Universal price impact functions of individual trades in an order-driven market

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The trade size ω has direct impact on the price formation of the stock traded. Econophysical analyses of transaction data for the US and Australian stock markets have uncovered market-specific scaling laws, where a master curve of price impact can be obtained in each market when stock capitalization C is included as an argument in the scaling relation. However, the rationale of introducing stock capitalization in the scaling is unclear and the anomalous negative correlation between price change r and trade size ω for small trades is unexplained. Here we show that these issues can be addressed by taking into account the aggressiveness of orders that result in trades together with a proper normalization technique. Using order book data from the Chinese market, we show that trades from filled and partially filled limit orders have very different price impact. The price impact of trades from partially filled orders is constant when the volume is not too large, while that of filled orders shows power-law behavior $r \sim \omega^{\alpha}$ with $\alpha \approx 2/3$. When returns and volumes are normalized by stock-dependent averages, capitalization-independent scaling laws emerge for both types of trades. However, no scaling relation in terms of stock capitalization can be constructed. In addition, the relation $\alpha = \alpha_{\omega}/\alpha_r$ is verified, where α_{ω} and α_r are the tail exponents of trade sizes and returns. These observations also enable us to explain the anomalous negative correlation between r and ω for small-size trades. We anticipate that these regularities may hold in other order-driven markets.

Keywords: Econophysics; Price impact function; Price-volume relation; Scaling laws; Data collapsing

1 Introduction

A well-known adage in the Wall Street states that it takes trading volume to move stock prices. The price-volume relation has been extensively studied, which composes of the positive correlations between trading volume $\omega(t, \Delta t)$ and the volatility (or the absolute value of return) $|r(t, \Delta t)|$ (the

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positive volume-volatility relation), and between trading volume and the return *per se* $r(t, \Delta t)$ (the positive volume-return relation) over fixed time intervals $(t - \Delta t, t]$ in financial markets (Karpoff, 1987). These relations are robust at various time scales including minutely (Wood et al., 1985), hourly (Jain and Joh, 1988), daily (Ying, 1966; Epps, 1977; Harris, 1987; Gallant et al., 1992), weekly (Richardson et al., 1986), to monthly horizon (Rogalski, 1978; Saatcioglu and Starks, 1998). In these studies, the main result is that the return $r(\omega)$ is linearly correlated with the volume ω and the ratio of price change to trading volume is greater for trades driving price down than for those driving price up (Karpoff, 1987). The price-volume relation is of significant relevance to the mixture of distributions hypothesis of returns (Clark, 1973; Epps and Epps, 1976).

In recent years, the price-volume relation has been studied at the transaction level (Chan and Fong, 2000; Lillo et al., 2003; Lim and Coggins, 2005; Næs and Skjeltorp, 2006). It is well-known that buyer-initiated trades drive the price up and seller-initiated trades drive it down. The difference between the volume-return relation and the volume-volatility relation vanishes at the transaction level. Equivalently, investigating the price-volume relation amounts to the study of the immediate price impact of trades of size ω. Contrary to the linear volume-return assumption at aggregated timescales, Lillo et al. (2003) found that the price impact is nonlinear and concave for US stocks at the transaction level.

Concerning the volume-return relation at the microscopic transaction level, one is interested in the determination of the immediate impact of trade size on the price. Using the Trade and Quote (TAQ) database, Lillo et al. (2003) unveiled a master curve for price impact function in the sense that the data collapse onto a single curve (LFM scaling)

$$r\left(\frac{\omega}{\langle\omega\rangle}, C\right) = C^{-\gamma} f\left(\frac{\omega}{\langle\omega\rangle}\frac{1}{C^{\delta}}\right) , \tag{1}$$

where r is the shift of logarithmic mid-quote prices right before and after a trade of size ω occurs, $\langle\omega\rangle$ is the average volume per trade for each stock, C is the stock capitalization, γ and δ are two scaling parameters, and $f(x)$ is found to be a concave function and has a power-law form for large ω. Lim and Coggins (2005) performed a similar analysis on the Australian Stock Exchange and a similar scaling was obtained, where the return and trade size were defined in a slightly different way. More interestingly, $r(\omega)$ is found to decrease with increasing ω in the Australian market when ω is smaller than certain value (Lim and Coggins, 2005). However, the underlying mechanism causing this counterintuitive behavior is unknown.

The power-law impact function for large trades plays an essential role in an unified theory explaining power laws of financial market fluctuations (Gabaix et al., 2003a,b; Farmer and Lillo, 2004; Plerou et al., 2004; Gabaix et al., 2006, 2007). It is found that the distribution of equity returns obeys the (inverse) cubic law:

$$\Pr(|r| > x) \sim x^{-\alpha_r} , \tag{2}$$

where $\alpha_r \approx 3$ (Gopikrishnan et al., 1998, 1999; Plerou et al., 1999) and that of trading volumes fulfills the half-cubic law

$$\Pr(\omega > x) \sim x^{-\alpha_\omega} \tag{3}$$

with $\alpha_\omega \approx 3/2$ (Gopikrishnan et al., 2000). If the price impact function has a power-law form $|r| \sim \omega^{\alpha}$, we have immediately that

$$\alpha = \alpha_\omega / \alpha_r , \tag{4}$$

which bridges the two tail exponents for returns and volumes. The unified theory of (Gabaix et al., 2003a) can thus be tested empirically.

In this work we report on the existence of two universal price-impact functions of two types of trades in an order-driven stock market, which do not depend on the stock capitalization. We also show that the relation (4) put forward originally by Gabaix et al. (2003a) can be verified also at the transaction level. The rest of the paper is organized as follows. Section 2 describes the data used in our study and briefly the trading system. Section 3 investigate the price impact functions and data collapse based on a proper normalization approach. In section 4, we adopt the methods utilized by Lillo et al. (2003) and Lim and Coggins (2005) for comparison. The relation between different power-law exponents is tested in section 5 using at the level of individual stocks and aggregate data of all stocks as well. Section 6 summarizes and concludes.

2 Description of data sets

We use a database recording all orders of submission and cancelation of 23 A-share stocks traded on the Shenzhen Stock Exchange in year 2003. The Shenzhen Stock Exchange (SZSE) was established on December 1, 1990 and started its operations on July 3, 1991. There are two separate markets for A-shares and B-shares. A-shares are common stocks issued by mainland Chinese companies, subscribed and traded in Chinese currency *Renminbi* (RMB), listed on mainland Chinese stock exchanges, bought and sold by Chinese nationals and approved foreign investors. The A-share market was launched in 1990 and opened only to domestic investors in 2003. B-shares are issued by mainland Chinese companies, traded in foreign currencies and listed on mainland Chinese stock exchanges. B-shares carry a face value denominated in RMB. The B Share Market was launched in 1992 and was restricted to foreign investors before February 19, 2001. It has been opened to Chinese investors since.

The Chinese markets have grown rapidly together with China's economy. At the end of 2003, there were 491 A-share stocks and 57 B-share stocks listed on the SZSE. Concerning the A-share market, the total market capitalization was 173.28 billion shares and the float market capitalization was 65.57 billion shares (Zhang et al., 2004). At the end of March 2008, the total market capitalization for 686 A-share stocks increased to 290.26 billion shares and the float market capitalization to 158.45 billion shares. Our sample stocks were part of the 40 constituent stocks included in the Shenshen Stock Exchange Component Index in 2003. The total market capitalization $C_{\rm tot}$ and float capitalization C, both in unit of million shares, of individual stocks are listed in table 1. We note that $C_{\rm tot}$ varies from 275.9 to 1994.1 and C ranges from 107.1 to 1406.5 spaning over one order of magnitude.

The Exchange is open for trading from Monday to Friday except the public holidays and other dates as announced by the China Securities Regulatory Commission. On each trading day, the trading time period is divided into three parts: opening call auction, cooling periods, and continuous double auction. The market opens at 9:15 am and entered the opening call auction till 9:25 am, during which the trading system accepts order submission and cancelation, and all matched transactions are executed at 9:25 am. It is followed by a cooling period from 9:25 am to 9:30. During cooling periods, the Exchange is open to orders routing from members, but does not process orders or process cancelation of orders. The information released to trading terminals also does not change during cooling periods. All matched transactions are executed at the end of cooling periods. The continuous double auction operates from 9:30 to 11:30 and 13:00 to 15:00 and transaction occurs based on automatic one to one matching due to price-time priority. The time interval between 11:30 am to 13:00 pm is another cooling period. Outside these opening hours, unexecuted orders will be removed by the system. Only the trades during the continuous double auction are considered in this work.

The 23 stocks investigated in this work are representative, which belong to a variety of industry sectors as shown in table 1. Although the Chinese stock market was in the middle of a five-year bearish phase in 2003 (Zhou and Sornette, 2004), the annual turnovers were still very high. The annual turnovers of the 23 stocks are tabulated in table 1. Hence, transactions are quite frequent, resulting in a large number of trades in our analysis. The total numbers N of trades for individual stocks are also presented in table 1.

