“Phantom” Markets: How Do Equity Markets Not Function?

Asim Ijaz Khwaja, Atif Mian*

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Abstract

We analyze a unique data set containing daily firm-level trades of every broker trading on the main stock exchange in Pakistan over a 32 month period. A detailed look at the trading patterns of brokers trading on their own behalf reveals some “strange” patterns suggestive of price manipulation attempts. Comparing profitability levels of these brokers with brokers who mostly trade for (several) different outside investors, reveals that the former earn an annual rate of return that is 5% to 8% higher than the average outside investor. This “manipulation” effect varies systematically across firms, with larger firms, and firms with more concentrated ownership less likely to be manipulated. We then directly identify and test for the manipulation mechanism. We find that, when prices are low, only manipulating brokers trade amongst themselves and raise prices to attract naive positive feedback investors. However, once prices have risen, the former exit leaving only the feedback traders to suffer the ensuing price fall. In contrast to developed markets, these price bubbles are “controlled” in that their onset (and extent) is not reliant on initial news but at the whim of the manipulating brokers. Our results shed light on the real world trading behavior of naive investors and why equity markets function poorly in developing economies.

*Kennedy School of Government, Harvard University; and Graduate School of Business, University of Chicago. Email: asim_ijaz_khwaja@harvard.edu, atif@gsb.uchicago.edu. We are very grateful to Mr. Khalid Mirza, and Mr. Haroon Sharif at the Securities and Exchange commission of Pakistan for providing us the data, and for answering an un-ending line of questions. However, none of the results in this paper necessarily reflect their views, or that of the SECP. We would also like to thank Toby Moskowitz, Owen Lamont, Nick Barberis, and seminar participants at SECP, and Chciago GSB faculty lunch. All errors are our own.

1 Introduction

Most developing countries have relatively young and weak market-based financial institutions such as stock markets. One influential view is that in the presence of weak regulatory and contractual enforcement, small investors are deterred from investing in the stock market. There are a couple of reasons suggested for this: First, poor corporate governance of firms leads to tunneling and revenue hiding. Second, outside investors stay out of the market for fear of being exploited by unscrupulous stock price manipulators and insider traders. Whereas significant attention has been paid in recent empirical literature to the first point, there has been very little work done that documents the existence or extent of price manipulation behavior in emerging markets, or specifically, in shallow markets where the players are large enough to affect prices and are relatively unchecked. This paper addresses this gap by analyzing a unique data set containing daily trades of all the brokers trading on the Karachi stock exchange (KSE), the main stock exchange in Pakistan.

The main results of the paper can be summarized as follows: Our primary finding is that brokers who, for a given firm, trade primarily on their own or for a few investors only ("Principal brokers") make both statistically and economically significantly higher returns than those who act as intermediaries (i.e. mostly trade for others/a large number of different investors). The annualized returns for these Prinicpal brokers are 5% to 8 % higher than that of the average outside investor. We interpret this result as indicative of a greater manipulation of the market on the part of the former. Moreover, we find that this result is driven precisely by the broker's acting as a principal for a given firm and not by any inherent attribute of the broker. In other words, it is only if a given broker acts as a principal in a firm that he earns the higher return. We also test the robustness of this result to different specifications and measures of the "prinipalness" of a broker and find that the manipulation effect remains significant and large.

We then go on to explore under what circumstances such manipulation is prevalent, and suggest some avenues through which such manipulation may take place. We find that the manipulation effect is smaller (though still present) for larger firms, and for firms with larger concentration (of stock holdings) suggesting that such manipulation is carried out by the ability of a broker to "move" the market and that it requires the presence of a substantial number of "outsider" investors who can be exploited. Moreover, a closer examination of trading patterns shows "buy-sell cycles" between two prinicipal brokers may be one method used to generate false trading and price expectations. Examining the micro-structure of trades bears this out as we find that on days where the price is (relatively) low, most of the trade is carried out by brokers acting as principals, whereas on high price days, most trade is done by intermediaries. This is consistent with behavior where the principal brokers make money off naive positive feedback investors by first artificially raising prices ("creating" bubbles) in order to attract the latter and then exiting the market before the price bubble collapses. We also see that a higher manipulation effect is associated with a higher variation in price of the firm, again suggesting that it is by manipulating prices that these brokers are able to exploit naive outsider investors. All these results confirm the anecdotal findings of such manipulation mechanisms.

On a broader note, there is sometimes a misconception that capital markets in emerging economies are uninteresting to look at because of their small size in relation to the overall economy. We obviously do not hold this view. Given the importance of sound capital markets for efficient allocation of resources in the economy, it is imperative that economists understand the factors that hinder the growth of such markets in developing countries. In principle there could be many factors preventing the average investor from participating in the capital markets. This paper focuses on the endemic problem of price manipulation, and insider trading that is potentially an important factor in limiting the success of the stock market in developing economies. Moreover, by exploiting cross-sectional variation across firms, we are able to give insight into questions like what kind of firms are likely to suffer most due to manipulation.

Whereas issues such as insider trading, and behavioral responses are applicable to stock markets all over the world, the question of strategic manipulation prices is of particular importance in emerging markets. The reason is that manipulation of prices is more likely to occur in newer and shallower markets. Such manipulation in turn can be responsible for limiting the depth and size of such markets. Price manipulation can thus be an important ingredient in understanding why capital markets in developing countries do not work very well. This is an issue that has been under-researched in the present literature on equity market development, that has put more emphasis on corporate governance problems at the firm level. Whereas we do not doubt the importance of good corporate governance for healthy equity markets, one of the aims of this paper is to also highlight the importance of proper governance of the trading activity for capital market development. This is an issue that we will discuss in more depth after presenting our empirical findings.

Relationship to history of equity markets

While this paper focuses on emerging markets, it also provides a very interesting historical analysis for how markets in developed countries matured: Early descriptions of the New York Stock Exchange and the manipulative practices of brokers are uncanny in their similarity to what we observe in our data from the KSE. While we do not have comparable data from the early days of the NYSE or the London stock exchange, there is a lot of anecdotal information that describes how prevalent "bluffing" was. In describing the NYSE in the 1920s, Gordon [2000] writes in what could just as easily be an accurate description of the KSE today:

> " By 1920 the phenomenal growth of the American economy in the preceding forty years and the accident of a world war fought in Europe had made the New York Stock Exchange the largest and most powerful institution of its kind in the world. But institutionally, it was still much the same as it had been in 1817 when it had come into formal existence. That is to say, it was a private club, operating for the benefit of its members, the seat holders, and not the investing public... The floor traders ... traded only for their own accounts. They had two great advantages over

> the ordinary investors and speculators who increasingly haunted the board rooms of brokerage offices as the decade progressed. Because they had access to the floor itself, they had the latest possible information on how the market, and individual stocks, were moving and could execute trades with lightning speed. And because they paid no brokerage commissions, they could move in and out of stocks and bonds as often as they liked, taking advantage of small swings in price much as the new "day traders" can do today on the Internet. Unlike today's day traders, however (at least so far), they could also conspire with each other and with specialists to manipulating the market to their advantage ... Pools, wherein several speculators banded together to move a stock up and down, were common. Although so-called wash sales (where brokers reported sales that had not, in fact, taken place) were prohibited, the pools carefully timed sales within the group, called matched orders. These sales could be used to produce a pattern on the ticker (called painting the tape) that would induce outside speculators to buy or sell as the pool wished. When their object had been achieved, they could close out the pool at a tidy profit, leaving the outside speculators holding the bag ... It was, at least for the quick-witted and financially courageous, a license to steal. Whom they were stealing from in general, of course, was the investing public at large But they sometimes stole even from less favored members of the club". [pg.213]

We highlight the similarity between these two markets both because studying emerging markets sheds light on the history of markets in developed countries but also to suggest that there is nothing inherently different between the two markets other than one has been around a lot longer than the other. From the perspective of emerging markets this similarity has immense value because it implies that the same measures that, for example, the NYSE took to curb such manipulative behavior may be used in emerging markets today and moreover, that there may be limits to how much one can curb such behavior.

