Price Manipulation by Intermediaries*

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Abstract

Governance of market intermediaries is an integral component of efficient equity markets especially in emerging economies. In this study, we investigate two main research questions using a unique individual trade level data from the Istanbul Stock Exchange (ISE): 1) Do brokers conduct manipulative behavior in the ISE? 2) Do these brokers gain returns out of their manipulative behavior? We examine the trade-based "pump and dump" price manipulation scheme following the identification methodology of Khwaja and Mian (2005). Using the complete trading history of stocks listed on the ISE over the 2003-2006 period, we find that significant percent of the trades conducted by brokers can be identified as consistent with "pump and dump" price manipulation scheme. More importantly, we conclude that brokers that conduct more manipulative trades earn significantly higher profits. We conducted many robustness analysis and our results are robust to alternative specifications.

Keywords: price manipulation, broker behavior, market structure

JEL Classification: G11, G14, G20

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1 Introduction

Investor participation and liquidity are essential to achieve efficiency in capital markets. Public confidence in intermediaries plays an incremental role in sustaining trust and participation of investors into equity markets. Many studies like Glaeser, Johnson and Shleifer (2001) show that strict enforcement of securities law is associated with rapid development of the stock market. This result presents that regulation of intermediaries is essential for especially developing capital markets. One important feature that might disrupt public confidence and prevent participation of investors is potential manipulation by intermediaries. Although it is very important, very little is known about the manipulative behavior of intermediaries as argued by Khwaja and Mian (2005) (KM).

In this study, we examine the behavior of intermediaries (brokers) from two perspectives:

- Do brokers conduct trades consistent with "pump and dump" manipulation scheme?
- What is the cost of the manipulative trading behavior by the brokers to investors? (What is the amount of profit that brokers earn when they conduct manipulative behavior?)

We make use of a unique data set which contains the complete trading history of all stocks listed on the Istanbul Stock Exchange (ISE) over the 2003-2006 period.[1] This data set contains detailed information about the brokers that

[1] This period is analyzed because the governing board of the Capital Markets Board of Turkey (CMB) provided us access to the ISE data set only for these years. The committee ruling number 759 dated 12 July 2007 provides the details on the conditions that the ISE data set would be made available for research purposes. Basically, the ruling states that the account numbers will be changed by the IT department of CMB without changing the uniqueness of

conducted each trade. Ozsoylev et al. (2011) use the same data set to examine trading behavior consistent with investor networks.[2] Aragon et al. (2007) compare institutional and individual investor performances at the ISE for the 1999-2003 period by using the same data set. We implement the methodology proposed by KM to identify brokers in the ISE who may manipulate stock prices. KM develops a methodology to characterize "strange" trade patterns which are consistent with the "pump and dump" manipulation scheme. Then we analyze whether brokers that engage in these trade patterns manage to earn significantly higher profits than "honest" brokers that only act as intermediaries and trade on behalf of their customers. Our analysis provides the following answers to the research questions mentioned above:

- A significant portion of trades can be identified as trades consistent with the "pump and dump" manipulation scheme. In our data set there are 1172 different brokers that trade for 269 stocks during the 2003-2006 period. There exist 228130 cases, broker*stock, in our data set.[3] The mean of percentage of manipulative trades, *PRIN* score, is equal to 0.76 when daily aggregated trades are used to identify manipulative trades.[4] In other words *on average* 76% of all trades coincide with the "pump and dump" scheme. It should be noted that the percentage serves to order brokers by principalness within the same stock. Thus, the value of the percentage

each account number to assess anonymity. Also, the ruling mentions that the data set can only be accessed at the premises of the CMB in Ankara.

[2] Ozsoylev et al. (2011) only use the data set for year 2005.

[3] Every broker does not trade in all of the stocks. That is why number of cases is smaller than 1172*269 = 315268.

