Quantitative Finance

ISSN: 1469-7688 (Print) 1469-7696 (Online) Journal homepage: www.tandfonline.com/journals/rquf20

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To cite this article: Carl Hopman (2007) Do supply and demand drive stock prices?, Quantitative Finance, 7:1, 37-53, DOI: 10.1080/14697680600987216

To link to this article: https://doi.org/10.1080/14697680600987216

Quantitative Finance, Vol. 7, No. 1, February 2007, 37–53

Routledge
Taylor & Francis Group

Do supply and demand drive stock prices?

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(*Received 30 June 2005; in final form 3 April 2006*)

In this paper, I find that the imbalance between buy and sell orders explains most of the stock price changes. I then show that this effect is driven largely by uninformed price pressure, and not only by private information. To obtain that result, I first establish that causality goes from orders to price. I then distinguish between private information and uninformed price pressure by looking at the implications of a private information model. For idiosyncratic returns, where one would expect private information to be important and the R^2 of return on order flow to be high, the R^2 is indeed around 41%. However, for the common market return, where one would expect private information to be minor, the R^2 is even higher at 70%. This argues against private information and in favor of uninformed price pressure. Moreover, the 70% of the market return that is generated by the order flow imbalance is too high not to include some transitory components of the market return, as defined in the literature on long-term mean reversion. This means that the order flow temporarily moves stock prices away from their fundamental value. This paper points toward a bigger role for uninformed price pressure than is usually assumed.

Keywords: Supply and demand; Stock prices; Order flow

1. Introduction

When there is no fundamental explanation for sharp price movements, the financial press often proposes supply and demand arguments. It attributes price drops to heavy selling (e.g. profit taking) or price increases to an excess of buyers (e.g. short covering). However, the imbalance in supply and demand is often ignored altogether, as it is taught, for instance, in some MBA programs. Indeed, some finance professors argue that there is no imbalance, because the volume bought by some is equal to the volume sold by others. Instead, the emphasis is placed on information, either public or private.

This divergence in focus started with the emergence of the efficient market paradigm, which argues that stock prices perfectly reflect their future discounted cash flows, with the information available at that point in time. Since most orders probably do not contain much information about the stock's fundamental value, price pressure was first seen as contradictory to this paradigm and refuted by the work of Scholes (1972), in particular.

An important problem for this paradigm has been raised by Roll (1988). His results suggest that public news cannot explain more than 30% of the price changes, instead of 100% as one could at first expect. This† R^2 includes the regression on the industry and principal components of the return. This means that, for the market- and factor-wide returns, he does not actually test whether they are driven by news, but assumes it. The real test is for the company-specific movements. To study these idiosyncratic price changes, Roll distinguishes days with company news from days without. The idea is that on days without company-specific news, the market-wide factors should be the sole determinants and the R^2 on these factors should be close to 100%. However, the difference in R^2 between days without news and all days together is less than two percentage points (and both R^2 are below 30%). It seems that a lot of the idiosyncratic variance exists without any idiosyncratic news. So for the idiosyncratic part of stock returns, where the effect of news is really studied, news does not seem to explain returns very well. This result has been an important puzzle since its

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†A basic statistical regression has a left-hand side variable, which we attempt to explain, and one or more right-hand side variables called explanatory variables, which help explain it. The R^2 of a regression measures the fraction of the variation of the left-hand side variable that can be explained by the explanatory variables. In most examples of the paper, the variable to be explained is the change in price of a stock.

Quantitative Finance
ISSN 1469–7688 print/ISSN 1469–7696 online © 2007 Taylor & Francis
http://www.tandf.co.uk/journals
DOI: 10.1080/14697680600987216

publication, and it is interesting to find variables that can account for price changes better than news does.

In a related paper, French and Roll (1986) confirm and quantify that public information does not have much effect on stock prices (less than 15%), and conclude that most price movements are due to private information.

In this paper I therefore do not address public information, concentrating instead on private information and mechanical price pressure. The importance of private information and the way it can affect prices as well as orders has been explored in the microstructure literature, with the work of Kyle (1985), in particular. In this context it is admitted that prices will move with supply and demand imbalance because the change in demand reveals private information. The price impact of orders is therefore made compatible with information efficiency.

However, a competing interpretation of price pressure separates prices from their fundamental value, thanks to the limits to arbitrage of DeLong, Shleifer, Summers and Waldmann (1990) (DSSW 1990). It is well known from the microstructure literature that uninformed orders can have a temporary impact: a buy order will push the price upwards for inventory reasons with a market maker and mechanically with a limit order market. However, information efficiency would suggest that this effect is very brief if some arbitrageurs know that this order is uninformed: these arbitrageurs will soon provide the necessary liquidity to bring the price back to its previous† level. But it is also possible that these arbitrageurs do not bring it completely back because the benefit is small and the risk is high (the price will indeed one day come back to its efficient value, but the arbitrageur may need to wait a long time and face huge price changes in between, as in DSSW (1990)). In sum, noise trades are not faced with infinite liquidity, and therefore can have a long-term impact on the price.

A microstructure foundation for uninformed price pressure was introduced by Stoll (1978) for markets organized around market-makers or dealers. In this framework, dealers are risk averse and need to be compensated for holding a suboptimal portfolio or inventory. Starting from their optimal inventory, they thus only buy a stock below its fundamental value, so that they have an expected gain in their purchase. By moving the price lower, they also attract other buyers which allow them to bring their inventory back to its optimal level. The main difference between DSSW (1990) and Stoll (1978) is the time frame involved. People usually think of dealers as relatively short-term investors, who balance their inventory regularly. Since, in this model, the price is at its fundamental value when the inventory is balanced, this type of model is usually understood as implying only short-term price deviations from their fundamentals. The other difference is that DSSW (1990) can apply to different types of market microstructures, including an automated exchange such as the Paris Bourse, and not only to dealer-based markets.

The original contribution of this paper is to provide empirical evidence in favor of uninformed price pressure. I establish that most of the stock price changes (70% in the case of the stock market) are explained by the order flow imbalance, much more than previous estimates. I then disentangle between two competing explanations for the price impact of orders: private information and mechanical price pressure. The first argument is that the price impact is very large for imbalances observed simultaneously on all stocks, although there is little potential for private information on the stock market as a whole. The second argument is that the fraction of the stock market variance explained by the order flow imbalance is larger than the documented permanent component of price changes, which implies that a large part of the price impact eventually mean-reverts.

Several previous papers distinguish buyer initiated and seller initiated transactions to explain price changes. Although their measure is based on realized transactions, it is still related to my measure of order flow imbalance, since an excess of limit buy orders is likely to generate aggressive buy orders that result in buyer initiated transactions. Hasbrouck (1991) uses NYSE transaction data and concludes that the impact of a trade is a positive, increasing and concave function of its size, with R^2 at 10%. Chordia and Avanidhar (2004) also use NYSE transaction data and find a price impact of contemporaneous and lagged‡ orders with R^2 around 20%. Hausman *et al.* (1992) use an ordered probit model to take directly into account the discreteness of the tick size. Evans and Lyons (2002) also use signed transaction data on the Foreign Exchange dealer market rather than on the stock market, and they find an R^2 similar to mine, showing that the imbalance explains the Forex returns quite well. Compared to mine, their data include realized transactions, without their volume or intra-day information on a sample of only 89 trading days. They interpret their finding in a private information framework. However, they call 'private information' the volume that traders are willing to buy or sell. This is something which noise traders with absolutely no information about the financial asset know as well. It is, therefore, not very different from a direct price pressure interpretation. Brandt and Kavajecz (2004) also use signed transaction data on the fixed income market and they find slightly smaller R^2, around 20 to 30%, showing that the imbalance is also an important factor for yield curve changes.

Other papers look at the impact of imbalances on stock prices by restricting themselves to large trades. This literature dates back at least to Scholes (1972). He finds that the impact of a trade does not increase

†Modified for the information which has arrived in between.
‡Similarly to my results in section 3.4, they do not find a reversal of the price impact in the next day. However, they do find a positive impact of lagged daily orders, whereas I only find that result intra-day. This could be driven by differences in the market microstructure between the NYSE and the Paris Bourse, the latter being, perhaps surprisingly, more efficient.

with the block size and concludes by rejecting the price pressure hypothesis. Yet in a later study of large trades, Holthausen *et al.* (1990) use high-frequency transaction data, which yields more precise estimates of the impact of large trades, and find that the impact does increase with the trade size (as Hasbrouk (1991) finds without restricting himself to large trades). In another study of large trades, Kraus and Stoll (1972) observed some short-term price pressure for these trades and found a partial reversal of the impact of block sales, which they ascribed to the need to compensate suppliers of liquidity.

Other papers document a consistent link between volume and volatility, surveyed, for example, by Karpoff (1987). This link is a direct implication of the impact of trades and orders on asset prices, by taking the absolute value on both sides.

Some of the most interesting papers on the interaction between prices and trades can be found in the econophysics literature. In particular, Lillo *et al.* (2003) study the concavity of the price impact of a trade and find that the impact is well described by a power function with a power between 0.1 and 0.5. Bouchaud *et al.* (2002) study the distribution of the order flow and the resulting average order book. Interestingly, they find that the average order book has a maximum away from the best bid (or ask), which can explain the concavity of the impact function for trades of size lower than that maximum. Finally, Bouchaud *et al.* (2004), in the same spirit as this paper, shed light on the relationship between market efficiency and price impact. Specifically, they address the question of the compatibility of autocorrelated orders and unforecastable return. They solve the apparent contradiction and propose that the 'bare' impact of each order decays quickly through time, at the same time as it is compensated by the 'bare' impact of later orders in the same direction.

In the next section, I describe the data from the Paris Bourse and I define the order flow measure, taking into account the concavity of the price impact of an order as a function of its volume. I provide some summary statistics and time series properties of the order flow imbalance. The third section presents the relationship between the aggregated order flow imbalance and the stock return, and differentiates the impact of predictable versus unpredictable orders. I then show that this impact is not reversed in the short† term and that the contemporaneous correlation is true for very different time horizons (up to three months). In the fourth section, I show that causality goes from orders to price changes. Then, I find that the strong relationship between market-wide orders and market-wide price changes is not consistent with asymmetric private information. Furthermore, the strong impact of orders on the market return together with the well-documented long run mean reversion of stock prices suggest that uninformed price pressure is the main source of this impact. Finally, I present a simple model of mechanical price pressure.

