Price Manipulation and "Phantom" Markets

An In-depth Exploration of a Stock Market*

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Abstract

We analyze a unique data set containing *all* daily firm-level trades of *every* broker trading on the stock exchange in Pakistan over a 32 month period. Examining broker behavior reveals that many brokers choose stocks in which they *only* trade for themselves rather than act as intermediaries for outside investors. We find that when brokers trade on their own behalf in a stock - act as "principals"- they earn 4% to 8% higher annual rates of return. While broker "ability" does not explain this effect, anecdotes suggest it is due to direct price manipulation by brokers. We find strong evidence for such manipulation: When prices are low, colluding brokers trade amongst themselves to artificially raise prices and attract naive positive-feedback traders. Once prices have risen, the former exit leaving the latter to suffer the ensuing price fall. Such manipulation of stock prices occurs in *all* types of stocks. However, the effect is *larger* in stocks of *smaller* firms, and of firms with *less* concentrated ownership. Finally, while the higher profitability of principals is not due to inherent broker attributes, we do find that *more* "able" brokers earn *higher* returns when they trade as a principal in a stock. These manipulating rents have important political economy consequences: Principal brokers stand to loose enough so as to stall reform efforts that may otherwise be beneficial for the market.

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1 Introduction

Most emerging economies have relatively young and weak market-based financial institutions such as stock markets. The influential view is that in the presence of weak regulatory and contractual enforcement small investors are deterred from investing in the stock market. There are a couple of reasons suggested for this: First, poor corporate governance of firms leads to tunneling and revenue hiding. Second, outside investors stay out of the market for fear of being exploited by unscrupulous stock price manipulators and insider traders. While attention has been paid in the recent empirical literature to corporate governance[1] as a potential obstacle, there is little work that looks at the existence or consequences of price manipulation.

This paper addresses this gap by analyzing a unique data set containing *all daily* trades of *each* broker in *every* stock trading on the Karachi Stock Exchange (KSE) - the main stock exchange in Pakistan. The high level of disaggregation in the data not only allows us to examine broker behavior in great detail and relate such behavior to profitability, but also identify mechanisms through which brokers may be systematically beating the market. We provide compelling evidence that price manipulation is one such mechanism. In fact, we are able to isolate a *particular* price manipulation mechanism through which brokers cheat the naive outside investor: When prices are low, colluding brokers trade amongst themselves to artificially raise prices and attract naive positive-feedback traders. Once prices have risen, the former exit leaving the latter to suffer the ensuing price fall.

Anecdotal evidence suggests that such manipulation in stocks is carried out by brokers who primarily trade for themselves in these stocks. We find that such behavior is quite pervasive among brokers in our data set: There are a surprisingly large number of brokers who appear to only trade for themselves and, while such a broker does not do so in all the stocks he trades in, almost all stocks do have such "principal" brokers. Our main finding is that these principal brokers who trade primarily on their own or for a few investors in a given stock, earn significantly higher returns than those who act as intermediaries in that stock.[2] The difference in returns is both statistically and economically highly significant: The annualized return on trades done by principal brokers in a stock is 4% to 8 % higher. We interpret this as the difference in profits between brokers who trade directly for themselves in a stock, and the outside investing public that trades through

[1] For example, Bertrand et al [2002]; Fisman [2001]; Boone et al. [2000]; La Porta et al [2000]

[2] While we do not know the number of investors a broker is trading for, we propose a strategy (section 2) that allows us to effectively make the distinction between principal and intermediary brokers.

brokers acting as intermediaries in that stock. The result does not depend on inherent broker attributes. We also test the robustness of this result to different specifications and measures of the "principalness" of a broker and find that the effect remains significant and large.

The difference in profitability begs the question: What do principal brokers know or do that the outside traders are unable to? A closer look at trading patterns of brokers reveals some "strange" and pervasive patterns, such as heavy and rapid back and forth trading of a stock by the same pair of brokers. Such trading patterns, coupled with the persistent anecdotal evidence from market observers, suggests that price manipulation by brokers is one of the primary suspects in explaining the return differential.

We indeed find strong direct evidence for such price manipulation in the data: On days when the stock-price is relatively low, most of the trade - both buys and sells - is done by brokers who act as principals in the stock, while on high price days, most trade is done by outside traders. Moreover, the characterization of trading days by who is buying and selling has strong predictive power for future returns. The pattern and direction of these predictive returns match perfectly with a price manipulation model where brokers constantly take advantage of naive outside positive-feedback traders: Weeks in which mostly principal brokers buy *and* sell stocks to each other have low relative prices followed by positive returns. This attracts the outside traders to trade, which further boosts up the prices. However, by the time prices have reached a relatively high point, most principal brokers have sold out of the stock. At this point only the outside traders are left to trade among themselves. The presence of mostly outside traders on both the buy and the sell side therefore predicts negative future returns. As prices keep dropping, the principal brokers slowly buy back their stock at lower prices. The cycle then repeats itself with principal brokers once again raising prices by buying and selling the stocks back and forth to one another. We therefore argue that our finding is consistent with the price manipulation theory and cannot be attributed to broker ability, institutional features, or factors such as liquidity.

The next question is how this return differential between principal broker trades and outside trades in a stock varies *across* firms of different types. Such an analysis can help us understand what firms are more susceptible to manipulation than others. We find that the return differential is smaller, though still positive and significant, for stocks of larger firms, and firms with higher concentration of stock holdings. We also see that for a given stock, a higher return differential between principal broker and outsider trades is correlated with higher stock price volatility. This suggests that it is the manipulation of prices that leads stocks to have higher price variability, and higher return differential at the same time. Finally, while the higher profitability of trades by principal brokers is not due to inherent broker attributes, we do find that *more* "able" brokers earn *higher* returns when they decide to trade as a principal in a stock with ability defined as the average profitability of trades done by/through a broker in *all* stocks.

The questions discussed in this paper relate to a wide range of literature. The issue of price manipulation is not only important for understanding financial under-development today, but is also related to the historical study of advanced financial markets. Historical accounts of US and European equity markets have a lot in common with the contemporary description of emerging equity markets. For example, early descriptions of the NYSE are rife with instances of price manipulation and "bluffing". The practices of U.S. brokers then are uncanny in their similarity to the behavior of Pakistani brokers now. Gordon's [2000] account of trading in NYSE in the 1920s summarizes these similarities [relevant parts emphasized]:

> " By 1920 the phenomenal growth of the American economy ... had made the New York Stock Exchange the largest and most powerful institution of its kind in the world. But institutionally, it was still much the same as it had been in 1817 when it had come into formal existence. That is to say, it was a private club, operating for the benefit of its members, the seat holders, and not the investing public... The *floor traders ... traded only for their own accounts.* They had two great advantages over the ordinary investors and speculators who increasingly haunted the board rooms of brokerage offices as the decade progressed. Because they had access to the floor itself, they had the latest possible information on how the market, and individual stocks, were moving and could execute trades with lightning speed. And because they paid no brokerage commissions, they could move in and out of stocks and bonds as often as they liked, taking advantage of small swings in price much as the new "day traders" can do today on the Internet. Unlike today's day traders, however (at least so far), they *could also conspire with each other and with specialists to manipulating the market to their advantage ... Pools, wherein several speculators banded together to move a stock up and down, were common.* Although so-called wash sales (where brokers reported sales that had not, in fact, taken place) were prohibited, the pools carefully timed sales within the group, called matched orders. *These sales could be used to produce a pattern on the ticker (called painting the tape) that would induce outside speculators to buy or sell as the pool wished. When their object had been achieved, they could close out the pool at a tidy profit, leaving the outside speculators holding the bag ...* It was, at least for the quick-witted and financially courageous, a license to steal. *Whom they were stealing from in general, of course, was the investing public at large* but they sometimes stole even from less favored members of the club". [pg.213]

The above description coupled with the evidence from the KSE suggests that distinguishing between "brokers who trade only for their own accounts" and those that act as intermediaries for outside investors, as we do, is important for understanding price manipulation.

Moreover, the similarity of broker practices in the NYSE in the 1900s and the KSE today suggests that our findings are not a unique or isolated phenomena. Such practices are likely to be common among other young and shallow markets as illustrated in the following quote from a case study of the Indian stock market:

> "Brokers were also often accused of collaborating with company owners to rig share-prices in pump-and-dump schemes." (A Tale of Two Exchanges – India, Bombay Stock Exchange late 80s. Khanna [1999])

To our knowledge, this paper is the first attempt to systematically document price manipulation in an emerging (or otherwise) equity market in such micro detail and one of the few papers that are able to undertake such an analysis of equity markets in general. The reason we are able to do this is the unique nature of our data set. Previous papers that have looked at trade level data on equity markets have focused on advanced economies (Barber and Odean [2001], and Grinblatt and Keloharju [2000], [2001a], and [2001b]). These papers analyze how investor attributes (gender, distance, language, culture etc.) *influence* trade but do not examine potential *obstacles* to trade such as price manipulation.[3] This is partly because certain micro-level questions for emerging economies, such as price manipulation, while prevalent in the early stages of markets in advanced economies, are no longer thought to be as salient. However, recent evidence on price manipulation in IPOs does suggest that such manipulation may still be present, though less blatant, in mature markets.[4]

Whether there is price manipulation in developed markets nowadays or not, this paper provides an interesting historical analysis of the initial stages of such markets. From the perspective of emerging markets this has immense value because it implies that the same measures that, for example, the NYSE took to curb such manipulative behavior may be employed in emerging markets today and moreover, that there may be limits to how much one can curb such behavior.

Finally, this paper is also related to the literature in behavioral finance that posits how "irrational" positive-feedback investment strategies can lead to inefficiencies in the equity markets (De Long et al [1990b], and Shleifer [2000]). By separating principal traders from outside "naive"

[3] Kyle (89) does consider situations where traders take into account the effect their demand has on price however, the context they consider is not price manipulation per se.

[4] The following quote serves as an example for the IPO price manipulation allegations: "The plaintiffs charged the underwriters of numerous IPOs, including the IPOs of U.S.-listed foreign firms, with allegedly failing to disclose their efforts to allegedly inflate the price of new IPOs through kickbacks given to those who promised to purchase the stock at elevated prices." [Case filed by Milberg Weiss Bershad Hynes & Lerach LLP on April 19, 2002 in the Southern District of New York. We thank Jordan Siegel for this reference]

traders, we are able to test and confirm in a *real world* setting that naive outside investors indeed trade using positive-feedback investment strategies. We believe that it is this type of belief that is able to sustain the inefficient equilibrium where principal brokers keep manipulating markets. Such manipulation profits have interesting implications for the political economy of reforms as well. When brokers earn hefty returns by continuously exploiting naive investors, they are likely to resist any move to reform the markets. The paper thus suggests that market failures such as price manipulation can turn real markets into "phantom" markets which instead of facilitating "real" economic activity, are marginalized into phantom gambling dens.

The rest of the paper is organized as follows: Section 2 provides the relevant institutional background, describes the data, and the construction of key variables in our analysis. Section 3 estimates the excess return that brokers who trade on their own behalf earn compared to the average outside investor and suggests that the former gain by engaging in stock-price manipulation. Section 4 then takes a closer look at the micro-structure of trading and provides direct evidence for the specific price manipulation mechanism used by principal brokers. Section 5 estimates how the manipulation effect varies across different types of firms. Section 6 then examines how inherent broker ability influences the desire to and success in achieving this higher profitability, and Section 7 concludes.

2 Institutional Background and Data

2.1 Basic Description

The Karachi stock exchange (KSE) is the largest stock exchange in Pakistan and was established soon after independence in 1947. In 2001 with 758 firms listed on the KSE, and a total market capitalization of \$5.2 billion, it captured 74% of the overall trading volume in Pakistan.[5] Figure 1 compares the size (market-cap/GDP) and turnover (dollar-volume/market-cap) of KSE relative to stock markets around the world (countries in Figure 1 are ordered by GDP per capita) and establishes a couple of stylized facts about KSE: It is one of the smaller stock exchanges in the world in terms of size but has a considerably higher turnover (0.88) as compared to other markets in the world. Specifically, KSE ranks at the 40$^{\text{th}}$ percentile in Market-cap/GDP, but at the 80$^{\text{th}}$ percentile in market turnover. Both the shallowness of the market and the high level of turnover are

[5] There are two smaller stock exchanges covering the remaining 26%; The Lahore stock exchange (22%), and the Islamabad stock exchange (4%).

of particular interest as the former makes it more amenable to, and the latter more indicative of, price manipulation. Moreover, Figure 1 also establishes that the KSE is not unique in this regard: Whereas low income countries do have consistently lower stock market size to GDP ratios compared to richer countries, many emerging economies have very high levels of turnover. Therefore, the potential for market manipulation facilitated by a combination of shallow markets and high turnover that is explored in this paper may not be unique to the KSE but also prevalent in other emerging markets.[6]

In addition to the high turnover and activity in the market, Figure 2 establishes a high degree of price volatility as well. It plots the KSE100 price index[7] over the five year period from 1997 to 2002, that includes the 32 months covered by our data set. During this period, the stock market experienced wild fluctuations, with the highest price almost three times the lowest. This is all the more surprising given that this activity and price volatility was in a period of relatively low real economic activity with no new issues in the equity market.

Finally, we should note that while the size-distribution of firms traded on the KSE is highly skewed, the distribution of broker size and coverage is fairly normal. Figure 3 shows the cumulative share of both total market capitalization and turnover for firms ranked by their market capitalization. Both shares are skewed, with the top 25 firms accounting for 75% of the overall market capitalization, and 85% of the overall turnover. Figures 4a-b plot the density functions (PDF) of broker size (total trading value of a broker) and coverage (number of firms a broker trades in) during our trading period and shows that these densities are not as skewed.