[4] We first calculate the percentage of manipulative trades in a case. Then we calculate the mean of these percentages. One might wonder about the percentage of manipulative trades among all trades. We could only calculate the average percentages because of computer limitations. The size of the complete data set is more than 40 GBs. Thus, we separated the data set into cases.

does not necessarily mean that 76% of all trades are "manipulated". These trades might also be motivated factors other than manipulation. For example, stock specific factors like stock liquidity and turnover can cause the broker to conduct trades consistent with the "pump and dump" scheme. [5] KM find that 58.3% of all trades are manipulative in the Karachi Stock Exchange (KSE). The average *PRIN* score is larger in the ISE compared to the KSE since there are 1172 brokers that trade for 269 stocks in the ISE whereas 147 brokers trade for 648 stocks in the KSE. This distinctive feature of the ISE indicates that calculating the *PRIN* score using daily aggregated trades of brokers might impose a bias on the percentage of manipulative trades, *PRIN* score.[6] To analyze whether using daily aggregated trades impose a bias on the *PRIN* scores we also calculate the *PRIN* scores using weekly aggregated trades. When individual trades are aggregated weekly, on average 62% of all trades are identified as manipulative.

- We conclude that there is a significant and positive relationship between percentage of manipulative trades and return of a broker. The magnitude of the results change but the significance and sign of the coefficients are robust to using weekly aggregates. This result indicates that brokers are able to earn returns out of their manipulative trading behavior. These returns are transfers from "honest" traders and might prevent investors to actively participate to the ISE.

[5] As stated by KM, "if there is more frequent and heavier trading in stock j, then on average all brokers in stock j have a lower *PRIN*.

[6] Since there are many brokers and fewer stocks a broker might only buy or only sell a stock in a day. The algorithm of KM identifies these trades in line with the "pump and dump" scheme. They argue that

> 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.

In addition to the results mentioned above we also contribute to the literature by taking into account intraday trades in calculating broker returns. KM use aggregated daily data and *daily average* stock prices to calculate returns. However, stock prices vary significantly during the day. The data set we use contains data about individual trades. This feature of the data allows us to use the exact stock price of each trade for return calculation. Thus, we eliminate the bias of KM and calculate broker returns using price of each individual trade. We label these returns as "unbiased" returns. To be able to compare our results with KM we also use average stock prices as in KM which we call "biased" returns. Thus, we are able to contribute to the discussion about the usage of daily aggregates instead of the actual trade price. The comparison of "unbiased" and "biased" returns[7] conclude that mean of "unbiased" returns are higher than "biased" returns as predicted by KM. We also deduce that our empirical results are robust to alternative return calculations.

This paper contributes to the literature that empirically examine trade based manipulation in the stock markets. Among many studies, Aggarwal and Wu (2006) investigate the price and volume effects of past manipulation cases which are prosecuted by the Securities Exchange Commission (SEC). They find that manipulation leads to a rise in volatility, liquidity and returns of the stocks. In general, prices rise in the mean time of the manipulation scheme but drop after the end of the manipulation period. Theoretical studies like Goldstein and Guembel (2008) display the harmful effect on the allocation role of prices on the financial markets. Comerton-Forde and Putnins (2010) study closing price manipulation cases. They construct an index of probability and intensity of closing price manipulation by using a sample of manipulation cases prosecuted by US and Canadian prosecutors. Allen, Litov and Mei (2006) examine stock market and commodity market corners from 1863–1980. They assert that large

[7]Returns calculated using average daily stock prices as in KM.

investors and insiders have market power that may let them manipulate prices and these manipulations with corners lead to increases in volatility. Merrick, Naik and Yadav (2005) investigate manipulation cases with a squeeze on the bond futures market. Mei et al. (2004) show that an uninformed manipulator could use investors' behavioral biases in order to profit by using pump and dump strategies.

The pump and dump manipulation scheme is also a matter of concern in other emerging economies. Khanna and Sunder (1999) argue that brokers involve in pump and dump schemes in the Indian stock market. Zhou and Mei (2003) present that manipulative trading behavior exist in many emerging markets including China. In a closely related study KM conclude that almost 60% of all trades can be identified as a part of pump and dump manipulation scheme in the KSE. They also conclude that manipulative brokers earn 50 to 90% points higher annual returns at the expense of outside investors.