2. Data, definitions and basic properties

2.1. The data

One of the most common arguments against the study of supply and demand for financial assets is that there is no imbalance. Indeed, shares bought are equal to shares sold for realized transactions. To get around this problem, some researchers have distinguished between buyer and seller initiated transactions. However, this distinction does not solve the equality objection in a pure market maker setup where no limit orders are allowed. Indeed, suppose that only market orders are available, with a market maker who clears his inventory regularly‡, then, even if the econometrician knows perfectly whether the market maker was on the buy side or the sell side, the total volume sold to the market maker is equal, after each inventory clearing, to the total volume bought from him. Therefore, there is never any imbalance in volume. This property limits the effectiveness of using transaction data to measure the order flow in a pure market maker setup and probably extends to markets where limit orders are rare.

This is the main reason why I use Paris Bourse data: limit orders are the norm not the exception, and their submission is available to the econometrician. Although in transaction terms the volume bought is still equal to the volume sold, in submission terms there can be many submitted orders that are never executed. There can, therefore, be an imbalance between submitted Buy and Sell orders (some are later executed, some are not) which I measure directly with this data set.§

†I believe that most of it is eventually reversed, but my data sample does not allow me to look at longer horizons.

‡This condition can be weakened to having a bounded inventory with the equality between buy and sell volume true in the limit.

§If one goes deeper, one could ask what happens to the unexecuted limit orders. They of course get cancelled, most of them automatically at the end of the day or the month. If the impact of all the cancellations is equal to that of all the submissions, then again the total net (submitted minus cancelled) volume of orders is equal on the buy and sell side with a monthly time frame (and both are equal to the transaction volume). However, submissions are usually made relatively close to the current best quote, whereas cancellations often happen automatically, after the price has moved away and the submitted order has remained. If one considers a cancellation as a negative submission, I show below that submitted orders, for a given volume, have a decreasing impact when submitted further away from the best quotes. As a first approximation, one can then argue that submissions are close enough to the best quotes to have an impact, whereas cancellations are not and can be ignored. This is the approximation I am forced to make, since I do not have the cancellation data. Having this data would allow me to have an even better estimation of the impact of supply and demand. As we will see, the approximation already yields very good results.

Although market participants may feel the imbalance on markets that rely on market-makers instead of limit orders, it is not obvious how to measure† their unrealized wishes, i.e. the supply and demand imbalance. On the contrary, on the Paris Bourse, limit orders are dominant and the imbalance is easy to measure. Besides, the Paris Bourse data are very clean and complete. Because the Bourse is a fully automated electronic exchange‡ the data are virtually free of errors.

The Paris Bourse is an order driven market, and there is no market maker or any appointed liquidity provider. Traders give their orders to brokers who pass them on to the central computer. It is then available on the traders' screen, usually within the next second. The Paris Bourse allows agents to place different types of orders. The most common is the limit order. Its main characteristic is to have a maximum price (for a buy order) at which the agent is ready to buy the stock (the buy and sell orders have exactly symmetric properties, so I will only describe buy orders). If a submitted buy order is higher than the current best ask, it is immediately executed. If not, it remains on the order book until either it is hit by a sell order, it is cancelled, or it has a preassigned finite life (all the orders are automatically cancelled at the end of each Bourse month). If two different buy orders are at the same price, then a time priority is given to the order first entered in the book.§

There are two types of market orders. The first type is executed in full only if its volume is less than the available volume at the ask price. If not, the remaining volume is transformed into a limit buy order at this old ask price. The second type of market order is immediately executed in full, against all the available counterparts in the sell order book (and not only against the volume available at the ask price).

The database goes from January 4, 1995 to October 22, 1999 inclusive. I only look at the continuous trading session, which, until September 19, 1999, started just after 10 a.m. and finished at 5 p.m. From September 20, 1999, it started at 9 a.m. and finished at 5 p.m.¶

The database includes all the transactions and all the orders that were submitted on the Paris Bourse, as well as the best quotes available at any time. In comparison, the TORQ (Trades, Orders, Reports and Quotes) database for the New York Stock Exchange (NYSE) misses about half the total volume of submitted orders (Kavajecz 1999).

The main French Index is the CAC40, which includes the 40 biggest stocks. I looked at the 40 stocks that were part of the CAC40 in January 1995. At the end of the sample, 34 of them were still quoted as independent companies, so the results of this paper are provided only‖ for these 34 stocks.

To make things more concrete, I sometimes present the results obtained for one company, Lafarge, which has average properties in many directions. But to show that the results are general, I always report the average results for the 34 stocks when possible.

2.2. *Variable definitions*

I calculate the (log) return using mid-quotes. I also performed robustness checks using transaction prices instead of the mid-quote and results were nearly identical.

I used different time horizons, from 10 min, 30 min, one day, one week, one month up to three months. At 10 min, there is still quite a bit of microstructure noise (as measured by the bid–ask bounce or negative autocorrelation which disappears at 30 min). On the other hand, at three months I have only 20 independent data points and, therefore, little statistical power. However, similar results were obtained for these widely different time intervals as reported in table 13. For horizons longer than one day, the return is calculated from close to close. For one day, one can either calculate the return from opening to close (night excluded) or from close to close (night included) and I present results for both cases.

I distinguish the different buy orders (and similarly the sell orders) according to the level of urgency chosen by the trader submitting the order. This corresponds to the speed with which it is likely to be executed. The reason for this distinction is that one would expect more urgent orders (of similar size) to have a bigger$ impact on the

†If one wanted to build an order flow imbalance measure on the NYSE, for example, one could do the following. First, identify buyer initiated trades from seller initiated, using the Lee and Ready or a similar algorithm. Because there are some limit orders on this market, there can be an imbalance in volume and one could use the net volume of trades. But because of the concavity described in section 2.4, using the SQRT aggregation defined in section 2.5 would be a better measure.

‡Biais *et al.* (1995) provide a detailed description of the microstructure of the Paris Bourse.

§When a limit order is submitted, it is possible to hide some part of it. The hidden part is not visible by any trader or broker until it gets executed. However, the impact of both parts are quite similar, and I do not distinguish between them in this paper.

¶There are also two call auctions, one just before the opening, the other at 5:05 p.m. which was created on June 2, 1998, but I remove all the order flow data they generated, because it is harder to define and measure order imbalance in these auctions.

‖The 40 companies allow me to check for survivorship bias. However, since the results were similar for the six stocks that disappeared, and to have comparable results, I report results only for the 34 surviving stocks.

$This is predicted by a mechanical impact, where market and spread orders have a direct impact on the price, whereas book orders affect the price only by reducing the impact of later market orders. It is also predicted by a private information setup, where a privately informed agent would want to use his information before others know it, so that urgent orders would on average be more informed.

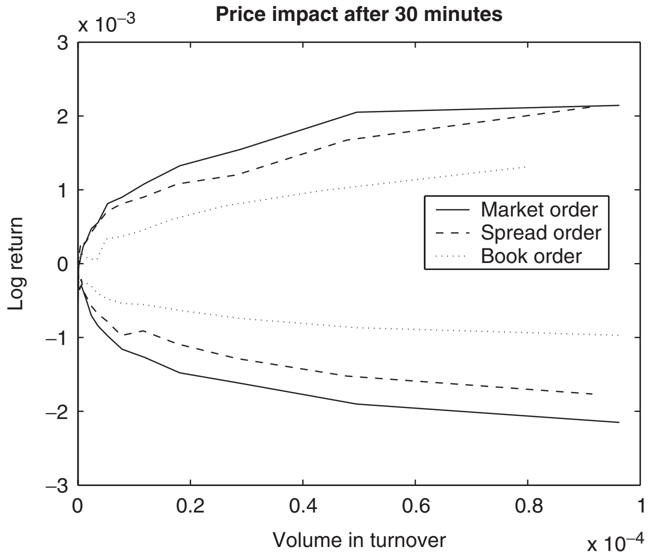

Figure 1. The 30 min impact of one order on Lafarge's price, as a non-parametric function of its volume. The log-return is calculated from just before the order arrives to 30 min after it has arrived. I use the Nadaraya–Watson kernel regression with Epanechnikow kernel. I distinguish the orders by their urgencies and between buy and sell orders. Buy orders have a positive impact, sell orders a negative one. The results are reported for the Lafarge stock.

price, as observed in figure 1. The basic distinction is between:

1. market orders, which are executed immediately;
2. spread orders, which are submitted between the best bid and ask (and thus change either the bid or the ask); and
3. book orders, which are submitted inside the order book.

To be more precise, after calculating the log-mid-quote $p_0 = (\ln(\text{bid}) + \ln(\text{ask}))/2$, I call a buy order:

1. market if executed immediately, i.e. all the market orders and limit orders such that $P \geq \text{ask}$;
2. spread if placed within the spread: $\text{ask} > P > \text{bid}$; and
3. book if $\ln(\text{bid}) \geq \ln(P) > p_0 - 0.005$.

To have consistent and symmetric definitions, I use the natural logarithm. However, one can consider the mid-quote as being roughly the arithmetic average between the bid† and the ask price. One can also think of book orders as being below the bid but above the mid-quote minus 0.5% (for buy orders).

The attentive reader will have noticed that I discard orders too far away from the best quotes. The reason is that I have found their impact to be negligible. One would actually expect book orders to have less and less impact on prices if they are placed further from the mid-quote, and this is what I have found using non-parametric bins defined according to that distance. It did not materially affect the results (in particular, the R^2), and to simplify the exposition I use only one bin for the book orders. It would also be possible to use a parametric function to take into account that decreasing impact, and one would expect to find similar results as using the non-parametric bins.

To measure the volume of an order, I follow the work of Lo and Wang (2000) and use the share turnover (the number of shares in the order divided by the number of shares outstanding) as a measure of the volume of each submitted order‡: I call v_i the volume in share turnover of each order i. Robustness checks confirm that using share volume or dollar volume gives similar results.

To measure liquidity, I use the Weighted Average Spread (WAS). This information is also available from the database at each point in time. It consists of the weighted average bid (W.A.Bid) and ask (W.A.Ask). The W.A.Ask is the price which would be reached by a large buy market order if it was fully executed against the current available book. The size of the large market order that is used to calculate the WAS is called the block size and is chosen by the Paris Bourse using liquidity criteria for that stock. For Lafarge, for example, it is 5×10^{-5} of the shares outstanding and the average one-sided WAS is 0.53%. A large WAS means it is hard to place large orders and is a proxy for illiquidity. I define:

- the WAS facing buy orders as ln(W.A.Ask)-mid; and
- the WAS facing sell orders as −(ln(W.A.Bid)-mid).

2.3. *Summary statistics*

Table 1 gives some summary statistics for Lafarge. Table 2 gives average summary statistics for the 34 stocks.