To our knowledge, this paper is the first attempt at understanding the behavior of equity markets in a developing country at a micro level. The prime reason we are able to do this is the unique nature of our data set. Previous papers that have looked at trade level data on equity markets have focused exclusively on advanced economies (examples include Barber and Odean [2001], and Grinblatt and Keloharju [2000], [2001a], and [2001b]). As we have already discussed above, the micro-level questions for developing countries, such as manipulation, are quite different than those for advanced economies. More work needs to be done in this direction if we are to understand why equity markets fail to develop in poor economies. This paper is also related to the literature in behavioral finance that posits that "irrational" positive-feedback investment strategies can lead to inefficiencies in the equity markets (De Long et al [1990b], and Shleifer [2000]). By being able to separate insider traders from outside "naive" traders, we are able to test and confirm in a real world setting that naive outside investors indeed trade using positive-feedback investment strategies. We believe that it is this type of irrational belief that is able to sustain the inefficient equilibrium where principal brokers keep on manipulating the markets. Such manipulation profits have interesting implications for the political economy of reforms as well. When brokers earn hefty returns by being able to continuously rip-off naive investors, they resist any move to reform the markets.

The rest of the paper is organized as follows. Section 2 describes the data, provides the relevant institutional background, and describes the construction of some key variables in our analysis. Section 3 measures the excess return that brokers who trade on their own behalf earn compared to the average outside investor. We call this the manipulation effect, as qualitative evidence as well as the trading patterns of individual brokers suggest that individual brokers are engaged in price manipulation activities. Section 4 estimates how this manipulation effect varies across different types of firms. Section 5 takes a closer look at the micro-structure of trading behavior and sheds light on the mechanisms through which this manipulation effect works. Section 6 concludes.

2 Data

2.1 Basic Description

The data set consists of the entire trading history for KSE over a 32 month period (21 December1998 to 31 August 2001). It contains the *daily* trades of *each* broker for *every* stock over the 32 month period. There were a total of 147 active licensed brokers and 741 firms[1] trading on KSE during our sample period. The data set thus contains almost 2.2 million observations at the broker-firm-date level. The data set was extracted from the trading computers at KSE.

Trading on KSE can only be performed by a licensed stock broker. Each trade order (buy or sell) is thus recorded under a particular broker name, and this is the data that we have (aggregated up to a day). For each broker-firm-date, our data set contains: (i) the number of shares bought or sold through the broker, and (ii) the closing, highest, and lowest price for the firm during the day. Only completed trades are recorded. So bids that are left unfulfilled are not included in the data set. We supplement this trade level data set with annual firm-level data that includes each firm's income, balance sheet and ownership information.

KSE is the largest stock exchange in Pakistan. It was established soon after independence in 1947, and in 2001 it captured 74% of the overall trading volume in Pakistan[2]. There were 758 firms listed on KSE with a total market capitalization of \$5.2 billion in 2001. *Figure* 1 compares the size (market-cap/GDP) and turnover (dollar-volume / market-cap) of KSE relative to stock markets around the world. The countries in *Figure* 1 are ordered by GDP per capita. A couple of facts are

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

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

worth mentioning in this regard. First, as far as KSE is concerned, it is one of the smaller stock exchanges in the world in terms of size but the level of turnover in KSE (0.88) is considerably high compared to other markets in the world. For example, among developing economies KSE ranks at the 33^{rd} percentile in Market-cap/GDP, and at the 81^{st} percentile in market turnover. The high level of turnover is of particular interest for this paper as it is consistent with a world with a high level of speculative manipulation of prices. The second observation worth noting from $Figure$ 1 is that whereas lower income countries have consistently lower stock market size to GDP ratios compared to richer countries [grey squares in figure 1], many developing countries (such as Pakistan) have very high levels of turnover [black squares in figure 1].

$Figure$ 2 shows the price volatility in KSE during our sample period. It plots the KSE100 price index[3] over the five year period from 1997 to 2002, that includes the 32 months covered by our data set. The aggregate stock market has experienced wild fluctuations: with the highest price almost three times the lowest.

It is worth noting that the size-distribution of firms traded on KSE is highly skewed. $Figure$ 3 plots the CDF of market capitalization and turnover for the firms in our data. The distribution of market-cap and turnover is highly skewed, with the top 25 firms accounting for 75% of the overall market capitalization, and 85% of the overall turnover.

2.2 "Intermediary" vs. "Principal" brokers

Given our data set, we first distinguish between regular outside investors, and investors who likely to be involved with activities related to stock price manipulation. Since our data is at the broker level, we argue that this translates into distinguishing between brokers who are intermediaries i.e. primarily trading on behalf of several (regular) outside investors, and brokers who are trading on behalf of very few (potentially manipulative) investors. We call the first type of brokers "intermediary brokers"

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

(IB), and the second type "principal brokers" (PB). Below we describe the qualitative and quantitative features about trading at KSE that allow us to characterize brokers as either intermediary or principal and why we maintain that the latter category includes far more "manipulators".

Qualitative Evidence on Stock Price Manipulation:

In the course of writing this paper we conducted detailed interviews with market participants (including a broker with whom we had enough trust to talk candidly), and officials at the Security and Exchange Commission of Pakistan (SECP) (including the chairman of SECP). The presence or at least allegations of stock price manipulation is common knowledge among the primary market participants. Moreover, it is the licensed brokers themselves (or their close associates) who are most often alleged to be involved in manipulative activities. It is alleged that individual brokers "collude" to artificially manipulate prices in the hope of attracting and eventually ripping off the naive outside investor. In fact special terms, such as *bhatta*, have been coined in *Urdu*, the local language, to define such behavior.

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

The perception that brokers themselves are involved in manipulation can be welljudged from the report that SECP wrote to the President of Pakistan:

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

The reform agenda that the quote above refers to was initiated in June 2000, and was particularly targeted at preventing the price manipulation activities of brokers. We will describe these reforms in more detail later, when we measure their impact on the price manipulation behavior.

Given the qualitative evidence on brokers acting as price manipulators, one natural way to separate out manipulative trading is to focus on trades done by the brokers on *their own* behalf. This is the methodology we adopt in this paper. The feature of the data that allows us to do this is that for a given firm, there are brokers who engage in little or no intermediation. We describe the classification of brokers for a given firm in more detail below.

Constructing the "principal-ness" measure:

To understand our method of classifying brokers as principals or intermediaries, it is instructive to look at a typical example from our data. *Table* 1 gives the trading history (last 20 trades for each) of two brokers for a given firm "FFC Jordan".[4] A striking dissimilarity in the trading patterns of the two brokers is that whereas the broker in column (1) is trading generally different numbers of buys and sells each day, the broker in column (2) either buys or sells on a given day.[5] It is quite clear from the

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

[5]It is also interesting to note the cyclical pattern in the Column (2) brokers sales and buys (i.e. he sells the amount bought in the previous period). This is suggestive not only of the broker acting

two columns that whereas the broker in column (1) is intermediating on behalf of many outside investors, the broker in column (2) is acting on behalf of a single individual.[6] The back and forth buying and selling of the stock by the broker in column (2) is also highly suggestive of an attempt at price manipulation. A trade pattern of this sort is certainly not consistent with any reasonable portfolio re-balancing strategy. We will discuss such and other "unusual" trading patterns of individual brokers in section X. Given the example in $Table$ 1, we classify the broker in column (1) as "intermediary", and the broker in column (2) as "principal". More generally, we construct a continuous principal-ness measure ($PRIN$) for a given broker-firm by computing the probability of the following event over our sample period: (i) buy >0 and sell =0, or (ii) sell>0 and buy=0, or (iii) sell=buy. The third condition is added as a single investor may buy and sell exactly the same number of shares within the same day. The probability of this event is zero if a broker is intermediating trades for a large number of people. In any case, all our results are robust to the definition of $PRIN$ that only includes conditions (i) and (ii) above. With this definition, the broker in column (1) gets a $PRIN$ value of 0.06, and the broker in column (2) a value of 1. Given $PRIN$, an "intermediary" broker is classified as one with a low value of $PRIN$, and "principal" as one with a high value of $PRIN$. Our results are robust to a wide choice of cutoff rules for $PRIN$, but the results we report in this paper use the continuous measure $PRIN$ directly as we feel that this way we better exploit the informational content of our data.