KM is the closest study to our paper. We implement the mechanism proposed by KM to identify manipulative behavior in the ISE. To distinguish our paper from KM, we would like to emphasize the differences of this study from KM. First of all, we investigate the "pump and dump" manipulative behavior by brokers in a more established, large and more liquid market than the Karachi Stock Exchange.[8] Second, the data set used in this paper is much more detailed than the one used in KM since our data set contains information about individual trades compared to daily aggregates in KM. This allows us to calculate "unbiased" returns by calculating returns using actual price of individual trades. KM argues that one of the limitations of their data is that it is aggregated at the day level. Our data set does not have this limitation and our data allows us

[8] The market capitalization of ISE is 162.4 billion US dollars at the end of 2006 which is similar to the Tel Aviv, Irish, Warsaw, Jakarta and Santiago Stock Exchanges.

to examine the following argument of KM: "...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. While this does preclude intraday analysis, we do not feel that this exclusion changes the quality of our results." (pg.214). Comparison of analysis with aggregated daily data and individual trade data shows that the results are not significantly affected by the aggregation. The mean of broker return calculated using individual trade prices are higher than average return calculated using daily aggregates. Finally, there are 147 licensed brokers and 648 stocks traded on the KSE whereas there are 1172 brokers that trade in 269 stocks in the ISE. Thus, a broker only buying or selling a certain stock in a day might not be because of manipulative behavior in the ISE. To be able to take into account this feature of the ISE we also implement an alternative identification scheme and identify manipulative trades using weekly aggregated data.

Empirical studies about trade based manipulation is very limited in the literature. Putnins (2011) states that "Further evidence on the issues identified above (*forms of market manipulation*) would be valuable, particularly empirical evidence, which is most lacking." In this paper, we make use of a unique data set about the individual trades in the ISE and provide empirical evidence about the existence of trades consistent with the "pump and dump" manipulation scheme. We also demonstrate that brokers (or colluding traders) can earn significant amount of profits by implementing this scheme. To sum up, this paper contributes to the literature by empirically analyzing a common form of market manipulation.

The paper is organized as follows: next section provides background information about the ISE and describes the data. Section three summarizes the methodology of KM implemented to identify manipulative trades. Section four examines whether brokers are able to earn profits by conducting manipulative trades and section five concludes.

2 Institutional structure of the ISE and data

2.1 Istanbul stock exchange

The Istanbul Stock Exchange (ISE) is founded in 1986 to provide a secure and stable environment for trading in equities, bonds and bills, revenue-sharing certificates, private sector bonds, foreign securities and real estate certificates as well as international securities. The ISE is a public corporation operating as an autonomous and professional institution.

The ISE operates through a computerized system. This system automatically matches buy and sell orders on a price and time priority basis. The stock trading activities are carried out in two separate sessions, 9:30-12:00 for the first session and 14:00-16:30 for the second session, on workdays. Settlement of securities traded in the ISE is realized by the ISE Settlement and Custody Bank Inc. (Takasbank), which is the sole and exclusive central depository in Turkey.

The market capitalization of ISE is 162.4 billion US dollars at the end of 2006 which is similar to the Tel Aviv, Irish, Warsaw, Jakarta and Santiago Stock Exchanges. At the end of 2006, there were 316 companies listed at the ISE. In 2006 the number of trading days was 250 with average daily turnover of 890.9 million US dollars. The average value of trades was 4.8 thousand dollars. Turnover velocity was 141.3%.

2.2 Data

The data set contains the complete trading history of the ISE for the 2003-2006 period. For each trade, these data set contains the timestamp, stock code, transaction price, quantity of shares traded, broker identification number of both buyer and seller. Compared to the daily aggregated data of KM, our data set contains information about each individual trade completed for that period. Because of the sensitivity of the data set, the empirical analysis are conducted at the premises of the Capital Markets Board of Turkey (CMB) in Ankara on a secured computer. The reliability and the security of the data set is governed by the IT department of the CMB.[9]

During the analyzed time period, there were 1172 licensed brokers and 356 equity related instruments trading on the ISE. We eliminated 87 instruments. Some of these eliminated instruments represent preferential rights of existing share holders which are traded separately than stocks. Also we eliminate all of the stocks which are subject to the merge process.[10]In other words, we used the stocks that we have complete information for the 2003-2006 period. The data set used for the analysis (1172 brokers, 269 stocks) contain 104463969 observations at the individual trade level. There are 228130 different cases, broker*stock. Trading on ISE is computerized and the data set is extracted directly from the system. Table 1 provides the descriptive statistics of some of the key variables.

(Table 1 about here.)

[9]The CMB committee ruling number 759 dated 12 July 2007 provides the details on the conditions that the ISE data set would be made available for research purposes.