2.2 Data

The data set we analyze consists of the entire trading history for the KSE over a 32 month period (21 December 1998 to 31 August 2001). What is unique about this data and allows us to look at micro-level trading behavior, is that it contains the *daily* trades of *each* broker for *every* stock over the 32 month period. During this period, there were a total of 147 active licensed brokers and 741 firms trading on the KSE.[8] The data set thus contains almost 2.2 million observations at the broker-stock-date level.

The data set was extracted from the trading computers at the KSE and as such the quality of

[6] There is similar anecodtal evidence from the Bombay stock exchange in India and, as we discussed above, in the NYSE and London stock exchanges in the early 20th century, and currently, in the recent IPO cases.

[7] A weighted price index of the top 100 firms listed on the stock market.

[8] The remaining 17 of the 758 firms listed on KSE were never traded during the 32 month data period.

the information is expected to be very reliable. Specifically, since trading on the KSE can only be performed by a licensed stock broker, each trade order (buy or sell) is recorded under a particular broker name. For each broker-stock-date, our data set contains: (i) the number of shares bought or sold through the broker on that date, and (ii) the closing, highest, and lowest prices for each stock traded during the day. Our analysis is conducted using a day as the primitive unit of time and the average price during the day as a proxy for the trade price. We do not have information at the investor level i.e. while we can identify the broker, we do not know the investor he is trading on behalf of. But as we will shortly show, we can construct proxies for whether the broker is trading on his own behalf or for outsiders. Finally, since only completed trades are recorded, we do not have information on unfulfilled bids.

In addition to the above data that provides us micro level trading information, we also have stock-level information. Specifically, we supplement the trade level data set with annual stock-level data that includes income, balance sheet and ownership information about the firm. In what follows, we first discuss the central distinction we make between brokers and then how we implement this distinction and construct profitability measures using the data.

"Intermediary" vs. "Principal" brokers

An interesting stylized fact that emerged from the anecdotal information and interviews conducted with market participants in Pakistan (investors, brokers, and officials at the Security and Exchange Commission of Pakistan - SECP) was that a substantial number of brokers act as principals (trade for themselves and/or a few investors) rather than intermediaries, and such brokers contribute to potentially undesirable activity in the market. To quote from an SECP report:

> *"Brokers mostly act as principals and not as intermediaries .....(this has led to) ..extremely high turnover ... extensive speculation ... (and) ...very little genuine investment activity, (with) hardly any capital raised .....To restore investor confidence: (i) stock exchange management should be freed from broker influence .... and (ii) government must support and visibly seen to be supporting the SECP's reform agenda." - SECP report to the President of Pakistan July 2001.*

Moreover, the presence or at least allegations of stock price manipulation is common knowledge among the primary market participants, as is the belief that it is generally these principal brokers themselves (or their close associates) who are involved in manipulative activities. A common form such manipulation takes is brokers colluding to artificially raise prices in the hope of attracting and eventually making money at the expense of naive outside investors. In fact special terms, such as *bhatta*, have been coined in *Urdu*, the local language, to define such behavior.

Conceptually as well, there are a couple of reasons why one may expect that principal brokers and their close associates are the ones more likely to engage in strategic price manipulation. First, manipulation of prices is likely to involve frequent buying and selling of large numbers of shares in the process of generating artificial volume and price changes. Anyone interested in such an activity would first want to minimize the transaction cost of such trades. Buying a brokerage license on the stock market is the natural step to take for such an individual.[9] Second, real time information about the movement in prices, volumes, and traders "expectations" are all factors crucial to the success of a manipulation strategy. Having a brokerage license that allows you to sit in close proximity to other market players and monitor all the information in real time is a big comparative advantage. This is particularly true in an emerging market like Pakistan where the information technology markets are not very well developed.

This qualitative evidence on principal brokers acting as price manipulators suggests that one natural way to identify and estimate the effect of manipulative trading is to compare trades done by the brokers on *their own* behalf (we will refer to these brokers as "principal brokers") to trades done by brokers who are trading primarily as intermediaries for outsiders ("intermediary brokers"). While our data does not have information on which/how many investors brokers are trading for, we argue below that we can still indirectly get at this distinction.

Constructing the "principalness" measure:

To understand our method for classifying brokers as principals or intermediaries, it is instructive to look at a typical example from our data. Table 1 gives twenty consecutive trades of three brokers in the same stock.[10] A striking dissimilarity in the trading patterns of the first and the remaining two brokers is that whereas the broker in column (1) is generally trading *both* buys and sells each day, the brokers in columns (2) and (3) either *only buy* or *only sell* on a given day. We argue that this difference is precisely what we would expect to observe between an intermediary and a principal broker: Since an intermediary broker acts on behalf of different investors it is unlikely that on any given day he is *only* buying or selling.[11] However, such behavior is far more probable

[9] The broker licenses are tradable and can be sold conditional on approval from SECP. We were able to locate an actual sale of a KSE license on Lexis-Nexis. The sale was a result of a defaulting broker and the license was sold for 30 million rupees (June 2, 2000. Business Recorder).

[10] The stock is ranked 27th in our data in terms of market cap (27 million dollars), and 10th in terms of turnover.

[11] We acknowledge that overall market sentiments or advice given by a broker to his investors may be strong and homogenous enough to cause all investors to either buy or sell but the likelihood of this occurring consistently is low.

if a broker is a principal since he is then only transacting for himself or for a close associate. This provides us with the means of identifying a principal from an intermediary broker in our data.

It is also worth noting that the back and forth buying and selling by the broker in column (3) of Table 1 is highly suggestive of attempts at price manipulation. Such a trade pattern is certainly not consistent with any reasonable portfolio re-balancing strategy, or trading based on real information. We will discuss such "unusual" trading patterns of individual brokers in detail subsequently.

Given the example in Table 1, we therefore classify the broker in column (1) as "intermediary" and the brokers in column (2) and (3) as "principals". More generally, we construct a continuous "principal-ness measure" ($PRIN$) for *each stock-broker* (i.e. a broker trading in a specific stock) by computing the probability of the following event over our sample period: (i) buy >0 and sell =0, OR (ii) sell>0 and buy=0, OR (iii) sell=buy. In other words, $PRIN$ is the probability that on a given day, for a given stock, a broker trades for an individual, i.e. he either only buys, or only sells, or buys and sells exactly the same amount. The third condition is added as a single investor may buy and sell exactly the same number of shares within a day. The probability of this event is zero if a broker is intermediating trades for a large number of people. In any case, our results are robust to the definition of $PRIN$ that only includes conditions (i) and (ii) above.

With this definition of $PRIN$, the broker in column (1) gets a $PRIN$ value of 0.1 for the 20 trades shown, and the brokers in column (2) and (3), 0.9 and 1. An "intermediary" broker is classified as one with a low value of $PRIN$, and "principal" as one with a high value of $PRIN$. Our results are robust to a wide choice of cutoff rules for $PRIN$, but the results we report in this paper use the continuous measure in order to fully exploit the informational content of our data.

Given the computation of $PRIN$ as above, we aggregate the data up to stock-broker level and are left with 49,038 stock-broker observations. A large fraction of these stock-brokers have a high value of $PRIN$ bearing out the claim made in the SECP report quoted above: 78% of stock-brokers have a $PRIN$ of greater than 0.9, while the remaining 22% have a $PRIN$ of less than 0.9. However, we should note that since our results will use stock fixed effects, what matters is the *relative* $PRIN$ value across brokers within a stock. Moreover, since 14,674 only accumulate or de-cumulate a stock during our data period, we drop these stock-brokers from our main data set.[12] The results of our paper are only strengthened if we include these stock-brokers in our regressions. We are thus left

[12] These are essentially brokers who for a given firm only do a few sell (or buy) transactions during our data period. The volume of trade done by these stock-brokers is less than 1% of the overall trade. Note that these firm-brokers will necessarily get a $PRIN$ value of 1.

with 34,364 stock-brokers in our main data set [13] and 648 firms.[14]

Table 2, Columns 1 and 2, give the distribution of stock-brokers by $PRIN$ both in terms of the number of stock-brokers, and also in terms of the trading volume of stock-brokers for different ranges for $PRIN$. Since, by definition, a principal broker trades only on his behalf, and an intermediary broker trades on behalf of many investors, the size (as measured by trading volume) of a stock-broker with a high $PRIN$ is typically less than the size of a low $PRIN$ stock-broker. It should also be emphasized here that the same broker can act as an intermediary for certain firms, and as principal for others. This is consistent with our discussions with market participants and SECP on the subject and our data that shows there is more variation in $PRIN$ for a given broker than when comparing across brokers: The *average* standard deviation of $PRIN$ within each broker (across the stocks he trades in) is 0.16, whereas the standard deviation of average $PRIN$ across brokers is 0.04. In terms of the results in this paper, this is an important observation. Whereas many brokers engage in manipulative behavior, they do not all select the same stock to manipulate in. Presumably "manipulation" rents are dissipated if a stock gets too crowded by manipulating brokers. This suggests each broker develops his own niche stocks to manipulate in, and refrains from interfering in other brokers' "territory" with repeated interactions among brokers sustaining such collusive arrangements. Moreover, this suggests that any manipulation effects we find are likely to arise from broker *behavior* rather than broker *ability*.

Constructing the profitability measure:

Given the above broker classifications at the stock level, we are interested in comparing our main outcome of interest, profitability, across this classification. In order to do so we construct an annualized rate of return (ARR) measure for each stock-broker using his entire trading history (i.e. buy and sell orders for the stock) over our sample period. We value the sale or purchase price on a given day at the average price of the stock that day.[15] A problem in calculating ARR over the sample period is that the trading history may not net out to zero. In particular, if a broker is a net accumulator or a net de-cumulator of a given stock over our sample period, we need to come up with a strategy to value his end of sample net holdings. We take the simple approach of

[13] These numbers do not match up with the sample size used in the regression because our final stock-broker sample also excludes brokers which are outlyers in terms of their estimated rate of returns. Including them only increases our estimates.

[14] Some firms are dropped after this restriction since these firms only experience trades by brokers who only accumulate/decumulate shares. This is not surprising given the highly skewed distribution of firms (Figure 3) i.e. there are some stocks that are just not traded much during our sample period.

[15] Calculated as the average of the high and low price for the stock during the day.

valuing his end of sample net holdings of a stock using the end of sample stock price. To put it differently, we "force" the stock-broker to liquidate any net positions at the average end of sample price.[16] On a given day, we then consider the sale of stock by the broker as a cash inflow and a buy of stock as a cash outflow for the broker. Using an annual 10% opportunity cost of capital,[17] we can then compute the annual rate of return on the stock. Thus in the simplest case where a broker buys a share of a stock at Rs 100 and then sells it a year later at Rs 112, his ARR in this stock will be 12%. A more elaborate example is described in the appendix to clarify the construction of ARR.[18] Note that since we observe each trade in the market during our sample period, and are neglecting dividend payments, the volume weighted mean of ARR in our sample is close to zero by construction.[19]

3 Results: How profitable is "Principalness"?

The $PRIN$ measure allows us to discriminate between brokers who intermediate on behalf of a number of investors, and brokers who trade on behalf of a single investor, which we assume to be either the broker himself, or his close associate. If, as is commonly alleged, such brokers are involved in stock price manipulation, then trades done by principal brokers should on average earn higher profits than trades by intermediary brokers since the latter trade on behalf of outside and potentially "naive" or unsophisticated investors who may be taken advantage of by the principal brokers. Since our profitability measure does not include trading commissions earned by brokers, we can directly focus on the profitability comparison between the trades done by principal brokers and trades done by outside investors through the intermediary brokers. However, for expositional clarity we will refer to the profitability comparisons as between principal and intermediary brokers, it being understood that the latter signifies profits accruing to the outside investors who trade through intermediary brokers.

[16] Note that we do not have to assume frictionless short selling necesarily to legitimately do this. An alternative explanation of a within-sample "short sale" is that the stock-broker is simply borrowing the stock from his net accumulation of the stock prior to the beginning of our sample period. It is certainly safe to assume that such "borrowing" is frictionless.

[17] 10% was the approximate nominal return (annualized) on 1-year government bonds during the sample period. The rate of inflation over the sample period was 5%.

[18] In addition to this measure we construct a variant where we take an alternate approach to the netting out problem. Rather than forcing liquidation at the end date we impose a "zero profit" condition i.e. we "net out" the ending position of the broker so that he makes 0 return from that position. The appendix describes this in more detail. Since our results are similar with this alternate definition, we stick to the simpler version of ARR.

[19] Due to the market clearing condition: one person's capital-gain is another person's capital loss. However, the mean is not exactly 0 since ARR is a ratio.

