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Unchecked intermediaries: Price manipulation in an emerging stock market☆

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Abstract

How costly is the poor governance of market intermediaries? Using unique trade level data from the stock market in Pakistan, we find that when brokers trade on their own behalf, they earn annual rates of return that are 50-90 percentage points higher than those earned by outside investors. Neither market timing nor liquidity provision by brokers can explain this profitability differential. Instead we find compelling evidence for a specific trade-based "pump and dump" price manipulation scheme: When prices are low, colluding brokers trade amongst themselves to artificially raise prices and attract positive-feedback traders. Once prices have risen, the former exit leaving the latter to suffer the ensuing price fall. Conservative estimates suggest these manipulation rents can account for almost a half of total broker earnings. These large rents may explain why market reforms are hard to

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implement and emerging equity markets often remain marginal with few outsiders investing and little capital raised.

JEL classification: G14; G15; G18; G24; D40

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1. Introduction

The governance of equity market intermediaries through the appropriate design and enforcement of law and regulation particularly in emerging markets has received increased emphasis recently (see Glaeser et al., 2001; La Porta et al., 2003). A belief is growing that emerging markets need improvements in their legal and institutional environment to develop. For example, Glaeser, Johnson, and Shleifer argue that self-regulation by brokers in emerging economies with costly law enforcement is unlikely to be successful. However, despite such concerns, little is known about the costs of misgovernance among market intermediaries. Poor regulation and weak enforcement of law lead to what kind of undesirable outcomes? What behavior of market intermediaries should regulation curb? What are the costs when legal and regulatory checks fail? This paper answers these questions by an in-depth analysis of broker behavior in an emerging stock market.

We identify brokers in the stock market who manipulate prices to their own advantage and at the expense of the outside investor. These brokers engage in frequent and strange trading patterns indicative of the anecdotally familiar "pump and dump" manipulation schemes. We show that these schemes result in substantial gains of 50 to 90 percentage points higher annual returns than the average outside investor. These large rents not only explain why many potential rational investors choose to stay out of the equity market, but also from a political economy perspective help provide an understanding of why entrenched players so often actively resist efforts to institute reforms. If such manipulation and its magnitude are substantial, then the results of this paper would add to an understanding of why equity markets fail to develop in many poor economies.[1]

The manipulation activity identified in this paper is likely to be prevalent among other emerging markets. Numerous accounts of emerging markets today show similar concerns. Khanna and Sunder (1999), in a case study of the Indian stock market, states that "brokers were also often accused of collaborating with company owners to rig share-prices in pump-and-dump schemes". Zhou and Mei (2003) argue

[1]In the United States, an estimated 50 million individuals, or about one-fifth of the population invest in the stock market directly or indirectly through mutual funds. Over 20% of financial wealth of the average U.S. household is held in equity and equity-linked instruments. In contrast, in an emerging market such as India, there are believed to be no more than 3 million to 4 million retail investors out of a population of more than 1 billion The Reserve Bank of India estimates that less than 2% of the financial wealth of Indian households is held in equity and equity-linked instruments comprised.

that manipulation is rampant in many emerging markets where regulations are weak and note that China's worst stock market crime in 2002 was a scheme by seven people accused of using brokerage accounts to manipulate company share prices.

Moreover, historical accounts of mature financial markets suggest that such manipulation is a common hurdle that young markets have to overcome. For example, the Amsterdam stock exchange in the 1700s and the New York Stock Exchange in the 1900s (Gordon, 2000) show a wide concern for the prevalence of price manipulation in these markets. The stated justification for the U.S. Securities Exchange Act of 1934 was to eliminate manipulation resulting from stock pools, whereby groups of traders jointly trade in a particular stock to manipulate prices.

While anecdotes abound, the lack of suitable data has made it difficult to test for these stories. This paper, to our knowledge, offers one of the first attempts at doing so by exploiting a unique trade-level data set. The data set contains all daily trades of each broker in every stock trading during a two and a half year period on the Karachi Stock Exchange (KSE) the main stock exchange in Pakistan. The micro nature of this data set allows us not only to test for a specific price manipulation mechanism, but also estimate the returns from manipulation activities in general.

Because anecdotal evidence suggests that market intermediaries (brokers) run manipulative schemes, the paper starts by differentiating between trades done by a broker on his own behalf and those done on behalf of the outside investor. Given this separation, we find that when brokers trade on their own behalf (act as principals) they earn at least 50 to 90 percentage points higher annual returns over, and at the expense of, outside investors.

We then test directly for some possible means of manipulation. While several mechanisms of market manipulation could exist, anecdotal evidence and cyclical trading patterns suggest a particular one. 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. While this mechanism is stylized, we find compelling evidence for it. First, on days when the stock price is relatively low, principal brokers trade amongst themselves, i.e., most of the trade (both buys and sells) is done by brokers who act as principal traders in the stock. Conversely, on high price days, most trade is done by outside traders, i.e., principal traders are out of the market. Second, trading patterns of principal brokers have strong predictive power for future returns. Periods when principal brokers buy and sell stocks only to each other lead to positive returns. Such within principal broker trading cannot, by definition, affect the profitability differential because it captures the difference in profits between principal brokers and outside investors. Moreover, there is no reason to suspect that this relationship is spurious and not causal (such trades and the future positive returns are both caused by some unobserved real factor). If this were the case, one would expect the more informed, principal brokers to be either buying or selling but not doing both back and forth. Third, further evidence that this relationship reflects manipulation is that the price increase from back and forth principal broker trading appears artificial. Prices collapse once the principal brokers exit the market (the absence of principal brokers in the market predicts negative returns).

Whereas these tests provide compelling evidence for the presence of price manipulation, one could argue that the profitability differential could also arise for reasons other than price manipulation. Two broad classes of alternative explanations are that (1) brokers are better at market timing because of front running or access to private information and (2) brokers are market makers (earn rents for liquidity provision services). However, we show through a series of tests that these cannot be sufficient explanations for the profitability result. For example, the profitability of high-frequency cyclical trades is hard to reconcile with market timing in any realistic informational environment. Similarly, inclusion of broker attributes or liquidity measures fails to account for the profitability differential.

Natural reasons exist to expect that brokers have a comparative advantage in engaging in manipulation activities. They have lower transaction costs in conducting the frequent trades that could be necessary to generate momentum in a stock. They have better real-time information about the movement in prices, volumes, and traders' expectations, and they possess a natural advantage in spreading rumors or false information in the market. All these factors are crucial to the success of a manipulation strategy.

Finally, our calculations suggest that such manipulation rents are large in absolute terms. Conservative estimates reveal a \$100 million (Rs 6 billion) a year transfer of wealth from outside investors to principal, manipulating brokers, which is around 10% of market capitalization. In a country with per capita gross domestic product (GDP) at \$450, this is a significant wealth transfer. Moreover, estimates suggest that this is significant relative to the total earnings of brokers (including estimated brokerage commissions), accounting for 44% of these earnings.

Our paper is related more broadly to the literature on institutions defined as the appropriate design and enforcement of law, contracts, property rights, and regulation. This literature has taken a central stage in the discussion of financial and economic development. Examples include a series of theoretical papers motivated by cross-country comparisons such as Acemoglu et al. (2001, 2002), Acemoglu and Johnson (2003), La Porta et al. (1997, 1998, 2000, 2002), and Shleifer and Wolfenson (2002). This theoretical interest has coincided with recent micro-empirical work that has attempted to identify channels through which weak institutions lead to corporate and financial inefficiencies (Johnson and Mitton, 2003; Fisman, 2001; Bertrand et al., 2002; Boone et al., 2000). These papers identify weak shareholder protection and crony capitalism as important forces contributing to the loss of minority and unconnected shareholder wealth.

However, while the theoretical literature emphasize the importance of institutions more broadly, the micro empirical work has primarily focused on corporate governance issues related to firm management. Thus an important complement that has remained unexplored, and that this paper tries to address, is the governance failure associated with the regulation of market intermediaries.

Our work is also related to the work of Morck et al. (2000) who show that stock prices in emerging markets are more synchronous. The collusive manipulation of stock prices to attract outside investors could be one explanation for this finding. Similarly, the particular manipulation mechanism that show in this paper is related to the literature in behavioral finance that examines how (irrational) positive-feedback investment strategies can lead to inefficiencies in equity markets (De Long et al., 1990b; Shleifer, 2000). In this direction, our paper provides evidence in a real-world setting that outside investors trade using positive-feedback investment strategies. While we do not feel we have to take a strong stance on whether such feedback trading is rational or not, the data suggest that such momentum trading by itself is not profitable.

Because evidence shows that the mature markets of today suffered similar episodes of manipulation in their early years, perhaps emerging equity markets can also overcome these difficulties by adopting similar measures that, for example, the U.S. Securities and Exchange Commission (SEC) took to curb such manipulative behavior. We briefly discuss some possible measures in the conclusion.

The rest of the paper is organized as follows. Section 2 provides relevant institutional background and describes the data. Section 3 examines broker trading behavior patterns, and Section 4 estimates the excess return that brokers who trade on their own behalf (principal brokers) earn compared with the average outside investor. Section 5 then tests for a specific trade-based price manipulation mechanism, Section 6 considers alternate explanations, and Section 7 concludes.

2. Institutional background and data

2.1. The context

Our data are from an emerging market, the Karachi Stock Exchange, (KSE) which is the main exchange in Pakistan. In this section, we highlight relevant market features, arguing that while some features are different from what one could expect in mature markets, they are fairly typical of emerging markets.

2.1.1. Basic features

The KSE was established soon after Pakistan independence in 1947 and is around the median age for exchanges around the world and somewhat older than the typical stock market in developing countries (see Bhattacharya and Daouk, 2002). In 2002, it had 758 stocks listed with a total market capitalization of about \$10 billion or 16% of GDP.[2] Despite the small size of the market, it experiences a surprisingly high turnover (88%). In contrast, a mature market such as the NYSE is much bigger (a market cap to GDP ratio of 92%) and has not as high a turnover (65%). However, Fig. 1 establishes that this feature of the KSE (a shallow market with high turnover) is common amongst emerging stock markets. It plots the size (market cap/GDP) and turnover (dollar volume/market cap) of stock markets around the world against the logarithm of GDP per capita and establishes that the KSE is by no means an outlier

[2]The KSE captures 74% of the overall trading volume in Pakistan. There are two smaller stock exchanges covering the remaining 26%: The Lahore stock exchange (22%), and the Islamabad stock exchange (4%).