2.4. *The impact as a concave function of the volume of each order*

To have a better idea of how each order affects the price in the 'long'§ run, I study the change in log price from before the order arrives to 30 min¶ after it has arrived.

†I use the best quotes available when the order is submitted, not outdated ones from the beginning of the time interval.
‡There are several reasons for this scaling which are detailed in Lo and Wang (2000). Let us just note that volume in number of shares would be subject to violent jumps each time there is a stock split, and that volume in dollar or euro will by construction be trending upwards or downwards with the market capitalization of each stock.
§The 30 min impact is not reversed later. If anything, it tends to increase a little as I verify with a 60 min non-parametric regression compared to the 30 min reported in figure 1. In addition, when regressing the 30 min return on the lagged 30 min order flow I also get a small but statistically significant positive coefficient which confirms the small continuation.
¶The 30 min interval is chosen because, at shorter horizons, the return is negatively autocorrelated (bid–ask bounce). On the other hand, the horizon is short enough to have as much statistical power as possible.

Table 1. Summary statistics for Lafarge over one day.

	Lafarge
Sample size	1202
Volatility (open to close) (%)	1.75
Volatility (close to close) (%)	2.06
Number of orders	
Market buy	250
Market sell	257
Spread buy	101
Spread sell	97
Book buy	172
Book sell	164
Average volume of one order $\times 10^6$	
Market buy	7.3
Market sell	7.0
Spread buy	9.6
Spread sell	9.7
Book buy	11.5
Book sell	12.4

The results are reported for the Lafarge stock over one day. Only the volatility measure changes when one uses the opening price or the previous day closing price as the beginning of the time interval.

Table 2. Summary statistics over one day.

	Mean	SD
Sample size	1202	0
Volatility (open to close) (%)	1.73	0.21
Volatility (close to close) (%)	2.13	0.46
Number of orders		
Market buy	241	126
Market sell	282	190
Spread buy	77	30
Spread sell	73	28
Book buy	166	90
Book sell	158	86
Average volume of one order $\times 10^6$		
Market buy	9.38	5.89
Market sell	8.49	5.33
Spread buy	12.3	8.90
Spread sell	12.1	7.73
Book buy	16.3	16.7
Book sell	15.6	10.8

The results reported are the average of the results on the 34 stocks, and the cross-section standard deviation.

I use the non-parametric Nadaraya–Watson kernel† regression to find out about nonlinearities in the price change as a function of the order's volume. The results are reported in figure 1 for Lafarge. Similar results are obtained for the other stocks.

One can see that the price impact is a concave function of the volume of the order. Similar graphs that study the concavity and the functional form of the impact function are produced in Lillo *et al.* (2003) and

Table 3. Power function estimate for the 30 min impact of an order as a function of its volume.

	Market buy	Spread buy	Book buy
$\lambda \times 10^3$	84	85	142
(Std. error $\times 10^3$)	(14)	(41)	(98)
δ	0.37	0.38	0.47
(Std. error)	(0.03)	(0.04)	(0.05)

The log-return is calculated from before the order arrives to 30 min after it has arrived. I use nonlinear least squares to estimate the impact as a power function of the volume. $r_t = \lambda v_i^\delta + \epsilon_t$. I report the coefficients λ and δ, and their standard errors estimated by block bootstrap. I report the estimates and standard errors averaged over the 34 stocks.

Bouchaud *et al.* (2004). Here it is also observed that more urgent orders have a larger impact, for a given volume. This second result has not, to my knowledge, been reported in the extant literature.

The curves that are obtained for 30 min look similar to a power function $r_t = \lambda v_i^\delta$. I use nonlinear least squares to estimate λ and δ, and report the results of this estimation for the three urgencies of buy orders in table 3. The standard errors are estimated using block bootstrap, with a block size of one week, to take into account overlapping data, temporal dependence and heteroscedasticity. Although the power δ appears to be slightly different between the different types of orders, I use the approximation $\delta = 0.5$ when doing the SQRT aggregation defined below.

This concavity result has been known since at least Hasbrouk (1991), and three explanations have been proposed. The first one, called stealth trading, is due to Barclay and Warner (1993). They argue that the price impact of orders increases with their private information content. They then propose that informed traders prefer medium orders because large orders reveal their superior knowledge while small ones face high transactions cost. A second explanation, due to Bouchaud *et al.* (2002) and Lillo *et al.* (2003), is the consequence of the shape of the order book. Bouchaud *et al.* (2002) have observed that the average order book on the Paris Bourse has a maximum away from the best bid (or ask). A market order faced with such an order book would naturally have a concave impact function, as smaller trades are faced with less liquidity than larger ones. The third explanation is due to Gabaix *et al.* (2003), who argue that large orders are placed by more patient traders, so that, for a given aggregate volume, they have a smaller impact than small, impatient, orders. This could be related to the conditioning explanation that I propose below, as patient traders might wait for periods of higher liquidity.

Indeed, the concavity observed in figure 1 is obtained unconditionally. However, it is possible to have even linear conditional impacts that become unconditionally concave. Indeed, suppose that when a buy order is faced by a lot of liquidity in the sell order book, it has

†I select the Epanechnikow kernel. I use a variable bandwidth to take into account the high density of small orders relative to large orders.

Table 4. Variations in impact λ and average order volume $\bar{V}$ according to liquidity quintile for the market buy orders.

Quintile	1 (most liquid)	2	3	4	5 (least liquid)	All quintiles
$\lambda \times 10^3$	145	191	238	305	541	255
(Std. error $\times 10^3$)	(28)	(28)	(31)	(43)	(60)	(22)
$\bar{V} \times 10^7$	133	107	100	94	83	105
(Std. error $\times 10^7$)	(14)	(7)	(6)	(6)	(5)	(5)

The five quintiles are constructed using the WAS facing buy orders: ln (W.A.Ask)-mid. A small spread (first quintile) indicates high liquidity, and a large spread (fifth quintile) small liquidity. The log-return is calculated from before the order arrives to 30 min after it has arrived. The impact is estimated with the square root approximation: $r_t = \lambda v_i^{0.5} + \epsilon_t$. I report for each quintile the average order volume $\bar{V}$ and the estimated λ, and their standard errors estimated by block bootstrap. I report the results, averaged across all 34 stocks, for the market buy orders.

a smaller impact. Suppose also that traders are willing to place larger orders in this condition because of the smaller impact. This results in large orders having a relatively small impact. Conversely, when there is little liquidity, there will be more small orders and they will have a relatively larger impact. The two states bundled together will create concavity: large impact for small orders and small impact for large orders, compared to the conditional linearity. This variation with liquidity is what I find and report in table 4.

Although it is not possible to condition perfectly on liquidity, the Weighted Average Spread (WAS) is a reasonable proxy. So I divide the buy orders into five quintiles depending on the WAS that they are facing. The conditional impact I find inside each quintile is not linear either, perhaps because the WAS is a noisy proxy for liquidity. However, the average volume and impact vary across the quintiles as I hypothesized above. Table 4 gives the average volume $\bar{V}$ and the impact λ obtained for each quantile of buy market orders, using the square root approximation for the impact, $r_t = \lambda v_i^{0.5} + \epsilon_t$.

The pattern of decreasing impact (this pattern is also found using kernel non-parametric functions of the volume, instead of the sqrt approximation) and increasing volume with increasing liquidity is found for the three urgencies, market, spread and book orders, and for both the buy and sell orders. It is a possible explanation for the unconditional concavity of the price impact as a function of an order's volume.

2.5. *An order flow measure*

Given the concavity documented above along with the possible explanations established, I now take it into account to construct a measure of the order flow imbalance over a fixed time interval. There are two main reasons why I aggregate over a fixed time interval, instead of continuing the study on tick by tick data. First, looking at the tick by tick level restricts our study to the very short horizons, where the discreteness of the tick size and other microstructure noises are important. Second, fixed time intervals can provide results on much larger and more economically relevant price movements.

A first natural measure would be to add the volume of each buy order and subtract the volume of sell orders:

$$V = \sum_{i \in \text{buy orders}} (v_i)^1 - \sum_{i \in \text{sell orders}} (v_i)^1.$$

Even if I used this volume measure, the fact that I have access to limit order data ensures that there is an imbalance between submitted buy and submitted sell orders: V measures the imbalance in investors' intention to trade. An alternative measure, suggested by the work of Jones *et al.* (1994), would have been to use only the net number of orders:

$$N = \sum_{i \in \text{buy orders}} (v_i)^0 - \sum_{i \in \text{sell orders}} (v_i)^0.$$

In fact, the impact of each order being well approximated by the square root function, I want to transform each order into something close to its own price impact, so as to obtain the 'total price impact' when adding up (the log return is additive). So the aggregate measure that I use is the SQRT measure:

$$\text{SQRT} = \sum_{i \in \text{buy orders}} (v_i)^{0.5} - \sum_{i \in \text{sell orders}} (v_i)^{0.5}.$$

This last aggregate measure, also used by Hasbrouck and Seppi (2001) and which I derived here from the observed impact of individual orders, also turns out to be the one which is best correlated with price changes over fixed time intervals, as I report in section 3.2.

The three order flow variables I use are thus:

1. market $= \sum_{i \in \text{market buy}} (v_i)^\delta - \sum_{i \in \text{market sell}} (v_i)^\delta$,
2. spread $= \sum_{i \in \text{spread buy}} (v_i)^\delta - \sum_{i \in \text{spread sell}} (v_i)^\delta$,
3. book $= \sum_{i \in \text{book buy}} (v_i)^\delta - \sum_{i \in \text{book sell}} (v_i)^\delta$,

where $\delta = 0.5$. In section 3.2, I also use $\delta = 0$ (net number) and $\delta = 1$ (net volume), which give qualitatively similar results but are not quantitatively as good.

Table 5 gives the correlation of the order flows between different urgencies.

Table 5. Correlation of order flows between different urgencies over one day.

	Market	Spread	Book
Market	1	0.32	0.09
Spread	0.32	1	0.30
Book	0.09	0.30	1

The results reported are the average of the results on the 34 stocks, using the SQRT aggregation.

Table 6. The VAR of the daily order flows (SQRT), with two lags, averaged across all stocks.