Before analyzing the relationship between "principalness" and profitability in a regression framework, Table 2 offers a first look by reporting the mean of ARR within different categories of $PRIN$. Column (3) in Table 2 shows a definite trend of increasing ARR with $PRIN$, providing evidence that trades done by individual brokers earn higher annual returns than trades of outside investors. Panel A in Table 2 examines how the mean ARR varies across four categories of $PRIN$ for the entire sample.[20] As is clear from the panel, the mean ARR values increases as we move to categories with higher $PRIN$ values.[21]

Given the larger number of stock-brokers in the higher $PRIN$ categories but with a lower trading volume, a concern is that the $PRIN$ effect we are capturing, while significant, is just driven by the few small (in terms of turnover) stock-brokers. Since the KSE has a few very large stocks and we would expect lower values and variation for the $PRIN$ measure and also lower price manipulation in such stocks. Panel B in Table 2 drops the top 15 firms (by trading volume) and shows that the mean ARR pattern remains almost identical, even though each category now has roughly the same weight (in terms of trading volume in that category), suggesting that our effect is also economically significant and prevalent. Panel C takes a look at these effects in the top 15 firms as well. We use a larger number of $PRIN$ categories (since most of the large stock-brokers have understandably lower $PRIN$ values, we need finer categorization at the lower end of the $PRIN$ distribution) and interestingly enough, even within these larger firms and hence on average, much larger stock-brokers, we see evidence of the $PRIN$ effect. However, not surprisingly, there are far fewer stock-brokers who have higher $PRIN$ values in such stocks and hence are able to make use of these gains.

Primary regression:

With the variables described as above, our primary regression of interest is:

$$ARR_{sb} = \alpha + \beta . PRIN_{sb} + \underline{\gamma} . \underline{S} + \varepsilon_{sb} \tag{1}$$

$\underline{S}$ refers to stock level fixed effects. β in (1) captures the superior returns that "principal" brokers ($PRIN = 1$) receive over "intermediary" brokers with the lowest possible value of $PRIN$ (0). Column (1) in Table 3 reports the results of the regression. Principal brokers earn an annual

[20] Given the highly (right) skewed $PRIN$ distribution these category cutoffs are drawn with smaller interval widths in the higher $PRIN$ values.

[21] Note that a large number (16,092) of stock-brokers have a $PRIN$ value of 1. This does not mean that all these brokers are involved in manipulation but, as we will describe below, that the $PRIN$ measure also assigns high values to brokers who may not be manipulators but either trade infrequently or are "badla" brokers.

rate of return that is 5.8% higher than intermediary brokers This "principal-broker" effect is highly significant at less than 1% significance level.[22] We only report results with stock fixed effects, but the results are very similar without stock fixed effects.

It is important to point out that whereas our definition of principal brokers is able to identify potential manipulators, some intermediary brokers may also be involved in similar profit-making activities as principal brokers but we are unable to observe such individual trades since we only observe their aggregate daily trades. We therefore expect that all the results that we present in this paper are an *underestimate* of the true effect.

Next we perform a series of robustness checks on the main result:

Robustness to Profitability Measure:

We first check for robustness to the definition of our profitability measure. Column (2) in Table 3 reports the results of a regression that uses a 0% opportunity cost of capital instead of 10% in computing ARR. The coefficient is still highly significant, but drops to 4.1 percent. This reflects the fact that higher discounting of cash flows favors principal brokers who tended to be net sellers when market reached its peak in the middle of the sample period, and net buyers later on. Another robustness check that we did (but do not report in the table) is with respect to the forced liquidation of any net stocks left at the end of sample. The robustness check consists of recalculating the ARR such that instead of liquidating net stocks at the end of sample price we "net out" a broker's ending position and hence guarantee a zero profit generating from any such net ending position. Since the results do not change much at all with this alternate measure, we are not concerned that our liquidation strategy creates any bias in our estimates (see appendix for details).

Broker Behavior or Ability?

We next check whether our results can be explained by inherent broker "ability". For example one could argue that high ability individuals who can "time" the market really well are also more likely to act as principal brokers i.e. they buy a license to trade directly on the stock market in order to save on transaction costs. These individuals would then get a high $PRIN$ value and earn higher returns. However, the result would not be driven by the manipulation of price by these brokers, but because of their higher ability.

As we pointed out in the previous section, good market-timing is unlikely to be an explanation

[22] The relatively low R-squared (8-9%) is to be expected since a single variable like the $PRIN$ measure is a noisy and crude proxy for trades done by brokers themselves. Moreover, if such $PRIN$ activity is to be profitable, it cannot have too much "predictive" power otherwise other players will arbitrage this advantage away.

for our results given the trading patterns in the data: It is very hard to reconcile trading patterns, such as back and forth buying and selling by two brokers, with legitimate portfolio optimization and market timing. Nevertheless, we can test for this concern explicitly by including broker fixed effects in our regression. The inclusion of broker fixed effects will remove the effect of any broker specific variation from the coefficient of interest. If our results are capturing innate broker ability, the $PRIN$ coefficient will drop significantly after the inclusion of broker fixed effects. Column (3) of Table 3 reports the results and shows that the coefficient of interest does not change much (in fact slightly increases to 5.93%), thus confirming that our results are not driven by better market timing or some other inherent attribute of principal brokers.

Restrictive PRIN definition:

We mentioned earlier that our estimated effect is likely to be an *underestimate* of the true profitability differential. The reason is that stock-brokers who intermediate for a large number of outside investors (and thus have a low $PRIN$) may also engage in profitable activities such as price manipulation. To the extent that part of the return of low $PRIN$ stock-brokers includes the higher return from such activity by the stock-broker himself, our regression coefficient will be biased downwards. We test for the direction of this bias by using a more restrictive definition of $PRIN$. Our original definition of $PRIN = 1$ included the case where a stock-broker's sale equals his purchase on a given day. We now exclude this case from the definition of principal brokers, and re-run the regression in column (1). Column (4) presents the results. Since in the more restricted definition of $PRIN$ some additional stock-broker are now incorrectly classified as intermediary, the estimated coefficient on $PRIN$ drops to 4.11 (from 5.8) as expected. This supports our claim that the profitability differential is an underestimate of the true differential.[23]

Non-linear Specification:

So far we have assumed a linear specification in all our regressions. However, Table 2 suggests that the effect of $PRIN$ on profitability is non-linear at $PRIN = 1$, as the profitability of stock-brokers suddenly jumps at that point. We therefore re-run (1) with an additional dummy for stock-brokers with $PRIN = 1$. Column (5) reports the result which confirm the pattern in Table 2. While there is a significant jump of 1.3% at $PRIN = 1$, the linear effect of $PRIN$ for $PRIN < 1$ remains relatively large at 3.16%.

[23] A related issue which can also lead to an underestimate concerns the proper unit of time. For example, in our paper the unit of time is a day, but as this unit becomes smaller everyone starts to look like a principal. Therefore for stocks with infrequent trades, even intermediaries can be classified as principals. However, this error will only bias our coefficient towards zero.

Value-weighted Regression:

The regressions presented so far give equal weight to all stock-broker observations regardless of the volume traded by the stock-broker. However, as Table 2 showed, there is significant variation in the total value of stocks traded by each stock-broker. Therefore, a more economically sound measure of the principal-broker effect might be one where each stock-broker is weighted by his relative size. There are two potential sources of variation in the stock-broker size: within stock variation, and across stock variation. The former is generated by the fact that different brokers trading shares of a given stock differ in the value of the shares traded. The across-stock variation comes from the fact that overall trading volume of some stocks is larger than other stocks. The highly skewed nature of this distribution was evident from Figure 3.

We account for the within and across stock variation in trading value separately. Section 5 will discuss the issue of across stock variation in detail. Here we focus on the within stock variation. To do so, we weight each stock-broker observation by the $fraction$ of the stock's total traded volume traded by the broker. Column (6) reports the results of regression (1) where each stock-broker is weighted by his relative size within the stock. The estimated coefficient on $PRIN$ is even bigger (7.93%) after weighting. This suggests that the weighting strategy correctly puts less emphasis on stock-brokers who had high $PRIN$ values but low activity. Such brokers are unlikely to be "manipulators" but are assigned a high $PRIN$ value *only* because they trade infrequently.

"Badla" Trades - Dropping "Badla" stocks:

An issue that we have not talked so far in the classification of $PRIN$ is that it also includes "badla" brokers. "Badla" is a local term for a forward trading facility used and recognized by the KSE (see Berkam & Eleswarapu [1998] for Badla in the Bombay Stock exchange). In a Badla transaction the borrower who "takes" the badla from a badla broker, in order to avoid funding (delivery) for a purchase (sale) transaction, carries forward his security exposure from the current settlement period to the next one by sale of his position in the present period and its repurchase in the subsequent settlement period at a predetermined price differential (the badla commission). The badla is a legal transaction allowed by the KSE provided that the deals are routed and reported settled through the KSE. Badla transactions are executed within the transactions premises of the KSE during prescribed badla hours (after the close of normal trading) for (31) high liquidity stocks.[24]

[24]Badla transactions can and do take place in other stocks. However, such transactions are not be recognized by the KSE. In fact brokers may individually decide on a badla and not go through the KSE at all.

A problem with the inclusion of "Badla" trades in our data set is that badla traders are likely to be assigned a high $PRIN$ measure. The reason is that "badla" traders only trade their *net* forward trading orders on the KSE. Moreover, the very definition of badla implies that these *net* forward trading orders are automatically reversed in a day or two. In other words, badla trades will look exactly like broker C in Table 1, and will be counted towards our $PRIN$ measure.

Since a broker who is providing badla in a stock is actually acting as an intermediary (and earning profits through the badla commission rather than stock returns) he should not be included in the $PRIN$ measure. Unfortunately, our KSE trading data does not distinguish between a badla transaction and an actual trade in the (ready) market. Moreover, brokers who only provide badla will typically be assigned a high $PRIN$ measure (as they only buy or sell on a given day). Since we do not expect badla trades to be indicative of manipulation, this suggests another reason that the estimate on $PRIN$ is an underestimate of the real effect. We run a few robustness check on this below.

Column (7) excludes the 31 large stocks for which the KSE officially allows badla thereby eliminating all official badla trades from our sample. The results show that the manipulation effect not only remains but, as expected, is even larger: the coefficient on $PRIN$ is 7.27%.

"Badla Trades - Separating "Badla" behavior:

An alternate that is less extreme than above is to try and separate badla trades from high $PRIN$ brokers in our data. This may be preferred because it addresses whether the $PRIN$ effect exists in the large 31 firms that were excluded before and whether the increased coefficient in column (7) is not just driven by the different sample of firms. One way to do this is to recognize that if a badla broker does appear with a high $PRIN$ value, then he will look exactly like the pattern in Table 1 for broker C. Specifically, if a broker is giving a badla, then on a given day he will buy (or sell) the same amount that he sold (or bought) in the previous period that he traded: His trades will look "cyclical".

Thus we can separate out the $PRIN$ measure into two measures; $PRINcycle$ and $PRINnoncycle$. The former includes both badla brokers and principal brokers (who are trading in cyclical patterns), while the latter includes principal brokers but is less likely to include badla brokers.[25] Specifically, for $PRINcycle$ we look at each day's trading for a given stock-broker and assign a value of 1 (0

[25] There still may be some badla brokers with a high $PRIN$ value who don't appear cyclical in the unlikely scenario that on a given day apart from the badla sale (or buy) they also sell (or buy) stock in the ready market as well. However, the likelihood of this happening for all their trades is very unlikely. Moreover, by all accounts while brokers are not exclusively badla brokers, if they do offer badla in a stock they tend not to trade directly in it.

otherwise) if the broker either only bought or only sold shares that day AND this buy (sell) is exactly equal to the sell (buy) the next time he trades (and he also only sells or buys that day). $PRINcycle$ is the average of this indicator over the entire trading history of the stock-broker. $PRINnoncycle$ estimates the "remaining" part of $PRIN$. Specifically, it looks at each day's trade for a given stock-broker and assigns a value of 1 (0 otherwise) if the usual $PRIN$ condition holds (i.e. the broker either only buys/sells or buys and sells the same amount on a given day) AND there is no "pure" cycle (i.e. today's buy/sell are not the same as the next trade's sell/buy - "pure" signifies that in addition at least one side of the trade - buy or sell - is zero). $PRINnoncycle$ is the average of this indicator over the entire trading history of the stock-broker. Thus a trade which is classified as $PRIN$ on a given day must either be a $PRINcycle$ OR a $PRINnoncycle$. Note however, the eventual $PRINcycle$ and $PRINnoncycle$ measures need not be mutually exclusive as they are averaged over all trades of the stock-broker.

Column (8) presents the results of this regression and shows that the coefficients on both $PRINcycle$ and $PRINnoncycle$ remain significant and, as expected, the latter is larger since it is less likely to include the badla brokers: The coefficient on $PRINcycle$ is 4.78%, and on $PRINnoncycle$ it is 6.38%. These results suggest that the badla issue is not a serious concern and, if anything, results in an underestimate of the real principal-broker effect.

There is an alternative interpretation of the regression in column (8), especially when run on "non-badla" firms. The results on this regression are similar (both $PRINcycle$ and $PRINnoncycle$ coefficients increase by a couple of percentage points). The large and significant coefficient on $PRINcycle$ cannot be reconciled with a story where brokers just have better information or ability. Neither ability nor information should result in the strange trading pattern of cycles. This leaves the manipulation hypothesis as the sole primary contender for an explanation of the results.

We have shown earlier that the principal-broker effect is based on broker behavior and not ability. Moreover, we suggested that an important part of such behavior is price manipulation on the part of principal brokers. While principal brokers could be using other means to gain an edge in trading such as differential access to information (insider trading), both anecdotal evidence and the results in Column (8) suggest that price manipulation is an important part: Despite being confounded by badla brokers, the large coefficient on $PRINcycle$ shows principal brokers who trade cyclically (likely to be associated with price manipulation) make almost as much profits as those who do not. In the next section we present direct evidence of price manipulation by principal brokers and argue that the principal-broker effect can be interpreted as a price-manipulation effect.