[10]In the ISE after a stock-split if the relevant firm has any potential to pay dividends to its shareholders newly issued stocks are traded separately from the old ones. They are merged together after the payout of dividends are realized. But in the mean time the new and the old stocks can be traded with different market prices. After the merge they are traded at a single price. This procedure makes it impossible to calculate the profits of brokers for these specific stock since we do not have the exact names of the stocks. In other words we do not know the names of the stocks but just the identification numbers assigned by the IT department of the CMB to provide anonymity of the data set. So we eliminate all of the stocks which are subject to the merge process. This elimination is conducted by the IT department of the CMB since we could not have access to the original data set with stock names.

3 Methodology

We adopt the methodology and terminology of KM to identify manipulative trades and calculate returns of brokers. Sections two and three of KM provide excellent descriptions of the methodology. We avoid repetition here and just summarize important components of the methodology.

3.1 Identification of manipulative trades

We follow the methodology of KM which is based on the argument that manipulative brokers are the ones who"... mostly act as principals and not as intermediaries". Thus, manipulative trades are identified as the unusual trades that can not be motivated by behaving as an intermediary. We refer to table 1 of KM (pg. 216) for the presentation of both intermediary and unusual (principal) behavior. Unusual trades can be summarized as the following:

1. Principal buys: A broker only buys the stock during the day (week).
2. Principal sales: A broker only sells the stock during the day (week).
3. Principal cycles: A broker only buys or sells on a given day and exactly reverses this trade the next day (week) or buys and sells the exact amount in the same day (week).

A trade is identified as manipulative if it satisfies one of the three conditions presented above.[11] Then for each case (stock, broker) we calculate a measure of manipulative behavior, *PRIN*, as in KM. The *PRIN* score is,

[11] As indicated above the occurrence of a principal trade does not certainly indicate a manipulative behavior. The percentage of principal trades are used to order brokers for each stock.

$$PRIN_{stock,broker} = \frac{Total\, number\, of\, manipulative\, trades\, by\, broker\, in\, stock}{Total\, number\, of\, trades\, by\, broker\, in\, stock} \tag{1}$$

KM states that

> *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. (pg. 218)

In other words, *PRIN* provides us the percentage of trades consistent with the "pump and dump" scheme of a broker in a certain stock.

Table II presents the descriptive statistics of the *PRIN* variable of 228130 cases calculated using daily aggregates. The average *PRIN* score is 0.76 which means that on average 76 percent of all trades are in line with the pump and dump manipulation scheme. There are cases (broker,stock) where the brokers do not conduct any manipulative trades and in 26% of the cases all trades are consistent with manipulative behavior.

(Table II about here.)

Figure I provides a visual description of *PRIN* scores. These results suggest that using daily aggregates might not be appropriate for the analysis of ISE because of very high number of brokers and low number of stocks compared to the KSE.

(Figure I about here.)

Table III displays the descriptive statistics of the *PRIN* variable calculated using weekly aggregates of individual trades. First, the trades of each broker are aggregated weekly. Then the weekly aggregates of each broker for each stock are identified as intermediary or principal following the algorithm described before. The average *PRIN* score is significantly lower, 0.62, then *PRIN* scores calculated using daily aggregated data. On average 62 percent of all trades are in line with the pump and dump manipulation scheme. This result is similar to the findings of KM who find that 58.7% of all trades are manipulative in the KSE. In 22% of the cases all trades are consistent with manipulative behavior.

(Table III about here.)

Figure II provides a visual description of *PRIN* scores calculated using weekly aggregates.

(Figure II about here.)

3.2 Trading profitability

For the analysis of whether manipulative trading is profitable we calculate the annualized nominal rate of return for each case. First we calculate the nominal values of returns earned by each account using the entire trading history of the account in a certain stock. Then, we derive returns per unit of capital for the regression analysis. In calculation of returns earned in each case we implement the methodology of KM. Appendix A of KM provides an excellent description of the methodology used to calculate returns. We avoid repetition here and only summarize the methodology.

Computation of the annual rate of return requires calculation of the overall profit earned by the investor, and the average capital needed by the investor to earn this profit. In summary the profits of each account are calculated as the following:

1. The value of net shares is calculated as revenue.

2. The net shares bought are treated as investment.

3. Net profit is the difference between revenue and investment.

4. The average capital needed by the investor is calculated. The capital needed is the value of the net inventory holdings of the investor at the time minus any profits she could have accumulated up to then. .

5. The overall rate of return is then computed as the total net profit divided by the average net capital used.

Because of limitations of using daily data KM uses average price of a stock when calculating profitability. KM argues that,

> ...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.

