3.219	3.277	3,331	3.219	3.239
Debt Ratio	5,614	0.619	0.789	3,331	0.654	0.839
ICR	5,361	1.745	8.924	3,178	1.606	8.149
RoA	5,614	0.095	0.093	3,331	0.096	0.094
Asset Tangibility	5,614	0.628	0.716	3,331	0.681	0.747
Sales Growth	5,614	0.089	0.038	3,331	0.084	0.042
Tobin's Q	5,459	0.705	0.909	3,239	0.724	0.895
Panel B: Financially Unconstrained Firms						
	High Judicial Inefficiency			Low Judicial Inefficiency		
	# Obs	Median	Mean	# Obs	Median	Mean
LN (1+CapEx)	6,391	4.153	3.994	3,182	4.146	3.976
LN(Assets)	6,400	7.677	7.742	3,186	7.539	7.577
LN(Age)	6,400	3.296	3.377	3,186	3.258	3.292
Debt Ratio	6,399	0.315	0.317	3,186	0.352	0.350
ICR	6,064	5.448	64.135	2,983	4.685	46.296
RoA	6,400	0.134	0.146	3,186	0.133	0.140
Asset Tangibility	6,400	0.453	0.506	3,186	0.559	0.604
Sales Growth	6,400	0.120	0.109	3,186	0.110	0.103
Tobin's Q	6,337	0.754	1.213	3,149	0.736	1.054

Figure 2 shows the relationship between judicial efficiency and corporate investment for two set of firms. The figure shows that financially constrained firms have lower investment level as against financially unconstrained firms. The curve for capital expenditure against duration for financially unconstrained firms (blue circles) is relatively flat, whereas the curve for financially constrained firms (red triangles) in downward sloping. On a conservative end, I find, the investment growth rate of financially constrained firms to be 18% lower in areas with low judicial efficiency.

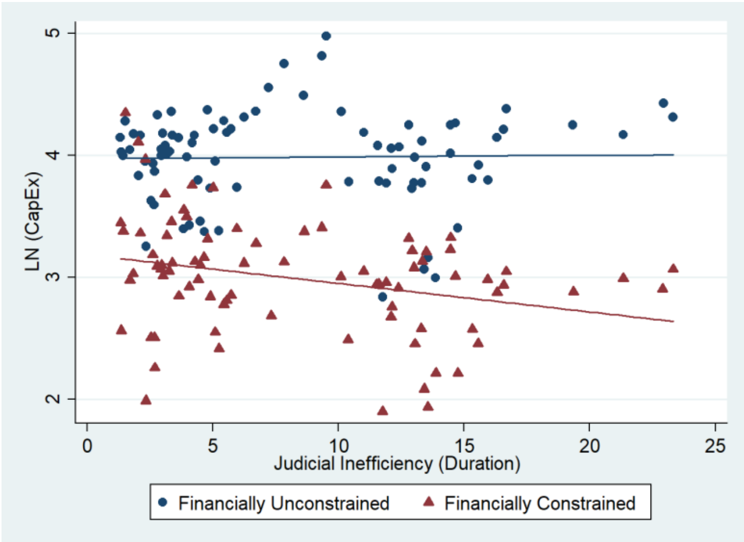

Figure 2: Capital Expenditure, Judicial Efficiency and Financing Constraint

Next, I restrict my sample to the crisis period (2008-2010) and use single banking relationships with the foreign and private bank to assess firm financing constraints further. The foreign and private banks suffered an exogenous supply shock during the Global Financial Crisis (GFC) as there was a flight to safety from foreign and private banks to state-owned banks. Firms in a single-banking relationship with these banks faced a supply shock. Consistent with the preliminary hypothesis, I show that firms in a single-banking relationship with a foreign (private) bank experienced a 34% (25%) decline in capital expenditure growth in judicially inefficient regions.