4 Principal Brokers and Price Manipulation

Our previous results show that trades done by brokers themselves earn significantly higher returns at the expense of trades done by outside investors. These results, combined with the trading patterns discussed in Table 1 and anecdotal evidence, suggest principal-brokers gain by manipulating stock-prices. In particular, the "buy-sell" cycles seen in Table 1, may be part of an effort by the principal brokers to manipulate the stock price.

In this section, we first explore the significance of this mechanism and then exploit the micro-structure of trading in our data and directly test for it. If we are able to identify the precise mechanism through which principal brokers are manipulating stock prices, it will give us direct evidence for the claim that principal brokers earn higher returns by manipulating prices rather than just through insider or smarter trading.

"Cycles":

Anecdotal evidence suggests that one of the ways principal brokers earn higher returns is by their ability to generate artificial market excitement through their trading activity. A simple procedure to generate such price and volume movements would be for a group of brokers to trade back and forth consecutively for a few periods. Such back and forth trading would look very similar to the cyclical trading patterns we saw earlier. Recall from section 3 that we separated the $PRIN$ measure into $PRINcycle$ and $PRINnoncycle$ where the former measure focused on high $PRIN$ brokers who also traded in cycles and the latter those who did not trade in cycles. If trading cycles are indeed an effective means of manipulating prices then we would expect that high $PRIN$ brokers make even more profits when they trade in cycles i.e. the interaction of $PRINcycle$ and $PRINnoncycle$ is positive. Column (1) in Table 4 shows that this is indeed the case. In fact, the magnitude of the interaction term is relatively large (7.48) suggesting that such cyclical behavior is an important means through which high $PRIN$ brokers earn higher returns.[26]

Trading Micro-Structure:

So far we have said that anecdotal evidence, couple with the cyclical trading patterns suggests that the profitability differential that we estimated cannot be attributed to superior ability or information, but is most likely a result of manipulation. However, the micro nature of our data set allows us to dig even deeper, and directly test for specific manipulation mechanisms. We do this by

[26] A broker who has a $PRINnoncycle$ value of 0.5 can increase his profits from 2.9 to 7.3% if he makes all his remaining 50% trades that were not even $PRIN$ before cyclical (i.e. his $PRINcycle$ changes from 0 to 0.5). Note that the coefficent on $PRINcycle$ is small which is consistent with such brokers (with high $PRINcycle$ but low $PRINnoncycle$) likely to be Badla brokers (see section 3).

testing the implications of a manipulation mechanism based on naive “trend chasers” or “positive feedback” investors. Figure 5 describes this mechanism in detail.

The manipulation mechanism is easier understood by first classifying each stock and date with a state variable $I_B I_S$, where I_B and I_S refer to the overall $PRIN$ category of buyers and sellers trading that firm's stock on that date. For simplicity, assume that I can take on two values: H for high, and L for low. There are thus four possible states for a given stock-date: HH, LH, LL, and HL. The state variable LH means that the average $PRIN$ of the brokers buying the firm's stock that day is low, whereas the average $PRIN$ of the brokers selling the stock that day is high. We define high and low relative to the average $PRIN$ value of brokers for a given stock throughout the data period: A buying index of L means that on that day, brokers buying the firm's stock have a lower $PRIN$ than usual for the firm.

The mechanism outlined in Figure 5 is simple: We start the cycle at the point where prices are at their lowest (point A). At this stage only the high $PRIN$ types are in the market and they trade among themselves. Therefore the state at point A is HH. The high $PRIN$ brokers act as manipulators, and start trading back and forth in an effort to attract the naive outside investors who have extrapolative expectations and thus follow positive-feedback investment strategies. As they raise prices, they attract these outside investors who chase the trend and start buying (branches B,C). When the buying pressure gets strong enough from the outside investors, the state changes from HH to LH i.e. on net intermediary brokers are buying from principal brokers. However, once the price has risen enough, the manipulators exit the market and trade only occurs between the outside noise investors (point D). The state when price is at its highest is thus LL. This artificially high price can no longer be sustained as the manipulators have gone out of the market. Consequently the “bubble” bursts and price starts to fall (branches E,F). The positive feedback traders start selling at this point which further depresses the price. When the price gets low enough, the manipulators get back into the market to buy back their stock at low prices (state HL). Finally, once the manipulators have bought back all their stock, the price is at its lowest again, and the whole cycle repeats itself (point G).

The positive feedback investment strategy assumed on part of the naive outside investor is familiar to the literature in behavioral finance. Surveys indicate that underlying such positive feedback behavior is often extrapolative expectations or trend chasing on the part of the naive trader. De Long et al [1990b], and Shleifer [2000] have hypothesized such investment strategies to explain stock market anomalies such as momentum, and bubbles. Thus our test of the manipulation cycle in Figure 5 can partly be thought of as a test for the presence of positive feedback investors in a real market setting.

An advantage of the manipulation mechanism in Figure 5 is that it offers precise predictions which can be tested given the nature of our data. The predictions relate both to the level, as well as the change in prices, conditional on the stock-date state. Column (2) in Table 4 reports the frequency with which we observe each of the four states. The frequencies are relatively evenly distributed with HH, LH, LL, and HL occurring 31.1, 21.4, 28.4 and 19.2 percent respectively.[27]

Test 1: Price Level Conditional on State

The manipulation mechanism in Figure 5 predicts that a stock's price will be highest at state LL, lowest at state HH, and intermediate at state HL and LH. To test this, we first normalize each stock's price on a given date by dividing it by the average stock price over the entire data period, and multiplying by 100. Since we are concerned about correlation across the same states for a given stock, we take the most restrictive specification possible and collapse all stock-day observations to stock-state observation with the normalized price now averaged over all days for a given state in the stock. Column (3) in Table 4 shows the result of regressing this mean normalized price on state dummies (since all variables are normalized for a stock, we do not need to use stock fixed effects). Our data confirms the price level prediction of Figure 5. The price of a stock is at its highest at LL, and lowest at HH, with HL and LH being in the middle. Specifically, the price level at state LL is 9.85% higher than the state HH, and the coefficient is highly significant.

Test 2: Price Change Conditional on State

Figure 5 also makes predictions about the direction of price change conditional on the state. It predicts that, (a) price changes are positive (higher) after states HH and LH, and negative (lower) after states LL and HL, (b) price changes are negative (lower) before states HH and HL, and positive (higher) before states LL and LH.

To carry out these tests, it is intuitive to construct the following hypothetical investment strategy: Imagine that during the course of a week 1, you as an investor, observe the average state (HH etc.) of all shares traded during that week. Based on this, on the first day of week 2, you buy an equal-weighted portfolio of all stocks that belonged to a particular state, say HH, that week. You hold onto this portfolio for the whole of week 2, and sell it on the beginning of week 3. Thus an HH-strategy would be to buy each share that had an average state of HH during week 1 at the

[27] This is almost by construction, since "high" and "low" states are defined around the mean value.

first day of week 2, sell these shares at the beginning of week 3 and simultaneously buy all shares that had an average state of HH in week 2 and so on.

Now all we have to do to test for our price change result is compare the average return (price change) on these portfolios constructed using the four state-contingent strategies. Given Figure 5, we would expect that the HH-portfolio would give us a higher return than the LL-portfolio: Stocks in HH state last period would earn positive returns, while stocks in the LL state last period would earn negative returns. The advantage of doing it this way is that it is both intuitive (if states were observable we are literally describing actual investment strategies and potentially, opportunities to consistently "beat the market") and that it collapses our data into a single observation each week and hence we do not have to worry about correlation of returns across stocks at a given time.[28]

Table 5 shows the returns from all four state-contingent strategies. Each cell in this table represents the mean "above-market" return from a different investment strategy where above-market simply means that we subtract the overall market return in a week from the state-contingent portfolio's return in that week. We look at above-market return since we are interested in looking at relative cycles. Thus the first cell (column 1 and HH) says that on average, an investment strategy which holds a portfolio of all HH stocks each week will earn a 0.17% higher weekly return as compared to the market return.

Column (1) in Table 5 reports the results of these estimates on future price changes. The first thing to notice is that *all* price changes go in the direction predicted in Figure 5. Price changes after HH and LH are positive and significant, and after LL and HL are negative. Moreover, the size of the coefficients is quite big.[29]

We also perform a more subtle test for the states HH and LL in column (1). Instead of holding a stock whenever its state is HH or LL, we only hold a stock if its state is HH but its future state is different from HH. We call such states $HHend$, and $LLend$ for LL. The idea is that when there are consecutive sequences of HH, the first few instances of HH may not lead to positive price change necessarily, but the last HH in the sequence should be the strongest predictor of future returns. This is indeed the case, as the magnitude of coefficients on $HHend$ and $LLend$ is greater

[28] Autocorrelation of returns remains a problem but our results are robust to correcting for this (using Newey-West standard errors).

[29] The difference in returns from holding a "winning" portfolio, vs. holding a "losing" portfolio is also significant (regressions not shown), where winning (losing) refers to state contingent portfolios with positive (negative) returns. For example, if a person had access to inside information about the state of the market, and systematically invested in only HH contingent stocks, while a naive investor only invested in an LL state, the difference in their weekly returns will be 0.43% (0.17+0.26), which is equivalent to a 25% annual return differential. Moreover, this is likely to be closer to the true annual return earned by price manipulation, and is consistent with our earlier claims that the "principal-broker" effect (i.e. 8%) is an underestimate.

than the coefficient on HH and LL. Note that the $LLend$ result also clears a slight confusion in the earlier results which showed that the coefficient on HL (-0.40) was larger in magnitude than that of LL (-0.26) whereas we would expect the price fall to be the greatest following LL. However, since the price fall prediction really applies on *exiting* the LL state, the larger negative coefficient on $LLend$ (-0.72) shows that this prediction is indeed true.

Next we test for state-contingent *past* price changes and present the result in Column (3). The methodology for computing these returns is exactly the same as before, except that now instead of the price change over the upcoming week, we look at the change from the previous week. Once again the results strongly support the predictions of our hypothesized manipulation mechanism. As predicted, price changes *before* HH and HL states are *negative*, while price changes *before* LL and LH states are positive.

Finally as a robustness check, we redo the exercise in column (1) and (3), but restricting ourselves to only the top 25% of firms by size. Column (2) and (4) report these results. The results remain essentially the same but are smaller, which is consistent with our finding in the next section that manipulation is strongest in smaller firms.[30]

Our examination of the micro-structure of trade provides strong evidence that principal brokers use the price manipulation mechanism described in Figure 5 as a means of generating higher returns. While such "price bubbles" and the reasons behind them - the exploitation of positive feedback traders by rational arbitrageurs - are similar to those in developed markets, a difference is that these cycles are not randomly created by the announcement of some exogenous news, but are instead started and managed by the manipulating brokers themselves.

While we acknowledge that principal brokers may employ other means as well for generating their higher returns; (i) our results on the trading patterns used by principal brokers, (ii) the fact that they make even more profits when they increase cyclical trades, and (iii) direct tests of the price manipulation mechanism used by principal brokers, all provide compelling evidence that higher returns for principal brokers are primarily driven by price manipulation. We henceforth interpret the principal-broker effect primarily as a price manipulation effect.

Other Hypotheses

In the previous section our results showed that the principal-broker effect could not be explained

[30] A related prediction of the manipulation mechanism in Figure 5 is with regards to the chronological sequence of states. While this sequence of states is implied by the future and past return results in Table 5, we also tested this directly by estimating the Markov transition matrix for the states and found that the sequence implied by Figure 5 is indeed the most likely.

by inherent broker attributes such as better information, or better market timing. Moreover, the large and significant coefficient on $PRINcycle$ in Column (8) Table 3 suggested the price manipulation was a possible explanation. We then presented direct evidence for a particular price manipulation mechanism that relies on collusive manipulating brokers making money off irrational positive feedback traders. In what follows, we briefly discuss alternative manipulation mechanisms and why they are not likely given our results.

The first alternative mechanism is similar to the one above but only requires the colluding principal brokers to act as monopolists in the market. In other words, they do not need to trade back and forth to create artificial volume and prices, A single principal-broker could in theory generate enough artificial momentum to raise prices and as before, make money of positive feedback traders. While this is possible, it is not prevalent in our data. In the trading patterns we see that principal brokers trade directly with other principals and in fact as Test 2 shows, it is precisely these trades that lead to positive returns. Trades by a single principal broker for a stock do not explain the higher returns (regressions not shown): it is collusion between different brokers that lead to positive future returns. Hence the monopolist story is unlikely.[31]

A second mechanism is one which does not rely on positive feedback investors but rather on naive "sleeper" investors i.e. clients of a broker who do not follow the market closely such as expatriate investors. In this case a broker may cheat his own sleeper investor by buying for him at increasing prices which eventually bust leaving the outside investor at a net loss. This story sounds appealing since it explains why each stock experiences some manipulation. However, we believe it does not explain our results satisfactorily. First, our results estimate the profitability difference *across* brokers and therefore do not capture profits a broker may be making of his own "sleeper" client. Second, while one could argue that brokers collude so that they do not cheat from their clients but from their non-principal partner broker's client so as not to be "caught" by a client, this seems to be inconsistent with the fact that the sleeper client is a sleeper i.e. has little information of what is happening in the market and so there seems little need to go through an elaborate means of stealing from him by teaming up with a non-principal broker.