Our data set contains data about each specific trade thus we are able to use actual price of the stock when the trade is conducted to calculate broker profitability. Our return measure which we denote as "unbiased" return also contains the profits that may have accumulated due to intraday trading. To be able to provide comparisons we also implement the methodology of KM and use average prices to calculate profits of brokers.

Table A.I in the Appendix presents the summary statistics of nominal broker returns. The first part of the table presents the "unbiased" returns where actual price of each individual trade is used to calculate profits. The second part displays "biased" returns calculated using daily aggregated data as in KM. The table also presents descriptive statistics of profits according to $PRIN$ score of each case. The most important result we can deduce from table A.I is the difference between unbiased returns and returns from aggregated daily data. The mean of unbiased returns is higher indicating that profits from intraday trading is not negligible.

The main research question of this paper is whether manipulative trades earn higher trading profits than intermediary trades. The next section focuses on this question.

4 Profitability of manipulative trades

In the previous section, we identified manipulative trades by brokers and calculated profits of brokers. We would like to analyze whether manipulative brokers earn significantly higher profits than intermediary brokers. Comparing profits provides us an analysis of the rents earned by manipulative brokers. Following KM we estimate the following regression equation to gauge the profits earned by manipulative trade patterns:

$$R_{stock,broker} = \beta_0 + \beta_1 PRIN_{stock,broker} + \Theta S + \varepsilon_{stock,broker} \qquad (2)$$

Profit measure, $R_{stock,broker}$, is represented as percentage of capital. The calculated profit measures the trading returns a stock broker earns per unit of capital invested. S is the matrix that contains stock dummy variables which presents stock level fixed effects. β_1 measures the monetary value of each additional percent of manipulative trade. By adding the fixed effects, S, we make sure that we only compare brokers within the same stock. Table IV presents the estimates of regression equation 2 where *PRIN* score is calculated using daily aggregated trades and the dependent variable is "unbiased" returns. A restricted definition of the *PRIN* score is also analyzed. Same day reversals (sale = purchase in the same day) are not considered as a cycle when calculating restricted *PRIN* scores.[12]

(Table IV about here.)

Table IV displays that coefficient of interest, β_1, is positive and significant in all regression specifications. This result indicates that brokers who conduct higher percentages of pump and dump trades earn significantly higher profits compared to "honest" brokers who conduct intermediary trades. The first column presents that brokers that conduct only trades consistent with "pump and dump" scheme earn 3.43% higher profits than brokers that only act as intermediaries. The coefficient of the conservative *PRIN* score in column 2 is significant and positive with a lower coefficient. Column 3 presents an alternative *PRIN* specification which uses a dummy variable. The dummy variable is one if all trades by a broker for a specific stock are principal trades in other words *PRIN* score is one. Column 3 displays that average return of a broker who only performs principal trades earn significant positive profits compared to "honest" brokers. They earn 2.11% more profits than intermediaries.

4.1 PRIN scores from weekly data

As discussed before the structure of the ISE might distort the calculation of *PRIN* using daily trade patterns. To control for that possibility, we estimate the regression equation 2 using *PRIN* scores that are calculated using weekly trade patterns. Table V shows these regression results.

[12] Similar to KM the top and bottom 1% outliers in broker profits are excluded from the data set. This accounts for 7235 observations which are excluded. The regression analysis is conducted with 220895 observations.

(Table V about here.)

The coefficients of *PRIN* are still significant with a positive sign. The magnitude of the coefficient is larger compared to the coefficients in table IV. All regression specifications conclude that brokers with higher *PRIN* scores gather significantly higher profits.

As a result, in this section we show that brokers who conduct manipulative trades earn significantly higher returns compared to intermediary brokers. We also present that this result is robust to alternative specifications of the *PRIN* score and return calculation.

5 Conclusion

In this paper, we make use of a unique data set to identify unusual trading behavior by brokers and the profits earned through those trades in an emerging market, ISE. We conclude that a significant portion of the trades by brokers are consistent with the "pump and dump" manipulation scheme. We also show that brokers earn significant profits by conducting those unusual trades.

The analysis conducted in this paper does not suffer from some of the potential biases of the previous studies caused by non-availability of individual trade data. Specifically, we are able to take into account intraday trades while calculating broker profits. We conclude that the main results of the paper are robust to alternative profit calculations. This result suggest that daily aggregated data can be used for the analysis of manipulation in equity markets.