Table 1: Basic statistics for the 23 SZSE. Shown in columns are the codes of stocks, the total market capitalization ($C_{\rm tot}$, million shares), the float market capitalization (C, million shares), the annual turnovers ($z\%$), the average returns ($\langle r_{\rm PB}\rangle$, $\langle r_{\rm PS}\rangle$, $\langle r_{\rm FB}\rangle$, and $\langle r_{\rm FS}\rangle$, multiplied by 1000) caused by filled and partially filled buys and sells, the numbers of trades (N, thousand shares), and the industry sectors.

Code	$C_{\rm tot}$	C	z	$\langle r_{\rm PB}\rangle$	$\langle r_{\rm PS}\rangle$	$\langle r_{\rm FB}\rangle$	$\langle r_{\rm FS}\rangle$	N	Industry
000001	1945.8	1406.5	149.9	1.19	-1.21	0.03	-0.05	889.7	Financials
000002	1152.3	929.5	166.8	1.55	-1.54	0.04	-0.05	509.4	Real estate
000009	958.8	579.1	210.5	2.23	-2.25	0.05	-0.06	448.0	Conglomerates
000012	377.9	107.1	529.5	1.63	-1.61	0.08	-0.10	290.4	Metals & Nonmetals
000016	399.1	224.0	182.3	1.86	-1.87	0.08	-0.10	188.6	Electronics
000021	732.9	199.5	309.3	1.35	-1.37	0.07	-0.09	411.6	Electronics
000024	327.2	170.2	151.9	1.65	-1.63	0.09	-0.09	133.6	Real estate
000027	1202.5	486.0	206.0	1.63	-1.63	0.06	-0.05	313.9	Utilities
000063	667.3	250.8	227.6	1.27	-1.24	0.07	-0.06	265.5	IT
000066	458.5	181.0	231.6	1.57	-1.59	0.08	-0.09	277.7	Electronics
000088	585.0	124.9	169.5	1.63	-1.60	0.10	-0.09	97.2	Transportation
000089	799.8	287.8	216.6	1.63	-1.64	0.06	-0.07	189.1	Transportation
000406	364.0	265.8	231.5	1.56	-1.58	0.05	-0.07	271.4	Petrochemicals
000429	953.4	274.1	118.2	2.35	-2.37	0.08	-0.09	117.4	Transportation
000488	526.1	235.6	136.8	1.72	-1.62	0.14	-0.17	120.1	Paper & Printing
000539	1994.1	391.5	114.0	1.88	-1.85	0.10	-0.14	114.7	Utilities
000541	275.9	146.7	95.2	1.56	-1.54	0.09	-0.09	68.7	Electronics
000550	519.2	117.5	604.5	1.60	-1.59	0.08	-0.09	346.7	Manufacturing
000581	348.0	215.9	123.5	1.84	-1.80	0.10	-0.10	94.0	Manufacturing
000625	876.7	168.0	582.8	1.60	-1.61	0.08	-0.10	397.6	Manufacturing
000709	1955.0	565.8	125.7	2.02	-2.04	0.04	-0.05	207.8	Metals & Nonmetals
000720	479.7	277.1	82.2	0.98	-1.15	0.05	-0.08	132.2	Utilities
000778	621.5	219.1	183.1	1.38	-1.33	0.07	-0.07	157.3	Manufacturing

Before July 1, 2007, only limit orders were allowed for submission in the Chinese stock markets and the tick sizes of all stocks are identical to 0.01 RMB. If a trade occurs at time t, we compute the percentage return

$$r(t+1) = [p(t+1) - p(t)]/p(t) \ , \tag{5}$$

where $p(t)$ and $p(t+1)$ are the mid-prices of the best bid and ask right before and after the transaction. Following Biais et al. (1995), the trades are differentiated into four types according to their directions (whether a trade is seller-initiated or buyer-initiated) and aggressiveness: buyer-initiated partially filled (PB) trades resulting from partially filled buy orders, seller-initiated partially filled (PS) trades resulting from partially filled sell orders, buyer-initiated filled (FB) trades resulting from filled buy orders, and seller-initiated filled (FS) trades resulting from filled sell orders. Since the price rises following buyer-initiated trades and falls following seller-initiated trades, the returns associated with buyer-initiated trades are non-negative and that with seller-initiated trades are non-positive.

The average returns corresponding to the four classes of trades for individual stocks are shown in table 1. We observe that partially filled trades have much larger impact on the price than filled trades:

$$\langle r_{\rm PB}\rangle \gg \langle r_{\rm FB}\rangle \quad \text{and} \quad -\langle r_{\rm PS}\rangle \gg -\langle r_{\rm FS}\rangle \ , \tag{6}$$

which means that, on average, partially filled trades are much more aggressive than filled trades. The magnitude of average return of a partially filled trade is about 0.0016 ± 0.0003 and that of a filled trade is about 0.00008 ± 0.00003. These very small values also indicate that the percentage return in Eq. (5) equals to the logarithmic return. We notice that the average number of shares per trade is $\omega_{\rm PB} \approx \omega_{\rm PS} \approx 4000$ for partially filled trades and $\omega_{\rm FB} \approx \omega_{\rm FS} \approx 2100$ for filled trades. The fact that partially filled trades have larger sizes further confirms that they are more aggressive.

3 Universal price impact functions

3.1 Price impact functions for individual stocks

For each stock, we determine the four types of trades (PB, PS, FB and FS). For each type of trades, we obtain a sequence of paired points (ω, r) for the transaction sizes and returns. The data points are divided into nonoverlapping groups by binning the ω-axis such that all groups have approximately same number of points. The means of r and ω in each group are calculated. The resulting price impact functions of each type of trades for individual stocks are illustrated in figure 1. Several intriguing features arise. We find that, for each type of trades, the price impact functions for different stocks have similar shapes showing that these stocks share similar underlying dynamic regularities. In addition, the shapes of buy trades and sell trades are similar as well.

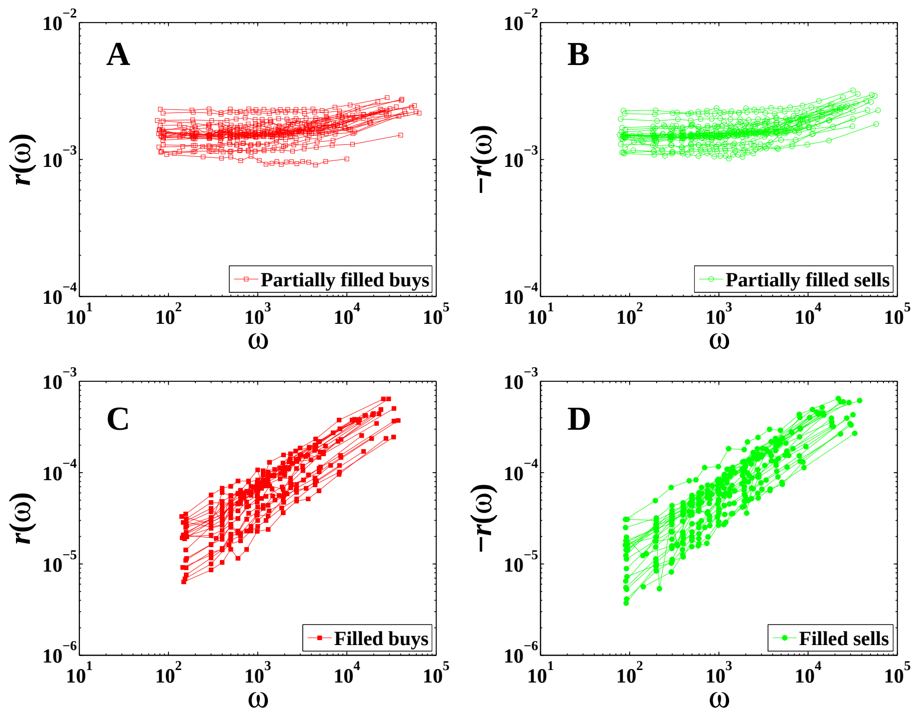

Figure 1: The price impact functions of different types of trades for 23 individual stocks traded on the Shenzhen Stock Exchange. The trades are classified into four types due to their directions and aggressiveness: (A) buyer-initiated partially filled trades, (B) seller-initiated partially filled trades, (C) buyer-initiated filled trades, and (D) seller-initiated filled trades.

However, the shapes of filled trades and partially filled trades are very different. For partially filled trades, $r(\omega)$ remains constant when ω is less than about 10000 shares and then increases. For filled trades, there are nice power-law relationships

$$r(\omega) = A\omega^{\alpha} \tag{7}$$

for the stocks under investigation, where A is a stock-dependent prefactor and α is the power-law exponent. We have fitted the power-law relation for each stock, which gives the average values of power-law exponents $\alpha_{\rm FB} = 0.65 \pm 0.08$ and $\alpha_{\rm FS} = 0.69 \pm 0.06$. A closer scrutiny shows that the stock 000720 does not exhibit nice power-law scaling especially for FB trades (see Zhou, 2007, Figure 8). A possible reason is that this stock was argued to be controlled by large investors who frequently manipulated the price. If we remove this stock, the average exponents are $\alpha_{\rm FB} = 0.66 \pm 0.05$ and $\alpha_{\rm FS} = 0.69 \pm 0.06$, where the standard deviation for FB trades decreases remarkably.