Finally, it is worth examining whether the positive feedback investors are in fact rational in the sense that momentum trading, while not as profitable as manipulating, may nevertheless be

[31] In addition, this also (along with the cyclic trading patterns) provides evidence against a story where broker's have differential information across stocks, since in such a case the better informed broker would have no reason to "pair-up". Thus a principal broker buying (or selling) by himself should have predictive power for prices but this is empirically not ture (regressions not shown).

a profitable strategy. This is possible if the extent and frequency of manipulation is low enough and there is sufficient momentum in the market so, in equilibrium, it remains profitable to be a momentum trader. However, results analogous to Test 2 (regressions not shown) show that it is not profitable to follow a momentum trading strategy - in fact the market consistently displays negative auto-correlation in returns so that momentum trading leads to losses.

Thus we have argued that the most likely explanation of our results is that principal-brokers collude to take advantage of irrational feedback traders. Moreover, the fact that such collusion and resulting manipulation occurs in most stocks and by most brokers shows that, in equilibrium, brokers implicitly develop niche stocks to manipulate and other brokers do not "invade" these stocks. Finally, the fact that there are positive feedback traders even when such an activity by itself is not profitable shows that there is limited information amongst outside investors and such traders do not consistently feedback trade and/or there is a high turnover in such outside traders so that those that "die off" are replaced by new naive feedback traders.

5 Results: Firm Heterogeneity

Interpreting the principal-broker effect as price manipulation suggests that the effect may vary across firms based on how *amenable* and *desirable* it is to manipulate the prices of stocks in these firms. In this section we exploit the heterogeneity in firm characteristics in order to do so. This is useful on two accounts: First, it helps us isolate the circumstances in which price manipulation works. For example, is the price manipulation effect negatively correlated with the size of a firm? If so, it would suggest that the difficulty of successful price manipulation goes up as the number of players and the size of the market increases. This clearly hints at the possibility of multiple equilibria: One with excessive manipulation and a small market size, and another with little/no manipulation and a large market size. Second, it allows us to do more robustness tests on our price-manipulation interpretation. For example, is it true that firms in which principal-brokers earn higher returns also experience greater price variability?

Firm Size:

Columns (1) and (2) in Table 6 examine how a principal broker's profitability varies across firms of different sizes. Given that price manipulation is likely to be harder in firms with a greater market capitalization, we would expect this effect to decrease in firm size. In column (1), we interact $PRIN$ with a dummy for small firms. The dummy variable is zero for the top 100 firms by size, as measured by the firm's market capitalization, and one otherwise. Column (1) reports the results of this regression. Whereas the effect is positive and significant (3.91%) for the top 100 firms, it is significantly larger for the smaller firms: It increases by 4.3% for the smaller firms and this difference is significant at the 1% level.

Column (2) disaggregates this effect by creating seven size categories,[32] with size now based on the turnover value of the firm in 2000.[33] With fewer firms in each category, the standard errors on the interaction coefficients increase, but the size of the interaction coefficients is still instructive: It steadily decreases as we move up firm size from category 2 to category 7.[34]

A note of caution in interpreting the relationship of size with the price manipulation effect needs to be raised: We mentioned earlier that our result is an underestimate due to not accounting for any manipulative activities of intermediary brokers. This underestimate is likely to be more severe for larger firms, as higher number of brokers will be involved in *both* intermediation and manipulation. Such differential under-estimation can partially account for the results of column (1) and (2). There is also some direct evidence on the presence of this effect, as the mean value of $PRIN$ for a given firm decreases with firm size.

Firm Ownership Concentration:

While the size and hence depth of trading in a firm may affect the *ability* of a broker to manipulate prices, the number of people holding shares in a firm may affect the *desirability* of such manipulation. Column (3) in Table 6 categorizes firms by their ownership concentration, and then interacts three ownership categories with $PRIN$.[35] The results show that principal brokers earn relatively lower (but still positive) profits in firms with *more* concentrated ownership: The profitability differential is highest (9.45%) for widely held firms and progressively smaller for more closely held firms (the differential drops to 4.78 and 3.02% respectively). This suggests that one needs a significant number (by shares held) of "outsiders" to make it worthwhile or effective to act as a principal broker, or as we interpret, to manipulate prices. If there are too few small outside

[32] The size categories are based on the (natural) logarithm of a firm's turnover value in 2000. The categories and cutoffs are: 1 if <16; 2 if <19; 3 if <23; 4 if <25; 5 if <28; 6 if <30; 7 if >=30. These cutoffs were chosen to give roughly equal log-intervals such that the number of stock-broker observations in each category was "reasonable" (for example the lowest category has around 50% of the firms but, since most of these are inactive, it has much fewer stock-broker observations).

[33] We also have data on the value of a firm's assets and it's market capitalization and the results remain similar if we use these measures instead of turnover (they are all highly correlated). We prefer using turnover because we have greater coverage for it across firms.

[34] Note that the coefficient rises when comparing size 1 to size 2 firms. This is not unusual since we would expect that manipulation is just not worth it in very small/inactive firms.

[35] The concentration indicators: CONC1 indicates that all shareholders with more than 5% shares cumulatively hold less than 40%, CONC2 that they hold 40-70% and CONC3 that they hold greater than 70% of the firm's shares.

traders in the firm, then brokers do not have enough "naive investors" to either make it worthwhile to exploit or to be able to generate enough positive (false) momentum so that outside investors start chasing the trend.

Firm Price Volatility:

A further check on whether price manipulation is an important means employed by principal brokers is that this effect should be larger in stocks that experience greater price volatility, since creating artificial movements in prices is one way principal brokers attract naive outside investors such as price feed-back traders. We test for this by correlating the coefficient of variation of price for each stock with the principal-broker effect. Column (4) in Table 6 shows this correlation is a positive and significant i.e. principal stock-brokers earn even higher returns in stocks that experience higher price variability. The size of the coefficient (20.35) is also quite large, as the coefficient of variation varies from 0 to 1 in our data. We should caution that we are not making any causal inferences here but simply using this result to establish a correlation we would expect given that principal-brokers use price manipulation as a means to generate profits.

6 Results: Broker Heterogeneity

The regression with broker fixed-effects [Column (3), Table (3)] showed that our main finding - principal brokers earn higher returns than outside investors - is not driven by broker level attributes but instead depends on broker behavior and in particular, on price manipulation carried out by these brokers. However, it is still possible that broker ability may affect the desire for and/or success in being a principal-broker and manipulating prices. This section examines whether this is the case using two different (inferred) measures of broker "ability".

The first measure of broker ability, $BABtot$, is constructed by looking at the results of a regression of ARR on broker fixed effects. $BABtot$ is the estimated coefficient on each broker dummy (re-scaled between 0 and 1). Thus $BABtot$ measures the profitability difference between brokers and attributes it to underlying broker ability (type). The second measure of broker ability, $BABnet$, takes a more restrictive definition of ability in that it "nets out" the stock-choice decision of the broker from the ability measure. It is constructed by considering a regression of ARR on broker *and stock* fixed effects. $BABnet$ is the estimated coefficient on each broker dummy (re-scaled between 0 and 1). Thus $BABnet$ measures the profitability difference between brokers *within a given stock* and attributes it to underlying broker ability. For each of these measures we answer both the desire to and ability in manipulating questions raised above.

Columns (1) and (2) answer the first question; are more able brokers also more likely to be principal brokers. Column (1) in Table 7 shows that *BABtot* is positively correlated with both *PRINcycle* and *PRINnoncycle*:[36] Brokers with greater (overall) ability are more likely to act as principals and engage in price manipulation. Column (2) repeats the same exercise for the *BABnet* measure i.e. broker ability within a stock. The interesting difference is that *BABNet* is not significantly correlated with either *PRINcycle* or *PRINnoncycle*. Thus once we net out the part of a broker's ability that makes him select the "right" stock to trade in, more (within-stock) able brokers are not more likely to act as principals or price manipulators. Column (3) then tries to identify broker characteristics that are correlated with overall broker ability. The results show that almost a quarter of the profit differential between brokers (*BABtot*) can be accounted for brokers acting as principals and manipulating prices: *PRINcycle* and *PRINnoncycle* are both significantly correlated with broker ability. However, other broker characteristics such as broker size (as determined by the logarithm of total trading value of the broker), depth (number of firms the broker trades in) and trade frequency (fraction of a firms' total trading days a broker trades in) show little correlation to broker ability suggesting that it is not broker attributes like wealth or the ability to provide liquidity that matter but rather how much a broker acts like a principal and manipulates prices.

Columns (4)-(7) then examine whether more able brokers are more successful when they act as principal brokers. Column (4) shows that indeed brokers with greater overall ability gain more when they act as principals i.e. the interaction between *PRIN* and *BABtot* is positive, large and significant (17.29). Therefore, while acting as a principal broker and manipulating prices is rewarding, this reward does require and increase in ability.[37] Interestingly, Column (5) shows that this interaction effect, while positive for both, is larger for *PRINnoncycle* than *PRINcycle*. This is consistent with either the *PRINcycle* measure being confounded with Badla brokers (see Section 3) or that broker overall ability has a greater impact on profits from acyclical behavior than cyclical trading behavior by principal brokers. Columns (6)-(7) show similar results using the *BABnet* measure i.e. broker ability within a stock: More able brokers earn more when they act as principals. Column (6) shows that the interaction term between *PRIN* and *BABnet* is still

[36] Since regressions in Columns (1)-(3) are at the broker level they have 147 observations and the *PRINcycle* and *PRINnoncycle* measures are therefore averaged over all firms a broker trades in.

[37] The insignificant level coefficient (-0.52) on *PRIN* suggests that for the least able brokers, acting as a principal has little effect or perhaps, what is more likely, these brokers are not really acting as "manipulating" principal-brokers but just get a high *PRIN* value because they trade for themselves.

positive and significant (19.78) and Column (7) that, as before, the interaction effect is larger for $PRINnoncycle$ than $PRINcycle$.

7 Concluding Remarks

This paper undertakes a detailed micro-level analysis of the stock market in Pakistan and uncovers pervasive manipulation of stock prices by brokers. What sustains this manipulation is the fact that brokers engaging in such activity earn substantially higher returns, *and* that there exists a continuous stream of irrational trend-chasers to be taken advantage of.

This begs the question as to whether these results are important from a macro perspective? Is the market-inefficiency documented in this paper likely to lead to serious bottle-necks in a country's development? Alternately, is this effect just an "interesting side-show" i.e. manipulation is bad, but other problems in equity markets such as weak corporate governance overshadow manipulation in terms of magnitudes. One can answer this question from either a partial-equilibrium perspective or a general-equilibrium one. From the partial-equilibrium perspective, the transfer of resources from outsiders to manipulators is likely to significantly discourage how much and how many outside investors choose to participate in the market. Moreover, the presence of manipulators and naive traders imposes large participation costs for rational and sophisticated agents trying to raise or invest capital in equity markets. Such participation costs form an important piece for solving the puzzle of financial under-development.

However, the general-equilibrium effects of manipulation from a political economy perspective could be even more serious. The large profits reaped by entrenched brokers have important political economy implications: Even if it is obvious what reforms need to be taken to improve the efficiency of the market, since such reforms are likely to make it harder to engage in manipulation, they will be resisted by the conspiring brokers. This will particularly be the case when in the post-reform improved equilibrium, we cannot guarantee the conspiring brokers a large enough share of the pie. This has indeed been the case in Pakistan where continual efforts by the SECP to initiate reforms have met with strong political opposition by lobbies working on the brokers' behalf.

This political economy story argues that rents earned by a small number of individuals can prevent reforms beneficial to the economy at large. This suggests that these rents must be large from the individual investor's perspective. In calculating the returns to manipulating brokers, we have already mentioned several reasons why our estimate is likely to be an under-estimate of the true manipulation profit of brokers. For the sake of illustration, lets assume that the *true* manipulation coefficient on $PRIN$ is 10%.[38] We can then calculate the expected manipulation profits for each broker using the fact that $PRIN$ for a given broker-stock can be interpreted as the percentage of shares traded by that broker in that stock on his own behalf. Therefore the estimated *level* profit a broker earns through manipulation is simply the amount he invests on his own behalf (the product of $PRIN$ and the discounted value of his total investment) times the estimated rate of return (10%) for such trades. We can then sum this expected profit across all stocks traded by a given broker. Figure 6 plots these expected profits for all the brokers. The distribution has a mean of 4.4 million US$, and a median of 2.2 million US$, with the higher profits ranging in the 10 to 45 million US$ range. These are *substantial* annual profits in a country like Pakistan (where per capita income is around 450 US$), and explains why brokers continuously resist any reforms aimed at limiting such behavior.

A related question is how risky are the manipulation strategies employed by brokers? Note that *all* our analysis in this paper revolves around comparing principal and outsider profits *within the same stock*. This implies that manipulating brokers are facing the same stock-specific risk. There can still be some strategy-specific risk within the same stock, that is higher for manipulating brokers than the outside investor. However, at least in terms of the aggregate market, if we divide the market into manipulators and outsiders, then since markets clear at each point in time, the level gain by one party exactly equals the level loss by the other party. In other words, it is a zero-sum game. This further strengthens our view that manipulating brokers are not exposed to extra risk compared to the outside investor.

To conclude, identifying inefficiencies like manipulation and the resulting significant rents accruing to individuals can help answer the more fundamental question of why countries fail to adopt or implement good governance and other laws needed to strengthen equity markets. Moreover, it also suggests that such rents, while small relative to the market, may lead to inefficiencies if the public/government is unable to guarantee transfers to rent-earning individuals to prevent them from blocking of reforms. Since these factors are likely to occur in emerging markets which are newer and shallower, they can in turn be *responsible* for limiting the depth and size of such markets leaving them in “infancy traps” in the absence of a positive reform. Such failures can help us understand how and why equity markets, whose job is to facilitate *real* economic activity, remain as *phantom* markets that seem to serve little economic purpose.