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Table I

Descriptive Statistics of Variables

	Mean	Std. Deviation	Min	Max
Average Number of Unique Brokers Engaged in Buy Transactions Over 269 Stocks	806	228	127	1165
Average Number of Unique Brokers Engaged in Sell Transactions Over 269 Stocks	810	233	117	1172
Average Number of Unique Accounts Engaged in Buy Transactions Over 269 Stocks	32772	30143	243	226944
Average Number of Unique Accounts Engaged in Sell Transactions Over 269 Stocks	36331	37130	196	316466
Number of Stocks	269			
Number of Observations	104463969			

Table II

Descriptive Statistics of Daily PRIN Scores

PRIN Scores are estimated using daily data of broker trades

Variable	Observation[1]	Mean	Standard Dev.	Min	Max
PRIN	228130	0.76	0.24	0	1
PRIN Sale	228130	0.31	0.24	0	1
PRIN Buy	228130	0.3	0.24	0	1
PRIN Cycle	228130	0.16	0.22	0	1
PRIN Restricted[2]	228130	0.67	0.28	0	1
PRIN = 1	Among 228130 calculated PRIN scores 59109 (26%) are equal to 1.				

1. Number of brokers*number of stocks that brokers traded. A PRIN score is calculated for a each broker for each stock that she trades.

2. As in Khwaja and Mian (2005) a restricted definition of cyclical behavior is used when calculating PRIN. Same they reversals (sale = purchase in the same day) are not considered as a cycle.

Table III

Descriptive Statistics of Weekly PRIN Scores

PRIN Scores are estimated using weekly data of broker trades

Variable	Observation[1]	Mean	Standard Dev.	Min	Max
PRIN	228130	0.62	0.3	0	1
PRIN Sale	228130	0.25	0.25	0	1
PRIN Buy	228130	0.25	0.24	0	1
PRIN Cycle	228130	0.14	0.22	0	1
PRIN Restricted[2]	228130	0.52	0.32	0	1
PRIN = 1	Among 228130 calculated PRIN scores 49024 (22%) are equal to 1.				

1. Number of brokers*number of stocks that brokers traded. A PRIN score is calculated for each broker for each stock that she trades.

2. As in Khwaja and Mian (2005) a restricted definition of cyclical behavior is used when calculating PRIN. Same they reversals (sale = purchase in the same day) is not considered as a cycle.

Table IV
Measuring Profitability of Principal Trades
(PRIN calculated using daily broker transactions)

Unbiased Percentage Return is calculated using individual stock prices of each transaction. Each observation is at the stockbroker level. The dependent variable is the annualized rate of return (ARR) on stock-broker's trades. PRIN is a measure of the principal-ness of a stockbroker, as described in Table II. The main explanatory variable, PRIN, is calculated using daily stock-broker trades. Similar to Khwaja and Mian (2005) the top and bottom 1% outliers in ARR are excluded from the dataset. 7235 observations are excluded. The dataset now contains 220895 observations.[1]

	Regression Specification		
	(1)	(2)	(3)
PRIN	3.43		
	(27.16)**		
Restricted PRIN		1.79	
		(16.32)**	
PRIN = 1			2.11
			(31.28)**
Number of Observations	220895	220895	220895

Notes: Regressions are estimated using stock dummy variables (firm fixed effects) and a constant. They are not displayed. Absolute value of t statistics in parentheses. * significant at 5%; ** significant at 1%

[1] Descriptive statistics of ARR without outliers:

Variable	Obs	Mean	Std. Dev.	Min	Max
ARR	220895	-2.31	13.45	-172.42	51.68

Table V

Measuring Profitability of Principal Trades

(PRIN calculated using weekly broker transactions)

Unbiased Percentage Return is calculated using individual stock prices of each transaction. Each observation is at the stockbroker level. The dependent variable is the annualized rate of return (ARR) on stock-broker's trades. PRIN is a measure of the principalness of a stockbroker, as described in Table II. The main explanatory variable, PRIN, is calculated using daily stock-broker trades. Similar to Khwaja and Mian (2005) the top and bottom 1% outliers in ARR are excluded from the dataset. 7235 observations are excluded. The dataset now contains 220895 observations.