	Mkt_{t-1}	$Sprd_{t-1}$	Bk_{t-1}	Mkt_{t-2}	$Sprd_{t-2}$	Bk_{t-2}	$\bar{R}^2$
Mkt_t	**0.20**	−0.10	−0.02	**0.07**	−0.11	−0.04	6.8%
(z-stat)	**(4.8)**	(−0.9)	(−0.4)	**(2.2)**	(−1.2)	(−1.3)	
$Sprd_t$	−0.01	**0.21**	0.01	0.01	**0.12**	0.00	8.5%
(z-stat)	(−0.6)	**(5.5)**	(0.3)	(0.4)	**(3.0)**	(0.0)	
Bk_t	−0.02	0.07	**0.18**	−0.02	0.06	0.07	5.8%
(z-stat)	(−0.7)	(1.0)	**(5.0)**	(−0.6)	(0.8)	(1.9)	

I regress the different daily order flows on past order flows. I distinguish between different urgencies, and aggregate using the SQRT function (SQRT $= \sum_{i\in \text{buy orders}} (v_i)^{0.5} - \sum_{i\in \text{sell orders}} (v_i)^{0.5}$). I report the VAR coefficients and the $\bar{R}^2$ corrected for the degrees of freedom. I also report the z-stat obtained from the quantiles of block bootstrap replications. The coefficients, $\bar{R}^2$ and z-stats are averaged across the 34 stocks.

Table 7. The return regressed on the simultaneous order flow (SQRT) for *Lafarge* over one day.

	$\lambda_{\text{market}} \times 10^3$	$\lambda_{\text{spread}} \times 10^3$	$\lambda_{\text{book}} \times 10^3$	$\bar{R}^2$
Estimate	57	25	21	53.1%
z-stat	19	5	11	
95% confidence interval				
Lower band	51	16	17	49.3%
Higher band	63	35	24	57.8%

I regress the one day log return (open to close) on the simultaneous order flow imbalance, distinguishing between different urgencies, and aggregating using the square root function ($SQRT = \sum_{i\in \text{buy orders}} (v_i)^{0.5} - \sum_{i\in \text{sell orders}} (v_i)^{0.5}$). $r_t = \alpha + \lambda_{\text{market}} SQRT\_market_t + \lambda_{\text{spread}} SQRT\_spread_t + \lambda_{\text{book}} SQRT\_book_t + \eta_t$. I report the λ coefficients and the $\bar{R}^2$ corrected for the degrees of freedom. I also report the z-stat and the 95% confidence interval obtained from the quantiles of block bootstrap replications. The results are reported for the Lafarge stock.

2.6. *Time series properties of the order flow*

To look at the dynamic properties of the order flow, I use the Vector Auto Regression (VAR) methodology. It turns out that orders are clustered: orders tend to be followed by orders in the same direction and with similar characteristics (such as their urgency). This result is also reported by Bouchaud *et al.* (2004) and Chordia and Avanidhar (2004).

In table 6, I observe that the order flow imbalance is autocorrelated. Orders placed one day and two days ago tend to be repeated today, in the same direction, and with the same urgency. It is not only an intra-day phenomenon as it has sometimes been thought in the microstructure literature, since it remains significant at the horizon of two days.†

The z-stats are obtained using block‡ bootstrap. Since the order flow is autocorrelated, it is possible that the residuals are also autocorrelated, which block bootstrapping takes into account, as well as heteroscedasticity.

There are different possible explanations for this autocorrelation. A first explanation is order splitting: institutions placing big orders will often split them into smaller orders, in the same direction and possibly of the same urgency. Another possible explanation is herd behaviour: humans have a well-know psychological tendency to imitate each other (in crowd behaviour, for example), which would also create the observed autocorrelation of orders. Since I do not have any information on who placed the orders, I cannot distinguish the two here. However, similar results obtained in Jackson (2002) for orders placed by individual investors, who have no reason to split their orders, suggest that part of it is herd behaviour.

Having defined the order flow imbalance as an imbalance of submitted orders which takes into account the concavity of the impact of each order, and having mentioned the autocorrelation property of this order flow measure, I now study the relationship between this order flow measure and price changes over fixed time intervals.

3. High correlation between return and order flow imbalance

3.1. *The basic regression of the return on the order flow imbalance over one day*

In table 7, I regress the one day log-return on the simultaneous order flow, distinguishing the three urgency levels and using the SQRT aggregation:

$$r_t = \alpha + \lambda_{\text{market}} \text{SQRT\_market}_t + \lambda_{\text{spread}} \text{SQRT\_spread}_t + \lambda_{\text{book}} \text{SQRT\_book}_t + \eta_t. \quad (1)$$

I find a relatively high R^2 of 53.1%, comparable to the results of Evans and Lyons (2002) on the foreign exchange. I also report the block bootstraps estimates of the 95% confidence interval and z-stats, obtained from the replication quantiles. I use block bootstrapping to take into account heteroscedasticity as well as any potential temporal§ dependence. In fact, returns are nearly unpredictable except with the 10 min interval and simple bootstrapping gives the same confidence intervals for time horizons longer than 10 min. Because the normalized regression coefficients are pivotal, bootstrap also provides a second-order correction for the confidence interval. This can be useful since we know that high-frequency returns are non-normal and fat tailed. The confidence intervals obtained with White (or Newey–West) standard errors do not include this second-order correction and are a little too narrow at intra-day frequency. Bootstrapping

†In my data, it is not significant at the three day horizon for most stocks.
‡The block size I use here is one month.
§The block size I use is one week.

Table 8. The return regressed on the simultaneous order flow (SQRT) over one day: *average results for 34 stocks*.

	$\lambda_{\text{market}} \times 10^3$	$\lambda_{\text{spread}} \times 10^3$	$\lambda_{\text{book}} \times 10^3$	$\bar{R}^2$
Estimate: ave.	54	49	25	47.7%
Estimate: SD	24	40	15	8%
z-statistic				
z-stat: ave.	14	6	8	
z-stat: SD	5	2	3	

I regress the one day log return (open to close) on the simultaneous order flow imbalance, distinguishing between different urgencies, and aggregating using the square root function ($\text{SQRT} = \sum_{i\in\text{buy orders}} (v_i)^{0.5} - \sum_{i\in\text{sell orders}} (v_i)^{0.5}$). $r_t = \alpha + \lambda_{\text{market}} SQRT\_market_t + \lambda_{\text{spread}} SQRT\_spread_t + \lambda_{\text{book}} SQRT\_book_t + \eta_t$. I report the λ coefficients and the $\bar{R}^2$ corrected for the degrees of freedom. I also report the z-stat obtained from the quantiles of block bootstrap replications. The results reported are the average of the results on the 34 stocks, and the cross-section standard deviation.

Table 9. The return regressed on the simultaneous *net number* of orders for Lafarge over one day.

	$\lambda_{\text{market}} \times 10^5$	$\lambda_{\text{spread}} \times 10^5$	$\lambda_{\text{book}} \times 10^5$	$\bar{R}^2$
Estimate	2.0	11.9	−2.6	10.5%
z-stat	3.6	9.4	−2.4	

I regress the one day log return (open to close) on the simultaneous order flow imbalance, distinguishing between different urgencies, and aggregating using the net number of orders ($N = \sum_{i\in\text{buy orders}} (v_i)^0 - \sum_{i\in\text{sell orders}} (v_i)^0$). $r_t = \alpha + \lambda_{\text{market}} N\_market_t + \lambda_{\text{spread}} N\_spread_t + \lambda_{\text{book}} N\_book_t + \eta_t$. I report the λ coefficients and the $\bar{R}^2$ corrected for the degrees of freedom. I also report the z-stat obtained from the quantiles of block bootstrap replications. The results are reported for the Lafarge stock.

Table 10. The return regressed on the simultaneous *net volume* of orders for Lafarge over one day.

	λ_{market}	λ_{spread}	λ_{book}	$\bar{R}^2$
Estimate	12.8	6.7	−0.4	46.4%
z-stat	13.1	6.0	−1.7	

I regress the one day log return (open to close) on the simultaneous order flow imbalance, distinguishing between different urgencies, and aggregating using the net volume of orders ($V = \sum_{i\in\text{buy orders}} (v_i)^1 - \sum_{i\in\text{sell orders}} (v_i)^1$). $r_t = \alpha + \lambda_{\text{market}} V\_market_t + \lambda_{\text{spread}} V\_spread_t + \lambda_{\text{book}} V\_book_t + \eta_t$. I report the λ coefficients and the $\bar{R}^2$ corrected for the degrees of freedom. I also report the z-stat obtained from the quantiles of block bootstrap replications. The results are reported for the Lafarge stock.

is also a simple way to get confidence intervals for the R^2, which is asymptotically normally distributed under the alternative hypothesis H1: $R^2 \neq 0$.

In table 8, I summarize the same results as in table 7 for all the 34 stocks. I report the average and cross-section standard deviation of the estimates, as well as the average and standard deviation of the z-stat. Again, we notice the high $\bar{R}^2$ and the significance of the results.

Table 11. The return regressed on *predicted* (pred) and *residual* (res) order flow (SQRT) over one day.

	$\lambda_{Mkt,\text{pred}}$ ($\times 10^3$)	$\lambda_{Mkt,\text{res}}$ ($\times 10^3$)	$\lambda_{Sprd,\text{pred}}$ ($\times 10^3$)	$\lambda_{Sprd,\text{res}}$ ($\times 10^3$)	$\lambda_{Bk,\text{pred}}$ ($\times 10^3$)	$\lambda_{Bk,\text{res}}$ ($\times 10^3$)	$\bar{R}^2$
Estimate	15	**56**	−11	**51**	**45**	**24**	49.5%
(z-stat)	(0.8)	**(15.3)**	(−0.6)	**(6.4)**	**(2.2)**	**(8.0)**	

I regress the one day log return (open to close) on the order flow imbalance previously obtained from a VAR with two lags, distinguishing between the prediction obtained from the VAR (pred), and the residual from the VAR (res). I also distinguish the different urgencies, and aggregate the orders using the square root function ($\text{SQRT} = \sum_{i\in\text{buy orders}} (v_i)^{0.5} - \sum_{i\in\text{sell orders}} (v_i)^{0.5}$). I report the average results across the 34 stocks.

These high $\bar{R}^2$ indicate that the SQRT measure of order flow imbalance is well correlated with price changes. In this sense, one can argue that it is a good measure of the order flow. In the next section, I investigate two possible alternative measures, the net volume and the net number, to check that the SQRT is indeed a good measure. Regressing the return on these alternative measures also provides an economic interpretation of the impact coefficient.

3.2. *The return/order regression with different powers of the volume*

In table 9, I report the same results as in table 7 for Lafarge, but with the net number of orders instead of the SQRT,

$$N = \sum_{i\in\text{buy orders}} (v_i)^0 - \sum_{i\in\text{sell orders}} (v_i)^0,$$

$$r_t = \alpha + \lambda_{\text{market}} N\_\text{market}_t + \lambda_{\text{spread}} N\_\text{spread}_t + \lambda_{\text{book}} N\_\text{book}_t + \eta_t.$$

I find that the $\bar{R}^2$ is lower than with the SQRT. This is also true for the other stocks. The average $\bar{R}^2$ across the 34 stocks is 47.7% for the SQRT and 10.6% for the net number of orders.