[38] The coefficient on WLS regression was about 8%. (see Table 3)

Appendix: Construction of ARR measure

This section describes how the main outcome measure, the Annual Rate of Return (ARR) is calculated for a given Stock-Broker.

We start with the simple example in Table A1. The Table gives the trading history (10 actual trading days) of a broker in a particular stock. On each day we can calculate the net shares of the given firm sold by the broker and the resulting revenue R_t (positive net sale) or investment I_t (negative net sale i.e. net purchase) received/undertaken by the broker. Note that since we do not know the price at which a particular trade occurred we can only calculate this revenue/investment based on the net position of the broker at the end of the trading day and we price this position at the average price of the stock during that day. For illustration assume no discounting. In this case we can simply sum up the brokers total revenue R_{tot} and total investment I_{tot} during his entire trading history. ARR would then simply be the annual rate of return that gives a total revenue of R_{tot} for an investment of I_{tot} over a period of T years (the total length of the brokers trading history) i.e. $I_{tot}(1 + ARR)^T = R_{tot}$. With discounting the only change would be that we discount the revenue stream forward to the last trading date and the investment stream back to the first trading date of the firm.[39]

However, an issue which arises with the ARR measure is immediate in the example in Table A1 - how do we treat a broker if the last trade we observe him do in our data sample period does not "balance" out all his previous trades i.e. in Table A1 the last trade the broker makes is in period 10 and after this trade he is left with a "inventory" of $98,500$ shares.[40] The issue is how should we treat this end net position. We offer the two solutions below.

The first solution is simpler and results in the ARR measure used in the paper. This solution assumes that any net position is liquidated at the end of last trading date for the particular stock. Thus in the example in Table A1 we "force" the broker to liquidate his net position on the last date anyone traded the firm's stock[41] i.e. we force the broker to sell the $98,500$ shares he had accumulated at the average price on this last date (2.2). We can recalculate total revenue earned and investments made by the broker by also including this last forced trade. In the example given in table A1 and assuming no discounting this would mean that ARR *is* given by the solution to $775,000(1 + ARR)^T = 981,200$ where T is the total trading length in number of years of the firm's stock. Thus if the firm traded for a total of exactly one year during our period, the ARR with no discounting would be 26.5%.

The second measure of the annual rate of return, $ARR2$, is meant more as a robustness check on our first: Instead of imposing that the broker clear his position by a forced liquidation on the last trading date of the firm, we "net out" his end net position. Effectively we are forcing the broker to earn 0 profits on his ending position. To illustrate this consider the example in Table A1 again.

[39] To make brokers comparable within a firm, we use the same first and last trading date for each broker i.e. the first date the firm was traded (by any broker) during our period and the last date the firm was traded (by any broker) during our period. In alternate ARR measures we have allowed each broker's start and end trading date to be the last date of his trade in the given firm. Doing so does not change our results (regressions not shown).

[40] Note that this "inventory" is calculated using the observed trading history of the broker during our sample period. Since we are only concerned with estimating returns of the broker accrued by trading activity during our sample period, it does not matter what his starting inventory level was (i.e. how many shares he held before his first observed trade).

[41] Forcing liquidation earlier is incorrect since we know that the broker hasn't traded in between his last observed trade and the last day anyone traded in the given firm. Forcing liquidation on date *after* the last date anyone traded the firm's stock is not possible since no price is available for such a trade.

Note that on date 7 the broker has a net "inventory" of exactly 0 and after this date, on net, each trading day he only accumulates shares. The $ARR2$ measure will ignore this last accumulation and create a "new" trading history for the broker in which we assume that he never trades after date 7. In our simple example this implies only looking at the date 1-7 trades of the broker.[42] Thus $ARR2$ (without discounting) in this example would be the solution to $578,500(1 + ARR2)^T = 764,500$ where $578,500$ is the total investments incurred through net share purchases during dates 1-7 and $764,500$ is the total revenue generated by net sales during dates 1-7. Assuming T is one year and no discounting as before gives an $ARR2$ of 32%.

However, as expected, both ARR and $ARR2$ are highly correlated and our results do not depend on which is used. We therefore stick to the simpler ARR measure in the paper.

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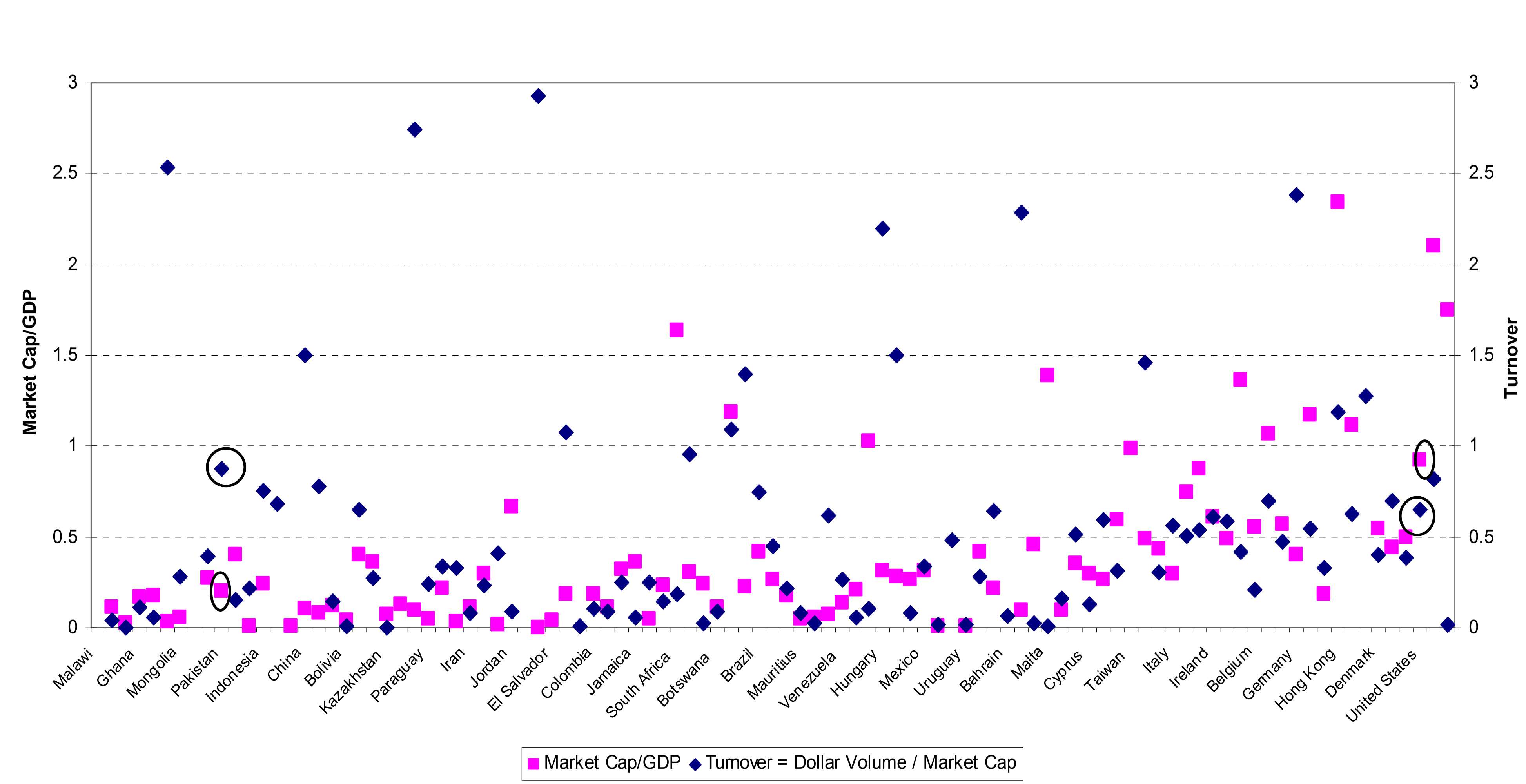
Figure 1: Market Size & Turnover across Countries

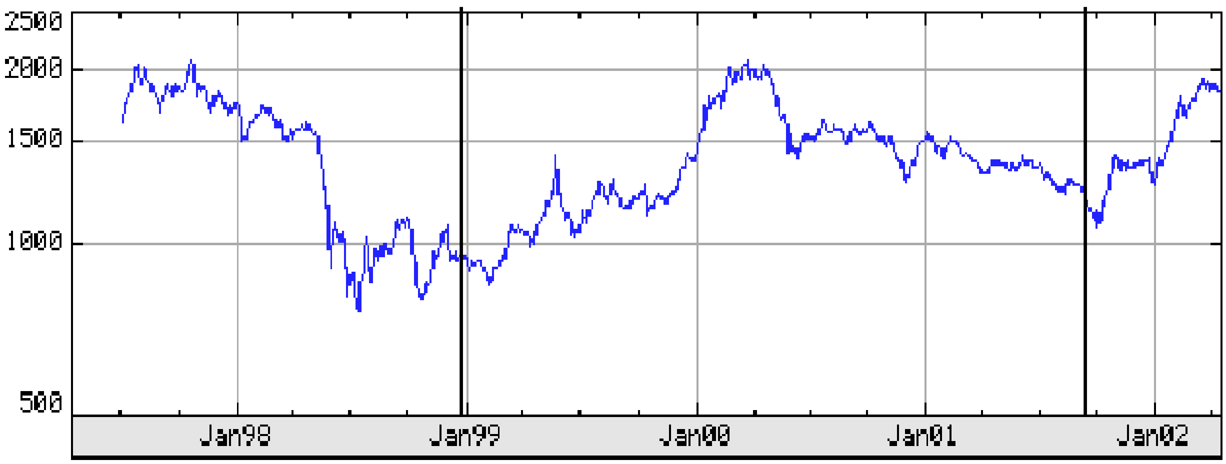


MC/GDP Outliers not shown: Bahrain=9, Namibia=8.9, Iceland=8.4

Turnover Outliers not shown: Ecuador=31, El-Salvador=11.1, Taiwan=4.3

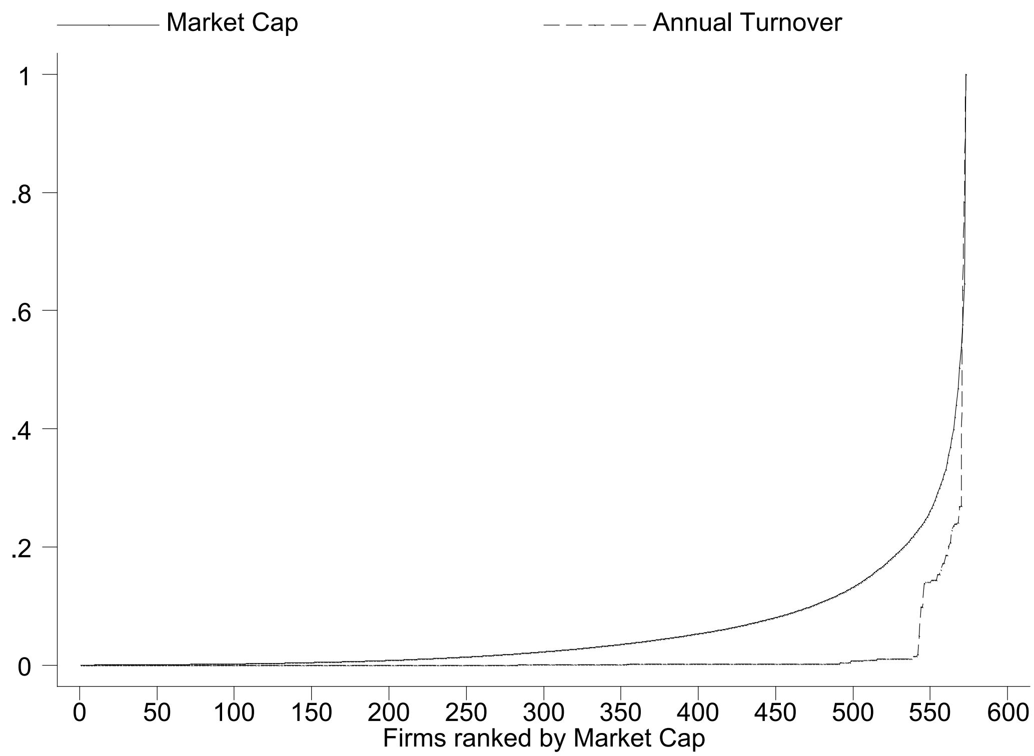
Every Third Country labeled on the above axis. Countries are sorted by GNP/capita. Complete list is as follows: Malawi, Nigeria, Tanzania, Ghana, Kenya, Bangladesh, Mongolia, Moldova, India, Pakistan, Zimbabwe, Armenia, Indonesia, Uzbekistan, Ukraine, China, Honduras, Sri Lanka, Bolivia, Philippines, Morocco, Kazakhstan, Ecuador, Swaziland, Paraguay, Egypt, Bulgaria, Iran, Russia, Romania, Jordan, Guatemala, Macedonia, El Salvador, Thailand, Namibia, Colombia, Tunisia, Peru, Jamaica, Latvia, Lithuania, South Africa, Turkey, Panama, Botswana, Malaysia, Estonia, Brazil, Slovakia, Lebanon, Mauritius, Costa Rica, Poland, Venezuela, Croatia, Chile, Hungary, Czech Rep, Trinidad and Tobago, Mexico , Zambia, Oman, Uruguay, Saudi Arabia, Argentina, Bahrain, South Korea, Barbados, Malta, Slovenia, Portugal, Cyprus, Greece, New Zealand, Taiwan, Spain, Israel, Italy, Australia, Canada, Ireland, France, United Kingdom, Belgium, Singapore, Finland, Germany, Netherlands, Austria, Hong Kong, Sweden , Iceland, Denmark, Norway, Japan , United States, Switzerland, Luxemburg. **Source:** Bhattacharya and Daouk [2002]. Pakistan and US encircled.