We also find that partially filled trades have much larger price impact than filled trades. In other words, partially filled trades are more aggressive than filled trades. This observation has been documented in (6) according to table 1. There is a trivial "mechanical" explanation for this. Consider a buy order submitted at time t with price π no less than the best ask price $a_1(t^-)$, before which the ask prices at each price level of the sell order book were $a_1(t^-) < a_2(t^-) < a_3(t^-) < \cdots$ and the best bid price was $b_1(t^-)$. The buy order eats orders waiting on the sell order book and the lowest price of the remaining orders submitted before t is $a_n(t^-)$. If the buy order is filled, then the new best ask and bid prices are $a_1(t^+) = a_n(t^-)$ and $b_1(t^+) = b_1(t^-)$ and the mid-price change is

$$\Delta p_{\rm FB} = [a_n(t^-) - a_1(t^-)]/2 \ . \tag{8}$$

If the buy order is partially filled, then the new best ask and bid prices are $a_1(t^+) = a_n(t^-)$ and $b_1(t^+) = \pi \geqslant a_1(t^-)$ since the unfilled part is left on the new best bid price. The mid-price change reads

$$\Delta p_{\rm PB} = \Delta p_{\rm FB} + [\pi - b_1(t^-)]/2 \ . \tag{9}$$

It follows immediately that $\Delta p_{\rm PB} - \Delta p_{\rm FB} = [\pi - b_1(t^-)]/2$, which is larger than half of the bid-ask spread. On the other hand, 91.05% of the FB trades have $\Delta p_{\rm FB} = 0$ and all PB trades have $\Delta p_{\rm PB} \geqslant 0.005$ RMB, half of the tick size. These considerations explain why PB trades have much larger price impact than FB trades. This analysis applies for seller-initiated trades as well. We note that 89.42% of the FS trades have $\Delta p_{\rm FS} = 0$.

3.2 Data collapse of normalized returns and trade sizes

We then adopt a simple method to normalize r and ω for each type of trades by their averages $\langle r \rangle$ and $\langle \omega \rangle$ for each stock. We stress that the main difference between our method and that of Lillo et al. (2003) and Lim and Coggins (2005) is that they did not normalize the returns. The results are depicted in figure 2. The data points of different stocks collapse onto a single curve for each type of trades. The scaling laws can be expressed in the following form

$$r/\langle r \rangle = f_{\rm type}(\omega/\langle \omega \rangle) \tag{10}$$

for different types of trades. For partially filled trades, the scaling function f is almost a constant when the independent argument $\omega/\langle \omega \rangle$ is not too large. For filled trade, the scaling function f has a power-law form.

3.3 Averaged price impact functions

Based on the remarkable scaling of price impact for the four types, we are able to determine the market-averaged price impact curves. For each type of trades, we put together all normalized returns and trade sizes of the 23 stocks. Then the paired points are divided into groups with roughly the same size by binning the $\omega/\langle \omega \rangle$-axis. Figure 3 plots the normalized return as a function of the normalized transaction size for each type of trades. It is found that there is no significant asymmetry between the buyer- and seller-initiated trades at the transaction level, which is in line with the cases of the USA and

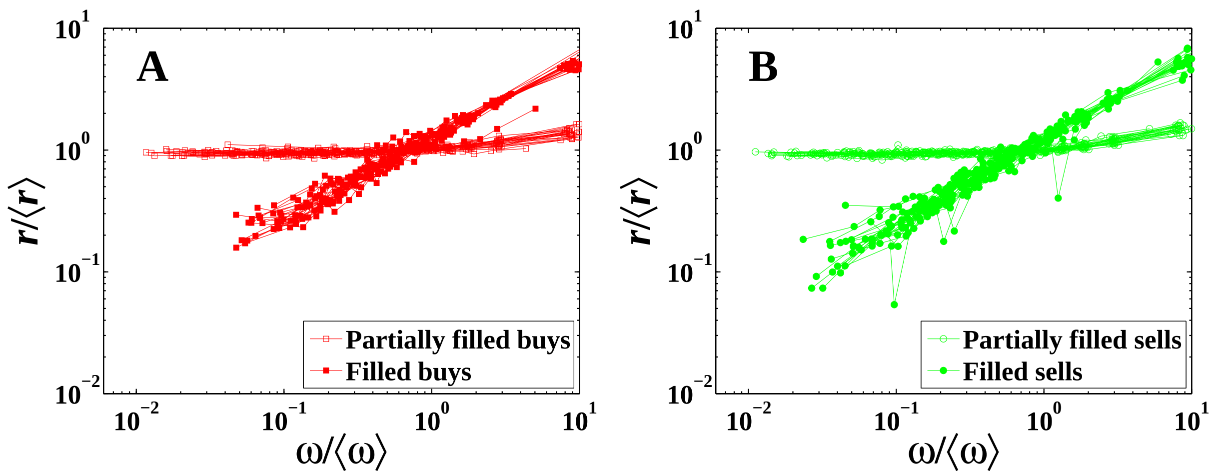

Figure 2: Scaling of price impact functions for different types of trades. For each trade, the price shift $r(\omega)$ and transaction size ω are normalized by the averages $\langle r \rangle$ and $\langle \omega \rangle$ of all the returns and sizes of trades belonging to the same type of trade for each stock.

Australian stock markets (Lillo et al., 2003; Lim and Coggins, 2005) and does not support the well-known conclusion that seller-initiated trades have stronger impact on price than buyer-initiated trades (Epps, 1975, 1977; Karpoff, 1987). Speaking alternatively, we find that $f_{\rm FB}(\omega/\langle\omega\rangle) = f_{\rm FS}(\omega/\langle\omega\rangle)$ and $f_{\rm PB}(\omega/\langle\omega\rangle) = f_{\rm PS}(\omega/\langle\omega\rangle)$. The power-law exponents are $\alpha_{\rm FB} = 0.66 \pm 0.03$ for FB trades and $\alpha_{\rm FS} = 0.69 \pm 0.03$ for FS trades.

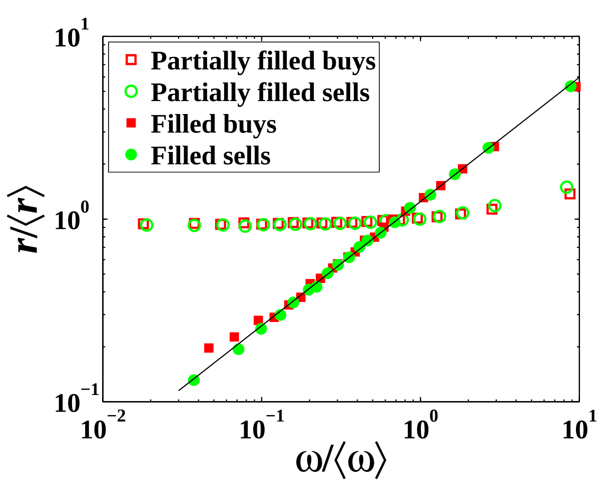

Figure 3: Market averaged price impact curves for the four types of trades. The solid line is a power-law function with the exponent $\alpha = 0.68$ to guide the eye.

The averaged price impact functions of all buyer- and seller-initiated trades are computed separately and presented in figure 4. The most interesting feature is that there is a negative correlation between r and ω for small-size trades, which exists for individual stocks as well. To the best of our knowledge, this anomalous phenomenon was first reported by Lim and Coggins (2005) for Australian stocks. We can derive the condition causing this anomalous negative correlation. Consider two adjacent groups 1 and 2 with mean returns r_1 and r_2 and mean trade sizes $\omega_1 < \omega_2$. Assume that the proportion of filled trade in group i is x_i and the average returns of filled and partially filled trades are $r_{{\rm F},i}$ and $r_{{\rm P},i}$, where $i = 1, 2$. We have

$$r_i = r_{{\rm P},i}(1 - x_i) + r_{{\rm F},i} x_i \; . \tag{11}$$

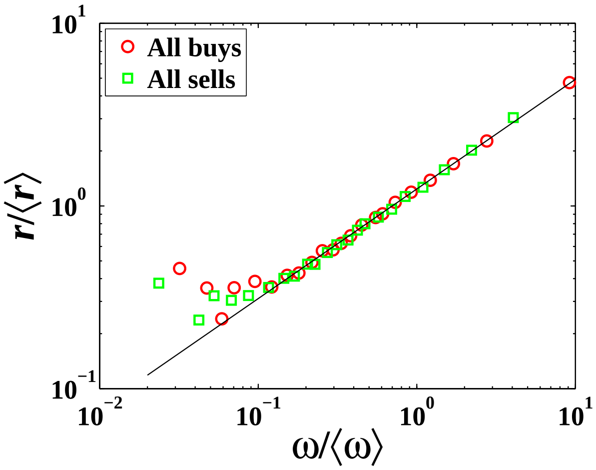

Figure 4: Anomalous price impact curves for all buyer- and seller-initiated trades. Smaller trades move the price more when ω is smaller than about 100 shares. For large trades, the price impact behaves as a power law with an exponent $\alpha \approx 0.60 \pm 0.03$.