With the computation of $PRIN$ as above, we can aggregate the data up to firm-broker level and are left with 49,038 observations. Since there are 741 firms and 147 brokers in the data set, this implies that on average there are 66 brokers trading shares for given firm over our sample period.[7] A very large fraction of the firm-brokers have

as a principal (not intermediary) but also illustrates one mechanism through which such brokers may be manipulating prices. We discuss in more detail the trading patterns of "principal" brokers in section X.

[6] Likely to be either himself, or a close associate.

[7] There is significant varaition in this across firms: the middle 50% of the distribution of brokers

a high value of $PRIN$. For example, 78% of firm-brokers have a $PRIN$ of greater than 0.9, while the remaining 22% have a $PRIN$ of less than 0.9. Since by definition, a principal broker trades only on his behalf, and an intermediary broker trades on behalf of many investors, the size (as measured by trading volume) of a firm-broker with a high $PRIN$ is typically less than the size of a low $PRIN$ firm-broker.

Of the 49,038 of the firm-brokers, $14,674$ only accumulate or de-cumulate a stock during our data period.[8] We drop these firm-brokers from our main data set. The results of our paper are only strengthened when we include these firm-brokers in our regressions. We are thus left with $32,650$ firm-brokers in our main data set.[9] $Table$ 2, Columns 1 and 2, give the distribution of firm-brokers by $PRIN$ both in terms of the number of firm-brokers, and also in terms of the trading volume of firm-brokers for four different ranges for $PRIN$. It should be emphasized here that the same broker can act as an intermediary for certain firms, and as principal for others. This is consistent with our discussions with market participants and SECP on the subject. Brokers differ in the particular firms that they "specialize" in manipulating. The data strongly supports this observation. The *average* standard deviation of $PRIN$ within each broker is 0.16, whereas the standard deviation of average $PRIN$ across brokers is 0.04 suggesting that there is more variation in $PRIN$ for a given broker than when comparing across brokers. We will test this more explicitly later, when we run regressions with broker fixed effects.

3 How profitable is manipulation?

The $PRIN$ measure allows us to discriminate between brokers who intermediate on behalf of a number of investors, and brokers who trade on behalf of a single investor,

trading in a given firm lies between 21 to 133 brokers per firm.

[8] These are essentially brokers who for a given firm only do a few sell (or buy) transactions during our data period. The volume of trade done by these firm-brokers is less than 1% of the overall trade.

[9] These numbers do not match up because our final firm-broker sample also excludes brokers which are outlyers in terms of their estimated rate of returns. This will be discussed in the section below.

which we assume to be either the broker himself, or his close associate. If, as is commonly alleged, brokers are involved in stock price manipulation, then principal brokers should on average be earning higher profits than intermediary brokers. This is due to the fact that trades done by intermediary brokers include trades ordered by their outside investors, some of whom include the "naive" or unsophisticated investors that are being ripped off by the price manipulators.

In this section, we formally test whether brokers with a higher $PRIN$ value actually earn higher profits. We therefore first construct an annualized rate of return (ARR) measure for each firm-broker using his entire trading history (i.e. buy and sell orders for the firm) over our sample period. A problem in calculating ARR over the sample period is that the trading history may not net out to zero. In particular, if a broker is a net accumulator or a net de-cumulator of a given stock over our sample period, we need to come up with a strategy to value his end of sample net holdings. We take the simple approach of valuing his end of sample net holdings of a stock using the end of sample stock price. To put it differently, we "force" the firm-broker to liquidate any net positions at the end of sample price.[10] On a given day, we then consider the sale of stock by the broker as a cash inflow and a buy of stock as a cash outflow for the broker. Using an annual 10%[11] opportunity cost of capital, we can then compute the rate of return on the stock on an annualized basis. An explicit example is described in *Appendix* 1 to clarify the construction of ARR. *Table* 2 reports the mean and standard deviation of ARR within different categories of $PRIN$. Since we observe each trade in the market during our sample period, and for now we are neglecting dividend payments, the volume weighted mean of ARR in our sample is equal to zero.[12]

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

[11] 10% was the approximate nominal return (annualized) on 1-year government bonds during the sample period. The rate of inflation over the sample period was 5%.

[12] Due to the market clearing condition: one person's capital-gain is another person's capital loss.

Table 2 shows a definite trend of increasing ARR with $PRIN$, suggesting a higher rate of return for brokers who act more like principals than intermediaries. We will analyze this relationship more systematically in the regressions below. In the first set of rows in *Table* 2 we examine how the mean ARR *varies* across four categories of $PRIN$.[13] As is clear from the table, the mean ARR values increases as we move to categories with higher $PRIN$ values. The first two columns of *Table* 2 also bear out one of our earlier claims: Despite having narrower categories for higher $PRIN$ values, there is a much larger number of firm-brokers in the higher categories but with a much lower trading volume. One of the concerns therefore is that the $PRIN$ effect we are capturing while significant, is just driven by the few small (in terms of turnover) firm-brokers. However, given that the KSE has a few very large firms and we would expect lower values and variation for the $PRIN$ *measure* and hence lower manipulation in such firms, the second group of rows in *Table* 2 drops the top 15 firms (by trading volume). While the mean ARR pattern remain almost identical, each category now has roughly the same weight (in terms of trading volume in that category) suggesting that our manipulation effect is also economically significant and prevalent. Finally the last set of rows takes a closer look at potential manipulation effects in the top 15 firms as well. We use a larger number of $PRIN$ categories (since most of the large firm-brokers have understandably lower $PRIN$ values, we need finer categorization in the lower end of the $PRIN$ distribution) and interestingly enough, even within these larger firms and hence one average much larger firm-brokers, we see evidence of the manipulation effect although, as expected, they are far fewer firm-brokers who have higher $PRIN$ values in such firms and hence are able to make use of these manipulation gains.[14]

Primary regression of interest:

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

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

[14] This explains why later on, when we examine heterogeneity in the manipulation effect, we see that is generally smaller for larger firms.

simply be written as:

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

$\underline{F}$ refers to firm level fixed effects. β in (1) captures the superior returns that "principal" brokers ($PRIN = 1$) receive over "intermediary" brokers with the lowest possible value of PRIN ($PRIN = 0$). $Column(1)$ in $Table$ 3 reports the results of the regression. Principal brokers earn an annual rate of return that is 7.01% higher than intermediary brokers. The result is highly significant (less than 1%). We only report results with firm fixed effects, the results are very similar without firm fixed effects as well. We next run a sequence of robustness checks on this result.

It is important to point out here that whereas our definition of "principal brokers" is able to cleanly separate out the potential manipulators and insiders, some of the "intermediary brokers" may also be involved in activities similar to the principal brokers, but that we are unable to observe, since we only see their aggregate daily trades which include trades by the naive outside investors. We therefore expect that all the results that we present in this paper are an *underestimate* of the true effect.

Robustness to Opportunity Cost of Capital:

Column (2) reports the results of a regression that uses a 5% opportunity cost of capital instead of 10%. The coefficient is still highly significant, but drops to 5.66 percent. This just reflects the fact that higher discounting of cash flows favors principal brokers who tended to be net sellers when market reached its peak in the middle of the sample period, and net buyers later on.

Manipulation or Ability?