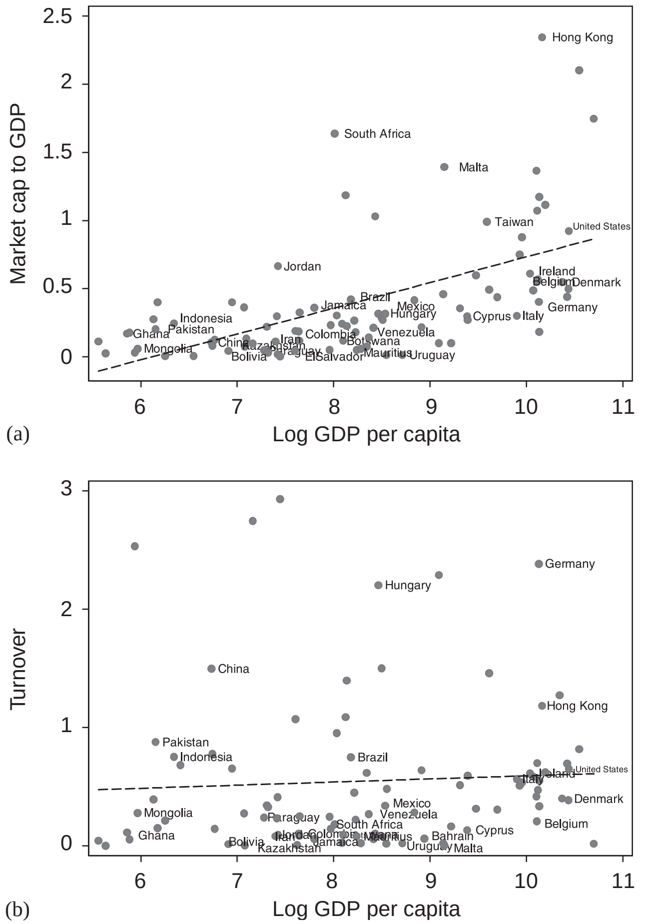

Fig. 1. Market size and turnover across countries. Every third country in this list (sorted by gross domestic product per capita) starting from Ghana is included in this figure. Nigeria, Tanzania, Ghana, Kenya, Bangladesh, Mongolia, Moldova, India, Pakistan, Zimbabwe, Armenia, Indonesia, Uzbekistan, 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. Outliers not shown: Bahrain = 9, Namibia = 8.9, Iceland = 8.4, Turnover outliers not shown: Ecuador = 31, El-Salvador = 11.1, Taiwan = 4.3 in the figure. Source: Bhattacharya and Daouk (2002).

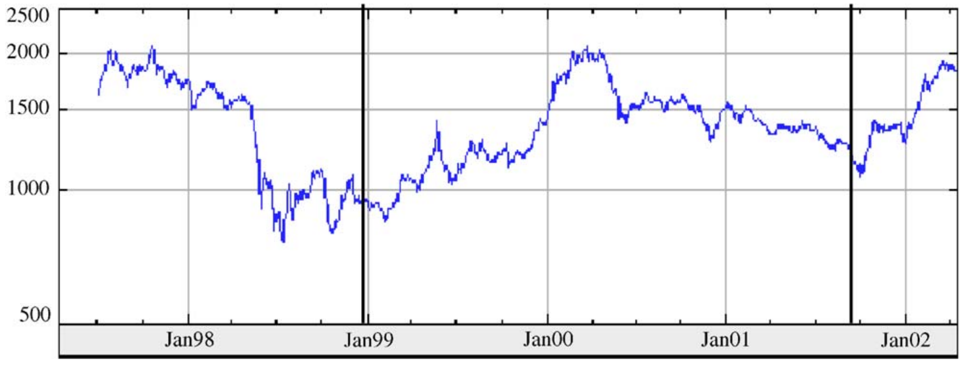

Fig. 2. KSE100 index (log), June 1997–March 2002. The dark vertical lines indicate the period for which we have broker-firm level daily trading data.

in having a small size yet high turnover. Moreover, the regression lines through Panels A and B suggest that while market size is highly correlated with richer economies (R^2 is 32%), market turnover has no significant relationship with per capita wealth (R^2 is 0.3%). Both the shallowness of the market and the high level of turnover in emerging markets are of particular interest as the former makes it more amenable to, and the latter more indicative of the problems arising from poor information, insider trading, liquidity, and manipulation.

Another aspect common to emerging markets is the limited role they play in raising capital. In the KSE, there were only two new listings raising $33 million and 18 delistings in the market in 2001. Other emerging markets fare similarly, with the majority seeing only a handful of new listings and little capital raised. In 2001, 28 out of 49 emerging markets had two or fewer new listings in the year, with 15 of these markets raising less than a million dollars. In contrast, of the 50 markets classified by the World Federation of Exchanges as non emerging, only seven had two or fewer new listings in 2001 and only eight raised less than a million dollars in new capital.

Fig. 2 shows that, in addition to the high turnover, the KSE has high price volatility. It plots the KSE 100 price index[3] over the five-year period from 1997 to 2002, including the 32 months covered by our data set. During this period, the stock market experienced large overall busts and booms as well as significant fluctuations over shorter time intervals. The standard deviation of monthly stock returns for the KSE 100 index during this period was 11.2 (as compared with 5.1 for the Dow Jones index). These movements are all the more surprising given the low level of real investment activity in the stock market. Again the high volatility is not atypical of emerging markets (see Bekaert and Harvey, 1997).

Finally, Fig. 3 highlights another aspect of the KSE that is common in emerging markets, a skewed size distribution of stocks traded. Of the 758 firms listed on the stock exchange, only 648 were actively traded during our sample period and of these,

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

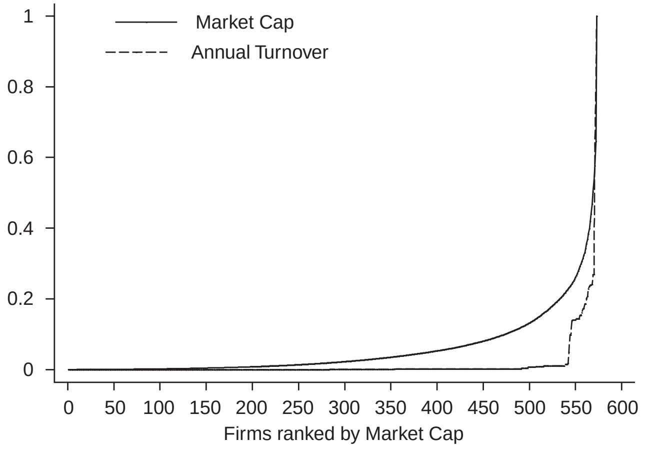

Fig. 3. Cumulative share of market capitalization and turnover by firm. Market capitalization for the firms is the average over our sample period and the annual turnover for each firm is for the year 2000. While we have turnover for all firms in our sample, because we have market capitalization for only 575 of those firms, to be consistent the above cumulative distribution functions (CDFs) are only for these firms. However, from our turnover numbers we know that these missing (market cap) firms are small and therefore will not affect the above CDFs qualitatively.

the top 25 stocks accounted for 75% of the overall market capitalization and 85% of the overall turnover. Such skewness is common even amongst smaller European markets (exchanges in Hungary, Iceland, Ireland, Portugal, etc.) with the five most traded shares comprising more than 70% of turnover. The corresponding share of the top five is 68% share for the KSE.[4] We are cognizant of the skewed size distribution of the stocks in our data set. As the empirical section makes clear, we adopt a number of procedures such as stock fixed effects, size-weighted regressions, and restricting sample to only the top decile of stocks, to ensure that none of our results is driven by the skewness of the data.

In comparison with stock size, the distribution of broker size and coverage for the universe of brokers (147) trading on the KSE is not as skewed. Fig. 4 plots the density functions (PDF) of broker size (total trading value of a broker) and coverage (number of stocks a broker trades in) during our trading period.

To summarize, a small and shallow equity market with high turnover, little real investment activity, high price volatility, and skewed size distribution are all features of KSE that are typical of emerging market stock markets around the world.

2.1.2. Regulatory environment

Before describing the role of brokers in the governance of the exchange, it is worth outlining the relevant regulatory environment in the country. In particular, it is

[4] In contrast, according to the Federation of European Securities Exchanges, the comparable percentage was around 24 for the London stock exchange in 2002.

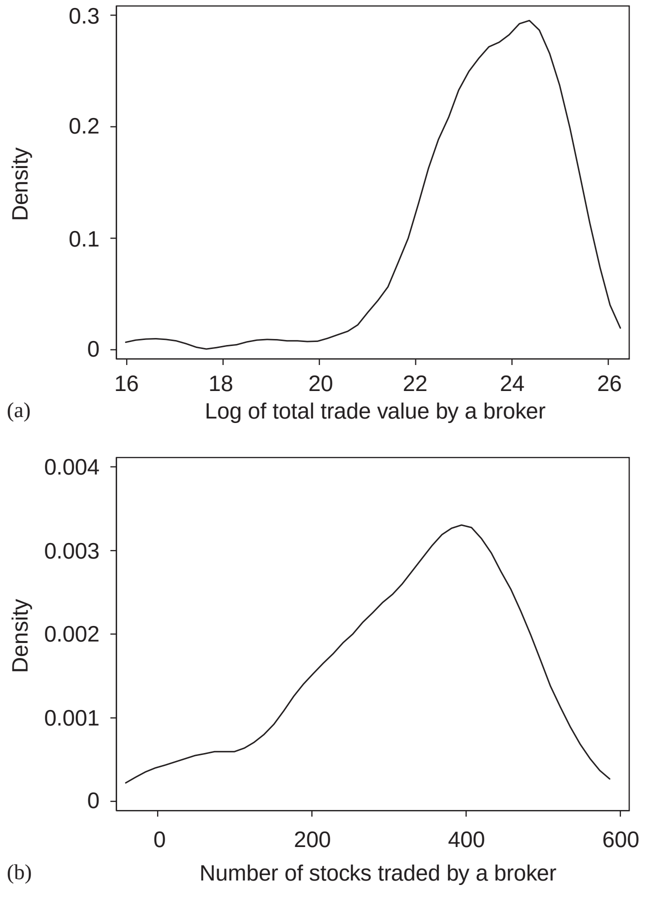

Fig. 4. In panel A broker size is proxied by the natural logarithm of the total trade value (value of all purchases and sales) of the broker during our sample period. In panel B broker coverage is the number of different stocks the broker ever traded in during our sample period: Panel A. Plotting the density function for broker size; Panel B. Plotting the density function for broker coverage.

useful to examine how Pakistan fares in terms of its regulatory laws pertaining to the stock market both in absolute terms and relative to other countries. We do so by drawing on a detailed categorization of securities laws conducted by La Porta et al. (2003) with the help of local attorneys in a sample of 49 countries with the largest stock market capitalization in 1993. They construct two broad measures to capture private and public enforcement implied by the securities laws. The former measure captures the extent to which securities laws reduce the costs of private contracting by standardizing securities contracts (by mandating disclosure requirements) and clarifying liability rules for inaccurate or incomplete disclosure. The latter measure, public enforcement, captures the extent to which a public enforcer (the Securities and

Exchange Commission of Pakistan (SECP), for example regulates the market as determined by the basic attributes (independence, etc.) and investigative powers of the regulator and the ability to impose non criminal and criminal sanctions for violations of security law.