Third, I employ the long-term persistence of the institutional differences between districts under direct and indirect British rule. The long-term effects of divergence between direct and indirect British rule originate from the fact that the rulers of native princely states with indirect British rule were under constant threat of being annexed in a case of misrule. This left a sword hanging on the neck of native rulers to provide better governance and institutions. Secondly, the native states had between four to five rulers during 1858-1947, whereas 24 Governor-Generals governed the states under direct British rule during the same period. The longer tenure of native rulers resulted in them having higher incentives in engaging in long-term investment. I show that financially constrained firms located in districts under direct British rule had 19% lower investment levels as compared to financially constrained firms in districts ruled by native rulers during the colonial period.

In 2006 a massive Information, Communication, and Technology (ICT) investment was announced. The technology adoption, due to the ICT investment, raised the expected future efficiency of courts. Taking data three years before and after the ICT adoption, I find results consistent with the baseline model. The results indicate a 24% increase in investment by financially constrained firms after the announcement. Figure 3 shows the impact of 2006 ICT adoption on the corporate investment by financially constrained firms. Furthermore, these results appear to be concentrated in regions with low judicial efficiency.

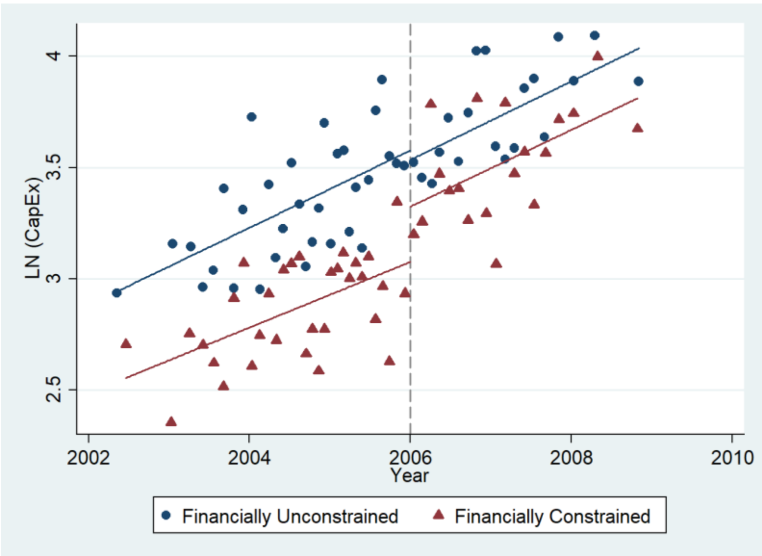

Figure 3: Capital Expenditure, Financing Constraint and Improvement in Judiciary

3. Policy Take-away

I contribute to the ongoing debate on the importance of ease of doing business in India. India has recently embarked on ease of doing business at the state-level, akin to the World Bank Doing Business indicators. Based on a 98-point action plan, simplifying regulatory burdens on business is a key component. A critical ingredient of the process is enforcing contracts (Area 8). This work informs policy makers on the importance of Area 8 and its differential impact on specific firm-types. Finally, I show that an efficient judiciary is a necessary condition for the successful implementation of new reforms and hence inform policymakers about the sequencing of crucial economic reforms.

Does Piggybacking on Insider Trades Benefit Brokers?

Aditi Khatri[1]

1. Introduction

Firm insiders typically have information about the firm and hence are able to trade profitably in their own firm's stocks in the secondary equity markets. The knowledge about the timing of an insider trade and imitation of that trade prior to when this information is made public can result in gains. The brokers executing trades of the firm's insiders are privy to this information and may utilize it to their advantage by tipping their other (non-insider) clients about the insider's trades.

Prior research pertaining to the U.S. markets has demonstrated that insider's brokers exhibit abnormal trading activity concurrently with insider trades. The level of tipping is gauged by the volume of trades executed by insider's broker for other clients in insider's firm's stock, in the same direction as that of the insider's trades. We study the tipping activity of brokers around the insider trades executed on Bombay Stock Exchange over three years- 2009 through 2011.

By providing profitable tips to the clients, the brokers benefit because of increased trading activity through these clients during insider trading period. But, do the brokers benefit in long term? Insider trades result in price impact on the firm's stock. We observe that firm insiders in the Indian capital markets on average trade over a window of few days. Thus, tipping may further move the prices and place the insider at a disadvantage. The insider would hence, dissociate with the broker.