Could our results be driven by the fact that high ability individuals who can "time" the market really well, buy a license to trade directly on the stock market so save on transaction costs? These individuals would then appear like principal brokers, and would earn higher returns not because they are manipulating, but because they have higher ability on average. As we pointed out in the previous section, this is unlikely to be the case given what their trading patterns look like. It is very hard to reconcile trading patterns, such as back and forth buying and selling by two brokers with legitimate portfolio optimization and market timing. Still we do an explicit test for this concern by including broker fixed effects in our regression. The inclusion of broker fixed effects will take away any broker specific variation from our results. Column (3) of $Table$ 3 reports the results. The coefficient of interest does not change much, thus confirming the belief that our results are not driven by better market timing by certain brokers.

More restrictive definition of PRIN:

We mentioned earlier that our estimated measure of profitability differential for high $PRIN$ firm-brokers is likely to be an *underestimate* of the true profitability differential. The reason is that firm-brokers who intermediate for a large number of outside investors (and thus have a low $PRIN$), may also engage in price manipulation activities of their own on the side. To the extent that part of the return of low $PRIN$ firm-brokers includes the higher return from manipulation activity by the firm-broker himself, our regression coefficient will be biased downwards. We try to test for the direction of this bias by using a more restricted definition of $PRIN$. Our original definition of $PRIN = 1$ included the case where a firm-broker's sale equals his purchase on a given day. We now exclude this case from the definition of principal brokers, and re-run the regression in column (1). Column (4) presents the results. Since in the more restricted definition of $PRIN$ some firm-broker as incorrectly classified as intermediary, the estimated coefficient on $PRIN$ drops to 5.31 from 7.01 in column (1).

Non-linear Specification:

So far we have assumed a linear specification in all our regressions. A look at $Table$ 2 would suggest that the effect of $PRIN$ on profitability is non-linear at $PRIN = 1$, as the profitability of firm-brokers suddenly jumps at that point. We therefore re-run (1) with an additional dummy for firm-brokers with $PRIN = 1$. Column (5) reports the result. The results confirm the overall picture presented by Table 2. There is a significant jump of 1.7% at $PRIN = 1$, and the linear effect of $PRIN$ for $PRIN < 1$

decreases to 3.64%.

Value-weighted Regression:

The regressions presented so far give equal weight to all firm-broker observations regardless of the volume traded by the firm-broker. As Table 2 showed, there is significant variation in the total value of stocks traded by each firm-broker. Therefore, a more economically sound measure of manipulation effect might be one where each firm-broker is weighted by his relative size. There are two potential sources of variation in the firm-broker size: within firm variation, and across firm variation. The within firm variation is generated by the fact that different brokers trading stock of a given firm differ in the value of the stock traded by them. The across-firm variation comes from the fact that some firms are much bigger than other firms in terms of the total number of shares listed and traded on the stock market. The highly skewed nature of this distribution was evident from figure 3. Given these two sources of variation in firm-broker size, we adopt the following weighting strategy. We weigh each firm broker observation by the $fraction$ of that firm's total volume traded by the firm-broker. We do not weigh each firm-broker observation by the dollar *level* of its trading volume because doing that would essentially drop all the small firms from our regression given the skewness of the firm-size distribution in figure 3. Instead in the following section, we compute the manipulation effect for different size categories of firms to see how this effect varies across the different types firms. Column (6) reports the results of regression (1) where each firm-broker is weighted by his relative size within the firm. The estimated coefficient on $PRIN$ gets even bigger to 8.65% after weighting.

4 Heterogeneity of manipulation effect across firms

So far we have been reporting the *average* difference in profitability between high $PRIN$ and low $PRIN$ firm-brokers. Results in Table 3 clearly indicate that principal brokers earn 5 to 8 percent higher return on an annualized basis. These results shed important light on why equity markets in developing countries fail to develop. In a world where the outside investor is continuously being exploited by the professional brokers, it is little surprise that the size and depth of the market is extremely limited.

In this section we exploit the heterogeneity in firm characteristics to explore how the manipulation effect varies across firms. This will be useful on two accounts. First, it helps us further isolate the precise channel through which manipulation works. For example, is the manipulation effect negatively correlated with the size of a firm? If so, it suggests the difficulty of successful manipulation as the number of players and the size of the market increases. This clearly hints at the possibility of multiple equilibria: one with high manipulation and low market size, and another with low/no manipulation and high market size. Second, heterogeneity of the manipulation effect allows us to do some more robustness tests. For example, is it true that firms with higher manipulation effect have higher coefficient of variation of price?

Firm Size:

Columns (1) and (2) in Table 4 measure how the manipulation effect varies across firms. In column (1), we interact the $PRIN$ variable with a dummy for small firms. The dummy variable is zero for the top 100 firms by size, and one otherwise. $Column$ (1) reports the results of this regression. Whereas the manipulation effect is positive and significant (4.56%) for the top 100 firms, it is significantly larger for the smaller firms. The manipulation effect increases by 5.7% for the smaller firms in the stock market, and the difference is significant at the 1% level. Column (2) further disaggregates the manipulation effect by creating seven size categories. With fewer firms in each category, the standard errors on the interaction coefficients blow up, but the size of the interaction coefficients is still instructive. The interaction coefficient steadily decreases as we move up firm size from category 2 to category 7. This suggests that manipulation is more rampant in the smaller stocks as one would expect.

A word of caution needs to be given in interpreting the relationship of size with manipulation. We have mentioned earlier that our estimate of manipulation is an underestimate due to the potential aggregation of manipulative activity with outside investors for intermediary brokers. This underestimation is likely to be more severe for larger firms, as higher number of brokers will be involved in *both* intermediation and manipulation. Such differential under-estimation can partially account for the results of column (1) and (2). There is also some direct evidence on the presence of this effect, as the mean value of $PRIN$ by firm decreases with firm size.

Firm Price Volatility:

Manipulation of prices could lead to a greater volatility in prices. For example, creating artificial movements in prices could be one way the manipulators can attract naive outside investors (such as price feed-back traders). In such a scenario, the manipulation effect within a firm will be positively correlated with the price volatility of the firm. We formally test for this correlation by first constructing the coefficient of variation of price for each firm, and then correlating it with the manipulation effect. Column (3) in Table 4 tests for this correlation. The result shows a positive and significant correlation between the volatility in stock price, and the manipulation effect. The size of the coefficient (31.71) is also quite large, as the coefficient of variation varies from 0 to 1 in our data.

Firm Ownership Concentration:

Column (4) categorizes firms by their ownership concentration, and then interacts the three ownership categories with $PRIN$. The results suggest that firms with *more* concentrated ownership are *less* likely to be manipulable, suggesting that one needs a significant number (by shares held) of "outsiders" to make it worthwhile to manipulate.

5 Understanding Trading

Our previous results have shown that high $PRIN$ brokers earn significantly higher returns than, and at the expense of, low $PRIN$ brokers. Moreover, we also saw that such "manipulation" is less prevalent in larger and more concentrated firms. These results, combined with the trading patterns discussed is Table 1, suggest mechanisms through which such manipulation is carried out. In particular, the "buy-sell" cycles seen in Table 1, may be an effort on the part of the high $PRIN$ brokers to manipulate the share price, and such efforts are likely to be inherently harder in larger firms and not worthwhile in more concentrated firms with little outside investors to exploit.

In this section, we exploit the micro-structure of trading in our data by directly testing for mechanisms through which prices are manipulated in the stock market. If we are able to identify the precise mechanism through which principal brokers are manipulating stock prices, it will give us a direct proof of the claim that principal brokers earn higher returns due to their manipulation of stock prices.

The exact manipulation mechanism that we test in the data is given in Figure 4. The manipulation mechanism is easier understood by first classifying each firm and date with a state variable $I_B I_S$, where I_B and I_S refer to the overall $PRIN$ category of buyers and sellers trading that firm's stock on that date. For simplicity, assume that I can take on two values: H for high, and L for low. There are thus four possible states for a given firm-date: HH, LH, LL, and HL. Thus the state variable LH means that the average $PRIN$ of the brokers buying the firm's stock that day is low, whereas the average $PRIN$ of the brokers selling the stock that day is high. We define high and low relative to the average $PRIN$ value of brokers for a given firm throughout the data period. A buying index of L then means that on that day broker buying the firm's stock have a lower $PRIN$ than usual for the firm.