While Pakistan is near the mean value of the private enforcement measure in the sample of 49 countries, it is the third worst in these measures when looking only at the 18 common law countries to which it belongs. What is perhaps even more telling of weak investor protection in Pakistan is that in public enforcement, while the country ranks very high in terms of the supervisor's attributes (independence etc.) and investigative powers, it does very poorly in terms of both non criminal and criminal sanctions that the supervisory agency can impose for violations of securities laws. Thus it is not surprising that to date there has hardly been any case in which a broker was prosecuted for improper activity.[5]

2.1.3. Broker influence

While the KSE does receive some oversight from the Securities and Exchange Commission of Pakistan, it is predominantly broker-managed, i.e., a majority of the exchange's board of directors including the chairman are brokers.[6] Moreover, trading on the stock exchange can be done only through one of 147 licensed brokers, and entry into the brokerage system is restricted. A new broker can enter only through the sale of an existing brokerage license.[7] These features are important from a governance perspective. If brokers are earning persistent rents from suspect activities in the market, and there are breakdowns in Coasian bargaining (e.g., future gains from reforms cannot be guaranteed to the rent-seeking brokers), then governance of the market is kept intentionally weak.

All these features and numerous anecdotes allude to a significant amount of broker control of the market. We highlight this aspect because, in focusing on potential market manipulation, most anecdotal evidence suggests a closer examination of broker trading patterns. Specifically, interviews of market participants in Pakistan suggest that a substantial number of brokers act as principals (trade for themselves or a few investors) instead of intermediaries and such brokers contribute to potentially undesirable activity in the market. According to a July 2001

[5]We are aware of only one instance in which a legal case was brought before a broker for any reason and section 17 of the regulatory code applied (a claim made on the broker's assets). This case arose not because of regulatory vigilance but because of what appears to have been a conflict between brokers. This resulted in a couple of brokers crossing their exposure limits and defaulting (they were unable to pay the difference between their position and the exposure limit).

To quote from the June 2000 issue of the Business Recorder, one of the leading financial papers in Pakistan regarding this incident: "It is not the issue of just payment, it is a war between the Karachi and Lahore based major groups who are struggling for their survival in the market, said an insider on condition of anonymity."

[6]This is not atypical. For example, in Turkey, of the five members of the board of directors, four are brokers and one is appointed by the government.

[7]In practice, such sales are rare because of the high price of brokerage seats, e.g. in 2000 the license of a defaulting broker was sold for US$0.5 million (per capita GDP is $450) and because these sales typically take place in thin markets with access limited to insiders.

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.

Moreover, the presence or at least allegations of market manipulation, particularly in the form of price manipulation, is common knowledge among the primary market participants, as is the belief that generally these principal brokers themselves (or their close associates) 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. Special terms, such as bhatta, have been coined in Urdu, the local language, to define such behavior. Similar pump and dump schemes are also believed to exist in other emerging markets (see Khanna and Sunder, 1999 for the Bombay Stock Exchange in India) and were prevalent in the early stages for developed markets as well. The account of the New York Stock Exchange in the 1900s by Gordon (2000, p. 213) is revealing and could be an accurate description of the KSE today (emphasizes added).

> 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 ... 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.

Recent reforms by the government regulatory authority, the SECP, such as appointing independent (non broker) members to the board of directors, have been targeted at weakening broker influence, although to date these reforms have had limited success. The issue of broker control historically has plagued markets during their early stages and appears present in emerging markets today.[8]

2.2. Data

One of the unique features of this study is the level of detail available in the data. The data set consists of the entire trading history for KSE over a 32-month period (December 21, 1998–August 31, 2001). What is unique about this data and allows us to look at broker-level trading behavior, is that it contains the daily trades of each broker for every stock over the 32-month period. We are not aware of any other work that is able to analyze trading for the entire universe of trades in a market and at the level of the broker. During the 32-month period, a total of 147 licensed brokers and 648 stocks traded on KSE. The data set thus contains almost 2.2 million observations at the broker-stock-date level.

Moreover, because trading on KSE during our sample period was all computerized (brokers submit their orders electronically to an automated system that then matches the orders for execution) and the data set was extracted directly from this system, the quality of the information is reliable. Specifically, because trading on the KSE can be performed only 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 the total number of shares bought or sold through the broker during the day and the closing, highest, and lowest prices for each stock traded during the day.

However, the data have some limitations. First, trades for a given broker in a given stock are aggregated at the day level. Therefore, 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.[9] While this does preclude intra day analysis, we do not feel that this exclusion changes the quality of our results. For example, given that we find brokers make profits through manipulation in inter day trading, not accounting for the intra day profits of these brokers is only likely to underestimate the true effect. Second, we do not have information at the investor level. While we can identify the broker, we do not know the investor on whose behalf he is trading on behalf of. However, as we will show, we can construct proxies for whether the broker is trading on his own behalf or on behalf of outsiders. In addition, because only completed trades are recorded, we do not have information on unfulfilled bids.

[8]While the NYSE has tried to minimize the conflict of interest likely to exist in a self-regulatory institution by having equal representation of industry (brokers) and nonindustry members (representing the investing public) on its board of directors, the potential for conflict still remains. This is apparent in the recent debate and concerns regarding governance issues in the NYSE (see http://www.nyse.com/home.html).

[9]Average price is constructed using an average of the highest and lowest prices during the day. Our results are unchanged whether we use the highest, lowest, or closing price as a proxy for trade price.

3. Broker trading patterns: is there anything unusual?

The substantial broker influence intimated in Section 2 and the concern by the market regulatory body that "brokers mostly act as principals and not as intermediaries" suggest that we should start by examining trading patterns to see if this concern is legitimate. More generally, we want to identify any unusual trading patterns, and a suitable normality benchmark, given the context, is whether a broker is acting as an intermediary for different outside investors. While we do not have data on whose behalf a broker is transacting, we use indirect means to identify such unusual (non intermediary) behavior. We should emphasize that we do not read too much in the label "unusual" for now and remain agnostic about such patterns because perfectly legitimate reasons why a broker would execute trades only on his own behalf during the day.

Table 1 provides an extract of the data to illustrate representative trading patterns. The two columns in Table 1 list the aggregate buys and sells on a given day of two different brokers in the same stock. For the broker in column 1, (Broker A) we list 20 consecutive aggregate day trades. We do not observe each individual trade done by the broker but the sum of all his buys (and sells) in a given stock on that day. Henceforth, we refer to such aggregate buys and sells simply as "trades", it being understood that we are always referring to the aggregate trades during the day and not a particular transaction. For the broker in column 2 (Broker B), we give three separate periods of consecutive trades to illustrate different trading patterns this broker displays.

Even a cursory examination of the trading patterns between the two brokers in Table 1 reveals a difference. Broker A both buys and sells stock on a given day (and usually in different amounts). This is not surprising. If a broker is intermediating on behalf of several independent investors, he would be both buying and selling the stock on the same day because it is unlikely (though possible) that different investors would all want to collectively buy (or collectively sell) on a given day.

Broker B, however, behaves differently from Broker A. On any given day he only either buys or sells (does not do both) or buys and sells exactly the same amount. As a first pass, we consider Broker B's trades as unusual in the sense that they are likely to reflect trading by a single investor or a group of investors who are in perfect agreement. We will refer to such trades as principal trades. While a few such trades are not surprising, a long sequence of such principal trades makes it far more likely that the broker is not intermediating for different investors but is acting as a principal investor (a single or, what will be observationally equivalent for us, a perfectly colluded set of investors). In addition to either only buying or selling, Broker B trades cyclically during period 2. He only buys (or sells) on a given day and then exactly reverses this trade the next time he trades (or reverses the trade within the same day). Such cyclical patterns of trades is also less likely for a broker who is intermediating on behalf of many independent investors.

While Table 1 illustrates unusual trades, it does not provide any sense of how prevalent such trades are. To do so, we categorize Broker B's unusual trades into three types: (1) Trades in which a broker only buys or sells on a given day and

Table 1
Principal and intermediary brokers trading

The table gives a snapshot of our original data set. We provide 20 trades for two different brokers trading the same stock. Each trade is at the day level, representing the total number of shares bought and sold by the broker during the entire day. The two brokers have different trading patterns, which are representative of our data. The broker in Column 1, (Broker A) is both buying and selling the stock during the same day. We classify such a broker as an intermediary as he appears to be trading on behalf of a number of outside investors. The broker in Column 2 (Broker B), only buys or sells the stock on a given day. This suggests that the broker is trading only on his own behalf or on behalf of a single party. Broker B is clearly not intermediating on behalf of many outside investors. For this reason we define Broker B as a principal. Whether a broker is a principal or not is captured by our "principalness" measure, *PRIN*, defined as the probability (over time) that a given broker in a given stock will behave as a principal. A broker on a given day is said to behave as a principal, if he does a buy transaction only or does a sale transaction only or buys and sells the same amount of a stock on a given day. Using this definition, the *PRIN* values calculated for Brokers A and B are 0.05 and 1, respectively.

Broker A (Intermediary) $PRIN = 0.05$			Broker B (Principal) $PRIN = 1$		
Trading day	Shares sold (1)	Shares purchased	Trading day	Shares sold (2)	Shares purchased
1	27,000	35,000	1	0	25,000
2	20,000	27,000	2	0	20,000
3	15,000	15,000	3	0	50,000
4	24,000	29,000	4	0	10,000
5	53,000	32,000	5	0	68,000
6	49,000	133,000	...	...	...
7	86,000	91,000	1	50,000	0
8	71,000	131,000	2	0	50,000
9	163,000	102,000	3	50,000	0
10	117,000	75,000	4	0	50,000
11	228,000	286,500	5	50,000	0
12	102,000	113,000	6	0	50,000
13	185,000	108,000	7	50,000	0
14	25,000	37,000	8	5,000	5,000
15	173,000	153,000	9	0	50,000
16	168,000	311,000	...	...	...
17	62,000	81,500	1	100,000	0
18	70,000	135,000	2	10,000	0
19	271,500	128,500	3	25,000	0
20	240,000	266,500	4	625,000	0

exactly reverses this trade the next day he trades OR trades in which the broker buys and sells exactly the same number of shares on a single day. We refer to such trades as "principal cycles" (Broker B's trades in period 2). (2) Trades ("principal buys") in which a broker only buys the stock during the day and does not reverse this position the next day, (Broker B's trades in Period 1). (3) Trades ("principal sales") in which a broker only sells the stock during the day and does not reverse this position the next day (Broker B's trades in Period 3).