The estimated λ also gives an economic estimate of the impact. All else equal, an imbalance of 100 orders submitted between the bid and the ask (spread orders have the largest average impact) will move the Lafarge stock price by 1.19%.

In table 10, I report the same results as in table 7 for Lafarge, but with the net volume of orders instead of the SQRT,

$$V = \sum_{i\in\text{buy orders}} (v_i)^1 - \sum_{i\in\text{sell orders}} (v_i)^1,$$

$$r_t = \alpha + \lambda_{\text{market}} V\_\text{market}_t + \lambda_{\text{spread}} V\_\text{spread}_t + \lambda_{\text{book}} V\_\text{book}_t + \eta_t.$$

I again find that the $\bar{R}^2$ is lower than with the SQRT. This is also true for the other stocks. The average $\bar{R}^2$ across the

Table 12. The one day return regressed on lagged order flow.

	Mkt_t	$Sprd_t$	Bk_t	$\bar{R}^2$
$r_{t+1} \times 10^3$	6	−2	4	0.6%
(z-stat)	(1.3)	(−0.4)	(0.7)	

I regress the one day log return (close to close) on lagged order flows. I distinguish between different urgencies, and aggregate using the SQRT function (SQRT $= \sum_{i\in\text{buy orders}} (v_i)^{0.5} - \sum_{i\in\text{sell orders}} (v_i)^{0.5}$). I report the regression coefficients and the $\bar{R}^2$ corrected for the degrees of freedom. I also report the z-stat obtained from the quantiles of block bootstrap replications. The results are averaged across the 34 stocks.

Table 13. The return regressed on simultaneous order flow (SQRT) over different time intervals, average results for 34 stocks.

	$\lambda_{\text{all}} \times 10^3$	z-stat	$\bar{R}^2$
10 min	67	35	38.7%
30 min	62	32	42.6%
One day (open–close)	41	19	43.5%
One day (close–close)	47	18	38.9%
One week	38	10.1	38.6%
One month	32	5.6	36.2%
Three months	21	2.6	26.9%

I regress the log-return on the simultaneous order flow imbalance, without distinguishing between different urgencies, and aggregating using the square root function ($SQRT = \sum_{i\in\text{buy orders}} (v_i)^{0.5} - \sum_{i\in\text{sell orders}} (v_i)^{0.5}$). $r_t = \alpha + \lambda_{\text{all}} SQRT\_all\_urgencies_t + \eta_t$. I report the λ coefficients and the $\bar{R}^2$ corrected for the degrees of freedom. I also report the z-stat obtained from the quantiles of block bootstrap replications. The results reported are the average of the results on the 34 stocks.

34 stocks is 47.7% for the SQRT and 35.8% for the net volume of orders.

The estimated λ also gives an economic estimate of the impact. All else equal, an imbalance in market orders of 0.1% of the shares outstanding will move the Lafarge stock price by 1.28%.

The regression results using the SQRT, the net number and the net volume confirm that the SQRT is the order flow measure best correlated with the price change over one day.

3.3. *The predictable order flow imbalance has nearly no impact on the price*

We have seen that the order flow is autocorrelated, and that it is well correlated with the contemporaneous return. However, we do not expect that the return will be easily predictable. Otherwise, a simple statistical arbitrage would be available. So it should be the case that the fraction of the orders that is predictable does not have much impact on the price. This is what I verify in table 11.

If a big fraction of the return were predictable, arbitrageurs would exploit it and remove most of the predictability. This strategy, diversifiable across time (and partly across stocks), would carry a relatively low risk.

It turns out to be nearly true. I distinguish the part of the order flow which is predicted (pred) using the VAR in table 6 from the residual order flow (res) which is unpredicted by the VAR. The predicted part usually has an insignificant impact on the return, whereas the unpredicted order flow has a very significant impact. So the return is nearly unpredictable. However, the predicted book orders have a barely significant impact on the price. This also means that, since the book orders are autocorrelated, yesterday's book orders will predict the return today. Although this might look like an opportunity for statistical arbitrage, it is more likely that the book orders needed to forecast the return were not known on the day they were submitted† so that arbitrageurs could not see and exploit this predictability in real time.

3.4. *No short-term reversal of the price impact*

We have seen in section 2.4 that each order has a price impact which lasts for at least 30 min.‡ In section 3.1 the aggregate measure of the order flow is shown to be highly correlated with price changes over one day. But this impact could be only short term and be reversed within the next day or so, as one usually expects from uninformed price pressure.

Table 12 checks if there is a reversal of the price impact during the next day. If there was, one would expect that a positive order flow imbalance today forecasts a negative return tomorrow, so as to remove part of today's impact on the price, and to find negative coefficients. This is not observed in table 12, suggesting that the price impact is either permanent, or that it is only very slowly reversed, so that the regression of table 12 cannot detect it. I cannot detect it at longer horizons either, perhaps partly because I do not have a long enough sample. However, I do expect most of the impact to be reversed eventually, which is consistent with the long run mean-reversion of stock returns, well documented and reported, for example, in Campbell (1991).

This absence of short-term reversal suggests that, with time horizons longer than one day, one should also find a co-movement of the stock price with the order flow imbalance. This is what I report in the next section.

3.5. *The return/order regression with different time periods*

In the previous sections I have mostly used the daily time period as the reference. However, it is also interesting to look at different horizons. The results are similar at shorter horizons, implying that this co-movement appears

†The Paris Bourse allows limit orders to be hidden and become visible only gradually, when they are met by opposite market orders.
‡It is not reversed in the next 30 min. If anything, there is a small increase of the impact in the next 30 min.

Table 14. No reverse causality, the 30 min order flow regressed on lagged return and order flow.

	r_{t-1}	Mkt_{t-1}	$Sprd_{t-1}$	Bk_{t-1}	$\bar{R}^2$
Mkt_t	**−0.66**	0.32	0.08	0.08	8.8%
(z-stat)	(**−4.7**)	(14.4)	(3.6)	(5.4)	
$Sprd_t$	**−0.32**	0.02	0.19	0.04	4.1%
(z-stat)	(**−6.1**)	(3.3)	(12.6)	(4.8)	
Bk_t	**−0.32**	−0.03	0.03	0.31	8.9%
(z-stat)	(**−3.6**)	(−2.4)	(1.5)	(18.4)	

I regress the different order flows on past return and order flows. I distinguish between different urgencies, and aggregate using the SQRT function ($\mathrm{SQRT} = \sum_{i \in \text{buy orders}} (v_i)^{0.5} - \sum_{i \in \text{sell orders}} (v_i)^{0.5}$). I report the coefficients, the $\bar{R}^2$ and the z-stat obtained from the quantiles of block bootstrap replications. The results are averaged across all 34 stocks.

in the microstructure and comes from the impact of each order, as was already suggested in section 2.4. The fact that the co-movement of orders and prices is also observed at horizons longer than one day suggests that this impact is not much reversed, at least for the next three months.

To have enough power at long horizons (only 20 data points with three month intervals), I only use one independent variable and do not distinguish between the different urgencies. To have comparable results, I do the same regression:

$$r_t = \alpha + \lambda_{\text{all}} \mathrm{SQRT\_all\_urgencies}_t + \eta_t,$$

with different time intervals: 10 min, 30 min, one day (open to close), one day (close to close), one week, one month, three months. I report the estimate for λ, the z-stat and the $\bar{R}^2$ of these regressions, averaged across the 34 stocks, in table 13.

As expected by the bigger sample sizes and more statistical power, the z-stats are very high for short time intervals and diminish all the way to three months. However, even at this horizon, λ is still statistically significantly positive for most stocks.

One also notices the diminishing $\bar{R}^2$ from one day to three months. This might suggest a partial reversal of the impact. However, when regressing future returns on past orders with various time horizons, I cannot find a statistically significant reversal of the price impact for most stocks and time intervals (there seems to be some economically important reversal after the six month horizon, but my short database does not yield statistically significant estimates). Another phenomenon which could better explain the decreasing R^2 is that future orders are (slightly but significantly) negatively correlated with past returns, as reported in table 14. When aggregated over long horizons, this negative lead–lag correlation can decrease the positive contemporaneous correlation. On the other hand, at very short horizons, the average R^2 is also smaller, which can be explained by microstructure noise (discreteness of the tick size, etc.).

The λ coefficient is also decreasing from short to long horizons. This effect is stronger than for the R^2 and can be explained by the positive autocorrelation of the order flow and the fact that predicted orders do not have an impact on the price, as we have seen. The combination of these two effects generates† a decreasing‡ λ.

3.6. A visual representation of the order flow and price

As a visual confirmation of the long-term correlation of return and order flow, I report a graphical representation of their movements in figure 2. The continuous line represents§ the cumulative log return of Lafarge, using daily closing prices. It is thus the graph of (log) prices. The dashed line represents the cumulative order flow imbalance, that is, the sum of daily imbalances from date 0 to date t. The order flow indicator is the SQRT of orders. To take into account the different impacts of market, spread and book orders, I used the coefficients of a daily regression (close to close) when adding the three together.

The similarity in the movements of the two lines is striking. The ups and downs of the price level are also present in the cumulative order flow imbalance. This is true not only for the daily changes, but also for longer horizons of weeks and months, perhaps years.

4. Interpretation

4.1. Causality

After analysing the dynamic properties of the order flow and its statistical relationship with the price, I now address the economic interpretation of this interaction. Specifically, I study whether the causal interpretation that I suggested when talking of the price impact of an order is justified: is it really the orders that cause price changes? Or is it the opposite: the return that causes

† It is easy to understand why with simplifying assumptions. Let us assume for now $r_t = \lambda f_t + \eta_t, r_{t+1} = \lambda f_{t+1} + \eta_{t+1}$, $f_{t+1} = \alpha f_t + 0 \times r_t + \epsilon_t$ with $\alpha > 0$ and $r_{t+1} = 0 \times f_t + 0 \times r_t + u_t$. This gives $r_{t+1} + r_t = \lambda^*(f_t + f_{t+1}) + v_t$ with $\lambda^* = \lambda[(2+\alpha)/(2+2\alpha)]$. So the impact coefficient λ is lower for longer horizons. Note that $R^{2^*} = [(1+\alpha/2)^2/(1+\alpha)]R^2$ is nearly constant, slightly bigger for longer horizons under these assumptions. Exactly the same results are obtained if one changes the notation to make explicit the fact that predicted orders have no impact on the price: $r_{t+1} = \lambda(f_{t+1} - \alpha f_t) + \eta_{t+1}$ and $r_t = \lambda(f_t - \alpha f_{t-1}) + \eta_t$.