Since $r_{\mathrm{P},1} \approx r_{\mathrm{P},2}$ and $r_{\mathrm{F},1} < r_{\mathrm{F},2}$ for small trades, the necessary condition of $r_1 > r_2$ is

$$x_2 > \frac{r_{\mathrm{P},2} - r_{\mathrm{F},2}}{r_{\mathrm{P},1} - r_{\mathrm{F},1}} x_1 \ , \tag{12}$$

where $(r_{\mathrm{P},2} - r_{\mathrm{F},2})/(r_{\mathrm{P},1} - r_{\mathrm{F},1})$ is less than but also close to 1. For individual stocks, we have $r_{\mathrm{P},i} \gg r_{\mathrm{F},i}$, as is shown in figure 1, and condition (12) can be simplified to $x_2 > x_1$. For normalized returns and trade sizes illustrated in figure 3, condition (12) becomes roughly that $x_2 > 0.9x_1$.

In the Chinese stock market, the size of a buy order is limited to 100 shares or an integer multiple of 100, while a seller can place an sell order with any size. It follows that the transaction size of a filled buy is 100 shares or its multiples and it is impossible to be less than 100. For a partially filled buy, its transaction size could be less than 100, if the volume of sell orders waiting on the opposite book it can eat is less than 100. Therefore, condition (12) is satisfied for buy-initiated trades, since the relation $x_2 \approx 1 \gg x_1$ holds.

For seller-initiated trades, the situation is a little more complicated. Here we provide a qualitative explanation. Since the market is not frictionless, it is costly to sell a very small amount of shares. We note that the majority of individual investors hold only several hundred shares (Mu et al., 2008), which is not irrational since the wealth distribution of people follows the Pareto law. All FS trades with the sizes less than 100 are caused by sellers who placed very small orders, which is very rare. Empirically, we find that there are 7029 partially filled trades with the sizes less than 100 out of the total 334516 PS trades, and 22651 filled trades with the sizes less than 100 out of the total 2527070 FS trades. In other words, $x_1 = 0.9790 < x_2 = 0.9910$. Again, condition (12) holds.

4 Testing the LFM scaling

4.1 Scaling exponents determination approaches

Since the LFM scaling was verified in the US stock market by Lillo et al. (2003) and in the Australian stock market by Lim and Coggins (2005), it is natural to test weather it holds or not in the Chinese stock market. We notice that there is a difference in the normalization of trade sizes in the two studies. Hence, we perform this test following Lillo et al. (2003) and Lim and Coggins (2005), respectively.

To avoid possible confusion, we rewrite the notations in the LFM scaling as follows

$$y(x, C) = C^{-\gamma} f(x/C^{\delta}) \; , \tag{13}$$

where y stands for the unnormalized return, x represents the normalized trade size and C is the capitalization.

To determine the scaling exponents δ and γ, Lillo et al. (2003) sorted and divided the x/C^{δ} data into bins and determined the values of δ and γ that minimize the mean $\langle\epsilon\rangle$ of the two-dimensional variance

$$\epsilon(\delta, \gamma) = \left[\frac{\sigma(yC^{\gamma})}{\mu(yC^{\gamma})}\right]^2 + \left[\frac{\sigma(x/C^{\delta})}{\mu(x/C^{\delta})}\right]^2 \tag{14}$$

where σ denotes the standard deviation and μ denotes the mean. This approach has also been adopted by Niwa (2005) in the scaling analysis of probability distribution of dimensions and biomass of fish schools. Alternatively, Lim and Coggins (2005) adopted the method proposed by Bhattacharjee and Seno (2001). Both approaches worked well in the scaling analysis of US and Australian stocks. Here we utilize the one proposed by Lillo et al. (2003).

In addition, we propose a quantity R to quantify the goodness of data collapse, which is motivated by a similar measure used by Lim and Coggins (2005). The quantity is calculated as follows

$$R = 1 - \frac{\epsilon(\hat{\delta}, \hat{\gamma})}{\epsilon(0, 0)} \; , \tag{15}$$

where $\hat{\delta}$ and $\hat{\gamma}$ are the estimates of the scaling exponents.

4.2 The Lillo-Farmer-Mantegna approach

We follow exactly the same approach of Lillo et al. (2003) to perform the scaling analysis in which stock capitalization is included as an independent, except that we do not divide the stocks into groups. In this case, the variables y and x in Eq. (13) are r and $\omega/\langle\omega\rangle$, respectively. The analysis is conducted for the four types of trades. The results are illustrated in figure 5.

The estimated values of scaling exponents δ and γ for each type of trades are listed in table 2. The results show that it is hard to collapse the data onto a single curve for each type of trades. This is also supported by the rather small values of R. When we analyze all buyer- or seller initiated trades, the LFM scaling does not work either.

Table 2: Estimates of the scaling exponents following Lillo et al. (2003).

	PB	PS	FB	FS
δ	0.0069	-0.0106	0.0020	-0.0417
γ	-0.0481	-0.0570	0.4174	0.2615
R	0.0157	0.0239	0.1969	0.0739

4.3 The Lim-Coggins approach

We also follow exactly the same approach of Lim and Coggins (2005) to perform the scaling analysis in which stock capitalization is included as an independent, except that we do not divide the stocks

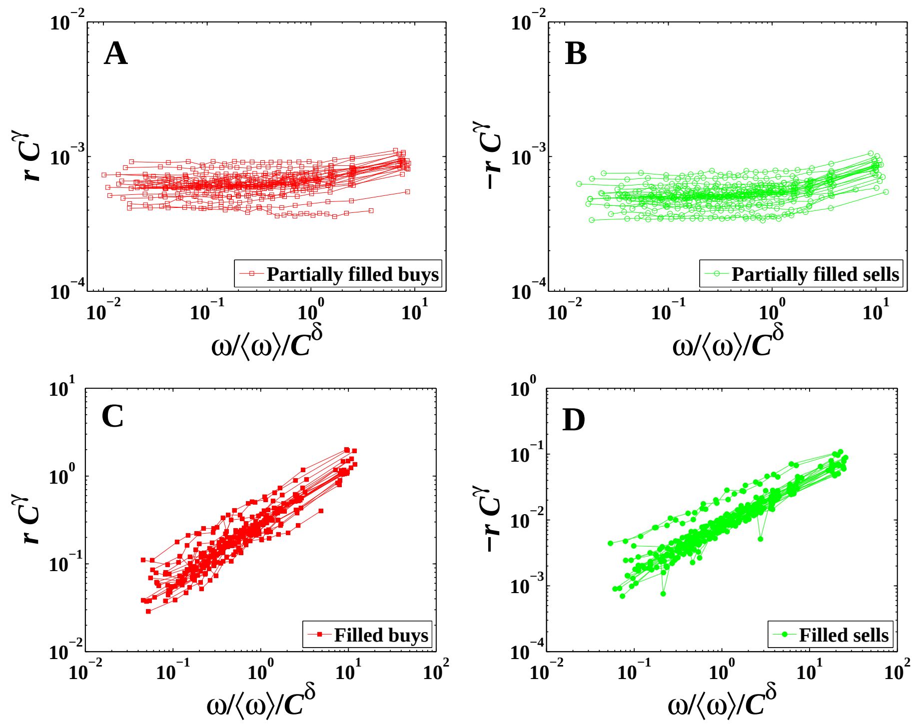

Figure 5: Scaling analysis of the price impact functions of different types of trades for the 23 individual stocks, following Lillo et al. (2003). The trades are classified into four types due to their directions and aggressiveness. The values of δ and γ for each type of trades are listed in table 2.

into groups. In this case, the variables y in Eq. (13) is r and x is the *normalized daily-normalized* volume

$$x_{ij} = \frac{\omega_{ij}}{\sum_{m=1}^{T_i}} \left(\frac{N}{\sum_{d=1}^{N} T_d} \right)^{-1} , \tag{16}$$

where ω_{ij} is the size of trade j on day i, T_i is the total number of trades on day i, and N is the total number of days of a stock. The analysis is carried out for the four types of trades. The estimated values of scaling exponents δ and γ for each type of trades are listed in table 2. The rather small values of R imply that it is hard to collapse the data onto a single curve for each type of trades. When we analyze all buyer- or seller initiated trades, no scaling is obtained (see Zhou, 2007, Figure 11).

Table 3: Estimates of the scaling exponents following Lim and Coggins (2005).

	PB	PS	FB	FS
δ	0.100	0.074	0.291	0.432
γ	-0.036	-0.029	0.196	-0.026
R	0.017	0.018	0.096	0.113

It is noteworthy that, for each stock, the price impact curve for partially filled trades remains constant for not too large trades, while that of filled orders exhibits a nice power law (see Zhou, 2007, Figures 9-10). We have fitted the power-law price impact functions and the average power-law exponent is $\alpha_{\rm FB} = 0.52 \pm 0.04$ for buyer-initiated filled trades and $\alpha_{\rm FS} = 0.53 \pm 0.05$ for seller-initiated filled trades. These exponents are significantly smaller than those in section 3. In addition, when we plot $r/\langle r \rangle$ against x, nice scaling appears again (see Zhou, 2007, Figure 12).