In contrast, all but one of Broker A's trades involve the broker both buying and selling a different number of shares for a given stock and day. We refer to these trades as intermediary trades because, we believe that such trades are more likely if a broker is intermediating on behalf of different investors during the day.

Based on this categorization, Table 2 establishes that the trades by Broker B are prevalent in the full sample Column 1 shows that 60% of all trades are one of the three types seen for Broker B (around 20% each). Columns 2 and 3 provide the same relative frequencies but weighted by the amount traded. In other words, they provide the probability that a randomly selected single-stock trade belongs to one of the four types. Given the skewed distribution of stock turnover (Fig. 3), we present the results separately for the top ten stocks (Column 3), and the remaining stocks (Column 2). Column 2 shows that, while most stocks are traded through intermediary trading, even by this criterion there is a significant share of trades of the type carried out by Broker B. Not surprisingly, the majority of activity in the top ten stocks is intermediary trades. Given that the total number of brokers is fixed, the larger a stock is in terms of its turnover, the more likely is a broker to intermediate this stock over and above his own personal trading. Consequently, for larger stocks, more trades appear like intermediary trades. In any case, it seems reasonable to conclude that the unusual trades we identified in Table 1 (Broker B) are not just chance occurrences but are frequent both in terms of incidence and volume.

Table 2 also presents a first pass at when these four types of trades are more likely to take place. Column 4 shows that principal buys occur at the lowest normalized (by sample period average) stock prices and intermediary trades at the highest. Moreover, because principal sales occur at higher prices than principal buys, this

Table 2

Types of trades

Each observation is at the stock-broker-date level. A trade refers to the aggregate of all trades done by a broker during a single trading day for a given stock. A trade by a broker is defined as a cycle if any one of these two conditions holds: 1. The trade is an only buy or an only sale, and it is exactly reversed the next time the broker trades. 2. Both buy and sale of the trade are exactly equal. For example, the trades in Period 2 of Broker B in Table 1 are all cycle trades. A trade by a broker is defined as a principal buy if he only buys in that trade (i.e. sale = 0). The trades in Period 1 of Broker B in Table 1 are all principal buys. A trade by a broker is defined as a principal sale if he only sells in that trade (i.e. buy = 0) i.e. trades in Period 3 of Broker B in Table 1 are principal sales. A trade by a broker is defined as Intermediary if both sale and buy are positive (but not equal to each other). Almost all trades of broker A in Table 1 are intermediary trades.

Trade type	Frequency observed (percent)	Percentage by volume		Normalized firm price	Normalized turnover
		All but top ten	Top ten firms		
	(1)	(2)	(3)	(4)	(5)
Cycle	21.2	19.6	3.7	100	116
Principal buy	20.1	7.4	1.9	98.3	76
Principal sale	17.4	7.7	2.0	100	85
Intermediary	41.3	65.2	92.2	108.8	167
Number	2.2 million	1.5 million	0.7 million	2.2 million	2.2 million

suggests that a broker who only engages in such principal trades will, all else being equal, earn positive profits. Column 5 shows that both intermediary trades and principal cycles are associated with relatively high turnover (turnover on a day is normalized by its average over the sample period for that stock). However, both the principal buys and principal sales occur on relatively low turnover days suggesting a potential liquidity provision role of such trades.

Thus our examination does reveal somewhat unusual broker trading behavior that is also systematically associated with stock prices and trading volumes. However, in mapping such unusual trades to brokers we need to understand who executes them. Specifically, do such unusual trades occur uniformly across all brokers or do some brokers (such as Broker B) systematically engage in such trades in a given stock. More important, if such behavior is systematic for a given broker, does it affect the overall trading profits generated by the broker?

4. Trading profitability

The description of the market and environment in Section 2 suggests that brokers, especially those who trade on their own behalf, could be trading strategically and in a potentially manipulative manner. Section 3 offers an indirect way of identifying such principal brokers. In this section, we formalize this identification strategy and check whether these principal brokers systematically generate greater trading profits.

Our main variable of interest in this paper is *PRIN*. It measures the extent to which a broker in a given stock is trading on his own behalf (i.e., acts as a principal) as opposed to trading on behalf of others.

Suppose that the three types of principal trades identified in Table 1 signify that the broker is trading on his own behalf that day. The assumption that a principal trade always reflects a broker trading on his own behalf does not need to be true all the time. All that we need is that principal trading is correlated with a broker trading on his own behalf. Then for each broker in a given stock, we can compute the probability that a broker will do a principal trade. This is our measure *PRIN*. More precisely,

$$PRIN_{SB} = \frac{\text{Number of times broker } B \text{ trades as a principal in stock } S}{\text{Total number of times } B \text{ trades in stock } S}. \tag{1}$$

The subscript *SB* is added to reiterate that *PRIN* is constructed separately for each broker *B* in every stock *S*. Thus, in our example of Table 1, Broker A has a *PRIN* value of 0.05 for the 20 trades shown,[10] and Broker B, a *PRIN* value of 1.

PRIN serves as a proxy for the extent to which a broker is trading on his own behalf for a given stock (interpreted more broadly as the broker trading on behalf of one investor or a perfectly colluded set of investors). *PRIN* serves to order brokers only by principalness within the same stock. For example, a high *PRIN* value in stock *i* cannot be compared with a low *PRIN* value in stock *j*. The reason is that the level of *PRIN* is affected not only by the principalness of a broker, but also by stock

[10] The third trade of broker A (15 thousand buys and sells) counts as a principal cycle.

specific attributes especially stock liquidity and turnover. In particular, if there is more frequent and heavier trading in stock j, then on average all brokers in stock j have a lower $PRIN$.

The measure in Eq. (1) therefore must be demeaned at the stock-level before it can be used in the analysis. We can use two approaches to de-mean $PRIN$. The first uses $PRIN$ with stock level fixed effects, to construct a cardinal ranking of brokers within each stock. The second approach uses $PRIN$ to construct an ordinal ranking of brokers within each stock separately. This ranking, $PRIN^{ord}$, reports the percentile of the broker in the $PRIN$ distribution for a given stock. While we primarily use the first, our results are robust to the second.

Using either the cardinal or ordinal version of $PRIN$, brokers with low values of $PRIN$ can be thought of as intermediaries, and those with high values of $PRIN$, as principals. Thus, in our example in Table 1, Broker A would be considered an intermediary and Broker B, a principal. Alternately, $PRIN$ can be regarded as a proxy for the probability that a broker is a principal.

The computation of $PRIN$ collapses our data to the stock broker level. In other words, the time component in our stock-broker-day data is collapsed to construct the $PRIN$ measure. For example suppose that Brokers A and B in Table 1 trade in a total of three hundred and four hundred stocks, respectively. After collapsing the time dimension to construct the $PRIN$ measure for each broker-stock pair, we will be left with three hundred observations (i.e., $PRIN$ values) for broker A and four hundred observations for Broker B. Applying this construction to all brokers in the actual data, we end up with 46,325 stock broker-level observations (as Panel B of Fig. 4 shows not every broker trades in each stock).

Given a measure of how much a broker trades on his own behalf, the question is: Do brokers who are more likely to trade on their own behalf (i.e., have a higher $PRIN$ for a given stock) make more money? To answer this question, we construct a measure of trading profits of a broker in a given stock.

We construct an annualized nominal rate of return (ARR) for each stock broker using his entire trading history (buy and sell orders for the stock) over our sample period. The ARR measure captures the trading profits a stock broker generates per unit of capital invested. Thus a 50% ARR implies that the stock broker is able to earn *Rs* 50 in a year on an average capital investment of *Rs* 100 during the year.

In constructing ARR, we need to be aware of issues that could arise from limitations of our data. While our results are robust to these concerns, it is nevertheless worth mentioning them. First, we value the sale or purchase price on a given day at the average price of the stock that day because we do not have data on the price at which each specific trade was conducted.[11] Second, a problem in

[11] Average price is the average of the high and low price for the stock during the day. Our results are robust to using high or low price instead. We do not necessarily have to assume frictionless short selling 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 inventory of the stock prior to the beginning of our sample period. It is certainly safe to assume that such borrowing is frictionless. Also there is no formal derivatives market in KSE during our sample period. There is a forward trading facility or badla market for brokers which is explained in detail in Section 6, Section 6.2.2.

calculating *ARR* over the sample period is that the trading history perhaps does not net out to zero. In particular, if a broker is a net accumulator or a net decumulator of a 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 valuing his end of sample net holdings using the end of sample stock price. To put it differently, we force the stock broker to liquidate any net positions at the end of sample price. However, our results are robust to more complicated solutions to this problem such as netting out end of period holdings, or imposing a zero-profit condition on end of period net holdings instead of forcing liquidation. The Appendix describes the *ARR* construction and these issues in more detail.

For the sake of clarity, *ARR* measures and what it does not capture. First, by construction, *ARR* measures only inter day profitability resulting from trading. It does not include any profits (or losses) that a broker has accumulated from intra day trading. Second, *ARR* does not include trading commissions or bid-ask spreads earned by brokers. Third, *ARR* computes profitability of a broker only during our sample period, and, as such, is unaffected by the value of a broker's inventory going into our sample period.

Finally, given some outliers in the *ARR* after construction, we winsorize the data at 1%.[12]

4.1. Primary regression

We can now compare trading profits principal brokers earn relative to intermediary brokers. In terms of interpreting any profitability differences, it is important to realize that we are looking only at trading profits and not brokerage commissions. Thus the profitability comparison is between principal brokers (the single, perfectly colluded investors behind them) and the outside investors who trade through intermediary brokers. For the purposes of this paper, we are particularly interested in making this comparison, because we care less about what brokers earn, than about what their trading strategies, and hence the investors behind them, earn. However, for simplicity, we treat a principal broker's trading profits as the broker's own earnings (this is true if the broker is trading on his own behalf because he does not earn any commission). While we could interpret these trading profits as the earnings of the single or perfectly colluded set of investors behind this principal broker, for our purposes the two are equivalent.[13]

Before turning to regression analysis, it is worth eye balling the aggregate data to detect any patterns in profitability. To do so, we first categorize $PRIN^{ord}$, the ordinal

[12]The results remain the same whether we winzorize the data, (the top and bottom 1% outliers in *ARR* are "assigned" the value at the 99th and 1st percentile respectively,) or simply exclude the outliers from the regressions. We prefer the former as it is standard practice and more consistent with the data.

[13]Clearly the interpretation of our results and policy implications vary slightly if the principal broker is directly profiting as opposed to a single or perfectly colluded set of investors behind him. However, given our data, we cannot make this distinction. Moreover, we feel that the point this paper is making, that unchecked and suspect (i.e. manipulative) trading by certain individuals systematically earns money off outsiders is well made under either interpretation.