Figure 2: KSE100 Index (log) June 1997-March 2002[*]



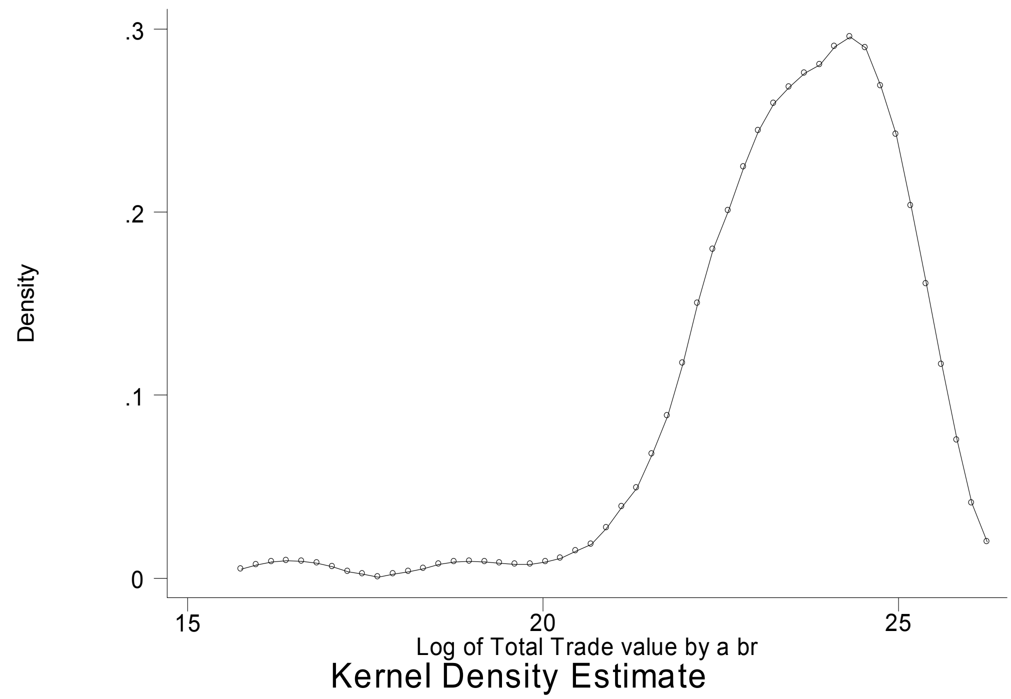
[*]The dark vertical lines in the figure above indicate the period for which we have broker-firm level daily trading data.

Figure 3: Cumulative Share of Market Capitalization and Turnover by Firm[$]



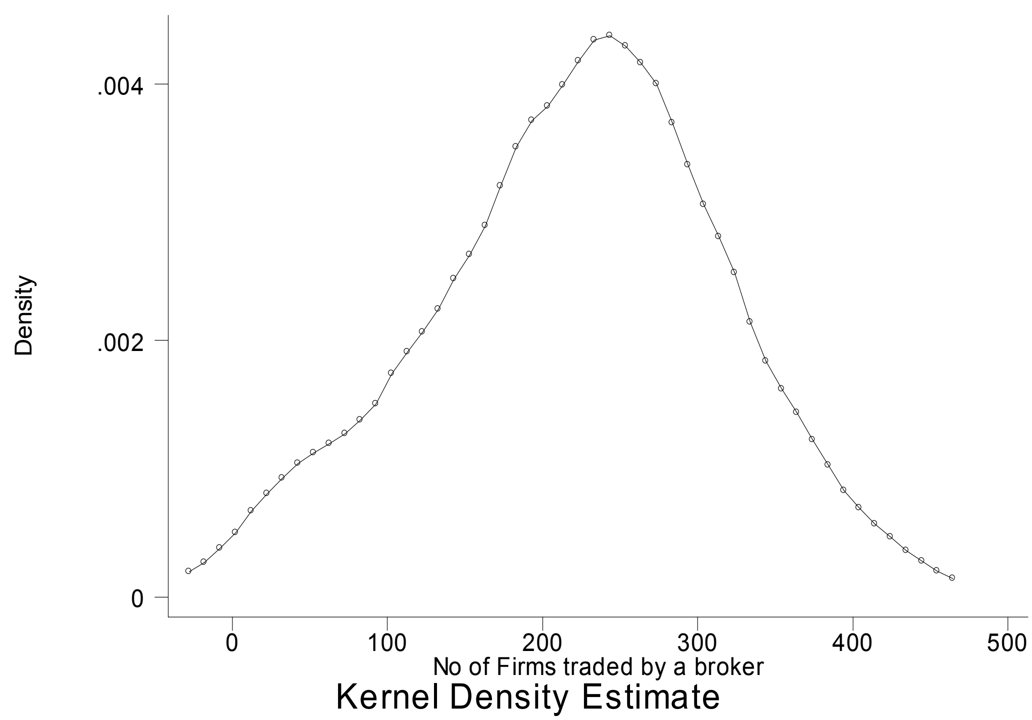
[$]Market Capitalization for the firms is the average over our sample period and the annual turnover for each firm is for the year 2000. While we have turnover for all the 714 firms in our sample, since we only have market capitalization for 575 of those firms, to be consistent the above CDFs are only for these firms. However, from our turnover numbers we know that these missing (market cap) firms are small and therefore won't affect the above CDFs qualitatively.

Figure 4a: PDF for Broker Size#



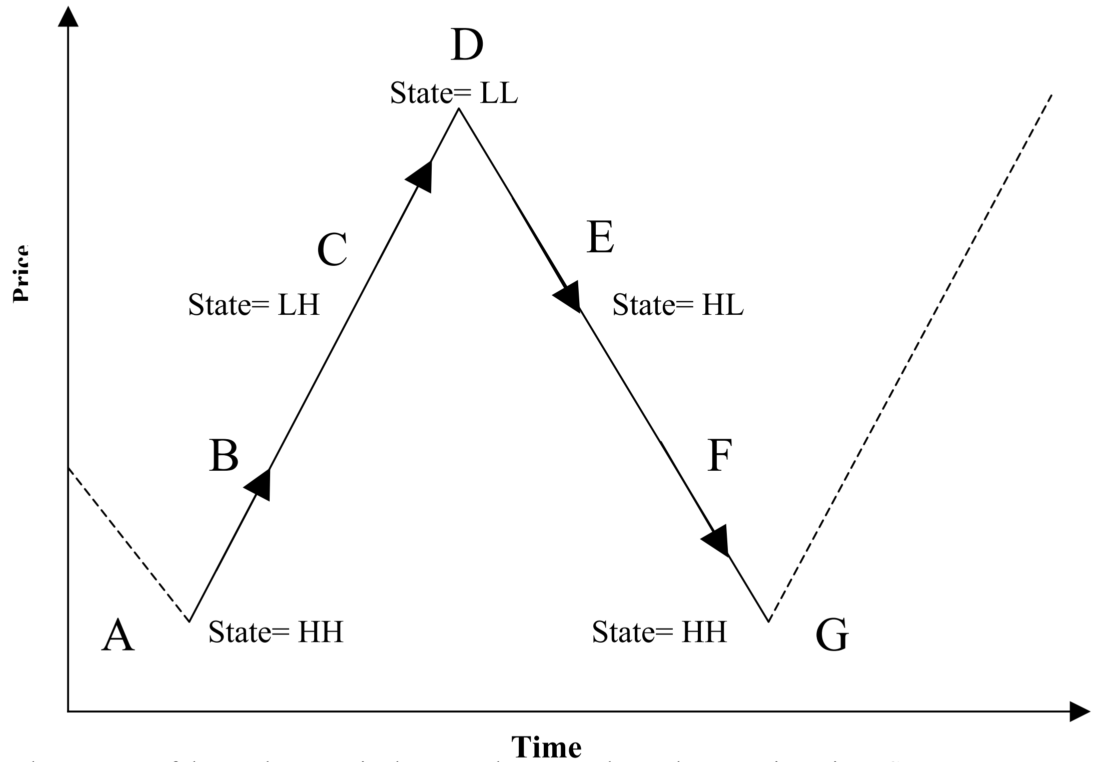
Broker Size is proxied by the natural logarithm of the total trade value (value of all purchases and sales) of the broker during our sample period.

Figure 4b: PDF for Broker Coverage$



$ Broker Coverage is the number of different firms the broker ever traded in during our sample period

Figure 5: Trading Cycles- a hypothetical example



Key

A: Naïve traders are out of the market. Manipulators trade among themselves to raise prices. State= HH.
B: "Artificial" price increases attracts naïve/positive feedback traders.
C: More naïve traders enter, as manipulators sell their last remaining stock. Some naïve investors also start selling to other naïve ones. State=LH
D: Price reaches its peak. Manipulators have sold everything to the naïve investors. With the manipulators out, the price starts dropping. State=LL
F: When price drops sufficiently, manipulators start buying again. State=HL
F: Price drops further. Manipulators start buying. *Pb*=H, *Ps*=L
G: Cycle restarts (as in A)

Figure 6: Estimated Annual Level Profits by Broker

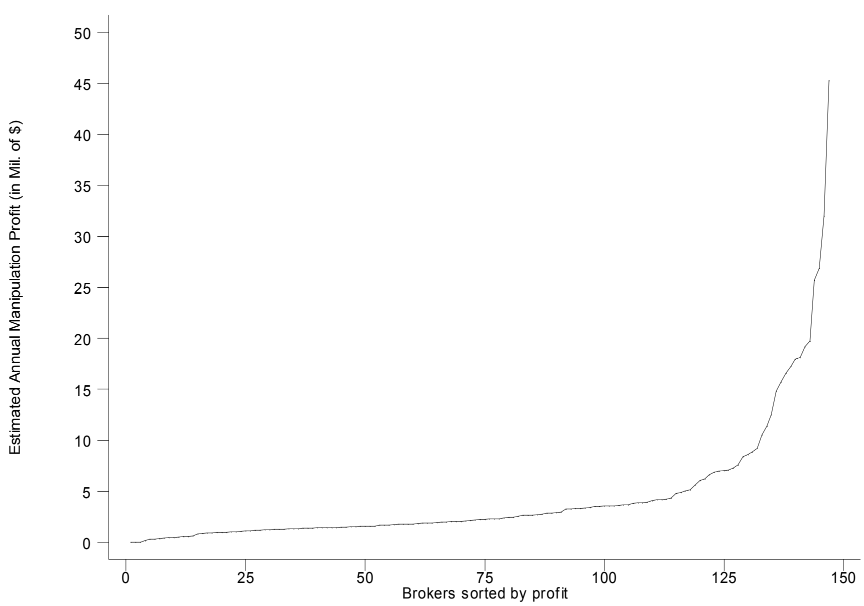


Table 1: Principal and Intermediary Brokers Trading – An Example

(1) Broker A (IB) *PRIN* = 0.1		(2) Broker B (PB) *PRIN* = 0.9		(3) Broker C (PB) *PRIN* = 1	
Shares Sold	Shares Purchased	Shares Sold	Shares Purchased	Shares Sold	Shares Purchased
427,000	100,000	6500	0	0	660,000
114,000	41,000	500	0	660,000	0
200,000	487,000	500	0	0	660,000
259,000	230,000	500	0	660,000	0
204,500	886,500	1000	0	0	660,000
123,000	393,000	500	0	660,000	0
121,500	80,000	1364000	520500	0	660,000
63,000	149,500	0	10000	660,000	0
75,000	37,000	0	25000	0	660,000
101,500	4,000	282500	0	660,000	0
143,000	139,000	500	0	0	900,000
151,000	120,500	156000	0	900,000	0
49,500	78,500	42500	0	0	900,000
0	42,500	150000	0	900,000	0
65,000	214,000	1212500	12500	0	850,000
77,000	256,000	1000000	0	850,000	0
31,000	43,500	0	147000	0	458,500
2,000	24,000	1000000	0	458,500	0
42,500	1,000	1000000	0	0	460,000
0	69,000	400000	0	460,000	0

The table gives 20 consecutive trades carried out by three different brokers for a given firm in our data. Broker A has a low *PRIN* values and is therefore an Intermediary broker whereas Brokers B and C, with high *PRIN* values are considered to be Principal brokers (i.e. brokers who only act for themselves or a single client). *PRIN* = the probability that a broker only buys, only sells or buys or sells the same amount of a stock on a given day. The *PRIN* values shown are calculated for the 20 trades shown.