Further, we observe that not all brokers demonstrate abnormal trading activity around insider trades. Hence, we analyse if there is a market disciplining mechanism that impacts the overall market share of the brokers of firm insiders depending on their propensity to tip.

2. Abnormal trading activity around insider trades

We look at how concentrated the insider firm's stock trades are within the brokers on BSE around insider trade days. The Herfindahl-Hirschman Index based on price and transaction volume reveals that the trading of insider firm stocks becomes more concentrated through

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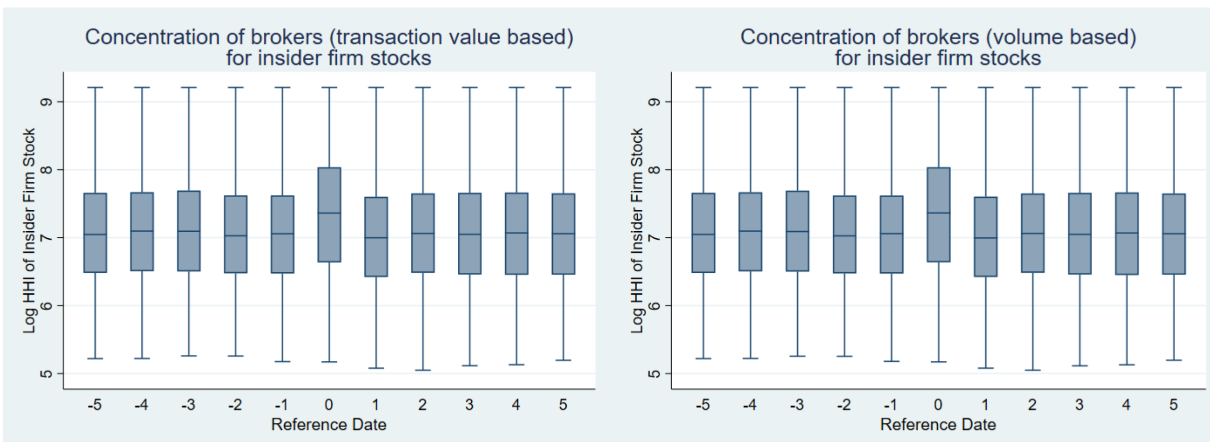
[1] Khatri is at Indian School of Business (email: aditikhatri92@gmail.com). This White Paper is adapted from Khatri, A (2018) "Does Piggybacking on Insider Trades Benefit Brokers?", NSE-NYU Stern Initiative Working Paper.

certain brokers when insiders trade. Fig 1 depicts the Herfindahl-Hirschman Index levels around insider trade days. On the insider trade date, the trades in the insider's firm's stocks become more concentrated through certain brokers. The increase in concentration is not only observed in terms of volume of stocks traded but also the transaction value of trades. The concentration levels subsequently return to pre-insider trade levels. This indicates certain brokers trade more aggressively in the insider firm stock.

Figure 1: Broker concentration for insider firm stocks

Reference Date 0 is the day of insider trading. The vertical axis plots logarithm of Herfindahl-Hirschman index evaluated based on the total daily transaction value and total daily trading volume. The horizontal axis plots the window around insider trade date.