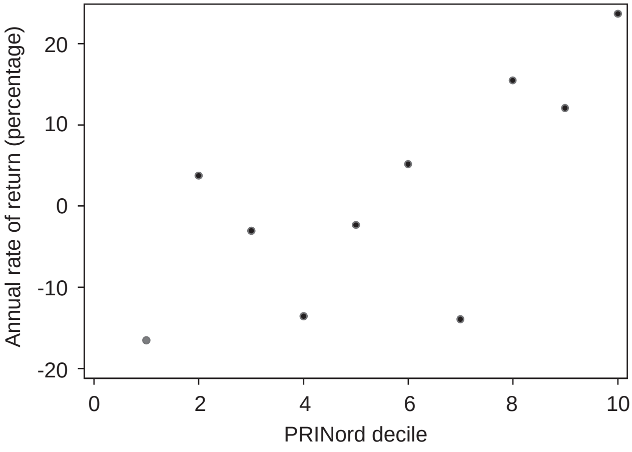

Fig. 5. Principal-trading profitability. $\mathrm{PRIN}^{\mathrm{ord}}$ is the percentile ranking of PRIN within each stock. For any given stock, we order brokers according to their PRIN rank in that stock. Each broker is given a value according to the decile in the PRIN distribution in which he belongs. Recall that PRIN is a measure of the principalness of a stockbroker as explained in Table 1. The annual rate of return is an aggregate measure. This means we sum all the level trading profits of stockbrokers for a given PRIN^{ord} decile and divide this profit by the total capital used by all these brokers. This gives us the return per dollar invested by the brokers.

percentile ranking of *PRIN* within each stock, into ten different bins with each bin representing a decile. Then, for each bin, we compute the aggregate profitability of stock brokers in that bin by dividing their total level profits by the total average capital used by each of the stock-brokers. In other words, we construct a single *ARR* number for each bin (ARR-cat) instead of taking the average of the *ARR*s for all the stock brokers in the bin. We can then compare the profitability across the ten $PRIN^{ord}$ deciles.

Fig. 5 shows a striking result. Not only do brokers in the top $PRIN^{ord}$ decile in each stock earn a high rate of return of over 20%, they do so at the expense of the low $PRIN^{ord}$ deciles. Brokers who trade as principals earn significantly higher returns over, and at the expense of, outside investors who trade through intermediary brokers.

While the figure suggests that this profitability difference is significant, we now turn to a regression framework to show this formally. We estimate

$$ARR_{SB} = \alpha + \beta.PRIN_{SB} + \underline{\gamma} . \underline{S} + \varepsilon_{SB}, \tag{2}$$

$\underline{S}$ refers to stock level fixed effects. β in Eq. (2) captures the superior returns that principal brokers ($PRIN = 1$) receive over intermediary brokers (outside investors) with the lowest possible value of *PRIN* (0). The fixed effects $\underline{S}$ ensure that we compare brokers only within the same stock. Columns 1 and 2 in Table 3 (Panel A) report the results of this regression. Column 1 takes a slightly naive but simpler approach in that it weighs each observation equally. However, the problem with

Table 3
Measuring profitability of principal trades

Each observation is at the stockbroker level. ARR is the annualized rate of return on stock-broker's trades. *PRIN* is a measure of the principalness of a stockbroker, as explained in Table 1. In Panel B *market volatility* is the standard deviation of monthly market return during the subsample. The number of observations in Panel B could be different from that in Panel A because not all Brokers (or even stocks) are active throughout the three subperiods. Robust standard errors are in parentheses. All regressions are weighted (except one) and include firm fixed effects.

Panel A. entire period

	ARR (unweighted)	ARR	ARR	ARR (40% margin)	ARR (20% margin)	ARR	ARR	ARR (top 10% stocks only)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
PRIN	34.65	48.44	48.42	71.71	88.80		34.39	48.57
	(11.05)	(11.55)	(11.62)	(28.75)	(32.46)		(19.15)	(11.60)
PRIN = 1?			0.29					
			(2.22)					
PRIN^{ord}-decile						26.8		
						(5.6)		
PRIN*KSE100?							14.46	
							(22.56)	
Number	46,325	46,325	46,325	46,325	46,324	46,325	46,325	9,458
R^2	0.11	0.10	0.10	0.06	0.05	0.09	0.08	0.09

Panel B. Three sub periods (dependent variable = ARR)

	December 1998 to October 1999	November 1999 to September 2000	October 2000 to August 2001
	(9)	(10)	(11)
Market volatility	15.0	10.8	9.5
PRIN	114.64	53.6	179.0
	(32.2)	(39.2)	(75.2)
Number	21,334	36,681	30,837
R^2	0.02	0.01	0.01

doing so is that, given the construction of the *PRIN* measure, several small stock brokers appear with a large *PRIN* value simply because they trade infrequently in the firm. Column 2 provides a more meaningful estimate that gets at the economic significance of the effect by weighing each observation by the average capital investments by the broker in the stock during the data period. Nevertheless, both versions show a large effect: Brokers who trade primarily as principals (whether cyclically or not) earn an annual rate of return that is 35-48% higher than those who trade as intermediaries. The effect is highly significant. We only report results with stock fixed effects, but the results are similar without stock fixed effects.

Our interpretation is that this effect is the profitability differential between trades conducted by a broker for himself or a few perfectly colluding investors (a principal trade) versus trades conducted by other brokers on behalf of independent outsiders (intermediary trades). To the extent that some of the trades conducted within a day by an intermediary broker could also be on his own behalf instead of for outsiders, our estimate of the profitability differential is in fact an underestimate of the true effect (because the *PRIN* measure incorrectly groups these as intermediary trades as well).

Before seeking explanations for this principal-trading effect, we perform a series of robustness checks. Because the weighting strategy correctly puts less emphasis on stock brokers who had high *PRIN* values only because they trade infrequently, we stick to weighted regressions. Such inactive brokers are unlikely to give rise to the principal-trading effect. While they are trading for themselves, their motivations for doing so could be entirely different from the strategic motivations of the active principal brokers.

4.2. Non linear specification

We have assumed a linear specification in our regressions. However, because the distribution of *PRIN* has greater mass at a *PRIN* value of one, we would like to ensure that our results are not driven by imposing a linear form. We therefore re-run Eq. (2) with an additional dummy for stock brokers whose *PRIN* is one. Column 3 shows that there is no non linearity when *PRIN* is one, and the linear effect of *PRIN* for *PRIN* less than one remains at 48%.

4.3. Allowing for margin trading

Our definition of profitability, *ARR*, takes a restrictive and conservative view as it does not allow brokers to trade on the margin. Specifically, in computing the capital required by the broker when trading in a particular stock, we impose a 100% margin requirement. At any time, the broker has to have as much capital as his net position on that day (less any profits he has earned in the trading we observe before). Thus, if on the first day we observe him a broker has a net buy of stock valued at Rs 100, we assume that he is required to hold capital worth Rs 100.[14] However, in reality, the KSE and other stock markets do allow brokers to trade on margin. While brokers on the KSE are even able to trade with a 10% margin, we use two conservative measures allowing for 40% and 20% margin requirements, respectively. Columns 4 and 5 show the results from allowing for margin trading and, as expected, the principal-trading effect increases to 72% and 89%, respectively. While we believe that these estimates are more likely to reflect the rates of returns that principal brokers are earning, we continue with the more conservative approach of adopting a 100% margin requirement in the remaining results.

[14]A net sale on the first day would be treated similarly. If a broker sold Rs 100 worth of stock, we would assume that he had to have Rs 100 worth of capital invested. See the appendix for more details.

4.4. *Ordinal and discrete* PRIN *measure*

One potential concern is that we are taking the continuous *PRIN* measure too literally and imposing cardinality could be driving our results. Column 6 addresses this concern by reestimating our primary regression using the ordinal measure of *PRIN*, $PRIN^{ord}$, to construct a decile rank. A measure that takes on ten possible values (zero to one) that are the within-stock *PRIN* deciles. The result shows that, while the loss in information as a result of using a more discrete and ordinal measure does reduce the principal-trading effect (27%), it is nevertheless large and significant.[15]

4.5. *Stock heterogeneity*

Given the skewed stock distribution (Fig. 3), a potential concern is that the principal trading effect is driven by some stocks only. In particular, if this effect were present only in the smaller, less traded firms, it would reduce the economic importance of the result. Column 7 addresses this by estimating the principal-trading effect separately for the KSE100 firms and the remaining (smaller) firms. The results show that the effect remains for the smaller firms (34%) and, if anything, the effect is larger for the KSE100 firms. Moreover, Column 8 reestimates the effect using only the largest 10% stocks and shows that it remains as large.

4.6. *Sample period*

As Fig. 2 shows, the market experienced a boom during the middle of our data sample. A concern could be that the principal-trading effect is driven by these overall market movements (high *PRIN* brokers just happened to be selling more during this period). While unlikely, we nevertheless test for it by estimating the principal trading effect separately in three equal sub periods (both the *PRIN* and profitability measures are constructed separately in each period). Columns 9-11 in Table 3 (Panel B) show that the principal-trading result is present in all three periods. Moreover, the correlation between *PRIN* measures across the three periods is very high, suggesting that brokers who trade as principal traders in a given stock continue to do so over time.

4.7. *Strategy risk*

While the principal brokers earn a higher level return, they could be exposed to greater risk thus leading to a lower risk-adjusted return than we obtain. However, we argue that this is unlikely. Our analysis compares principal and outsider profits

[15] In addition, one could wonder whether our requirement that a (cyclical) trade be classified as principal only if the buy and sells exactly match could be too restrictive or could influence the results. However, more generous measures, which allow for a trade to be classified as principal as long as the buys and sells are close, give similar results. For example, allowing for a 5% or less difference gives a *PRIN* effect of 49.9%, hardly a change from the 48.4% effect in Table 3 column 2.

within the same stock and thus principal brokers are facing the same stock-specific risk. Admittedly, there can still be strategy-specific risk within the same stock that is higher for principal brokers than the outside investor. However, if we divide the market into principal brokers and outsiders, because markets clear at each specified 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 and therefore principal brokers are not exposed to extra risk as compared with the outside investor. We acknowledge that there could still be risks of legal prosecution if a principal broker is involved in manipulation, but this does not seem common in practice.

5. Evidence for price manipulation

Brokers who trade on their own accounts earn significantly higher returns at the expense of outside investors trading through intermediary brokers. While the return differential is high enough to be of concern as a deterrence to the average investor from entering the market, we have no reason to believe that this differential is suspect. Principal brokers could simply have greater ability or be in a better position to time the market. This is not surprising given that the outside investor in an emerging market is unlikely to be as experienced or trained. However, what is of greater concern is if this differential is driven by brokers exploiting insider information or engaging in manipulative practices.

In this section we take a first step toward understanding what could be causing the large profitability differences by directly testing for a particular trade-based manipulation mechanism suggested by the institutional description, anecdotes, and patterns of trades highlighted in the previous sections.