Figure 4 shows that during a manipulation cycle, when price reaches a low point, only the high $PRIN$ types are left in the market. Therefore the state at this price is HH (point A in figure 4). These high $PRIN$ brokers then act as manipulators, and start trading back and forth in an effort to attract the naive outside investors who have extrapolative expectations and thus follow positive-feedback investment strategies. As they raise prices, they attract the outside investors who chase the trend and start buying (branches B,C). When the buying pressure gets strong enough from the outside investors, the state changes from HH to LH. However, once the price has risen enough, the manipulators exit the market and trade only occurs between the outside noise investors (point D). The state when price is at its highest is thus LL. This artificially high price can no longer be sustained as the manipulators have gone out of the market. Consequently the "bubble" bursts and price starts to fall (branches E,F). The positive feedback traders start selling at this point which further depresses the price. When the price gets low enough, the manipulators get back into the market to buy back their stock at low prices (state HL). Finally once the manipulators have bought back all their stock, the price is at its lowest again, and the whole cycle repeats itself (point G).

The positive feedback investment strategy assumed on part of the naive outside investor is familiar to the literature in behavioral finance. Surveys indicate that often underlying such positive feedback behavior is extrapolative expectations or trend chasing on the part of the noise traders. De Long et al [1990b], and Shleifer [2000] have hypothesized such investment strategies to explain stock market anomalies such as momentum, and bubbles. Thus our test of the manipulation cycle in figure 4 can partly be thought of as a test for the presence of positive feedback investors in the market.

The manipulation cycle in figure 4 offers precise predictions which can be tested given the nature of our data. The predictions relate to both the level, as well as the change in prices conditional on the firm-date state. Table 5a reports the frequency with which we observe each of the four states. The frequencies are evenly distributed with HH, LH, LL, and HL occuring 31.1, 21.4, 28.4 and 19.2 percent respectively.[15]

Test 1: Price Level Conditional on State

The manipulation mechanism in figure 4 predicts that a given firm's price will be highest at state LL, lowest at state HH, and intermediate at state HL and LH. To test this, we first normalize each firm's price on a given date by dividing it by the average firm price over the entire data period, and multiplying by 100. For each firm we then calculate the mean normalized price in each of the four states. Table 5a shows the result of regressing the mean normalized price on state dummies. Our data

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

confirms the price level prediction of figure 4. The price of a firm is at its highest at LL, and lowest at HH, with HL and LH being in the middle. The price level at state LL is 9.85% higher than the state HH, and the coefficient is highly significant.

Test 2: Price Change Conditional on State

Figure 4 also makes some sharp predictions about the direction of price change conditional on the state. It predicts that, (a) price changes are positive (higher) after states HH and LH, and negative (lower) after states LL and HL, (b) price changes are negative (lower) before states HH and HL, and positive (higher) before states LL and LH.

To carry out these tests, we first convert our daily data into weekly data. Using daily prices, we compute the return on a stock during each week, and also construct the state variable for each firm-week. There are a total of 141 weeks spanning our data period. To compute state contingent future returns, we follow the following strategy. At the end of each week, we construct a portfolio made up of firms that had the given state that week. So for example, if we are interested in calculating one week future return after state HH, then at the end of a week we include all firms in our portfolio that had a state of HH in that week. We then hold these firms for one week. The average weekly return on this portfolio then gives us the state-contingent future price changes. Since we are interested in looking at cycles, we subtract the market return from this portfolio, where market return is the return one gets from holding all the firms all the time. Column (1) in Table 5b reports the results of these estimates. The first thing to notice is that as predicted *all* price changes go in the right direction. Price change after HH and LH is positive and significant, and after LL and HL it is negative. Moreover, the size of the coefficients is also quite big. Column (1) also reports the difference in returns from holding a "winning" portfolio, vs. holding a "losing" portfolio, where winning (losing) refers to state contingent portfolios with positive (negative) returns. For example, if a person had access to inside information about the state of the market, and systematically invested in only HH contingent stocks, while a naive investor only invested in an LL state, the difference in their weekly returns will be 0.43%, which is equivalent to a 25% annual return differential.

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

Next we test for state-contingent *past* price changes. The methodology for computing these returns is exactly the same as before, except that now instead of keeping track on one week ahead price change, we keep track of one week before price change. The results of this exercise are shown in column (3). Once again the results strongly support the predictions of our hypothesized manipulation mechanism. As predicted, price changes before HH and HL are negative, while price changes before LL and LH are positive. The differences between positive and negative price changes are also significant as column (3) shows.

Finally as a robustness check, we redo the exercise in column (1) and (3), but restricting ourselves to only the top 25% of firms by size. Column (2) and (4) report these results. The results remain essentially similar. Overall the returns tend to converge towards zero slightly. This is consistent with our earlier finding that manipulation is strongest in smaller firms.

Our examination of the micro-structure of trade confirms that the high $PRIN$ brokers use price manipulation as a means of generating higher returns. While such "price bubbles" and the reasons behind them - the exploitation of positive feedback traders by rational arbitrageurs - are similar to those in developed markets, the crucial difference is that these cycles are not created (randomly) by the announcement of some exogenous (good) news, but are instead started and managed by the manipulating brokers themselves.

6 Discussion and Concluding Remarks

This strategic manipulation and resulting profits reaped by entrenched principal brokers has important implications for the political economy of reform. Reforms which are good for improving efficiency of the market, but make it harder to engage in manipulation will naturally be resisted by the principal brokers. This has indeed been the case in Pakistan where the SECP has been trying to push the reform agenda, whereas the brokers have been actively resisting all such moves through political pressure. However, recently new reforms have been instituted in the stock market. These reforms include moving to the T+3 trading system, tighter margin requirements, and restriction on ownership of firms by brokers. In our subsequent work, we will be looking at the impact of these reforms on the trading activity in KSE.

We analyze a unique data set containing daily firm-level trades of every broker trading on the main stock exchange in Pakistan over a 32 month period. A detailed look at the trading patterns of brokers trading on their own behalf reveals some "strange" patterns suggestive of price manipulation attempts by them. Comparing profitability levels of these brokers with brokers who mostly trade for (several) different outside investors, reveals that the former earn an annual rate of return that is 5% to 8% higher than the average outside investor. This "manipulation" effect varies systematically across firms, with larger firms, and firms with more concentrated ownership less likely to be manipulated. We then present direct evidence for price manipulation as suggested by the "buy-sell" cycles evident in trading. We find that, when prices are low, only manipulating brokers trade amongst themselves and raise prices to attract positive feedback investors. However, once prices have risen, the former exit leaving only the feedback traders to suffer the ensuing price fall. In contrast to developed markets, these price bubbles are "controlled" in that their onset (and extent) is not reliant on initial news but at the whim of the manipulating brokers. Our results shed light on the real world trading behavior of naive investors and why equity markets function poorly in developing economies.

Appendix I

Construction of ARR measure

This section describes in more detail how our main outcome measure, the Annual Rate of Return (ARR) for a given Firm-Broker is calculated. We first describe the construction of this measure and then go through a hypothetical example to illustrate this construction.

The ARR measure is specific to "Firm-Broker" (FB) i.e. a particular broker in a specific firm. In order to construct this measure we first consider the entire trading history of this broker in the firm and then calculate the discounted value of his investments (i.e. all buys of the firm's stock). These investments are discounted back to a common start date for all brokers (we take Jan 1 1998 as this is prior to any observation in our data). Let us refer to this investment as I. Next we discount all cash flows (i.e. all sales of the firm's stock) of the broker *forward* to the last date in our data (31 August 2001). We will refer to this end of period aggregate cash earnings as C. Since we only have daily prices (and not the price at the instant the stock was traded) we only consider the daily "net" position of the FB in constructing these two streams. That is if an FB bought 100 and sold 200 shares in the same day and the average price that day was Rs 50 , for our purposes we will consider that he (net) sold shares worth Rs 500 that day. This number is then discounted back to a hypothetical start date, Jan 1 1998, in our case (since our data starts after that date). The cash flow and investment steams are discounted at a daily rate of approximately 0.026%, the equivalent of a 10% annual rate (5% inflation and 5% risk-free rate of return).