	Regression Specification		
	(1)	(2)	(3)
PRIN	4.45		
	(44.68)**		
Restricted PRIN		3.19	
		(33.99)**	
PRIN = 1			1.997
			(27.74)**
Number of Observations	220895	220895	220895

Notes: Regressions are estimated using stock dummy variables (firm fixed effects) and a constant. They are not displayed. Absolute value of t statistics in parentheses. * significant at 5%; ** significant at 1%

Appendix:

Table A.I
Summary Statistics of Nominal Broker Return Values
Monetary values of broker returns are displayed.
Return is Calculated using both Daily Data (As in Khwaja and Mian (2005)) and using individual trade data (unbiased return, each transaction is multiplied by its true price)

Variable	Observation[1]	Mean	Standard Dev.	Min (in Millions)	Max (in Millions)
	Unbiased Returns Calculated using Individual Stock Prices of each Transaction				
Profit	228130	835.96	4395964	-795	618
Profit if PRIN > 0.5	194137	23835.03	4291393	-795	618
Profit if PRIN ≤0.5	33993	-130513.8	4949050	-215	291
Profit if PRIN > 0.75	132951	10344.58	2752660	-555	618
Profit if PRIN ≤0.75	95179	-12446.18	5977774	-795	499
Profit if PRIN > 0.95	62714	-3362.43	459517.7	-85	30
Profit if PRIN ≤ 0.95	165416	2427.69	5154702	-795	618
Profit if PRIN = 1	59109	-1544.29	428388.7	-85	30
Profit if PRIN ≠ 1	169021	1668.37	5100824	-795	618
	Returns Calculated using Average Daily Stock Prices				
Profit	228130	34.38	4582818	-799	614
Profit if PRIN > 0.5	194137	23190.47	4498085	-799	614
Profit if PRIN ≤ 0.5	33993	-132212.1	5037540	-219	258
Profit if PRIN > 0.75	132951	11275.02	2977046	-492	614
Profit if PRIN ≤ 0.75	95179	-15667.12	6161091	-799	484
Profit if PRIN > 0.95	62714	-3305.874	599487.4	-936	504
Profit if PRIN < 0.95	165416	1300.77	5369224	-799	614
Profit if PRIN = 1	59109	-2283.323	531771.4	-936	289
Profit if PRIN ≠ 1	169021	844.9143	5314898	-799	614