5 Price impacts and the distributions of returns and trade sizes

We now turn to investigate the relation between the power-law exponents of price impacts, returns and trade sizes for filled trades. For the normalized returns and trade sizes, we estimate the empirical complementary cumulative distribution functions for either buyer-initiated or seller-initiated trades. The results are illustrated in figure 6. We find that each of the four probability distributions has a power-law tail. The tail exponents are estimated within the scaling range $[15.9, 141]$ delimited by the two vertical dashed lines. We find that, $\alpha_r = 3.45 \pm 0.17$ and $\alpha_\omega = 2.30 \pm 0.10$ for buyer-initiated trades and $\alpha_r = 3.44 \pm 0.13$ and $\alpha_\omega = 2.36 \pm 0.06$ for seller-initiated trades. Again, the difference between the buyer- and seller-initiated trades are negligible. Although the two distributions deviate respectively from the inverse cubic law and the half-cubic law, the relation between the tail exponents $\alpha_\omega/\alpha_r = \alpha$ is nevertheless validated. Indeed, the two ratios are 0.666 for buy trades and 0.686 for sell trades, which are in excellent agreement with the corresponding power-law exponents $\alpha_{\rm FB} = 0.66 \pm 0.03$ and $\alpha_{\rm FS} = 0.69 \pm 0.03$ of the price impact function.

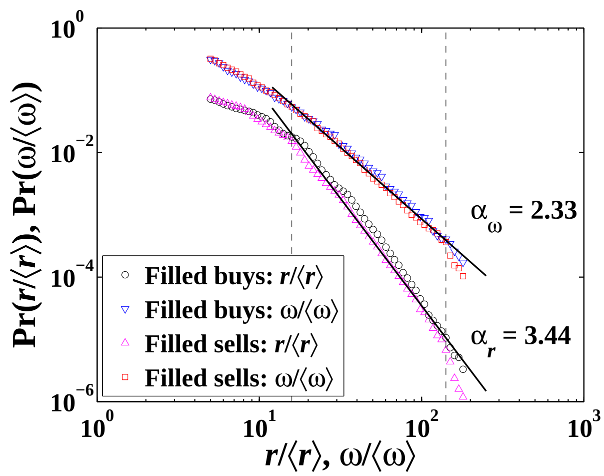

Figure 6: Empirical complementary cumulative distributions of the normalized returns and trade sizes for buyer- and seller-initiated filled trades. The solid lines are power laws. The two curves for trade sizes have been shifted upwards by a factor of 10 for clarity.

The above analysis is conducted based on the data aggregated across different stocks. It is natural to ask if the relation $\alpha_\omega/\alpha_r = \alpha$ holds at the level of individual stocks. We perform such a test separately for buyer- and seller-initiated filled trades. For each type of trades of each stock, the tail exponents α_ω and α_r of the distributions of returns and trade sizes and the power-law exponent α of the price impact function are determined. The value of α_ω/α_r is then calculated, which should be compared with α. To quality the extend to which α_ω/α_r is equal to α, we calculate the relative deviation as follows

$$D = \left(\frac{\alpha_\omega}{\alpha_r} - \alpha\right)\frac{1}{\alpha} \ . \tag{17}$$

All these values (α_ω, α_r, α_ω/α_r, α, D) are depicted in table 4. We also show the means and standard deviations of α_ω, α_r, α_ω/α_r, and α and the corresponding values extracted from figure 3. According to table 4, we see that most of the D values are reasonably small. The worst case is recognized for the buyer-initiated filled trades of stock 000720, which is not surprising since its price impact function does not exhibit power-law form. We thus figure that the relation between the exponents of price impacts, returns and trade sizes also holds for individual stocks.

Several relevant remarks are in order. According to table 4, the returns of Chinese stocks at the transaction level follow the well-known cubic law. The cubic law of returns was well-established for

Table 4: Testing the relation $\alpha_\omega/\alpha_r = \alpha$ for buyer- and seller-initiated filled trades. All values of D are calculated as the relative deviations of α_ω/α_r from α. Each value (except D) in the row "*MEAN*" is the mean of the values in the corresponding column over the 23 individual stocks and the row "*STD*" shows the standard deviations. The values in the row "*ALL*" are determined from the normalized returns and trade sizes aggregated across different stocks.

Code	Buyer-initiated filled trades					Seller-initiated filled trades				
	α_ω	α_r	α_ω/α_r	α	D	α_ω	α_r	α_ω/α_r	α	D
000001	2.12	2.97	0.71	0.69	0.04	2.21	3.38	0.65	0.71	-0.07
000002	2.09	3.17	0.66	0.67	-0.01	2.04	3.12	0.65	0.70	-0.07
000009	2.28	3.46	0.66	0.71	-0.06	2.48	3.22	0.77	0.74	0.04
000012	2.72	3.09	0.88	0.66	0.33	2.41	3.37	0.71	0.69	0.03
000016	2.38	3.32	0.72	0.69	0.04	2.35	3.33	0.71	0.69	0.01
000021	2.34	3.48	0.67	0.65	0.03	2.47	3.73	0.66	0.72	-0.07
000024	1.95	2.96	0.66	0.61	0.08	2.51	3.32	0.76	0.69	0.10
000027	1.90	3.41	0.56	0.71	-0.21	2.58	3.44	0.75	0.75	0.00
000063	2.17	3.07	0.70	0.62	0.12	2.47	3.66	0.68	0.63	0.07
000066	2.53	3.24	0.78	0.67	0.15	2.75	3.11	0.88	0.72	0.23
000088	2.22	3.37	0.66	0.60	0.09	2.35	3.44	0.68	0.53	0.29
000089	1.84	2.93	0.63	0.67	-0.06	1.71	2.94	0.58	0.74	-0.21
000406	2.04	3.03	0.67	0.70	-0.03	2.51	3.26	0.77	0.74	0.03
000429	2.15	3.15	0.68	0.73	-0.07	2.15	2.69	0.80	0.75	0.06
000488	2.18	3.17	0.69	0.56	0.22	2.24	3.90	0.58	0.57	0.01
000539	1.78	2.69	0.66	0.63	0.05	1.60	2.77	0.58	0.58	-0.00
000541	1.81	2.69	0.67	0.59	0.14	2.11	3.28	0.64	0.69	-0.07
000550	2.28	3.18	0.72	0.68	0.04	2.39	3.49	0.69	0.68	0.00
000581	1.91	2.87	0.66	0.64	0.03	2.00	2.90	0.69	0.66	0.03
000625	2.10	2.78	0.76	0.65	0.16	2.36	3.25	0.73	0.73	-0.00
000709	2.27	3.67	0.62	0.74	-0.16	2.47	3.26	0.76	0.77	-0.01
000720	3.45	3.34	1.03	0.35	1.98	2.38	2.84	0.84	0.73	0.14
000778	1.65	2.52	0.65	0.72	-0.09	2.53	3.27	0.78	0.71	0.08
MEAN	2.18	3.11	0.70	0.65	0.07	2.31	3.26	0.71	0.69	0.03
STD	0.37	0.29	0.10	0.08	/	0.27	0.30	0.08	0.06	/
ALL	2.30	3.45	0.67	0.66	0.01	2.36	3.44	0.69	0.69	0.00

US stocks by Gopikrishnan et al. (1998) and Plerou et al. (1999) and for US indexes by Gopikrishnan et al. (1999) at different timescales from 1 minute to a few days. Plerou and Stanley (2008) further showed that the cubic law is universal across three distinct markets, NYSE, London Stock Exchange (LSE) and Paris Bourse, at the timescale of 5 minutes. For the Chinese stocks, Gu et al. (2008) reported that the cubic law holds at the transaction level and the distribution of returns has power-law tails, in which the tail exponent increases from 3 to 4 when the timescale increases from 1 minute to 32 minutes.

The issue of the distribution of trade sizes is more controversial. Gopikrishnan et al. (2000) analyzed the transaction data for the largest 1000 stocks traded on the three major US markets and found that the distribution of trade sizes follow a power-law tail with the exponent being 1.53 ± 0.07, known as the half-cubic law, and that of the aggregated share volumes at timescales from a few minutes to several hundred minutes has a power-law tail exponent 1.7 ± 0.1. Plerou et al. (2001, 2004) confirmed this analysis. Maslov and Mills (2001) found that the trade sizes of several NASDAQ stocks have power-law tails with the exponent close to 1.4. Plerou and Stanley (2007) extended this analysis to other two markets (LSE and Paris Bourse) and found quantitatively similar results across the three distinct markets. All these tail exponents are well below 2, within the Lévy regime. Alternatively, Eisler and Kertész (2006, 2007) reported that the tail exponents of the traded volumes at a timescale of 15 minutes for six NYSE stocks are 2.2 and 2.8. Racz et al. (2008) argued that the tail exponents of the traded volume were underestimated. They investigated the 1000 most liquid stocks traded on the NYSE for the same period as studied by Plerou and Stanley (2007) and found that the average tail exponent is 2.02 ± 0.45. There is additional evidence supporting the point that the tail exponent is outside the Lévy regime for stocks in other markets, such as the Korean stocks (Lee and Lee, 2007) and the Chinese stocks (Mu et al., 2008). The tail exponents reported in table 4 are in line with these results.