Panel A: HHI based on Transaction Value — Panel B: HHI based on Trading Volume

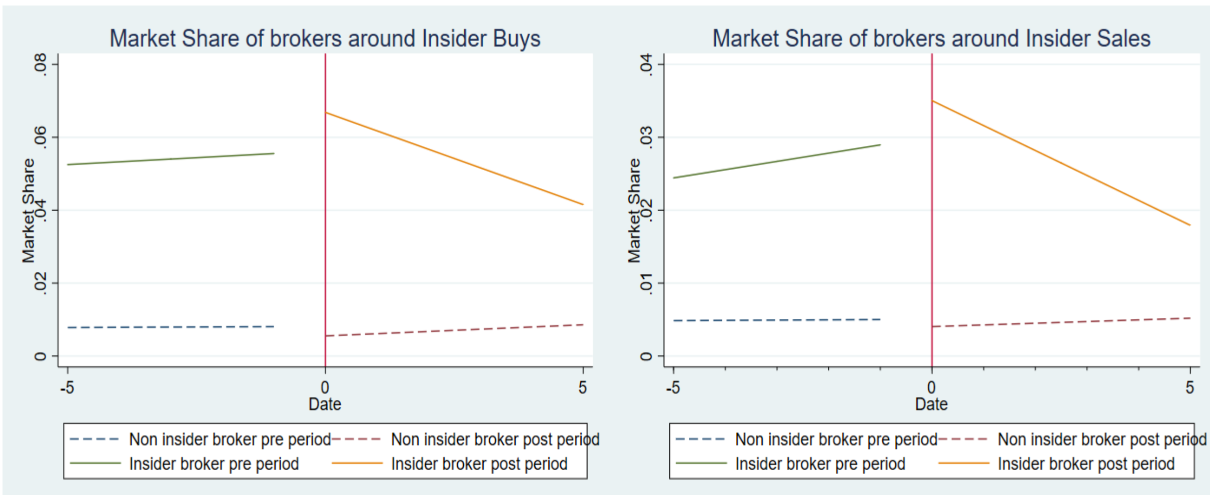


Next, we analyse the trading in insider's firm's stock through all the brokers on Bombay Stock Exchange. Fig. 2 plots the market share of insider and non-insider brokers around insider trade days. Market share of a broker is defined as her total daily volume traded (excluding volume of insider trades) in a stock as a percentage of the total volume of the stock traded on BSE (excluding volume of insider trades). It reveals that the insiders generally trade with larger brokers, which is evident from the market share of insider's brokers which is consistently higher than that of non-insider brokers. Furthermore, for insider purchases, there is 30% increase in the market share of the insider broker on insider trade day as compared to their market share one day earlier. A 27% increase is observed in the market share of insider brokers on insider sale days as compared to that on a day earlier. Whereas, the market share of non-insider brokers within insider firm stocks doesn't change much around insider trade days for both-purchases and sales.

Figure 2: Market share of brokers on BSE

Date 0 is the day of insider trade. The vertical axis plots directional market share of brokers within insider firm stock. Market share is evaluated as the fraction of volume of insider firm stock traded via a particular broker (excluding insider trades) and total volume of the stock traded on BSE (excluding volume of insider trades). The horizontal axis plots the window around insider trade date.

Panel A: Insider Buys | Panel B: Insider Sales



Thereafter, we focus on the trades through insider brokers in the stocks of insider's own firm. In order to identify insiders' trades and brokers, we utilize proprietary equity trade book data from BSE. The insiders report their trades in own firm's stocks to the exchange within 2 trading days. We use these publically available filings to identify insider trades (including their accounts and brokers) within the trade book.

Fig 3 plots the abnormal market share of insider broker in insider's own firm's stock over a 5 day window around insider trading days. Abnormal market share is the difference between market share on a day and historic market share. The historic values are evaluated over a period of 40 days, 20 days prior to insider trade day. Average abnormal market share of 0.04 and 0.03 is observed during insider purchases and sales respectively. This abnormal increase in the directional trading through the insider broker accompanying insider trades alludes to tipping.