Once we have these two streams we can now think more simply of the FB as just having performed two trades: At the start date, Jan 1 1998, he bought $Rs\ I$ worth of the firms's shares and then at the last date in our data period (31 August 2001) he sold these shares at a value of $Rs\ C$. In calculating the latter we assumed that the FB held the shares till the end of our data period and that he had invested these shares in the risk-free asset (paying him a nominal return of 10%). Now to compute his ARR we ask what the actual annual rate of return would have to be to have resulted in the FB being able to earn $Rs\ C$ over the $\frac{1337}{365}$ year period with an initial investment of $Rs\ I$. In other words, $ARR\ is$ given by:

$$I(1+ARR)^{\frac{1337}{365}} = C$$

The following hypothetical example will illustrate the above construction: Consider Broker A who trades in Firm B. The broker's trading history is as follows. On Jan 1 1998 he buys 100 shares. The average price that day for the stock is Rs. 10. A bit over a year later, on August 31 1999, he sells the 100 shares and the average price is Rs. 12/share that day. Finally on Jan 1 2000 he again buys 100 shares and that day the share price averaged Rs. 12.1. After that we do not see him trade again. Finally, the last date anyone trades shares in the firm is on August 31 2001 at Rs. 16.

One of the issues that is immediately obvious is how to take into account the last 100 shares bought. We consider two annual rate of return measures. Our main measure, ARR, assumes that any net position is liquidated at the end of of last trading data period for the particular firm. We detail the construction of this measure first below.

For the ARR measure we first construct the discounted back value of the investments. $I = 10 * 100 + \frac{12.1*100}{(1+0.1)^2} = Rs\ 2,000$.

Next let us consider the cash flow at the end of the trading data i.e. on 31 August 2001. Discounting his two sales, a real one on August 31 1999 and the "forced liquidation" on August 31 2001 forward we get $C = 12*100(1+0.1)^2 + 14(100) = Rs$ $3,052$

Therefore using the above equation we get that

$$2000(1+ARR)^{\frac{1337}{365}} = 3052$$

and hence ARR is around 12.23%.

Our second measure of the annual rate of return, $ARR2$, is meant more as a robustness check on our first and here instead of imposing that the broker clear his position by a forced liquidation on August 31 2001, we instead "net out" his ending net position. Effectively what we are doing is forcing him to earn 0 profits on his ending position. This is illustrated in the example above. If we did not force end liquidation, by August 31 2001 we know that the broker has 100 shares in his possession. Rather than try to price these shares, what we do is we look back in the broker's trading history and "net out" all his previous purchases which these shares may have come from and in doing so construct a new "netted" trading history which ensures that the broker ends a a 0 net position. In our simple example, this means tracing back and seeing where the 100 shares came from. In doing so we see that these shares were bought on Jan 1 2000. We net out the shares on this date so that the new trading history of the broker is now simply that on Jan 1 1998 he bought 100 shares and sold them on August 31 1999. Now we can solve for ARR as before on this new trading history. Doing so we see that $I = 10 * 100 = Rs\ \ 1,000$ and that $C = 12 * 100(1 + 0.1)^2 = Rs\ 1,452$. This gives us

$$1000(1 + ARR)^{\frac{1337}{365}} = 1452$$

and a new $ARR2$ of 10.7%.

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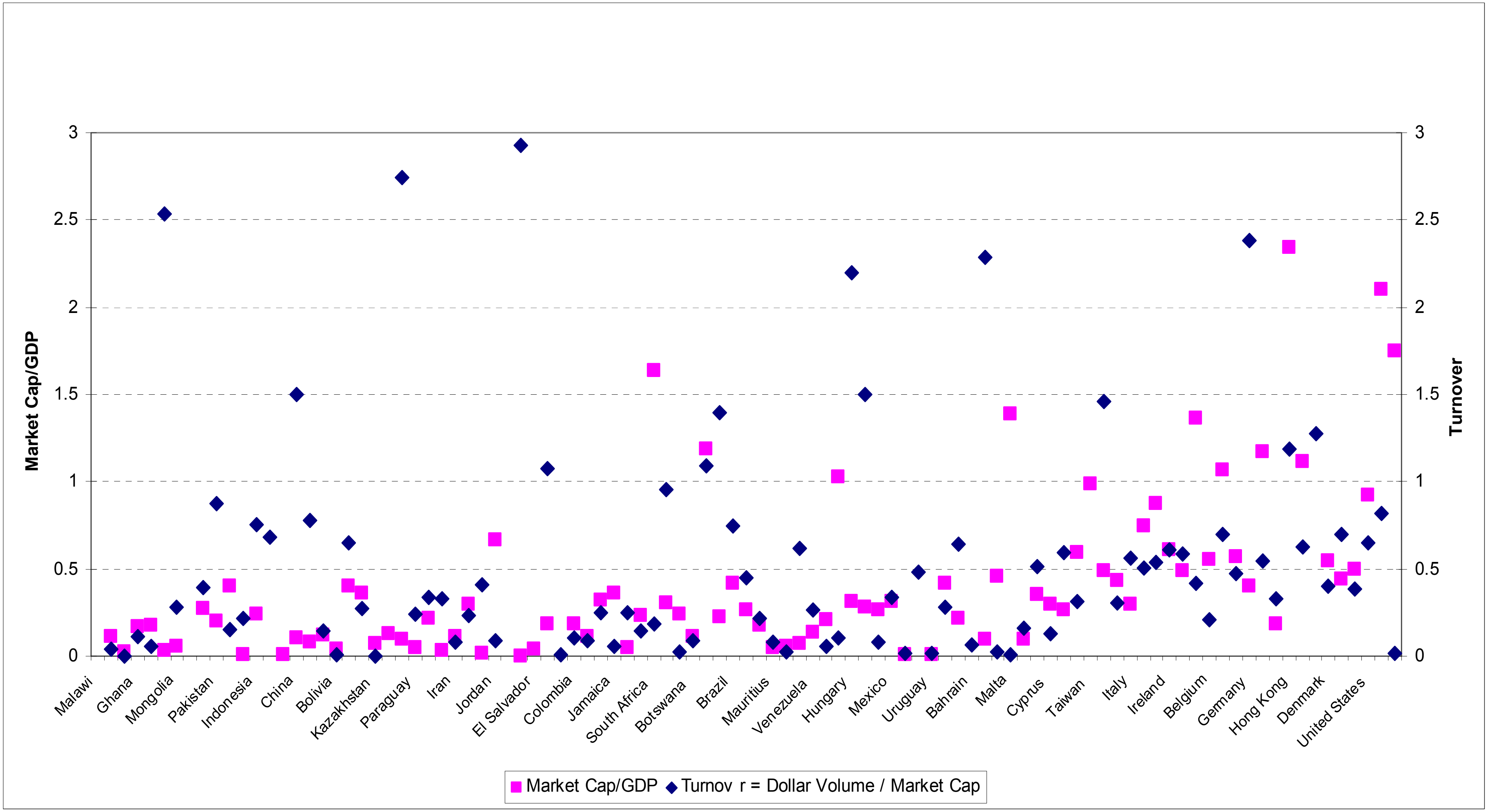
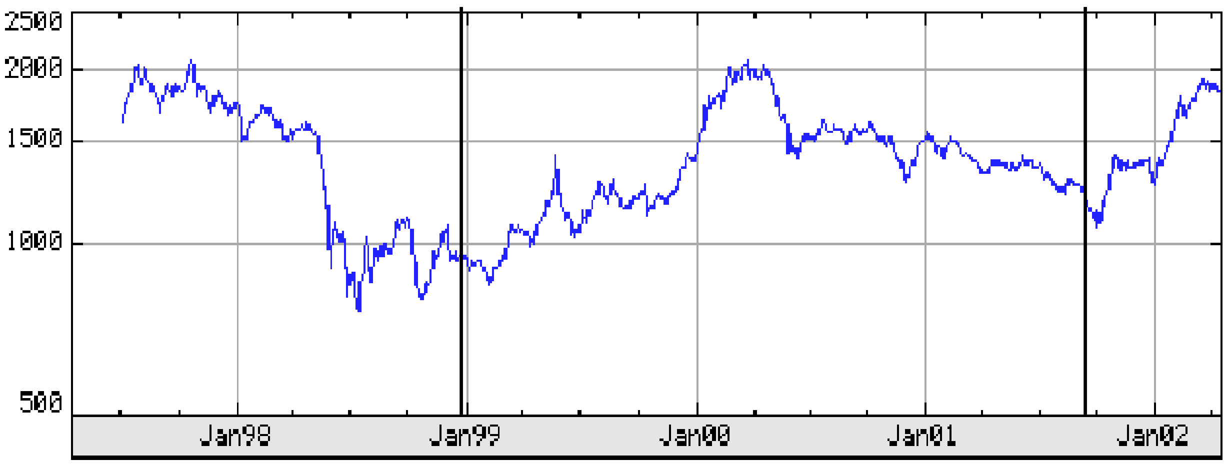