From table 4, the power-law exponent of price impact is roughly constant across distinct stocks. Similar phenomenon was observed in the Australia market for large trades by Lim and Coggins (2005). However, the exponents were found to vary between 0.21 and 0.41, much smaller than those in table 4. For the US stocks, Lillo et al. (2003) found that the exponent is around 0.2 for different groups of stocks. Farmer and Lillo (2004) investigated several LSE stocks and the exponent is found to be about 0.26. Alternatively, Bouchaud and Potters (2001) and Bouchaud et al. (2004) proposed a logarithmic price impact relation $r \propto \ln \omega$ for several stocks listed on the Paris Bourse. These two formalisms are not inconsistent since the power-law exponent is small. Gabaix et al. (2003a, 2006, 2007, 2008) studies the price impact function of aggregate trading volumes theoretically and empirically, which leads to a self-consistent exponent of about 0.5.

Combining all these results, several remarks follow. Although the values of α_ω and α in our paper are remarkably different from those of Gabaix et al. (2003a), the relation (4) still holds. We would like to stress that the unified theory of Gabaix et al. (2003a) was tested with variables at fixed time intervals, while our study is carried out at the transaction level. Therefore, our work has empirically confirmed and extended the theory of Gabaix et al. (2003a). In addition, different values of α_ω and α does not falsify the theory. Indeed the relation (4) can be derived, if the three power laws in the distributions of returns and trade sizes and the price impact hold, no matter what is the underlying mechanism causing these power laws. Our work also suggests that it might be better to test the relation (4) in order-driven markets by properly classified trades.

6 Conclusion

In previous studies concerning the price-volume relationship using transaction data, the trades are usually differentiated into two types being buyer- or seller- initiated. We have found that there is no difference in the price impact functions between buyer- or seller-initiated trades. In contrast, the price impact function is more sensitive to the aggressiveness of the trades. In addition, two universal price impact curves for filled trades and partially filled trades appear when both returns and transaction size are normalized by their stock-dependent averages. The scaling analysis is independent of the capitalizations of stocks. To be more conservative, our study does not deny the possibility that the scaling relation in terms of stock capitalization when we group stocks. Unfortunately, we do not have the whole database of all stocks traded in the A-share markets. It is also interesting to see if the B-share stocks have different behavior in the immediate price impact. These researches can be carried out when the data are available.

We figure that these universal price impact functions are unambiguous targets that any empirical model of order-driven market must hit. This result calls for further extension of the existing models (Challet and Stinchcombe, 2001; Daniels et al., 2003; Farmer et al., 2005; Mike and Farmer, 2008). The observed phenomena may be present in other order-driven markets as well. This conjecture can be tested when the order book data are available for other markets, which may extend the universality of the two impact functions.

There are also open problems unsolved in this work. The most interesting one is to understand why the price impact of partially filled trades is roughly the same for different trade sizes and why the price impact of filled trades follows a power law. We hope to address these questions in future research.

Acknowledgments

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SUPPLEMENTARY INFORMATION

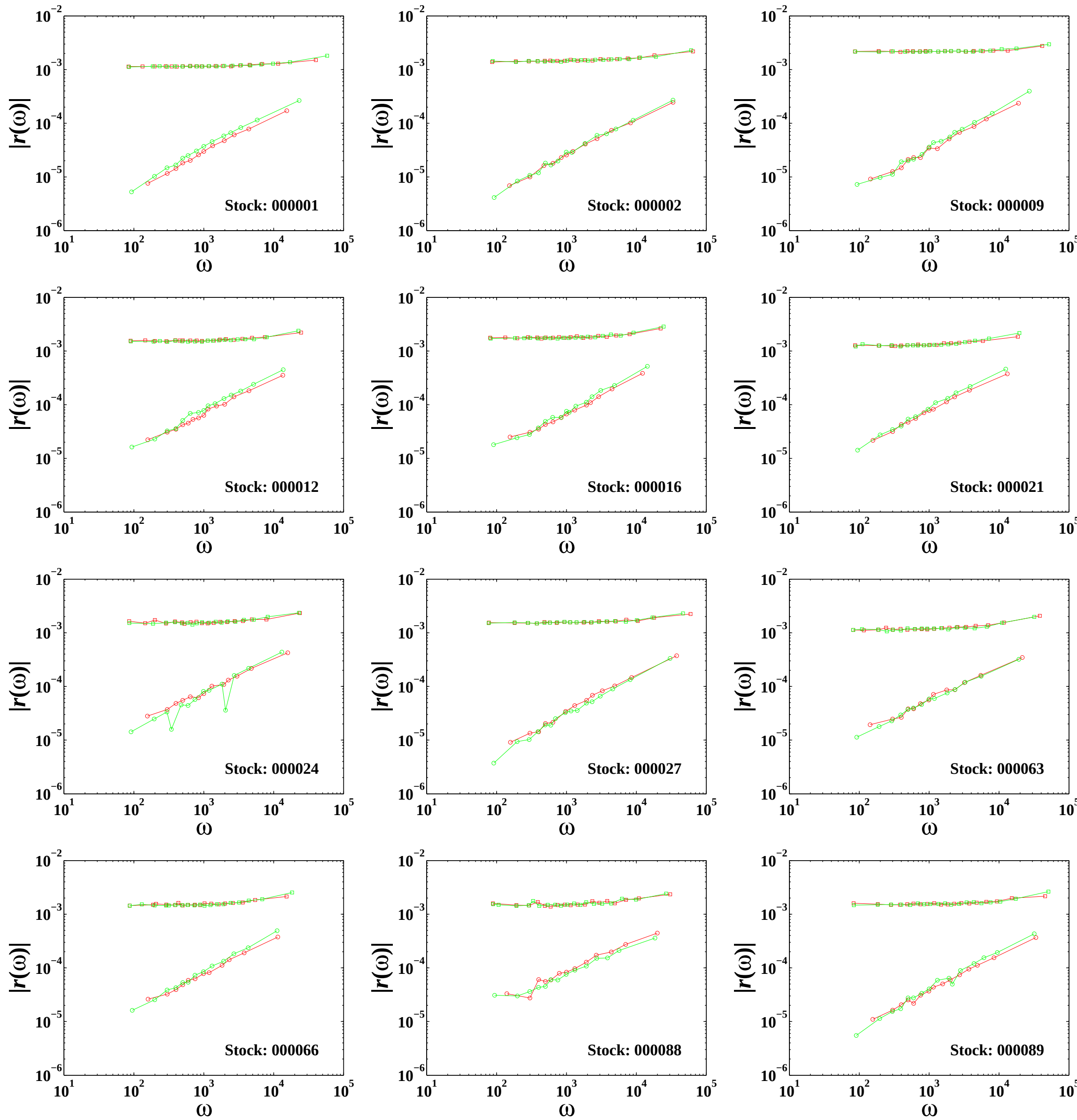

Figure 7: Dependence of $|r|$ with respect to ω for the four types of trades for individual stocks. Note that the price impact of buyer- and seller-initiated trades is symmetric and unfilled trades have greater price impact than filled trades.