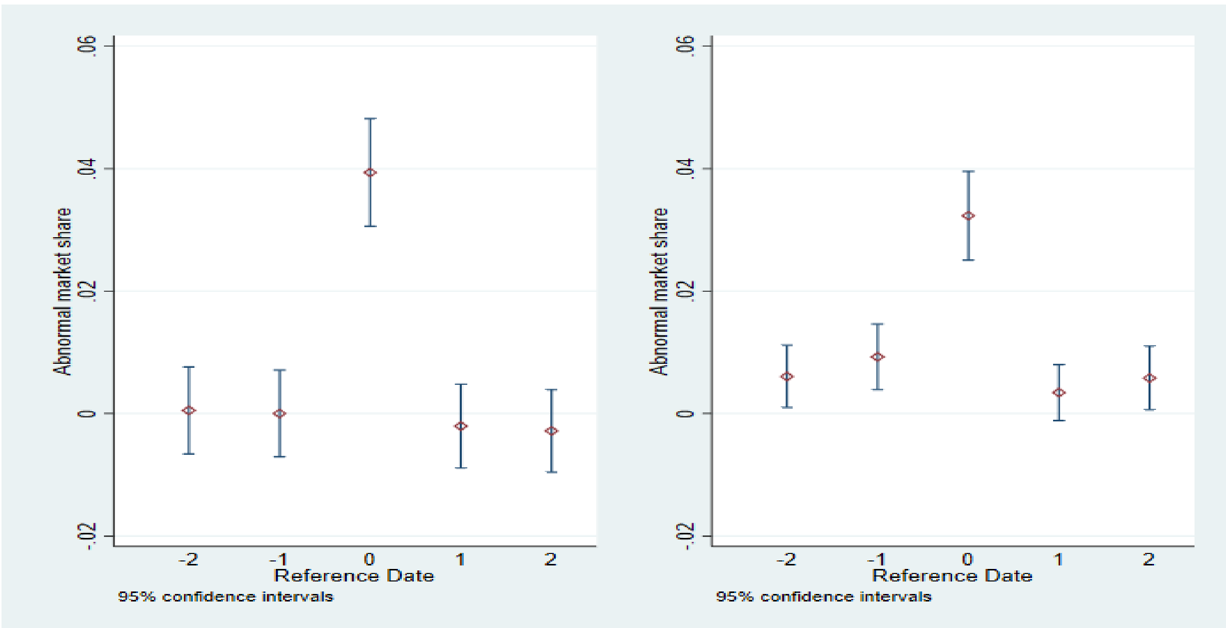
3. Effect of tipping on future trades through insider brokers

We next explore the impact of tipping on the future trades by insiders through their brokers. The average number of consecutive days over which insiders trade in their own firm's stock is 2 days. Therefore, any immediate information leakage would affect their returns on the

Figure 3: Abnormal market share of Insiders' Brokers

Reference Date 0 is the day of insider trade. The circle shows the average abnormal market share of insider broker. The line shows the error bounds (95% confidence interval) around the average. Abnormal market share is evaluated as average market share of insider broker during the day minus historic market share evaluated over a period of 40 days, 20 days prior to the insider trade day.

Panel A: Insider Buys   Panel B: Insider Sales



trades. Hence, firm insiders should reduce trading with brokers who leak information to non-insider clients about their trades.

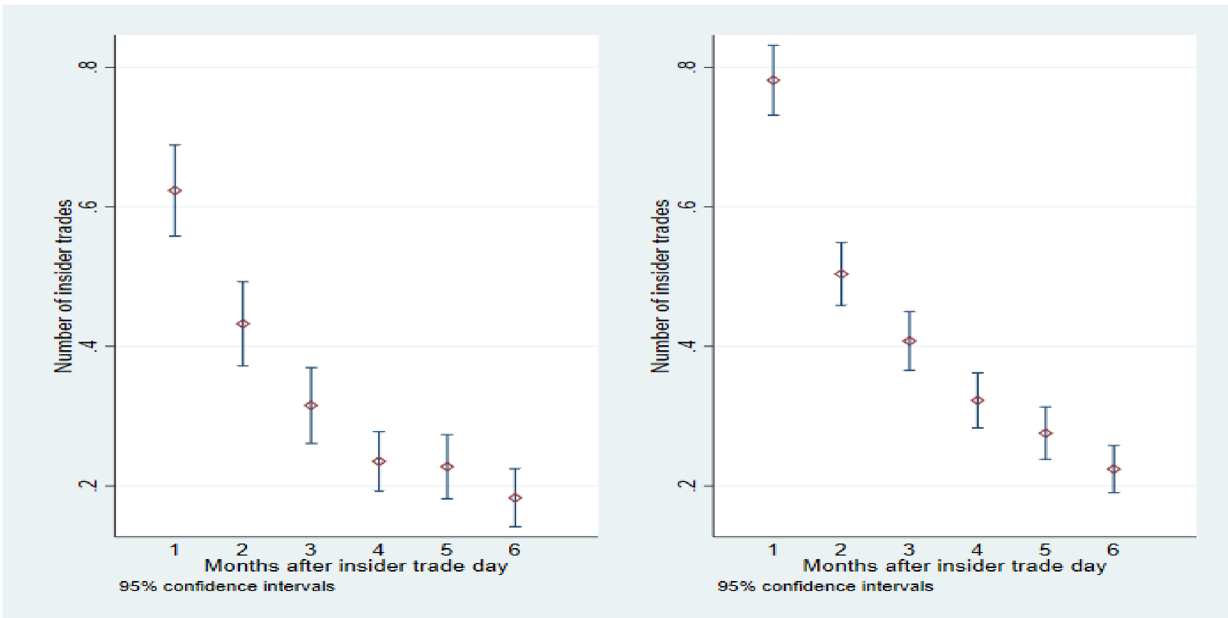
In Fig 4 we plot the number of trades in each month by an insider through a broker over the next 6 months after an insider trades through the broker. We study this separately for insider trades that were accompanied by a tip and those that were not. We consider that the insider trade was accompanied by a tip if the abnormal market share of the insider broker is positive on that day. We observe for insider purchases that are accompanied by tips, the number of trades by the same insider through the broker, are significantly lower over the subsequent 4 months. Whereas, for insider sales, there isn't much difference.