Before describing and testing the manipulation mechanism, it is important to explain why we believe the principal trading result could stem from manipulation. Conceptually, one may expect for a couple of reasons that those who intend to resort to market manipulation, particularly trade-based manipulation, would be more likely to be principal brokers. 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 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. 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 one to sit in close proximity to other market players and monitor information in real time is a big comparative advantage. This is particularly true in an emerging market where the information technology markets are not well developed.

5.1. Pump and dump manipulation

To use the Allen and Gale (1992) classification, manipulation can be information, action- or trade-based. The first relies on spreading false information (Enron, Worldcom, etc.), the second, on non trade actions that could effect stock price (such as a take over bid), and the third, on traders directly manipulating prices through their trading behavior. The mechanism we are interested in testing is of the last type. Moreover, given the several theoretical models of trade-based manipulation (see Zhou and Mei, 2003 for a review), we do not model the mechanism but describe it in some detail and relate it to the existing theoretical literature. Amongst these models, Zhou and Mei's model is closest in spirit to what we describe.

The mechanism suggested by the anecdotes and trading patterns is a pump and dump mechanism that entails brokers creating artificial excitement by trading back and forth in a stock in the hope of attracting trend chasers and then exiting the market profitably before the bubble bursts.

Fig. 6 illustrates a stylized version of this mechanism but one that we believe reflects reality reasonably well. We first classify each stock-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 respectively trading the stock's stock on that date. For simplicity, assume that I can take a *H*(igh) or *L*(ow) value giving 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 stock's stock that day is low, whereas the average *PRIN* of the brokers selling the stock that day is high.[16] The stylized mechanism works as follows. Start at a point where prices are at their lowest (point A). At this stage, manipulating brokers (with high *PRIN*) trade back and forth among themselves (the state at point A is *HH*) to create artificial momentum and price increases in the stock. This eventually attracts outside investors with extrapolative expectations (positive-feedback traders) to start buying (branches B and C). However, once the price has risen enough, the manipulators exit the market leaving only outsiders to trade amongst themselves (point D). The state when price is at its highest is thus *LL*. This artificially high price cannot be sustained and eventually the bubble bursts (branches E and F) and the outside investors start selling. Once prices are low enough, the manipulators can get back into the market to buy back their stock at low prices and potentially restart another pump and dump cycle (point *G*).

The above mechanism is extremely stylized, and it is unlikely that it can be continuously used. Moreover, it relies on the existence of momentum traders and assumes that groups of brokers get together to manipulate prices as opposed to an individual trader doing so. However, because we are testing for this mechanism directly, this also implies testing for these assumptions.

The mechanism implies that stock-date states can be used to predict price levels and changes. Examining price levels shows that, as in the mechanism described, price is the lowest when trade is mostly between principal brokers (state *HH*) and peaks when trade is between intermediaries (state *LL*). In particular, the normalized stock price is 106.1 when the state is *LL*, and 94.6 when the state is *HH*. The normalized price is constructed by dividing the stock price on a given day by its average during

[16] 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* on a date means brokers buying the firm's stock have a lower *PRIN* than usual for the firm.

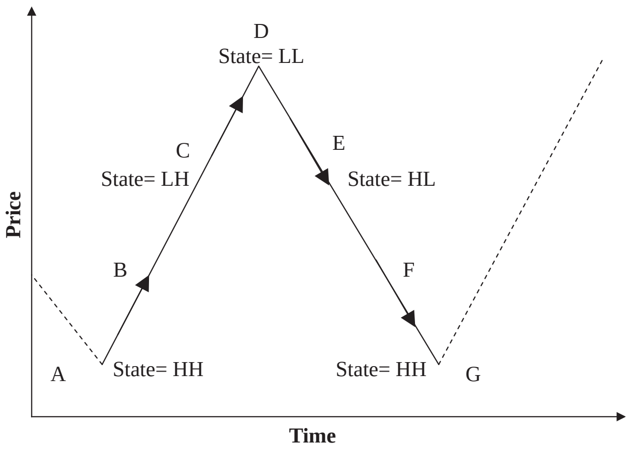

Fig. 6. A hypothetical example of trading cycles. A: Naïve traders are out of the market. Manipulators trade among themselves to raise prices. State = HH. B: Artificial price increases attracts naïve or positive feedback traders. C: More naïve traders enter, as manipulators sell their last remaining 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).

the entire sample period. The result confirms the prediction of Fig. 6 that stock prices are generally at their highest in the *HH* state and lowest in the *LL* state.

The next and more challenging test for the price manipulation scheme described above is to establish that principal brokers are able to influence future prices. Specifically, we would like to identify principal broker behavior that is able to predict future price changes. The price mechanism above suggests that this behavior is when the market consists mostly of principal brokers trading amongst themselves. While we cannot identify who a broker trades with, we know that on *HH* days principal brokers are, by construction, only trading with similar types. Thus the test would be to see whether the *HH* state predicts future price changes. There is no reason, other than the manipulation mechanism suggested, to suspect that this state by itself should be directly related to higher future returns. In addition to *HH* predictability, a further test that such broker behavior influences future prices artificially is if it is subsequent absence predicts a price fall (as in Fig. 6, the *LL* state predicts negative returns). Columns 1–4 in Table 4, present these tests and show that not only do *HH*-states predict future price increases but *LL* states also predict future price falls.

An intuitive way to conduct these tests is to construct the following hypothetical investment strategy: Imagine that during the course of 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 on the 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. The advantage of this construction is that, if states were observable we are describing actual investment strategies and opportunities to consistently beat the market. Moreover, doing so 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 date. Autocorrelation of returns remains a potential problem, but we control for that by using Newey-West standard errors.

Now we can test for the price change results by comparing the average return on the portfolios constructed using such *HH* and *LL* strategies. Given Fig. 6, we expect that the *HH* state would predict positive returns, while stocks in the *LL* state last period would earn negative returns. To correct for overall market trends, we look at above-market returns for these investment strategies. We subtract the overall market return in a week from the state-contingent portfolio's return that week.

Column 1 shows that an *HH* strategy results in 0.12% higher weekly return as compared with the market return. The *HH* state predicts positive future returns. Column 2 shows that the *LL* state predicts negative future returns, leading to a weekly loss of 0.20%.

However, Fig. 6 makes a prediction about positive (negative) returns when one is near exiting state *HH* (*LL*). When there are consecutive sequences of *HH*, the first

Table 4
State contingent returns

Columns 1–4 regress the 141 weekly excess or above-market returns from using different strategies. A strategy X refers to holding each week a portfolio that contains all the stocks with a state X the previous week. A stock is in *HH* state in a given week if the average *PRIN* of both buyers and sellers of the stock that week is high (in other words mostly the principals are trading amongst themselves that week). A stock is in *LL* state in a given week if the average *PRIN* of both buyers and sellers of the stock that week is low (in other words, mostly the intermediaries trading amongst themselves that week). *HHend* and *LLend* have similar definitions to *HH* and *LL*, differing only in that the state next week must not be *HH* and *LL*, respectively. Robust standard errors are in parentheses.

Weekly excess return using strategy:	HH	LL	HHend	LLend
	(1)	(2)	(3)	(4)
Panel A: High or low cutoff at firm's median PRIN				
Constant	0.12	−0.20	0.56	−0.64
	(0.08)	(0.076)	(0.15)	(0.15)
Number	141	141	141	141
	(5)	(6)	(7)	(8)
Panel B: Top two deciles stocks only				
Constant	0.04	−0.08	0.24	−0.68
	(0.11)	(0.07)	(0.15)	(0.16)
Number	141	141	141	141

few instances of *HH* do not lead to positive price change necessarily, but the last *HH* in the sequence should be a strong predictor of future returns. Columns 3 and 4 perform these more nuanced tests: Instead of holding a stock whenever its state is *HH* or *LL*, we hold a stock only if its state is *HH* but its future state is different from *HH*. We call such states *HHend* and *LLend*. The results show even larger effects as expected. *HHend* predicts weekly gains of 0.56% and *LLend* losses of 0.64%.[17] As a robustness check, we repeat the price change tests (Panel B of Table 4) for only the top two deciles by market capitalization of stocks and get similar results.[18]

Thus these results suggest that the pump and dump mechanism is used by principal brokers to earn profits. However, this does not preclude the other explanations we suggested, including the less suspect ones such as better market timing or ability. In Section 6, we take a closer look at these alternate explanations and argue that little support exists for them. Before doing so, it is worth contrasting the mechanism we describe with other trade-based manipulation mechanisms and noting some aspects of feedback trading in the data.

5.2. *Other manipulation mechanisms*

While we have presented direct evidence for a specific price manipulation mechanism in which two or more brokers trade amongst themselves to generate artificial momentum, there could be other such mechanisms at work.

The first such mechanism is similar to the strategic manipulation mechanisms described by papers such as Aggarwal and Wu (2003). Such mechanisms do not require colluding principal brokers unlike the one we discussed. Instead, asymmetry in information can allow even a single principal broker to artificially move prices and make money off investors with less information. While this is theoretically possible, it does not seem to be supported in the data. In the trading patterns, we see that principal brokers trade directly with other principals. As the test in Column of Table 4 shows, these trades lead to positive returns. Similar tests constructed by defining states based on trade types of a single principal broker do not predict future returns (regressions not shown). The collusive trading behavior between different principal brokers predicts positive future returns and not the behavior of any one broker alone.

A related mechanism that is closest in spirit to the pump and dump mechanism, in that it does not rely on informational asymmetries but is purely trade-based, is Zhou

[17] In addition to testing price predictability for the *HH* and *LL* states one may also interpret Fig. 6 literally, and hypothesize that *HL* and *LH* states will predict negative and positive future returns respectively. While we maintain that this is too literal an interpretation of the price manipulation mechanism, for what its worth, these tests (regressions not presented) also hold - weekly returns after *HL*-states are -0.38% and after LH-states, 0.64%.

[18] The standard errors are higher given that we have substantially reduced the number of stocks over which we compute these returns. However, the returns to the strategies of interest, *HHend* and *LLend*, remain similar. In addition, we also tested (regressions not shown) the robustness of the Panel A results to using a more restrictive definition of high and low *PRIN* (categorize the top third *PRIN* values as high and the bottom third as low instead of splitting at the median) and all the results in Panel A hold.

and Mei (2003). However, their model assumes that a single investor is large enough to manipulate prices. In contrast, the mechanism we test involves two or more brokers trading together to raise prices. The Aggarwal and Wu (2003) examination of stock market manipulation cases pursued by the US Securities and Exchange Commission leads them to also conclude that “indeed, most manipulation schemes are undertaken jointly by several parties”. Nevertheless, while the single trader as manipulator model is ruled out for the same reasons as the mechanism, above a slight modification of Zhou and Mei’s model to allow for brokers to pool together to manipulate prices would be consistent with our mechanism and empirical tests.