‡ The same two assumptions also create the increase in λ from daily open–close to daily close–close, which includes the previous night. Indeed, the orders that follow the night are probably correlated to the unobserved orders (placed on similar stocks in foreign markets) that happened during the night. So the night return is correlated with the following day orders, which increases the λ.

§ Evans and Lyons (2002) produce a similar graph for the foreign exchange market.

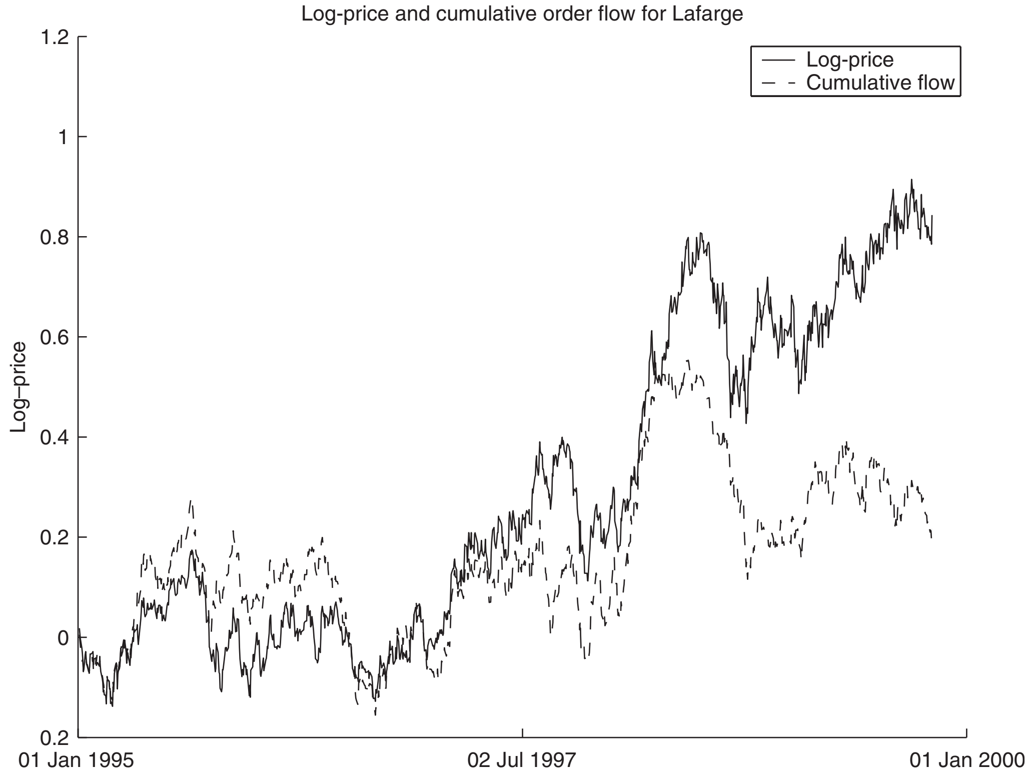

Figure 2. Cumulative return and cumulative order flow imbalance for Lafarge. The continuous line is the cumulative return of Lafarge (using daily closing prices). The dashed line is the cumulative order flow imbalance. The order flow indicator is the SQRT of orders ($SQRT = \sum_{i \in \text{buy orders}} (v_i)^{0.5} - \sum_{i \in \text{sell orders}} (v_i)^{0.5}$). To take into account the various impacts of the three different urgencies, I used the three coefficients from daily regressions (close to close) when adding together the different buy and sell orders.

traders to place orders in the same direction? Or is it a common factor that drives both? I first look at reverse causality and then address the common factor interpretation.

If there is reverse causality and the price change stimulates traders to place orders in the same direction, the traders need a little time to observe the price change before they can trade on it. So by looking at short enough time intervals, we should find that past returns are correlated positively with future orders. With a one day horizon, the coefficients are insignificant. In table 14, with a time interval of 30 min, the order flow is indeed correlated with past return, but with a negative coefficient: people provide liquidity and sell the stock when the price has previously moved up. This is the opposite of what reverse causality requires, and we can reject this interpretation.

Now suppose there was a common factor that prompted people to buy, at exactly the same time as it triggered the 'market makers' (there are no official market makers on the Paris Bourse but some brokers, providing liquidity at the bid and ask price, can play the same role) to push the price upward. This factor is what the literature usually labels public information: something that everyone knows at the same time. If there is absolutely no informational advantage, investors and market makers all react to information simultaneously, and the price moves at the same time as the order flow is submitted.

To address this alternative, I need to show that price changes are not strictly contemporaneous to the order flow, but actually happen a little after the orders are placed. This is what is observed by comparing figure 3 with figure 1, where the price change is the immediate price change vs. the 30 min price change. For example, the book orders have an immediate impact† which is roughly 0, but a 30 min impact which is large and significant. Similar results are obtained for the other types of orders, where the 30 min impact is larger than the contemporaneous impact.

These two graphs show that the order occurs before the price movement, and thus establish the causality from the order flow to the price change. So it rejects a very extreme version of public information, where there is absolutely no information asymmetry. However, it does not reject a slightly less stringent version of public information, where people all share the same information, but some know it a few seconds or minutes before others, and so can place

†By definition, since book orders do not result in a trade, nor in a change in the bid and ask, they should have no effect at all on the price at the second after they are placed. However, it is possible that other orders, placed exactly at the same second, do move the price. This is what we observe, and these other orders have a small impact in the opposite direction as the book order.

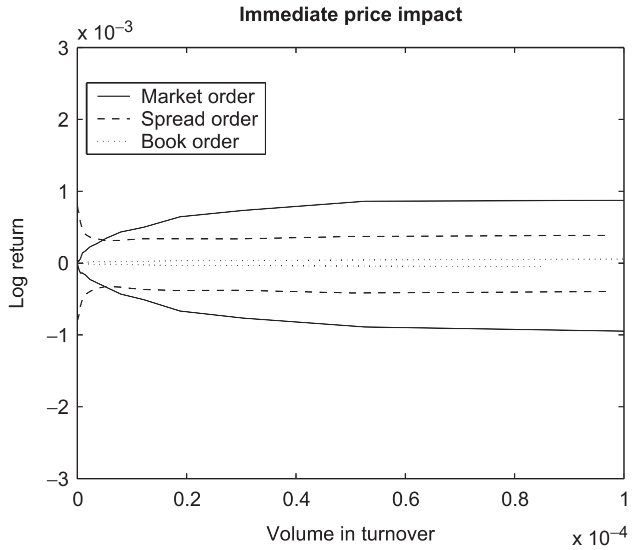

Figure 3. The *immediate* impact of one order on Lafarge's price, as a non-parametric function of its volume. The log-return is calculated from the last mid-quote before the order arrives to the mid-quote when it arrives. I use the Nadaraya–Watson kernel regression with Epanechnikow kernel. I distinguish the orders by their urgencies and between buy and sell orders. Buy orders have a positive impact, sell orders a negative one, except for book orders where it is the opposite. The results are reported for the Lafarge stock.

Table 15. Example, the order book before a market buy order arrives.

Buy	Sell
€ 99 (10 shares)	€ 101 (10 shares)
€ 98 (30 shares)	€ 102 (10 shares)
€ 97 (20 shares)	€ 103 (40 shares)

orders before the price actually changes. I do not address this version of public information further, but refer the reader to French and Roll (1986). In this paper, the authors show that public information explains only a small part of stock returns. They study stocks on days when the New York Stock Exchange is closed but the rest of the economy is active, and find that the two-day variance on these days and the next day is on average 1.145 times a normal one-day variance (whereas for other days, the two-day variance is roughly twice the one-day variance, as expected). This suggests that when the NYSE is closed, the variance is only 14.5% of what it is when the exchange is open. Since the flow of public information is at least as big during these exchange holidays (which include Presidential elections), their results suggest that only 14.5% of a stock's daily variance can be attributed to public information. So public information, including information which is not shared immediately, but within the current or the next trading day (since they use the two-day variance), does not seem to explain price changes very well. As a benchmark for how long public information needs to be incorporated in the price, intra-day event studies usually find no impact beyond one hour, and daily event studies usually find no impact on the next day. So their study shows that public information, even allowing for some time to incorporate the news, has only a small effect on stock prices.

Now that I have verified that the causality is from orders to price, it is justified to think in causal terms, and to speak of the 'price impact of an order', which I used anticipatively above. In the remainder of the paper, I distinguish two sources for causal impacts, private information and mechanical price pressure.

4.2. *Mechanical price pressure*

A causal impact of orders would usually be interpreted as private information. However, I show below why this interpretation is not supported by the data. The other causal interpretation which I consider is mechanical price pressure. We already know, thanks to the work of Stoll (1978), how price pressure can exist in a dealer market, and its foundation in the microstructure of this type of market. He shows how inventory considerations induce the market maker to move the price when he is faced with an uninformed order flow imbalance.

I show here that an even simpler mechanism can generate mechanical price pressure in an automated exchange such as the Paris Bourse. For this type of market, let us follow a simple example to see how orders can mechanically impact the price. Let us assume that the order book is given by table 15, when an uninformed buy market order of 40 shares is submitted. It matches the book at €101, €102 and buys 20 shares at €103. The new ask price is €103. The mid-quote has gone up from €100 to €101. If markets are information-efficient and arbitrageurs know that this order was uninformed, this impact will be temporary and the price will soon come back to its fundamental value. But this presupposes that some arbitrageurs will bring the price back to its fundamental value. The incentives for the arbitrageurs to do so may not be high enough, in the spirit of DSSW (1990): the arbitrageur may need to wait a long time and face huge price changes before he benefits from his knowledge of the fundamental value. Therefore, the short-term impact may take some time to disappear: if this mechanical impact is the main explanation for the observed causal impact of orders on prices, table 13 suggests that this impact has not disappeared at the three month horizon.

This example clearly shows how a market order can affect the price. I now turn to limit orders, which have only an indirect impact: they reduce the direct impact of opposite market orders. Because sell limit orders provide additional liquidity on the sell side, a buy market order will have a smaller positive price impact. In my example, if someone places a limit sell order of 40 shares at €101, the market buy order will result in a transaction price of only €101 and a mid-quote of only € 100. So it prevents the market order from moving the mid-quote up to €101. This is how sell limit orders have an indirect negative impact on the price.