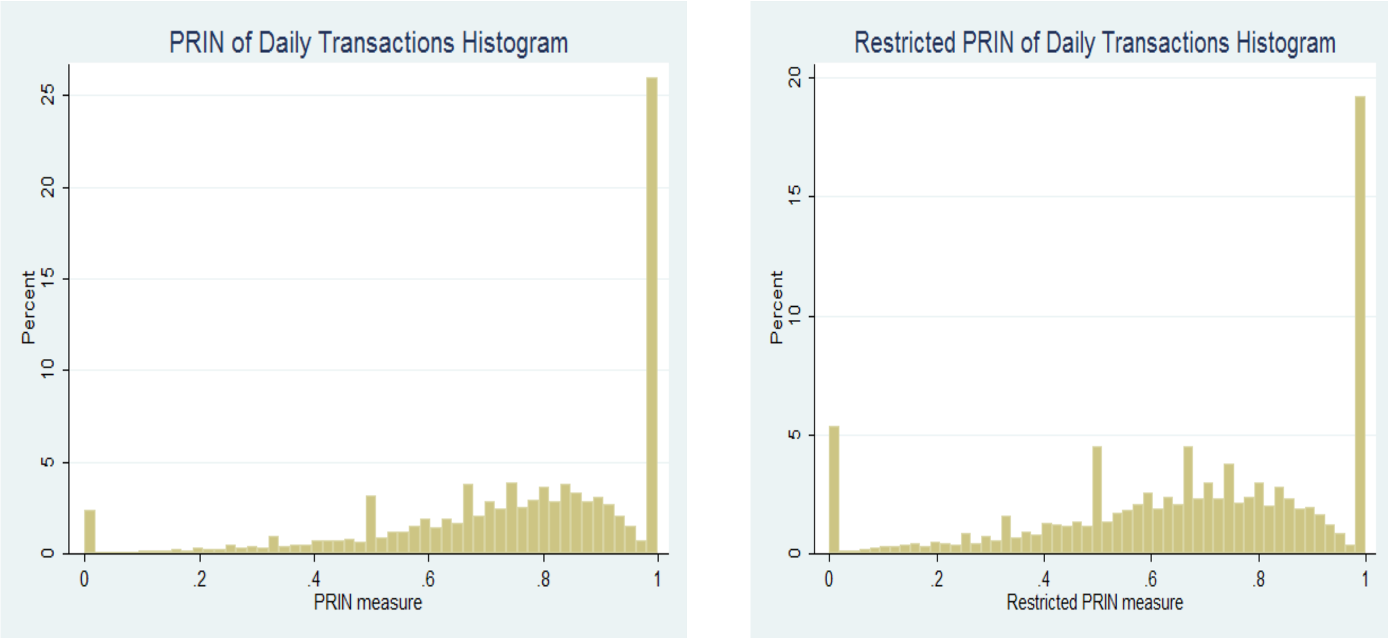

Figure I: Histogram of PRIN and restricted PRIN scores calculated using daily transaction data

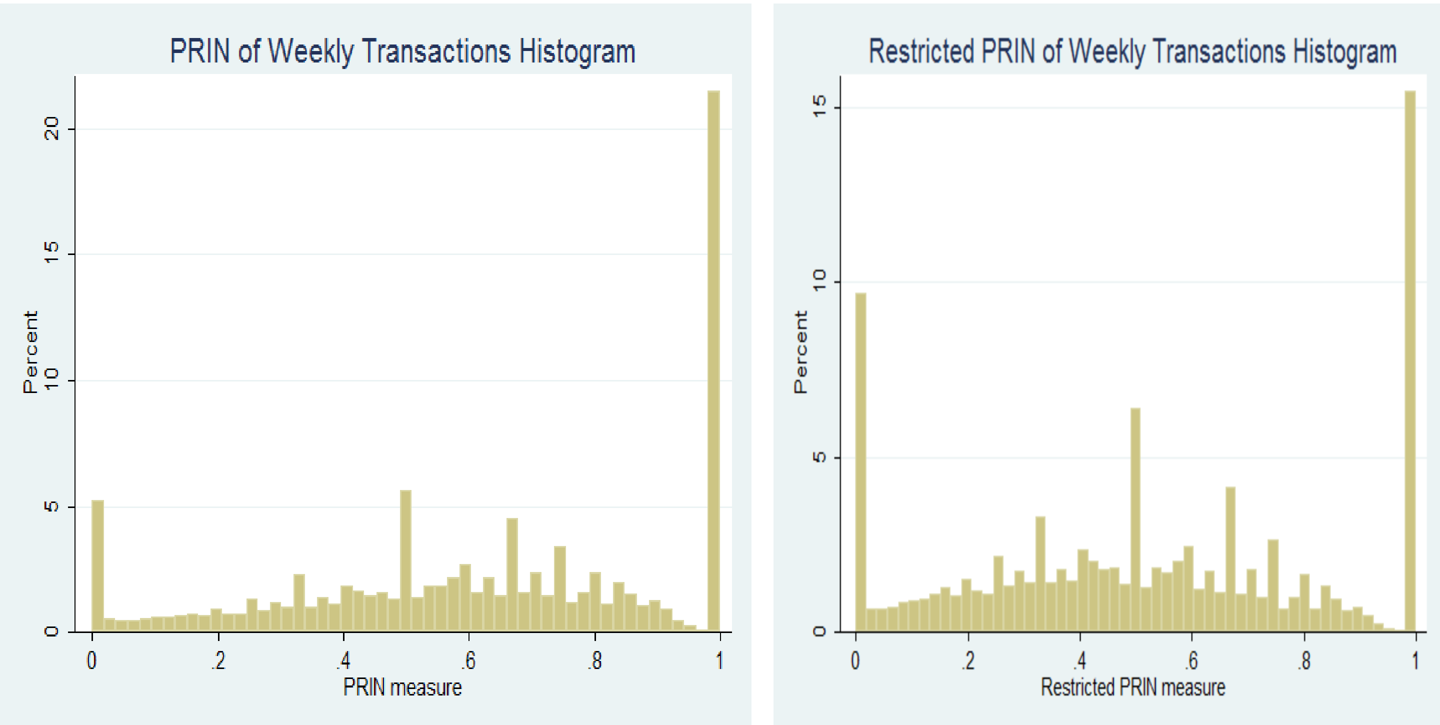

Figure II: Histogram of PRIN and restricted PRIN scores calculated using weekly transaction data