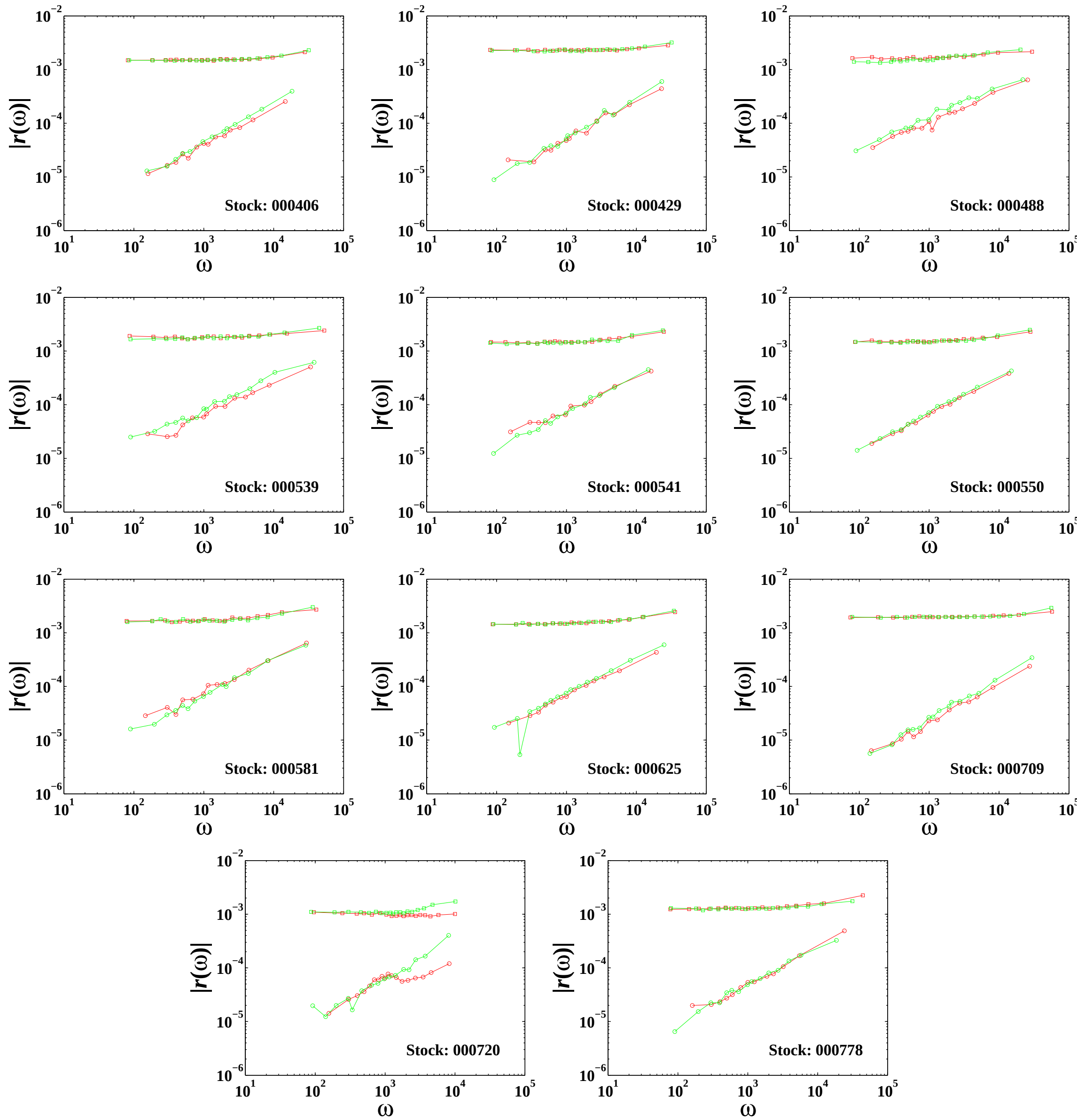

Figure 8: Dependence of $|r|$ with respect to x for the four types of trades for individual stocks. Note that the price impact of buyer- and seller-initiated trades is symmetric and unfilled trades have greater price impact than filled trades (*continued*).

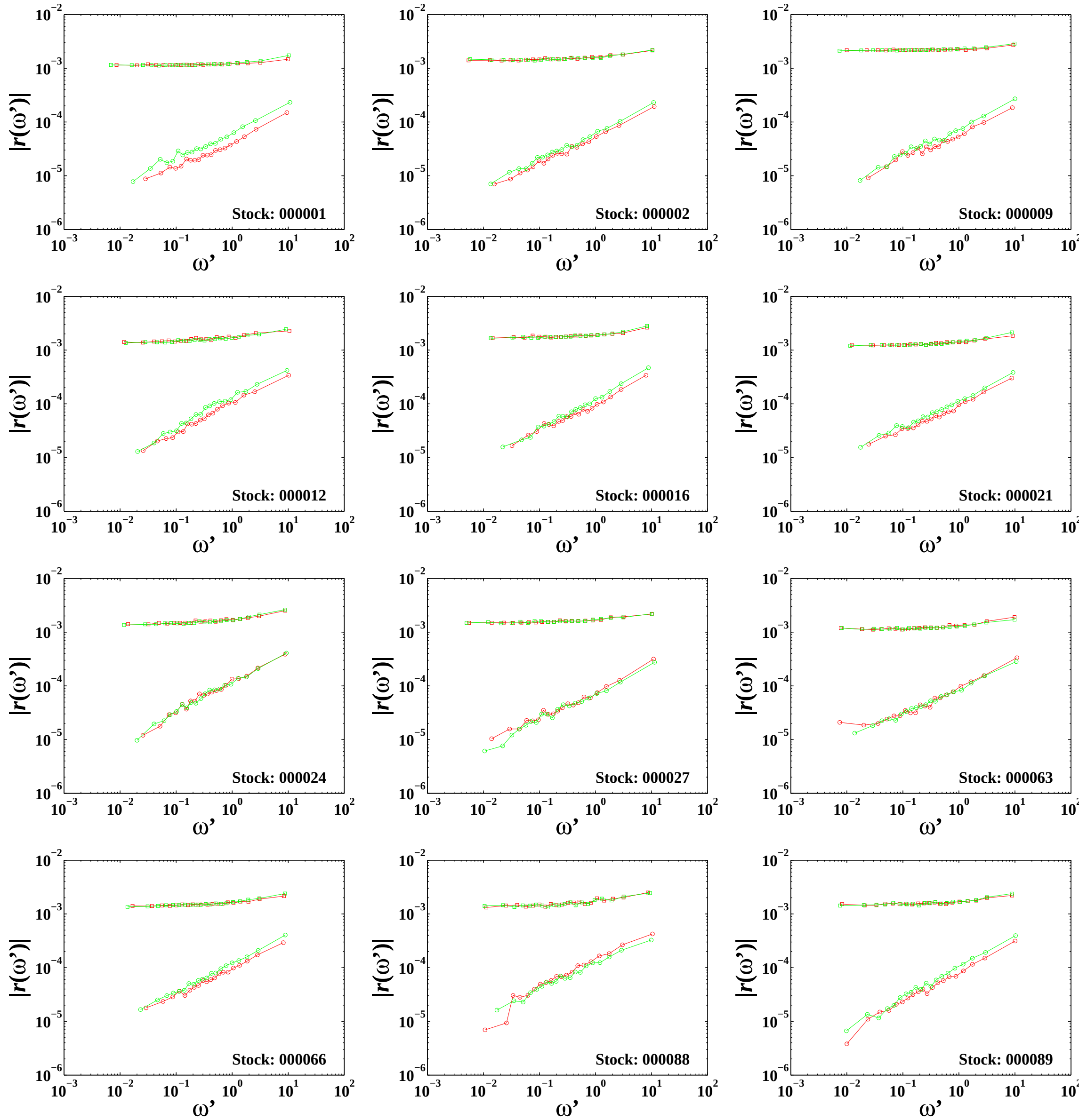

Figure 9: Dependence of $|r|$ with respect to x for the four types of trades for individual stocks. The normalized trade size $x = \omega'$ is obtained following Lim and Coggins (2005). Note that the price impact of buyer- and seller-initiated trades is symmetric and unfilled trades have greater price impact than filled trades.