4.3. Testing for private information

In this section, I use two empirical approaches to distinguish between private information and uninformed price pressure. First, I look at the relationship between market-wide orders and market-wide price changes, where one would expect to find little private information, but where I find a large price impact. Second, I argue that the fraction of price changes due to the order flow is too large not to mean revert, which implies that the order flow has moved prices away from their fundamental value.

To clarify, what I mean by private information is that some investors have superior information to others about the true value of the security. The standard model for private information was derived by Kyle (1985). In this model, a market maker† will adjust prices to any order, whether it is informed or not, because he cannot distinguish between them. This model predicts that buy orders will have a positive impact, consistent with the observed price change.

Other papers have sometimes called private information some settings that I actually include in price pressure. In particular, I categorize the private information in Wang (1994), Vayanos (1999) and Evans and Lyons (2002) as price pressure because, in these models, investors do not have special information on the financial asset itself. The private information relates to their own demand for shares, which varies due to an exogenous endowment, private investment opportunities, or risk aversion. These models are very similar to mechanical price pressure, except that they give justifications for the noise trades. Indeed, even noise traders with absolutely no information about the financial assets know before the others what order they are going to submit. This is why I do not distinguish these models from uninformed price pressure.

4.3.1. Company-specific vs. market-wide orders. Although private information à la Kyle is certainly part of the reason for the causal impact of orders on the price, I argue that it is probably not the only one. In this section, I study different assets or portfolios where one would expect very different levels of private information. More precisely, I distinguish between company-specific returns and market-wide returns. Whereas there is a lot of potential for leakage at the company level (the CEO, key employees, managers, their family and friends, inquisitive analysts or fund managers, etc.), it is difficult to find much potential for information asymmetry on the whole market. It therefore seems likely that only a small fraction of market-wide movements should be driven by private information.

The two alternatives I consider are private information and uninformed price pressure. Models of either of them can be written down using the same specification:

$$\Delta P = \lambda(v_{\mathrm{buy}} - v_{\mathrm{sell}}) + \epsilon, \tag{2}$$

where ϵ can incorporate public information as well as model misspecification.‡

If private information is the only source of the price impact, and there is no uninformed price pressure, then one can write for the R^2 of this regression

$$R^2 \leq \frac{\sigma^2_{\text{private information}}}{\sigma^2_{\text{total information}}}, \tag{3}$$

where $\leq$ would be replaced by $=$ if there was no model misspecification.

I now define the market order flow and the company-specific (or idiosyncratic) order flow. I use 30 min intervals to have more statistical power (16 878 observations) and the SQRT aggregation.§ I start by aggregating and normalizing the three types of orders for each company: I regress each stock's return on its market, spread and book order flow imbalance:

$$r_{it} = \underbrace{\alpha_i + \lambda_{i,\mathrm{market}}\mathrm{market}_{it} + \lambda_{i,\mathrm{spread}}\mathrm{spread}_{it} + \lambda_{i,\mathrm{book}}\mathrm{book}_{it}}_{f_{it}} + \eta_{it},$$
$$r_{it} = f_{it} + \eta_{it}.$$

I call this aggregate f_{it} company i's order flow imbalance. The reason for the aggregation is to simplify the rest of this section, by having only one order flow variable per stock.

I then define the market return as the equally weighted return for the 34 stocks. Similarly, I define the market order flow (interestingly, the first principal component of the order flow is, similarly to that of the return, close to an equally weighted average, which justifies the concept of market order flow) as the equally weighted¶ order flow:

$$r_{mt} = \frac{1}{N}\sum_{i=1}^{N} r_{it},$$
$$f_{mt} = \frac{1}{N}\sum_{i=1}^{N} f_{it}.$$

I then define the idiosyncratic return for stock i as the residual of stock i's return after regressing on the market return:

$$r_{it} = \theta_i + \beta_i r_{mt} + r_{it}^{\mathrm{idio}}. \tag{4}$$

†Although there is no official market maker on the Paris Bourse, it is reasonable to assume that some rational 'liquidity providers' play a similar role.
‡An example of model misspecification that I have already reported in this paper would be to use the linear volume instead of the SQRT measure of the order flow. This would lead to a smaller R^2, which translates into a larger variance of ϵ.
§Similar or even stronger results are obtained for the net number and the net volume of orders.
¶I also used other definitions of market return and market order flow. For instance, I extracted the first principal component of the return and used the resulting eigenvector for both the return and order flow. This alternative definition gave very similar results, and the first principal component from the order flow did as well.

Table 16. The market return regressed on the market order flow.

	λ_m	$\bar{R}^2_m$
Estimate	1.02	69.7%
(Std. error)	(0.02)	(0.9%)

I regress the 30 min equally weighted market return on the equally weighted order flow imbalance: $r_{mt} = k_m 1 + \lambda_m f_{mt} + \xi_{mt}$. I report the λ_m coefficient and the $\bar{R}^2$ corrected for the degrees of freedom. I also report the standard errors obtained from the quantiles of block bootstrap replications. The aggregation of orders is done using the square root function: $\text{SQRT} = \sum_i (v_i)^{0.5}$. The order flow of each stock incorporates the three urgencies.

Table 17. The idiosyncratic return regressed on the idiosyncratic order flow, averaged over 34 stocks.

	λ_i^{idio}	$\bar{R}^2_{i,\text{idio}}$
Estimate	0.99	41.1%
(Std. error)	(0.04)	(1.7)%

I regress the 30 min idiosyncratic return (the residual after regressing on the equally weighted market return) on the idiosyncratic order flow imbalance (the residual after regressing on the equally weighted order flow imbalance): $r_{it}^{\text{idio}} = k_i 1 + \lambda_i^{\text{idio}} f_{it}^{\text{idio}} + \xi_{it}$. I report the λ_i^{idio} coefficient and the $\bar{R}^2$ corrected for the degrees of freedom. I also report the standard error obtained from the quantiles of block bootstrap replications. The aggregation of orders is done using the square root function: $\text{SQRT} = \sum_i (v_i)^{0.5}$. The order flow of each stock incorporates all urgencies. The results are the average results over 34 stocks.

Similarly, the idiosyncratic order flow is the residual of stock *i*'s order flow after regressing on the market flow:

$$f_{it} = \vartheta_i + b_i f_{mt} + f_{it}^{\text{idio}}. \tag{5}$$

The regressions of interest can now be written as

$$r_{mt} = k_m 1 + \lambda_m f_{mt} + \xi_{mt}, \tag{6}$$

$$r_{it}^{\text{idio}} = k_i 1 + \lambda_i^{\text{idio}} f_{it}^{\text{idio}} + \xi_{it}. \tag{7}$$

The empirical results† are reported in tables 16 and 17. As described earlier, one would expect a large R^2 for the idiosyncratic return, where private information is important, and a smaller R^2 for the market return, where it is not. The result I find empirically is exactly the opposite: for each of the 34 stocks, the idiosyncratic R^2 is smaller than the market R^2 and this difference is economically and statistically highly significant, using block bootstrapping. One can argue that the low R^2 found for the idiosyncratic order flow is due to estimation error, or some other model misspecification.‡ For this reason, I emphasize not the low R^2 of the idiosyncratic regression, but the high R^2 of the market regression, which is a lower bound of the fraction of the variance due to private information, as equation (3) makes clear. For the market portfolio, the R^2 of return on order flow is 70%, which, in absolute and economic terms, is extremely high. Economically, it seems far-fetched to argue that 70% of market-wide movements are due to private information.

4.3.2. A long term mean-reverting price impact. The previous section shows that private information, which is expected to be small for the market as a whole, is difficult to reconcile with the empirically large impact of market orders on the market return.

However, it would be nice to also have a result that directly points to uninformed price pressure. The observation that would do that is a reversion of the price impact of orders. Indeed, if uninformed price pressure moves the price away from its fundamental value, this deviation is expected to revert once some rational arbitrageurs have enough financial incentive to take advantage of it, as I argue in more depth in the next section.

Although I did not find any reversion in my five year data set, a branch of the finance literature has documented that a large fraction of the stock market return is mean-reverting in the long run. In particular, Campbell (1991) finds that only one-third to one-half of total market movements are permanent, whereas one-half to two-thirds are mean-reverting. This implies that the 70% driven by the order flow cannot all be permanent (70% > 50%), which suggests that orders are generating mean-reverting price changes. This means that a large fraction of the orders are moving prices away from their fundamental value, forcing the prices to eventually come back. It is a direct indication in favor of uninformed price pressure, which confirms the previously observed inconsistency of private information with the market-wide price impact.

† The results of tables 16 and 17 can at first be surprising. Indeed, the λ coefficient is the same for both regressions, but the R^2 is higher for the market. In fact, the two results are compatible if the variance of the market order flow is large relative to the variance of the market return, which will happen if the market factor is relatively more important for the order flow than it is for the return. This pattern is what I observe empirically when regressing equations (4) and (5), i.e. the standard CAPM regression for the return and the equivalent for order flow. The R^2 of these regressions is a measure of the importance of the market factor relative to the idiosyncratic component. In equation (4) the average R^2 for the return is 24.9%, whereas it is 34.2% for the order flow in equation (5).

‡A possible econometric explanation for the low R^2 of the idiosyncratic regression would be that the idiosyncratic regression is more misspecified. Indeed, let us assume for now that orders have widely time-varying impacts. Then a fixed λ will create a lower R^2 than should be found with a perfect model. If, moreover, these time-varying λ average out for the market portfolio, and if a fixed λ is a better approximation for the market portfolio, then the R^2 of equation (6) will be less underestimated than for equation (7). Thus the idiosyncratic R^2 could be low just due to model misspecification.

4.4. Some implications of price pressure

I now propose a very simple model† of the implication of price pressure on the price in the medium to relatively long term. Limit orders provide liquidity, whereas market orders demand liquidity. However, both can have a mechanical impact on the price, as I have argued. To understand the implications of price pressure, I do not model the endogenous choice between liquidity demand and supply, that is market vs. limit orders.‡ Instead, I assume that all orders have the same impact on the price: buy orders push the log-price by $+\lambda$ and sell orders by $-\lambda$. I also assume that the direction of orders is distributed randomly between buy and sell, with an iid Bernoulli distribution, like flipping a coin.§ If there are N_t orders between time 0 and t, the log-price change can be written as

$$p_t - p_0 = \lambda \sum_{i \leq N_t} \epsilon_i,$$

where $\epsilon_i = +1$ for a buy order and -1 for a sell order.