5.3. Irrational trend chasers?

The above price manipulation mechanism relies on positive feedback investment strategy assumed on the part of outside investors. Such behavior is familiar in the behavioral finance literature. Surveys indicate that often extrapolative expectations on the part of the naive trader underlies such positive feedback behavior. 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 Fig. 6 can partly be thought of as a test for the presence of positive feedback investors in a real-market setting. However, what is not clear from these tests is whether these outside investors are naive in the sense that they are consistently losing money (and therefore irrational) or that momentum trading is on the whole a profitable strategy. This is possible if the extent and frequency of manipulation is low and there is sufficient momentum in the market so, in equilibrium, it is profitable to be a momentum trader. While we do not take a stance on the rationality or irrationality of feedback traders, because both are consistent with the price manipulation mechanism we describe, the data suggest that momentum trading by itself is not a profitable strategy (regressions not shown).

6. Alternate explanations

Section 5 presented convincing evidence that principal brokers pool together to manipulate prices and earn at the expense of outsiders. However, to what extent is the manipulation mechanism we described the only means through which principal brokers are making profits? While it would be naive and not empirically possible to argue that such trade-based mechanism is the only means used, we can present evidence on the likelihood of other explanations. In particular, we consider two broad classes of alternate explanations: market timing and liquidity provision. Neither of these explanations implies the price level and returns state-predictability results that we obtained above. However, neither are these results a refutation of these explanations. Instead, the approach we take is more direct, we simply attempt to understand to what extent the principal trading result could be driven by these alternate explanations.

6.1. Market timing: broker ability or private information

Principal brokers could earn greater profits because they are better at market timing for a variety of reasons. For example, brokers could have superior ability to predict future stock performance. Alternatively, they could have better or insider information on a stock that they can use to time the market.[19] Either the ability or information story implies that brokers will buy a stock when its price is low and sell when high. Because "buying low and selling high" by definition leads to higher profitability, the market timing explanation in general is not testable. However, the micro-nature of our data set allows us to perform some direct tests of this hypothesis.

We start with the assumption that the market timing capability of a broker (whether the result of ability or information) is constant across stocks. Then a simple test of the market timing hypothesis is to include broker fixed effects in our primary regression and see if the profitability differential result remains. Column 1 in Table 5 shows that, while the profitability differential changes, it is still large at 37%. Therefore, our results are not driven by systematically better market timing by the same set of brokers.

Although the above test is informative, it does not exclude more subtle market-timing explanations. For example, the assumption that broker market-timing capability is constant across stocks perhaps does not hold. Brokers could have a stock-varying capability to time the market. They could differ in their ability or access to insider information across stocks. In this case, broker fixed effects are ineffective.

We appeal to the micro nature of our data set to test for the plausibility of this more nuanced market-timing explanation. In Table 1, Broker B also engaged in a series of cyclical trades we referred to as principal cycles. Can the market-timing explanation be consistent with the existence of principal cycles? Perhaps a single cycle can be justified by market timing: A broker could buy one hundred shares of a stock on receiving good insider news about the stock and then sell these one hundred shares next day once this news is realized. But it is extremely unlikely if not impossible under the market timing hypothesis that a series of such cycles could exist sequentially (e.g., first seven trades in Period 2, Table 1). Such cycles could be consistent with other explanations, but they are not consistent with market-timing explanations.

Therefore, a test for stock-varying market-timing hypothesis, and the market-timing hypothesis in general, would be to exclusively focus on consecutive cycles. If market timing is the dominant explanation, then consecutive cycles on their own should not be correlated with higher profitability. To perform this test, we separate the *PRIN* measure into principal trades that consist of at least three consecutive cyclic trades, *PRIN3cycle*, and those that do not but are principal trades, *PRINnon3cycle*. Specifically, for *PRIN3cycle* we look at each day's trading for a

[19] For example, Bhattacharya et al. (2000) in a study of the Mexican stock market show that there is no public reaction to corporate news, and suggest insider trading before the news as an explanation.

Table 5
Testing alternate theories. Each observation is at the stockbroker level

ARR is the annualized rate of return on stock-broker's trades. *PRIN* is a measure of the principalness of a stockbroker, as explained it Table 1. Three-cycles are a subset of the cycles described in Table 1, with the added condition that such cycles should be observed consecutively and for at least three times. Robust standard errors are in parentheses. All regressions are weighted and include firm fixed effects. Column 1 also includes broker fixed effects.

	ARR Broker FEs (1)	ARR (2)	ARR (3)	ARR (4)	ARR (5)
PRIN	37.33		46.94	48.30	
	(12.45)		(11.67)	(11.57)	
Three-cycle component of PRIN		30.67			
		(12.73)			
Non three-cycle component of PRIN		50.94			
		(12.17)			
Share of stock volume traded by the broker			−52.02		
			(41.15)		
Average normalized turnover on days the broker trades				0.37	
				(0.46)	
Cycle component of PRIN					35.96
					(12.57)
Noncycle component of PRIN					54.82
					(12.48)
Number	46,325	46,325	46,325	46,325	46,325
R^2	0.20	0.10	0.10	0.10	0.10

given stock-broker and assign a value of one (zero otherwise) if it is part of a three cycle, i.e., a sequence of only buying or selling that is exactly reversed on three consecutive trading days (e.g. days 1-4 in sequence 2 of Table 1 form one three-cycle). $PRIN3cycle$ is the average of this indicator over the entire trading history of the stock broker. $PRINnon3cycle$ estimates the "remaining" part of $PRIN$. Thus a trade which is classified as $PRIN$ on a given day must either be a $PRIN3cycle$ or a $PRINnon3cycle$.

If market timing is the only explanation for our results then the coefficient on $PRIN3cycle$ should not be significant, given that such trades are unlikely to reflect broker ability or information. Column 2 in Table 5, however, shows that this is not the case. The $PRIN3cycle$ coefficient is 31% and remains highly significant. Although the coefficient on $PRINnon3cycle$ is larger (51%), this partly reflects the stringent repeat cyclical trading definition used.

To conclude, better market timing is unlikely to be a complete explanation for the principal-trading effect given the above results and trading patterns in the data: Not only do the results remain robust to the inclusion of broker fixed effects but the profitable trading patterns, such as back and forth buying and selling by two brokers, also are hard to reconcile with legitimate portfolio optimization and market timing.

6.2. Liquidity provision

The second class of alternate explanations is that the principal-trading effect could reflect a premium for liquidity provision. In KSE, liquidity is provided through standard market-making activity or through an after-market repo transaction facility referred to locally as ‘‘badla’’ trading.

6.2.1. Market makers

Table 2 shows that the acyclic principal buy and sell trades are likely to take place on relatively low-turnover days, suggesting that the principal-trading result could reflect the return to market-making. While there is little disagreement that market makers earn a premium for providing liquidity, what is not clear is why market makers are more likely to engage in principal trades (have a high *PRIN* value). Nevertheless, we can directly test for a liquidity explanation by controlling for broker attributes that are correlated with liquidity provision. Because we control for broker fixed effects in column 1, any stock-invariant broker attributes that lead a broker to engage in liquidity provision, such as wealth or size, cannot explain our results.

One could still appeal to a stock-varying liquidity explanation, i.e., brokers differ across stocks in their ability to provide liquidity. We test for such an explanation by controlling for two stock-broker level attributes likely to be correlated with liquidity provision. The first measure we use is the share of a given stock's volume traded by a given broker during the sample period. Column 3 in Table 5 shows the robustness of our results to the inclusion of this liquidity control.

Second, one could argue that the return to liquidity provision primarily accrues on days on which there is low turnover to begin with (the majority of traders want to buy (sell) the stock but there are not enough traders willing to sell (buy), and on these days a broker can offer to be this seller (buyer)). Such a broker could engage in a principal trade (will only buy or sell) because he is trading to clear the net position. However, this explanation is not consistent with the result in Table 2 that cyclical principal trades happen on very high turnover days. More important, column 4 controls for the average stock turnover on the days that a given stock broker trades, and shows that the principal-trading result is unaffected.

6.2.2. Badla trades

Besides the results in Columns 3 and 4, another problem with the market-maker explanation is that it cannot explain the profitability of brokers who engage in cyclical trading patterns. However, there could still be a liquidity-based institutional explanation for observing cycles. Such an explanation is based on repo or badla trades. ‘‘Badla’’ is a local term for a forward trading facility used and recognized by the KSE (see Berkman and Eleswarapu, 1998 for Badla in the Bombay Stock Exchange). A badla transaction is essentially a repo transaction carried out in a separate after-hours market where the borrower who takes the badla from a badla broker 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. Thus badla traders appear as cyclical principal traders and hence are assigned a high *PRIN* measure.

While badla trades could explain the cyclical patterns, there is no reason to suppose that those who engage in badla trading also make more trading profits. The return for providing badla, while similar to a liquidity premium, is paid in terms of an explicit badla commission (set daily in the after-hours badla market) and is therefore not reflected in the trading profits. Thus, in the absence of a liquidity premium explanation, a badla trader can earn higher trading profits only if he strategically uses the badla, i.e., he exploits the fact that he could affect future stock prices by offering or withholding the badla facility.

The simplest way to test for such an explanation would be to explicitly identify badla trades (they are conducted in a special after-hours market). Unfortunately our data does not record these trades separately. They do not distinguish between a badla transaction and a trade in the (ready) market. However, if we impose the plausible condition that badla and repo transactions are reversed, then one can identify them by separating cyclic and acyclic principal trades as in Table 2 and then constructing analogous measures to *PRIN* at the broker (stock) level: *PRINcycle* and *PRINnoncycle*.[20] The former includes both badla brokers and principal brokers (all principal cycle trades), while the latter includes only principal buy and sell trades and is thus less likely to include badla brokers.

If badla trading is responsible for the principal-broker effect, then acyclic principal trading should not be profitable. Column 5 in Table 5 presents the results of this regression and shows that the coefficients on both *PRINcycle* and *PRINnoncycle* are large and significant (36% and 55%, respectively).

Revisit the findings in Table 5 in light of the price manipulation explanation. We have argued that explanations relying solely on either market making or liquidity are hard to reconcile with the results, in particular the cyclical patterns of trading and the profitability of brokers involved in principal cycles. Such trade patterns do not seem consistent with any reasonable portfolio rebalancing strategy or trading based on real information. The back and forth buying and selling by the broker in Column

[20]Specifically, for *PRINcycle* we look at each day's trading for a given stock-broker and assign a value of one (zero otherwise) if the broker 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*. It looks at each day's trade for a given stock-broker and assigns a value of one (zero otherwise) if the usual *PRIN* condition holds (i.e. the broker either only buys and sells or buys and sells the same amount on a given day) and there is no pure cycle (i.e. today's buy and sell are not the same as the next trade's sell and 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.