Table 2: Summary Statistics by Firm-Broker PRIN categories

PRIN category	Number of Firm-Brokers	Aggregate Turnover of Firm-Brokers	"Excess"[$] Annualized Rate of Return (ARR) of Firm-Brokers (%)
	(1)	(2)	(3)
Panel A: All Firms			
0≤*PRIN*<0.5	1,942	4.44E+12	-0.09
0.5≤*PRIN*<0.9	8,573	3.92E+11	0.49
0.9≤*PRIN*<1	6,043	2.65E+10	1.23
PRIN=1	16,092	6.35E+09	2.75
Panel B: Top 15 Firms dropped[*]			
0≤*PRIN*<0.5	494	8.96E+10	-0.28
0.5≤*PRIN*<0.9	7,915	1.36E+11	0.47
0.9≤*PRIN*<1	6,005	1.98E+10	1.21
PRIN=1	16,078	5.92E+09	2.74
Panel C: Only Top 15 Firms			
0≤*PRIN*<0.04	165	1.66E+12	-0.19
0.04≤*PRIN*<0.08	132	1.15E+12	-0.15
0.08≤*PRIN*<0.2	314	8.97E+11	-0.06
0.2≤*PRIN*<0.5	837	6.41E+11	0.04
0.5≤*PRIN*<0.9	658	2.56E+11	0.68
0.9≤*PRIN*<1	38	6.67E+09	3.80
PRIN=1	14	4.32E+08	4.90

[$]ARR = the nominal rate of return based on a brokers total investments (purchases discounted back) and cashflows (sales discounted forward). Since the ARR definition assumes a 10% nominal discount rate (see Appendix), we present these results as the extra return over this nominal return (i.e. as ARR – 10) so make the zero-sum aspect of the returns clear i.e. market clearing implies that the weighted (by trading volume) sum of the ARR's in each *PRIN* category is zero. Recall *PRIN* = the probability that a broker only buys, only sells or buys or sells the same amount of a stock on a given day.

[*]Panel B presents the same statistics but drops the top 15 (by trading volume) firms. We suspect that in such large firms there would be little variation in the PRIN measure and most brokers would be acting as intermediaries (as is borne out in table). Panel C presents the results for only these top 15 firms.

Table 3: The effect of Manipulation on Profitability – Regression Results

	(1) ARR	(2) ARR with no discounting	(3) ARR with Broker FEs	(4) ARR	(5) ARR	(6) ARR (WLS)	(7) ARR ("Badla" firms excluded)	(8) ARR
PRIN	5.76***	4.09***	5.93***		3.16***	7.93***	7.27***	
	(0.57)	(0.47)	(0.68)		(0.54)	(0.91)	(0.94)	
*PRIN*rest				4.11***				
				(0.52)				
*PRIN*dum					1.31***			
					(0.19)			
PRINcycle								4.78***
								(0.59)
PRINnoncycle								6.38***
								(0.60)
Observations	32666	32666	32666	32666	32666	32666	28417	32666
R-squared	0.08	0.08	0.09	0.08	0.08	0.18	0.08	0.08

Robust standard errors in parentheses except column (6).
All regressions include firm fixed effects.
*** significant at 1%

Recall ARR = the nominal rate of return based on a brokers total investments (purchases discounted back) and cashflows (sales discounted forward) and *PRIN* = the probability that a broker only buys, only sells or buys or sells the same amount of a stock on a given day. "ARR with no discounting" (Col 2) is similar to ARR except that it uses a 0% discount rate instead of using 10%. *PRIN*rest (Col 4) uses a more restrictive definition of *PRIN* i.e. *PRIN*rest = the probability that a broker only buys or only sells a stock on a given day. *PRIN*dum (Col 5) is an indicator variable for *PRIN*=1. Column 6 reports weighted least squares, where the weight for each firm-broker is the fraction of overall trade in that firm done by the broker. Column 7 excludes the 31 (liquid) firms where Badla trade is officiall allowed by the KSE. Column 8 "splits up" the *PRIN* measure into *PRINcycle* and *PRINnoncycle* where *PRINcycle*= the probability that a broker only buys, or only sells AND buys (or sells) the same amount of the stock on a given day as the next trade days' sell (or buy). *PRINnoncycle*= the probability of the (PRIN condition AND a that the trade is not a pure-cycle) where a pure cycle event indicator is that the trade is cyclic (today's buy/sell or equal to next trade's sell/.buy) and pure (only a buy or sell is made on a given day).

Table 4: Cyclical Profitability and State Contingent Prices

	(1)	(2)	(3)
	ARR	**Frequency the state is observed**	**Normalized Price**
PRINcycle	1.37*		
	(0.83)		
PRINnoncycle	5.78***		
	(0.63)		
*PRINcycle*PRINnoncycle*	7.48***		
	(1.61)		
HH		31.1%	-9.85***
			(0.73)
HL		19.2%	-3.97***
			(0.80)
LH		21.4%	-4.31***
			(0.81)
Constant (LL omitted state)		28.4%	105.2***
			(0.57)
Observations	32666		2187 [$]
R-squared	0.08		0.07

Robust standard errors in parentheses
Regression in Col (1) includes firm fixed effects
*** significant at 1%

Recall ARR = the nominal rate of return based on a brokers total investments (purchases discounted back) and cashflows (sales discounted forward) and *PRIN* = the probability that a broker only buys, only sells or buys or sells the same amount of a stock on a given day. *PRINcycle*= the probability that a broker only buys, or only sells AND buys (or sells) the same amount of the stock on a given day as the next trade days' sell (or buy). *PRINnoncycle*= the probability of the (PRIN condition AND a that the trade is not a pure-cycle) where a pure cycle event indicator is that the trade is cyclic (today's buy/sell or equal to next trade's sell/.buy) and pure (only a buy or sell is made on a given day).
In Columns (2) and (3) the state classification variable is $I_B I_S$, where I_B and I_S refer to the overall *PRIN* category of buyers and sellers trading that firm's stock on that date.

[$] The number of observations is a lot smaller because we are in fact not running the regression at the firm date level but at the firm category level: We collapse all observations for a given category in a given firm by computing the mean price and then run a regression on this reduced sample. This is the most demanding way of correcting for any correlations in errors across the same category for a given firm. A less severe alternate would be to cluster errors at the firm-category level (our results are very similar if we do).

Table 5: State Contingent Returns

State	State Contingent Future Return		State Contingent Past Return	
	(1)	(2)	(3)	(4)
	ALL FIRMS	TOP 25%	ALL FIRMS	TOP 25%
HH	0.1686**	0.0967	-0.1509**	-0.1840**
	(0.0813)	(0.0999)	(0.0667)	(0.0815)
LL	-0.2571***	-0.1086	0.1773**	0.2230**
	(0.0750)	(0.1014)	(0.0728)	(0.0879)
HL	-0.4037***	-0.4039***	-0.2201*	-0.3454**
	(0.1068)	(0.1369)	(0.1281)	(0.1402)
LH	0.5964***	0.4390***	0.1635	0.0899
	(0.1111)	(0.1318)	(0.1077)	(0.1308)
HHend	0.5281***	0.3177*		
	(0.1385)	(0.1619)		
LLend	-0.7192***	-0.6973***		
	(0.1489)	(0.1566)		

Robust standard errors in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%

Each cell in the table represents the result of a different regression on weekly data (a total of 141 weeks). Specifically, we regress the weekly (future/past) "above-market" return from holding each week a portfolio that had a given type (*HH* etc.) in the past week, on a constant (i.e. the coefficient estimate is therefore just the mean return from holding such weekly-portfolios over the 141 weeks). The state classification variable is $I_B I_S$, where I_B and I_S refer to the overall *PRIN* category of buyers and sellers trading that firm's stock on that date. Thus an *HH*-portfolio in this case, is the portfolio of stocks that had an average state of *HH* during the week. An *HHend*-portfolio is like the *HH*-portfolio except that for this portfolio in addition, the average state in the next week does NOT remain HH. Recall *PRIN* = the probability that a broker only buys, only sells or buys or sells the same amount of a stock on a given day.

Table 6: Heterogeneity Across Firms

	(1)	(2)	(3)	(4)
	ARR	ARR	ARR	ARR
PRIN	3.91***	6.20*	9.45***	-0.08
	(0.46)	(3.65)	(1.50)	(1.47)
*PRIN*SMALL*	4.30***			
	(1.26)			
*PRIN*SIZE2*		3.12		
		(4.27)		
*PRIN*SIZE3*		1.42		
		(3.86)		
*PRIN*SIZE4*		-0.47		
		(3.91)		
*PRIN*SIZE5*		-1.58		
		(3.77)		
*PRIN*SIZE6*		-2.12		
		(3.73)		
*PRIN*SIZE7*		-4.34		
		(3.70)		
*PRIN*COVPR*				20.35***
				(5.80)
*PRIN*CONC2*			-4.67***	
			(1.80)	
*PRIN*CONC3*			-6.43***	
			(1.73)	
Observations	32666	32490	26308	32666
R-squared	0.08	0.08	0.08	0.08

Robust standard errors in parentheses
All regressions include firm fixed effects
*** significant at 1%

Recall ARR = the nominal rate of return based on a brokers total investments (purchases discounted back) and cashflows (sales discounted forward) and *PRIN* = the probability that a broker only buys, only sells or buys or sells the same amount of a stock on a given day. *SMALL* is an indicator for whether the firm is small i.e. not one of the top 100 firms (by market cap). *SIZE1* through *SIZE7* are indicator variables indicating the size category of a given firm, with *SIZE7* being the largest group of firms. *COVPR* is the firm-specific coefficient of variation of price. *CONC2-3* are dummies that indicate the degree of concentration of holdings in the firm where *CONC1* (the dropped dummy) indicates that those shareholders with more than 5% shares cumulatively hold less than 40%, CONC2 40-70% and *CONC3* greater than 70% of the firm's shares. (Note that we do not have the ownership concentration numbers for all the firms).

Table 7: Heterogeneity Across Brokers

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dependent Variable:	*BABtot*	*BABnet*	*BABtot*	ARR	ARR	ARR	ARR
Ability Measure:	*BABtot*	*BABnet*	*BABtot*	*BABtot*	*BABtot*	*BABnet*	*BABnet*
*PRIN*BAB(tot/net)*				17.29***		19.78***	
				(2.71)		(6.66)	
*PRINcycle*BAB(tot/net)*					11.02***		13.61***
					(3.42)		(7.51)
*PRINnoncycle*BAB(tot/net)*					19.72***		25.81***
					(2.85)		(7.53)
PRIN				-0.52		-6.36	
				(1.27)		(4.21)	
PRINcycle	0.68***	0.37	0.64**		1.55		-2.8
	(0.28)	(0.33)	(0.33)		(1.51)		(4.76)
PRINnoncycle	1.30***	0.30	1.13***		-1.22		-9.86**
	(0.28)	(0.30)	(0.40)		(1.33)		(4.76)
logBtval			0.007				
			(0.010)				
Bnofirms			0.0002				
			(0.0002)				
Bfreq			-0.36				
			(0.71)				
Adj Rsq	0.21	0.03	0.23	0.07	0.07	0.07	0.07
No of Obs	147	147	147	32666	32666	32666	32666

Robust standard errors in parentheses.
Columns (4)- (7) include both firm and broker fixed effects.
*** significant at 1%; ** significant at 5%

Recall ARR = the nominal rate of return based on a brokers total investments (purchases discounted back) and cashflows (sales discounted forward) and *PRIN* = the probability that a broker only buys, only sells or buys or sells the same amount of a stock on a given day. *PRINcycle*= the probability that a broker only buys, or only sells AND buys (or sells) the same amount of the stock on a given day as the next trade days' sell (or buy). *PRINnoncycle*= the probability of the (PRIN condition AND a that the trade is not a pure-cycle) where a pure cycle event indicator is that the trade is cyclic (today's buy/sell or equal to next trade's sell/.buy) and pure (only a buy or sell is made on a given day). *BABtot* = coefficients on broker dummies from a regression of *ARR* on broker fixed effects, *BABnet* = coefficients on broker dummies from a regression of *ARR* on broker *and firm* fixed effects. *LogBtval* = natural logarithm of the total trade value (value of all purchases and sales) of the broker during our sample period. *Bnofirms* = number of different firms the broker ever traded in during our sample period. *Bfreq* = fraction of a firms' total trading days a broker trades in.
Regressions in Columns (1)-(3) are at the broker level and hence use *PRINcycle* and *PRINnoncycle* measures averaged over all firms a broker trades in. The remaining regressions are at the Firm-Broker level.

Table A1: Profitability Calculation Example

Date	*Shares Sold*	*Shares Bought*	*Net Shares Sold*	*Share "Inventory"*	*Stock Price*	*"Revenue"*	*"Investment"*
1	143,000	139,000	4,000	-4,000	1	4,000	
2	151,000	120,500	30,500	-34,500	1	30,500	
3	49,500	78,500	-29,000	-5,500	1		29,000
4	0	42,500	-42,500	37,000	1		42,500
5	65,000	214,000	-149,000	186,000	1		149,000
6	77,000	256,000	-179,000	365,000	2		358,000
7	408,500	43,500	365,000	0	2	730,000	
8	2,000	24,000	-22,000	22,000	2		44,000
9	2,500	10,000	-7,500	29,500	2		15,000
10	0	69,000	-69,000	98,500	2		138,000
Last			*98,500*	0	2.2	216,700	
Total						*981,200*	*775,500*

ARR = the nominal rate of return based on a brokers total investments (purchases discounted back) and cashflows (sales discounted forward). *ARR* is calculated by the forced sale at date = "Last" and price =2.2. *ARR* solves $775{,}000*(1+ARR)^{T} = 981{,}200$ (assuming no discounting) where T is the total trading length in number of years of the firm's stock. For T=1 year, *ARR* = 26.5%. *ARR2* instead "nets out" last trades such that a broker ends up at a 0 net position. In the Table this implies netting out the last 3 trades so that only dates1-7 are considered. Therefore *ARR2* solves $578{,}500*(1+ARR2)^{T} = 764{,}500$ (assuming no discounting). For T=1 year, *ARR* = 32%.