This simple model predicts that the log-price follows a random walk, thanks to the Central Limit Theorem. This result, which is often attributed to information, also comes naturally from this simple model. Moreover, this price pressure model predicts that the log-price will follow a random walk in transaction time¶ and not in physical time, as has been empirically documented by Ané and Geman (2000).

Finally, this random-walk result shows the fallacy of a common criticism of behavioural models. That is, if irrational individuals place random orders, they will compensate each other and have no impact on average. Although this is true in expectation (the expectation of the random walk is 0), it is not true for any given path. It shows that irrational traders can have an impact even if they are not systematically in the same direction: random orders will not perfectly cancel each other. Instead, this imperfect cancellation produces a random walk as above. So one does not need a systematic crowd behaviour to move stock prices.

This model is very simplistic. Among other things‖, it predicts that prices deviate infinitely from fundamentals.$ To be more realistic, we need to assume that some rational arbitrageurs are ready to short the market when it is grossly overvalued and leverage their investment in the stock market when it is undervalued instead. This will create a dividend yield effect in the time series, as reported by Fama and French (1988), as well as the long-term mean-reversion reported by Poterba and Summers (1988). When prices are high relative to fundamentals, they come back down. When they are low, they come back up. This model then produces slow but large deviations from fundamentals, as Summers (1986) studies in detail, and explains the excess volatility of Shiller (1981). It is also consistent with Campbell (1991) and the large fraction of stock market movements that mean-reverts.

5. Conclusion

In this paper, I first explain how there can be an imbalance in supply and demand for financial assets, as soon as one considers not only realized transactions, but also unrealized wishes using limit order data. Building on this observation, I construct a new measure of order flow imbalance that also takes into account the concavity of the price impact as a function of an order's volume. This order flow measure is highly correlated with contemporaneous price changes, with R^2 around 50%. Besides, part of the order flow is predictable, but the predictable part has nearly no impact on the price, as one would expect from a well arbitraged market. I do not find any short-term reversal of this price impact, which is observed for very different time horizons, from the micro-scale 10 min to the macro-scale three months.

†This model can be derived from equation (3) in Huang and Stoll (1997) if one sums the price change over time and assumes uncorrelated orders.

‡Implicitly, I assume that there are enough sell limit orders to provide liquidity for the buy market orders, to avoid market breakdowns, and the other way around for sell market orders.

§Again, this is a simplification, because the order flow is autocorrelated. However, the part of the order flow that is predictable has no impact on the price, because of statistical arbitrage, as reported in table 11. So what I model here is the unpredictable part, which is reasonably well described by the iid distribution.

¶In this simple model, the distinction between market orders (which produce a transaction) and limit orders (which do not) is blurred. Empirically, however, the intensity of limit and market order submission is very correlated, so that the result of Ané and Geman (2000) would probably extend with order time instead of transaction time.

‖In this simple model, I have only considered one asset (the stock market). However, my empirical results show that the price pressure also works for each stock individually. Price pressure is harder to model in this case, because risk-averse 'arbitrageurs' can build portfolios with apparently very high Sharpe ratios, and therefore remove a big fraction of the mispricing even with a relatively small fraction of the global wealth. Indeed, an 'arbitrageur' could invest in a long/short portfolio, which removes the market component of risk, and diversify the idiosyncratic risk. However, there are several difficulties in following this strategy. First, this long–short portfolio will be heavily loaded in the book-to-market factor of Fama and French (1993). So it is in fact risky. Second, there is a lot of uncertainty in the distribution of future returns. The true fundamental value is difficult to estimate (a high price relative to book value could signal a growth company as well as an overvalued company). And the true time-varying covariance structure with many assets is also hard to estimate, which makes diversification harder. So even without the book-to-market factor, it would be difficult to build a very high Sharpe ratio portfolio due to the uncertainty of the expected return and the covariance matrix.

$The cumulative imbalance between supply and demand can go to infinity over time, because it is an imbalance in submitted orders, not in realized transactions. So not even the total number of shares outstanding is a limit.

I then provide an economic interpretation of the co-movement of the order flow imbalance with price changes. I first establish the causality from orders to price changes, by observing that orders occur before the price changes. I then distinguish between two possible causal interpretations of the price impact, one based on private information, and the other based on mechanical price pressure. Although private information is certainly part of the reason why orders affect the price, I argue that price pressure can be present even for uninformed orders.

The first argument in favor of mechanical price pressure comes from the distinction between market return and idiosyncratic return. More precisely, one would expect only a small fraction of market-wide movements to be driven by private information, since there is little information asymmetry about the whole market. However, the R^2 of return on orders is 70% for the market returns, significantly higher than the 41% obtained for idiosyncratic returns, and economically higher than most estimates of private information for the market as a whole. Therefore, private information does not seem to be the only reason for the co-movement. Furthermore, 70% is higher than the upper bound (50%) of market movements that Campbell (1991) finds to be permanent, and thus reflecting fundamental value. A large fraction of the price impact does not appear to reflect fundamental value and is best explained by uninformed price pressure.

Acknowledgements

I would like to thank Cécile Boyer, Denis Gromb, S.P. Kothari, Jonathan Lewellen, Andrew Lo, Angelo Ranaldo, Dimitri Vayanos, Jiang Wang, and two anonymous referees for their comments on earlier drafts of this article. I would also like to thank Mathias Auguy, Patrick Hazart and Bernard Perrot from the Paris Bourse for their help in making the data available. Finally, I am especially grateful to Xavier Gabaix for many stimulating discussions and continuous encouragement for this project.

References

Ané, T. and Geman, H., Order flow, transaction clock and normality of asset returns. *J. Finan.*, 2000, **55**, 2259–2284.

Barclay, M.J. and Warner, J.B., Stealth trading and volatility. *J. Finan. Econ.*, 1993, **34**, 281–305.

Biais, B., Hillion, P. and Spatt, C., An empirical analysis of the limit order flow in the Paris Bourse. *J. Finan.*, 1995, **50**, 1655–1689.

Bouchaud, J.-P., Gefen, Y., Potters, N. and Wyart, M., Fluctuations and response in financial markets: the subtle nature of 'random' price changes. *Quant. Finan.*, 2004, **4**, 176–190.

Bouchaud, J.-P., Mézard, M. and Potters, M., Statistical properties of stock order books: empirical results and models. *Quant. Finan.*, 2002, **1**, 251–256.

Brandt, M.W. and Kavajecz, K.A., Price discovery in the US treasury market: the impact of orderflow and liquidity on the yield curve. *J. Finan.*, 2004, **54**, 2623–2654.

Campbell, J.Y., A variance decomposition for stock returns. *Econ. J.*, 1991, **101**, 157–179.

Chordia, T. and Avanidhar, S., Order imbalance and individual stock returns: theory and evidence. *J. Finan. Econ.*, 2004, **72**, 485–518.

DeLong, J.B., Shleifer, A., Summers, L. and Waldmann, R.J., Noise trader risk in financial markets. *J. Polit. Econ.*, 1990, **98**, 703–738.

Evans, M.D.D. and Lyons, R.K., Order flow and exchange rate dynamics. *J. Polit. Econ.*, 2002, **110**, 170–180.

Fama, E.F. and French, K.R., Dividend yields and expected stock returns. *J. Finan. Econ.*, 1988, **22**, 3–25.

Fama, E.F. and French, K.R., Common risk factors in the returns on stocks and bonds. *J. Finan. Econ.*, 1993, **33**, 3–56.

French, K. and Roll, R., Stock return variances: the arrival of information and the reaction of traders. *J. Finan. Econ.*, 1986, **17**, 5–26.

Gabaix, X., Gopikrishnan, P., Plerou, V. and Stanley, H.E., A theory of power law distributions in financial market fluctuations. *Nature*, 2003, **423**, 267–270.

Hasbrouck, J., Measuring the information content of stock trades. *J. Finan.*, 1991, **46**, 179–207.

Hasbrouck, J. and Seppi, D.J., Common factors in prices, order flows, and liquidity. *J. Finan. Econ.*, 2001, **59**, 383–411.

Hausman, J., Lo, A.W. and MacKinlay, A.C., An ordered probit analysis of transaction stock prices. *J. Finan. Econ.*, 1992, **31**, 319–379.

Holthausen, R.W., Leftwich, R.W. and Mayers, D., Large-block transactions, the speed of response, and temporary and permanent stock-price effects. *J. Finan. Econ.*, 1990, **26**, 71–95.

Huang, R.D. and Stoll, H.R., The Components of the bid–ask spread: a general approach. *Rev. Finan. Stud.*, 1997, **10**, 995–1034.

Jackson, A., The aggregate behavior of individual investors. Working Paper, London Business School, 2002.

Jones, C., Kaul, G. and Lipson, M., Transactions, volume, and volatility. *Rev. Finan. Stud.*, 1994, **7**, 631–651.

Karpoff, J.M., The relation between price changes and trading volume: a survey. *J. Finan. Quant. Anal.*, 1987, **22**, 109–126.

Kavajecz, K.A., A specialist's quoted depth and the limit order book. *J. Finan.*, 1999, **52**, 747–771.

Kraus, A. and Stoll, H.R., Price impacts of block trading on the NYSE. *J. Finan.*, 1972, **27**, 569–588.

Kyle, A.S., Continuous auctions and insider trading. *Econometrica*, 1985, **53**, 1315–1335.

Lillo, F., Farmer, J.D. and Mantegna, R.N., Single curve collapse of the price impact function for the New York stock exchange. *Nature*, 2003, **421**, 129–130.

Lo, A. and Wang, J., Trading volume: definitions, data analysis, and implications of portfolio theory. *Rev. Finan. Stud.*, 2000, **13**, 257–300.

Poterba, J.M. and Summers, L.H., Mean reversion in stock prices: evidence and implications. *J. Finan. Econ.*, 1988, **22**, 27–59.

Roll, R.W., R^2. *J. Finan.*, 1988, **43**, 541–566.

Scholes, M.S., The market for securities: substitution versus price pressure and the effects of information on share price. *J. Bus.*, 1972, **45**, 179–211.

Shiller, R.J., Do stock prices move too much to be justified by subsequent changes in dividends? *Am. Econ. Rev.*, 1981, **71**, 421–498.

Stoll, H.R., The supply of dealer services in securities markets. *J. Finan.*, 1978, **33**, 1133–1151.

Summers, L.H., Does the stock market rationally reflect fundamental values? *J. Finan.*, 1986, **41**, 591–601.

Vayanos, D., Strategic trading and welfare in a dynamic market. *Rev. Econ. Stud.*, 1999, **66**, 219–254.

Wang, J., A model of competitive stock trading volume. *J. Polit. Econ.*, 1994, **102**, 127–168.