2 of Table 1 is highly suggestive of attempts at price manipulation. Such cycles arise naturally in direct manipulation schemes (brokers pair up and buy and sell rapidly to each other to create excitement), although one can imagine such manipulation being carried out in acyclical ways as well (e.g. a broker buys and sells differing amounts or buys sequentially for a few periods with another broker buying). Thus both types of principal trading, cyclic or acyclic, arise naturally under market manipulation. Moreover, one would expect that, to the extent such types of principal trading reflect manipulation, they will all be profitable. Thus the results in Table 5, particularly Columns 2 and 5, are consistent with the market manipulation hypothesis.

While we acknowledge that principal brokers could also employ other means for generating higher returns. Our results on the trading patterns used by principal brokers, direct tests verifying the price manipulation mechanism used by principal brokers, and little evidence for alternate explanations all lead us to conclude that market manipulation is an important part of what explains why principal brokers earn high returns off outsiders.

7. Concluding remarks

This paper uncovers unusual trading patterns and systematic profitability differences arising from trades between brokers and outside investors in emerging markets. While market-timing and liquidity-based explanations could account for some of the results, we argue that the evidence is indicative of manipulation of stock prices by collusive brokers.

How significant are these manipulation-based rents, particularly in relation to what brokers earn by trading honestly (by intermediating for outside investors)? While it is hard to come up with precise numbers, we can provide estimates by making assumptions about trading behavior and brokerage commissions. Specifically, we assume that a fraction *PRIN* of a broker's trades in a given stock are manipulative and a fraction $1 - PRIN$ are intermediary trades. We can then arrive at estimates of earnings by using a 50% return on the manipulative trades (a conservative estimate of the *PRIN* effect) and a 1% brokerage commission (the average commission rate in the KSE) on intermediary trades. The former gives us what the broker earns from manipulation in a given stock and the latter his earnings (total brokerage commission) from honest trading in the stock.[21] We can then compute a broker's total manipulation and honest trading earnings by summing the respective numbers across all the stocks he trades in.

Doing so reveals a couple of findings. First, manipulation rents are a significant part of the overall market: 44% of total broker earnings in the market.[22] Moreover,

[21]Specifically, manipulation return for broker B in stock S is $0.5{*}PRIN_{SB}{*}Average - Capital_{SB}$ and honest return for broker B in stock S is $0.01{*}(1 - PRIN){*}Value - Traded_{SB}$.

[22]Annual revenues are estimated to be Rs 6 billion from manipulation and Rs 7.6 billion from honest trading.

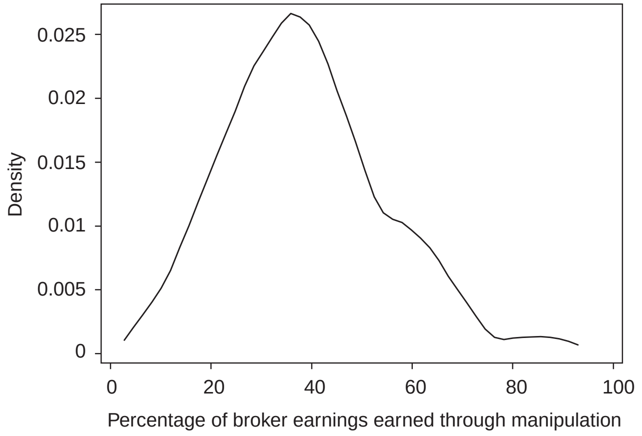

Fig. 7. Manipulation rents as a percentage of total broker earnings. Total broker earnings are made up of manipulation rents computed using a 50% return on trading done by broker on their own behalf (our conservative estimate in the paper) and brokerage commissions computed using a 1% commission rate on the value of trading done by a broker on behalf of outsiders.

these rents are likely to be an underestimate. Second, examining the earnings from honest and manipulative activity for each broker reveals that most brokers are earning significant manipulation rents. Fig. 7 gives the distribution of the share broker's earn through manipulation and shows that most brokers are clustered around the single mode (40%). This in turn has implications for regulation because it implies that instead of focusing only on a few brokers, regulation must correct for the presence and extent of manipulation in general.

The broader question then raised by our results is how important are the market inefficiencies, identified in this paper, from a country's financial development perspective? Our view is that, in terms of direct costs, the large transfer of wealth from outsiders to insider manipulators is likely to significantly discourage how much and how many outside investors choose to invest in the market. The presence of manipulators and naive traders imposes large participation costs for rational and sophisticated agents trying to either invest or raise capital in equity markets. Such participation costs form an important piece in solving the puzzle of financial underdevelopment. If manipulation becomes more difficult as the number of players and the size of the market increases, then there is a possibility of multiple equilibria: one with excessive manipulation and a small market size, and another with little or no manipulation and a large market size. Furthermore, the manipulation activity we show can be responsible for excessive volatility in the market and in turn impose additional participation costs.

An important agenda for future research is to understand and show what additional mechanisms used by market intermediaries could increase the participation costs and lead to excessive volatility in these markets, as discussed by

Kindleberger (1978) in his seminal work *Manias, Panics, and Crashes*. Such work leads to a better understanding of what reforms are successful in limiting the misgovernance of markets by intermediaries. Such reforms could include a greater presence of independent members (nonbrokers) in the exchange's board of directors; facilitating entry and competition amongst brokers, including the setting up of new exchanges; better systems of surveillance; tighter enforcement of existing and new regulation, such as stricter margin and capital adequacy; and information disclosure requirements that protect outside investors and prevent undesirable activities in the market.

Our results also suggest that, to the extent that a significant part of the market turnover reflects such manipulative practices, increased market turnover is unlikely to either lead or even reflect overall growth in the economy. Thus, in trying to find positive correlations between market turnover and growth using cross-country data (e.g. Levine and Zervos, 1998), emerging economies such as Pakistan (and Fig. 1 suggests there could be several others) appear as outliers. However, we should be careful in drawing inferences. Our results do not imply that financial markets have little to contribute to growth but that observing an active market should not automatically lead one to conclude that such a role is being played.

Identifying inefficiencies such as market manipulation and the resulting significant rents accruing to individuals can help begin to answer the more fundamental political economy question of why countries fail to adopt and implement good governance and other laws needed to strengthen equity markets. Even if it is obvious what reforms need to be taken to improve efficiency, because such reforms are likely to limit manipulation, they will be resisted by the conspiring brokers. This will be the case when, in the post-reform improved equilibrium, one cannot guarantee these brokers a large enough share of the pie, i.e., the Coase theorem no longer holds. This seems to be the case in Pakistan, where efforts by the SECP to initiate reforms have met with strong political opposition by lobbies working on the brokers' behalf.

To conclude, because the rent-seeking activities identified in this paper are likely to occur in newer and shallower emerging markets, 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. The concern is that equity markets, whose job is to facilitate real economic activity, could remain as phantom markets that serve little economic purpose.

Appendix A

This appendix describes how our main outcome measure, the annual rate of return (*ARR*) is calculated for a given stock broker.

We start with the simple example in Table A.1. Columns 1 through 3 give the trading history (ten trading days) of a broker in a particular stock. For each day we can calculate the net shares of the given stock bought by the broker (Column 4), and then keep track of the overall inventory of the broker by summing all past net trades

Table A.1
Profitability calculation example

ARR = the annualized nominal rate of return based on the brokers total net profit (186,000) for a given average capital investment (192,800). Thus, using this example the rate of return for the trades shows would be 96%. *ARR* would then be the annualized equivalent of this rate of return.

Date	Shares sold	Shares bought	Stock price	Net shares bought	Share inventory	Revenue	Investment	Gross capital required	Net running profit	Net capital required
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
		Raw data		(2) - (1)	Running Sum of (4)	(3)*-(4): if (4) < 0	(3)*(4): if (4) > 0	|(5)|*(3)		
1	143,000	139,000	1	−4,000	−4,000	4,000	-	4,000	4,000	-
2	151,000	120,500	1	−30,500	−34,500	30,500	-	34,500	34,500	-
3	49,500	78,500	1	29,000	−5,500	-	29,000	5,500	5,500	-
4	0	42,500	1	42,500	37,000	-	42,500	37,000	(37,000)	74,000
5	65,000	214,000	1	149,000	186,000	-	149,000	186,000	(186,000)	372,000
6	77,000	256,000	2	179,000	365,000	-	358,000	730,000	(544,000)	1,274,000
7	408,500	43,500	2	−365,000	0	730,000	-	-	186,000	-
8	2,000	24,000	2	22,000	22,000	-	44,000	44,000	142,000	-
9	2,500	10,000	2	7,500	29,500	-	15,000	59,000	127,000	-
10	0	69,000	2	69,000	98,500	-	138,000	197,000	(11,000)	208,000
End of period liquidation			2	−98,500	0	197,000	-	-	186,000	-

(Column 5).[23] To be able to compute the annual rate of return in this example, we need to compute the overall profit earned by the broker, and the average capital needed by the broker to earn this profit.

Before calculating the overall profit, we must address what to do with the stock inventory remaining at the end of period. For the *ARR* measure used in the paper, we choose the simple rule of liquidating the end of period inventory at the prevailing market price. We also mention an alternate measure but because the results are similar, we retain the simpler *ARR* measure. Treating the value of net shares sold on a given day as revenue (Column 6), and the net shares bought a given day as investment (Column 7), we can compute net profit as the difference between revenue and investment. Column 9 computes the net running profit by differencing out the sum of investments from the sum of revenue up to that point. Thus the running profit at the end of period is the total profit (or loss) earned by the broker over the entire period.

Calculate the average capital needed by the broker over the sample period, we compute the capital needed at any given time. The capital needed is the value of the net inventory holdings of the broker at the time minus any profits he could have accumulated up to then. This is given by Column 10. The average capital needed is then a time-weighted average of the capital computed in Column 10.

The overall rate of return in this example is then simply total net profit divided by the average net capital used. This in Table A.1 this return is 96% for the ten trades shown. Depending on the duration of this trading period we annualize these returns to obtain the *ARR* measure.

The second measure of the annual rate of return, *ARR*2, 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 stock, we net out his end net position. Effectively we are forcing the broker to earn zero profits on his ending position. To illustrate this consider the example in Table A.1 again. On date 7 the broker has a net inventory of exactly zero and after this date, on net, each trading day he only accumulates shares. The *ARR*2 measure ignores 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.[24] Then *ARR*2 is calculated like *ARR* on this new netted series. However, as expected, since both *ARR* and *ARR*2 are highly correlated, our results do not depend on which is used. We therefore stick to the simpler *ARR* measure in the paper.

[23]This inventory is calculated using the observed trading history of the broker during our sample period. Because 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).

[24]In a more realistic example, we could have to split a day's net trade to exactly net out the broker's ending position.

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