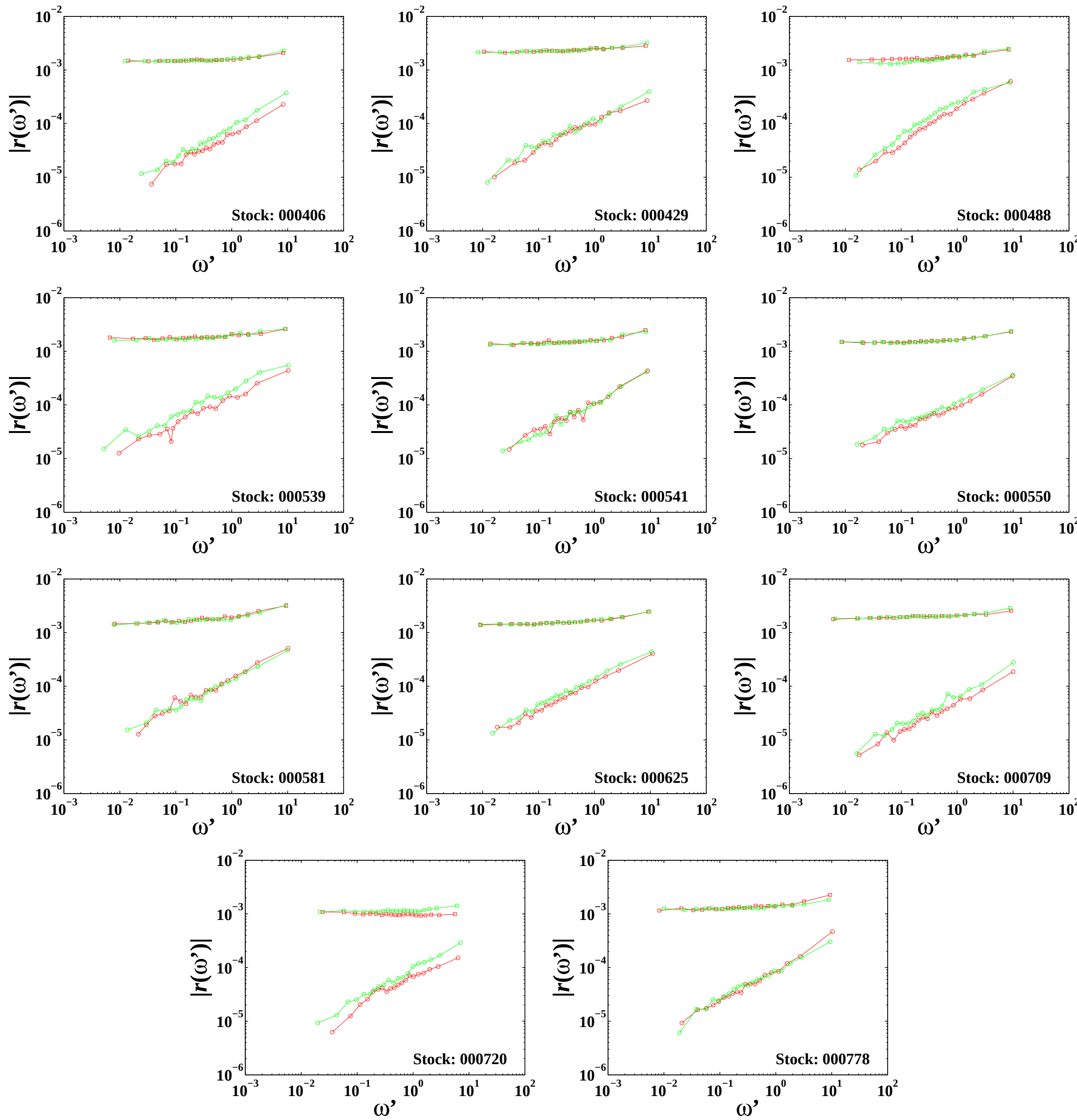

Figure 10: Dependence of $|r|$ with respect to $x = \omega'$ for the four types of trades for individual stocks. The normalized trade size x is obtained following Lim and Coggins (2005). Note that the price impact of buyer- and seller-initiated trades is symmetric and unfilled trades have greater price impact than filled trades (*continued*).

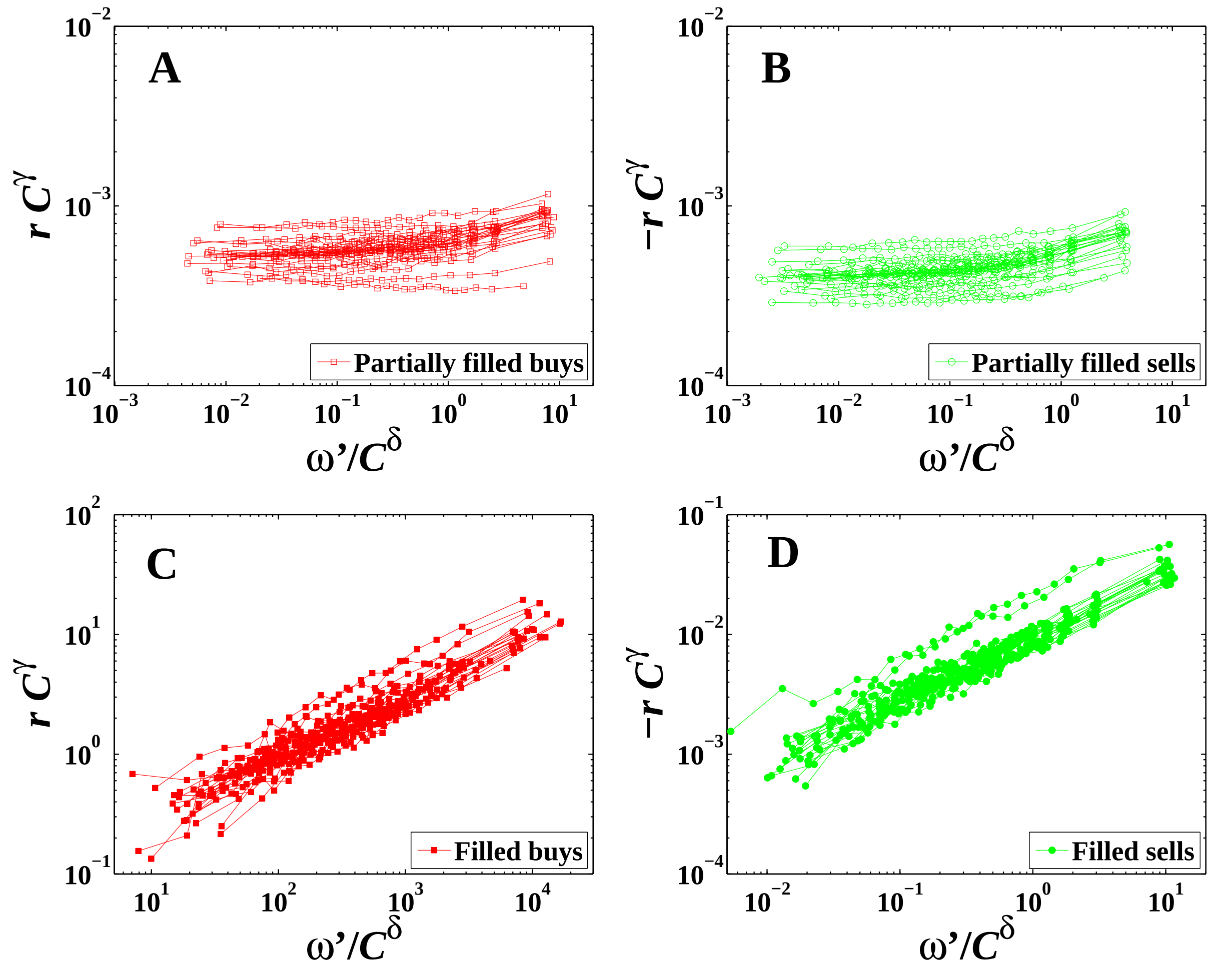

Figure 11: Scaling analysis of the price impact functions of different types of trades for the 23 individual stocks, following Lim and Coggins (2005). The trades are classified into four types due to their directions and aggressiveness. The values of δ and γ for each type of trades are listed in table 3.

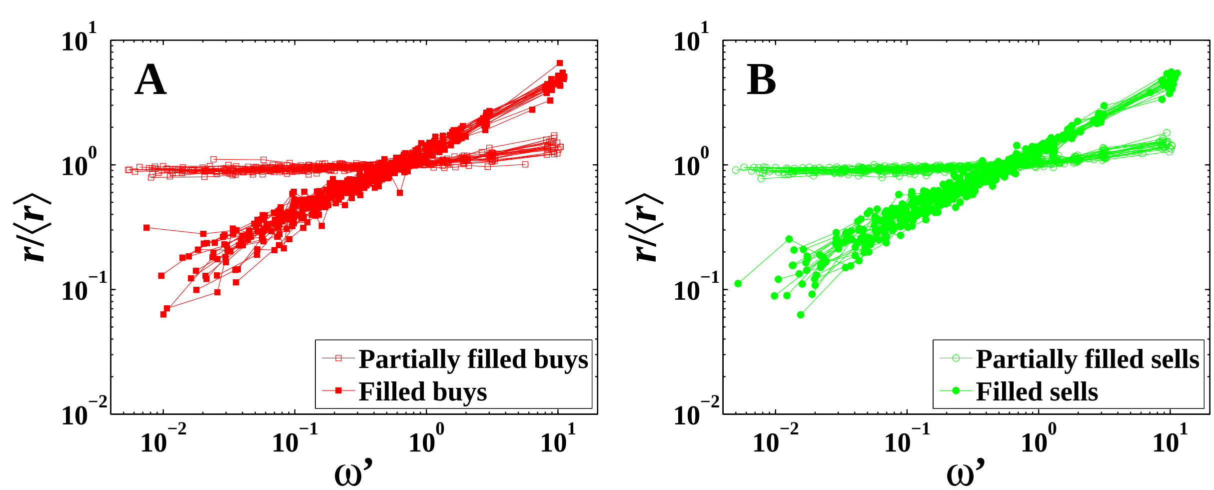

Figure 12: Scaling of price impact functions for different types of trades. The trade sizes are normalized following Lim and Coggins (2005).

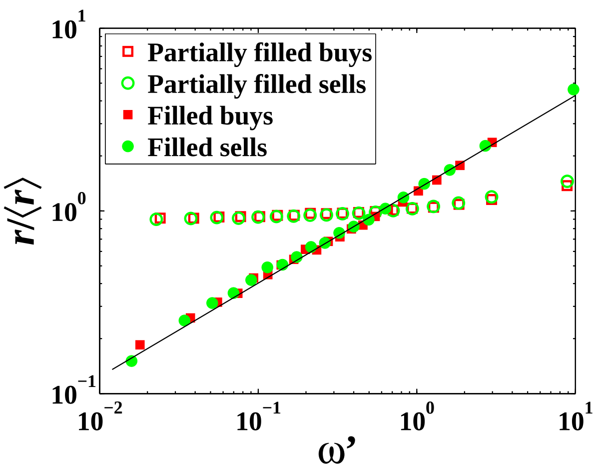

Figure 13: Market averaged price impact curves for the four types of trades. The trade sizes are normalized following Lim and Coggins (2005). The solid line is a power-law function with the exponent $\alpha = 0.50$ to guide the eye.