MC/GDP Outliers not shown: Bahrain=9, Namibia=8.9, Iceland=8.4

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

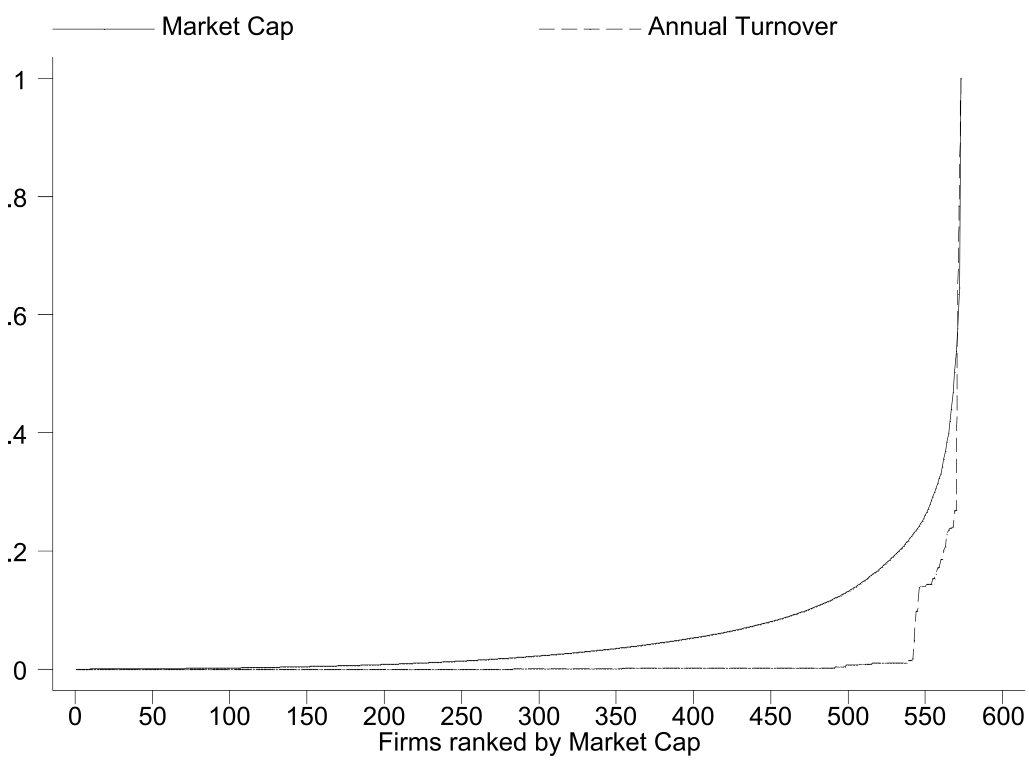
Every Third Country labeled on the above axis. Countries are sorted by GNP/capita. Complete list is as follows:
Malawi, Nigeria, Tanzania, Ghana, Kenya, Bangladesh, Mongolia, Moldova, India, Pakistan, Zimbabwe, Armenia, Indonesia, Uzbekistan, Ukraine, China, Honduras, Sri Lanka, Bolivia, Philippines,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

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



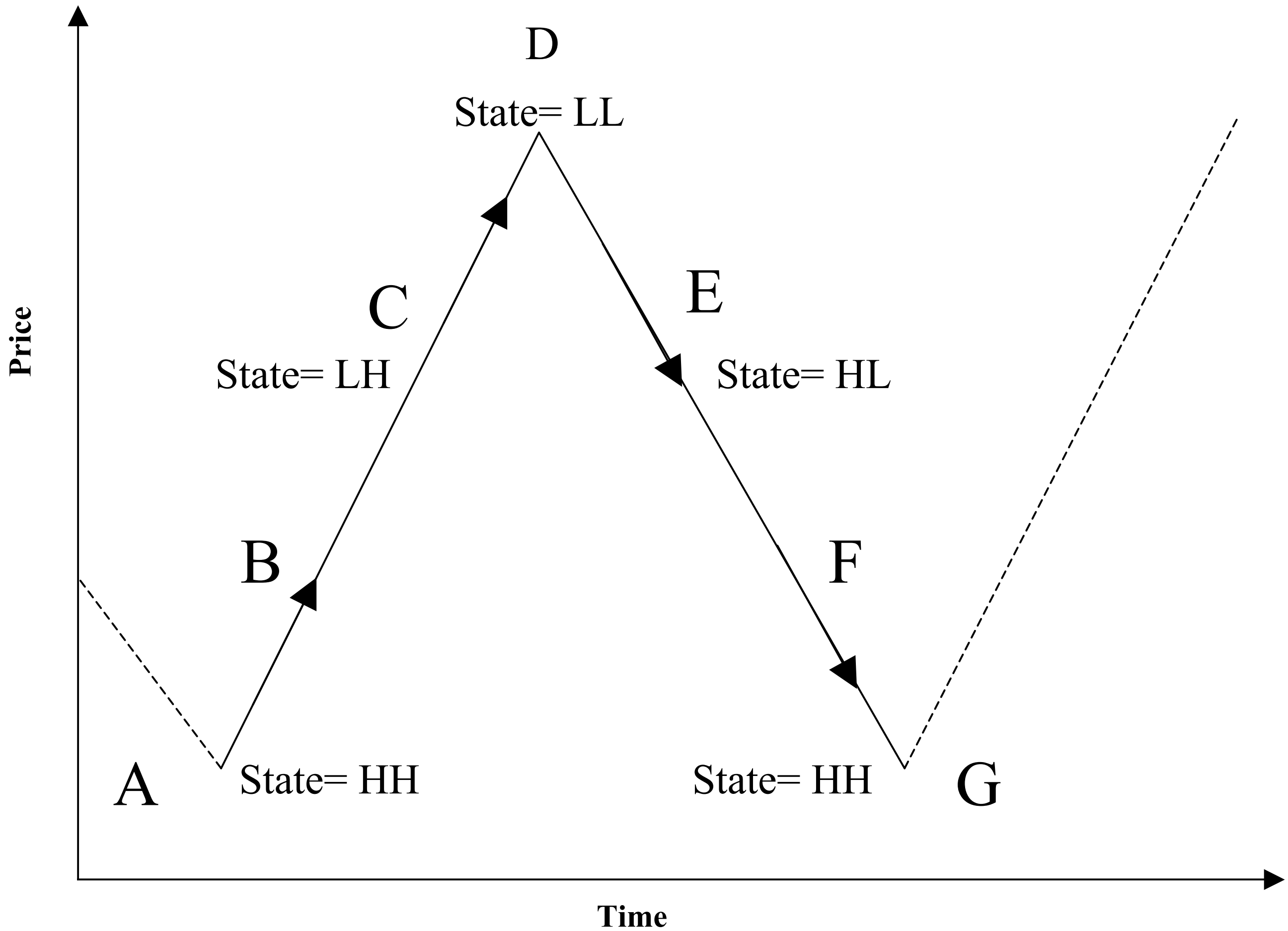
*The dark vertical lines in the figure above indicate the period for which we have broker-firm level daily trading data.