We observe that not all insider brokers tip their non-insider clients about the insider trades. Among the 3558 insider trading events studied, in 1751 instances the insider broker does not undertake any trade in insider's firm's stock apart from that of the insider's on the day of the insider trade day. If tipping is indeed profitable and the law enforcement is poor, then most brokers should have engaged in tipping. The reduction in future insider trades post tipping could be a deterrent as these are essentially the source of information for the broker.

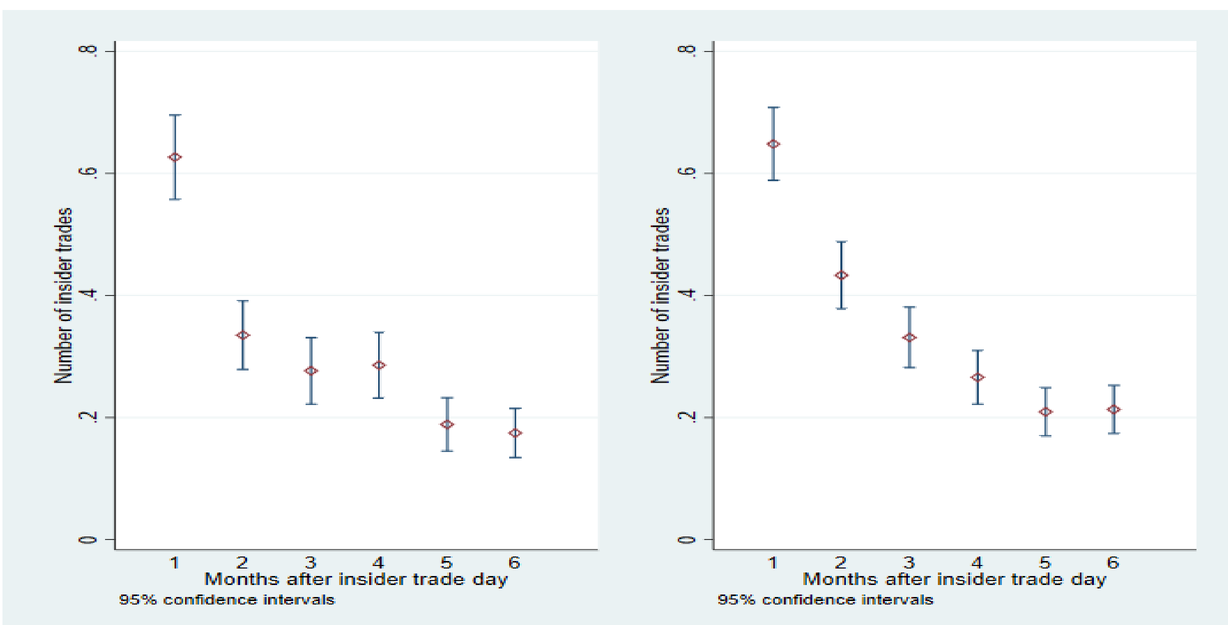
Figure 4: Future Insider Trades

Vertical axis has the number of trades by an insider through a broker in the subsequent months, following a trade in their own firm. The horizontal axis shows number of months. The circle shows the average number of trades by the insider through a particular broker. The line shows the error bounds (95% confidence interval) around the average.

Panel A: Insider Buys accompanied by tip | Panel B: Insider Buys without tip



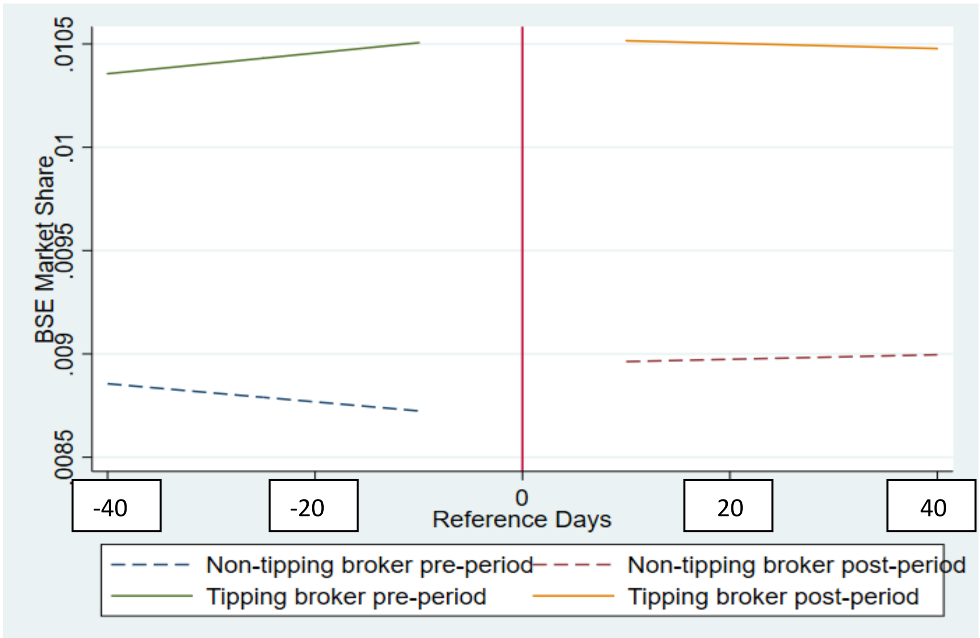
Panel A: Insider Sales accompanied by tip | Panel B: Insider Sales without tip



But, is there an incentive to tip? To analyze this, we look at the change in overall market share of an insider broker on BSE around insider trades. Fig 5 plots, the overall market share of the insider broker on BSE over a period of 4 months around insider purchases. The market share of non-tipping brokers increases by 1.7 basis points over the next two months following an insider trade as compared to their market share during the previous two months. Whereas, the market share of tipping insider brokers doesn't change.

Figure 5: Tipping and market share of insider brokers on BSE

Reference Days 0 is the insider purchase date. The vertical axis has overall market share of insider broker on BSE. The pre-period start 45 trading days prior to the insider purchase date and ends 5 days before it. The post-period start 5 trading days after insider trade day and ends 45 days after it.



4. Conclusion

This study establishes that-

i) The directional trading in insider's firm's stock abnormally increases following the insider trade through the broker with whom the insider trades. The increased activity is due to the non-insider clients of the broker. This indicates that the non-insider clients could have been tipped by the insider's broker.

ii) Firm insiders reduce future trading over the next 4 months with brokers who tip as compared to brokers who do not tip.

iii) Market share of insider brokers engaged in tipping reduces over the next few weeks following the insider trade.