Figure 3: Cumulative Distributions of Market Capitalization and Turnover$



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

Figure 4: Trading Cycles- a hypothetical example



Key

A: Naïve traders are out of the market. Manipulators trade among themselves to raise prices. State= HH.

B: "Artificial" price increases attracts naïve/positive feedback traders.

C: More naïve traders enter, as manipulators sell their last remaining stock. Some naïve investors also start selling to other naïve ones. State=LH

D: Price reaches its peak. Manipulators have sold everything to the naïve investors. With the manipulators out, the price starts dropping. State=LL

F: When price drops sufficiently, manipulators start buying again. State=HL

F: Price drops further. Manipulators start buying. *Pb*=H, *Ps*=L

G: Cycle restarts (as in A)

Table 1: Principal and Intermediary Brokers Trading – An Example

Broker A (IB) *PRIN* = 0.06			Broker B (PB) *PRIN* = 1		
Date	**Shares Sold**	**Shares Purchased**	**Date**	**Shares Sold**	**Shares Purchased**
7-Feb-00	427,000	100,000	20-Dec-00	0	660,000
8-Feb-00	114,000	41,000	21-Dec-00	660,000	0
9-Feb-00	200,000	487,000	1-Jan-01	0	660,000
10-Feb-00	259,000	230,000	2-Jan-01	660,000	0
11-Feb-00	204,500	886,500	5-Jan-01	0	660,000
14-Feb-00	123,000	393,000	8-Jan-01	660,000	0
15-Feb-00	121,500	80,000	12-Jan-01	0	660,000
16-Feb-00	63,000	149,500	15-Jan-01	660,000	0
17-Feb-00	75,000	37,000	19-Jan-01	0	660,000
18-Feb-00	101,500	4,000	22-Jan-01	660,000	0
21-Feb-00	143,000	139,000	26-Jan-01	0	900,000
22-Feb-00	151,000	120,500	29-Jan-01	900,000	0
23-Feb-00	49,500	78,500	2-Feb-01	0	900,000
24-Feb-00	0	42,500	6-Feb-01	900,000	0
25-Feb-00	65,000	214,000	9-Feb-01	0	850,000
28-Feb-00	77,000	256,000	12-Feb-01	850,000	0
29-Feb-00	31,000	43,500	16-Feb-01	0	458,500
1-Mar-00	2,000	24,000	19-Feb-01	458,500	0
2-Mar-00	42,500	1,000	23-Feb-01	0	460,000
3-Mar-00	69,000	0	26-Feb-01	460,000	0

The above Table gives 20 trades carried out by two different brokers for a given firm, FFC Jordan. Broker A has a low *PRIN* values and is therefore an Intermediary broker whereas Broker B, with a high *PRIN* value is considered to be a Principal broker (i.e. a broker who only acts for himself or for a single client)

Table 2: Summary Statistics by Firm-Broker PRIN categories

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

*The second group of rows presents the same statistics but drop the top 15 (by trading volume) firms. We suspect that in such large firms there would be little variation in the PRIN measure and most brokers would be acting as intermediaries (as is borne out in table).

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

	(1)	(2)	(3)	(4)	(5)	(6) [$]
	ARR	ARR with no discounting	ARR with Broker FEs	ARR	ARR	ARR (WLS)
PRIN	5.76*** (0.57)	4.09*** (0.47)	4.30*** (0.23)		3.16*** (0.54)	7.93*** (0.91)
*PRIN*dum					1.31*** (0.19)	
*PRIN*rest				4.11*** (0.52)		
Observations	32666	32666	32666	32666	32666	32666
R-squared	0.08	0.08	0.01	0.08	0.08	0.18

Robust standard errors in parentheses except column (6).
All regressions include firm fixed effects, except column (3).
*** significant at 1%

[$] Column 6 reports weighted least squares, with the weight for each firm-broker being equal to the fraction of overall firm-trade done by that broker.
*PRIN*dum is an indicator variable for *PRIN*=1. *PRIN*rest uses a more restrictive definition of *PRIN* (see Text)

Table 4: Heterogeneity of manipulation effect across firms

	(1)	(2)	(3)	(4)
	ARR	ARR	ARR	ARR
PRIN	3.91***	6.20*	-0.08	9.45***
	(0.46)	(3.65)	(1.47)	(1.50)
*PRIN*SMALL*	4.30***			
	(1.26)			
*PRIN*SIZE2*		3.12		
		(4.27)		
*PRIN*SIZE3*		1.42		
		(3.86)		
*PRIN*SIZE4*		-0.47		
		(3.91)		
*PRIN*SIZE5*		-1.58		
		(3.77)		
*PRIN*SIZE6*		-2.12		
		(3.73)		
*PRIN*SIZE7*		-4.34		
		(3.70)		
*PRIN*COVPR*			20.35***	
			(5.80)	
*PRIN*CONC2*				-4.67***
				(1.80)
*PRIN*CON3*				-6.43***
				(1.73)
Observations	32666	32490	32666	26308
R-squared	0.08	0.08	0.08	0.08

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

SMALL is an indicator for whether the firm is small i.e. not one of the top 100 firms (by market cap). *SIZE1* through *SIZE7* are indicator variables indicating the size category of a given firm, with *SIZE7* being the largest group of firms. *COVPR* is the firm-specific coefficient of variation of price. *CONC2-3* are dummies which indicate the degree of concentration of holdings in the firm where *CONC1* (the dropped dummy) indicates that the top 5% shareholders hold less than 40%, CONC2 is 40-70% and *CONC3* is greater than 70%. (Note that we do not have the ownership concentration numbers for all the firms)

Table 5a: State Contingent Prices

	(1)	(2)
State	**Normalized Price**	**Frequency the state is observed**
HH	-9.85***	31.1%
	(0.77)	
HL	-3.97***	19.2%
	(0.76)	
LH	-4.31***	21.4%
	(0.77)	
Constant (LL omitted state)	105.2***	28.4%
	(0.0049)	

Table 5b: State Contingent Returns

State	State Contingent Future Return		State Contingent Past Return	
	(1)	(2)	(3)	(4)
	ALL FIRMS	TOP 25%	ALL FIRMS	TOP 25%
HH	0.1686**	0.0967	-0.1509**	-0.1840**
	(0.0813)	(0.0999)	(0.0667)	(0.0815)
LL	-0.2571***	-0.1086	0.001773**	0.2230**
	(0.0750)	(0.1014)	(0.0728)	(0.0879)
HL	-0.4037***	-0.4039***	-0.2201*	-0.3454**
	(0.1068)	(0.1369)	(0.1281)	(0.1402)
LH	0.5964***	0.4390***	0.1635	0.0899
	(0.1111)	(0.1318)	(0.1077)	(0.1308)
HH-LL	0.4257***	0.2053	-0.3282***	-0.4070***
	(0.1429)	(0.1698)	(0.1174)	(0.1408)
HH-HL	0.5723***	0.5006***		0.1614
	(0.1506)	(0.1896)		(0.1852)
LH-LL	0.8535***	0.5476***		-0.1331
	(0.1412)	(0.1831)		(0.1889)
LH-HL	1.0001***	0.8429***	0.3836**	0.4353**
	(0.1764)	(0.2170)	(0.1742)	(0.1983)
HHend	0.5281***	0.3177*		
	(0.1385)	(0.1619)		
LLend	-0.7192***	-0.6973***		
	(0.1489)	(0.1566)		
HHstart			0.3095**	0.0314
			(0.1410)	(0.1232)
LLstart			-0.1275	-0.2458*
			(0.1461)	(0.1427)

The regressions are run using weekly data. Total 141 weeks.
Robust standard errors in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%