WORKING PAPERS

N° TSE- 818

June 2017

Who supplies liquidity, how and when?

Bruno Biais, Fany Declerck and Sophie Moinas

Who supplies liquidity, how and when?

Bruno Biais, Fany Declerck, Sophie Moinas[1]

Toulouse School of Economics (CNRS-CRM)

June, 2017

Abstract

Who provides liquidity in modern, electronic limit order book, markets? While agency trading can be constrained by conflicts of interest and information asymmetry between customers and traders, prop traders are likely to be less constrained and thus better positioned to carry inventory risk. Moreover, while slow traders' limit orders may be exposed to severe adverse selection, fast trading technology can improve traders'ability to monitor the market and avoid being picked off. To shed light on these points, we rely on unique data from Euronext and the AMF enabling us to observe the connectivity of traders to the market, and whether they are proprietary traders. We find that proprietary traders, be they fast or slow, provide liquidity with contrarian marketable orders, thus helping the market absorb shocks, even during crisis, and earn profits doing so. Moreover, fast traders provide liquidity by leaving limit orders in the book. Yet, only prop traders can do so without making losses. This suggests that technology is not enough to overcome adverse selection, monitoring incentives are also needed.

Keywords: Liquidity, high-frequency trading, proprietary trading, adverse selection, electronic limit order book, short–term momentum, contrarian.

JEL codes: D82, D53, G01.

[1]This research was conducted within the FBF IDEI Chair on Investment Banking and Financial Markets. Bruno Biais benefitted from the support of the European Research Council, grant 295484 TAP.

1 Introduction

In perfect markets, buyers and sellers immediately find each other and reap gains from trade at frictionless prices. Real markets, however, can fall short from delivering such welfare improvements, due to frictions.

Market frictions, indeed, can prevent final sellers from rapidly locating final buyers. In this context, intermediaries can provide liquidity to impatient sellers, by purchasing their assets and holding inventories, until they find final buyers. Such market–making services have been analyzed theoretically by Ho and Stoll (1981, 1983), Grossman and Miller (1988) and Weill (2007).[2] What are the characteristics of intermediaries which enable them to supply liquidity? In fragmented markets, intermediation services can be provided by those agents with the best network linkages and the greatest search ability, which can be enhanced by high–frequency trading technology. Even if the market is centralized, delays can arise, reflecting that not all potential buyers and sellers are permanently monitoring the market, and that it takes time for investors to identify their trading needs, as analyzed theoretically by Biais, Hombert and Weill (2014). In this context, as in that of fragmented markets, Gromb and Vayanos (2002) show that arbitrageurs, able to take positions in different markets, can provide valuable liquidity. Market makers, however, bear costs when holding inventories, e.g., because they are risk–averse and reluctant to carry unbalanced inventory positions, as analyzed theoretically by Ho and Stoll (1981), or because the principals of market makers set position limits to discipline their agents. This suggests that the agents best placed to offer liquidity are those with the best inventory holding ability, i.e, those with the greatest risk–tolerance or the least acute agency problems. Because the aggregate inventory bearing capacity of market makers is limited, however, liquidity shocks have a transient impact on prices, i.e., there are "limits to arbitrage," and liquidity supply is profitable (Shleifer and Vishny, 1997, and Gromb and Vayanos, 2002, 2010, 2015).

Another market friction limiting liquidity is adverse selection. As first shown by Akerlof (1970), adverse selection can magnify the price impact of trades and even lead to market breakdown. As shown by Glosten and Milgrom (1985) and Kyle (1985), adverse selection leads market makers to post relatively high ask prices, and relatively low bid prices. Here again, however, the question arises: which

[2] Symmetric arguments hold for the case of impatient buyers. In that case, market makers can provide liquidity by selling assets they hold in inventory, or by short–selling the asset.

agents will play the role of market makers, and why? Efficiency suggests that the intermediaries should be the agents who are best able to mitigate adverse selection. Such ability could reflect better market monitoring technology, enabling intermediaries to cancel their orders before they are picked off. This, however, could worsen the adverse selection problem for other investors, with less efficient monitoring technologies. Adverse selection for these investors could be further amplified if intermediaries took advantage of their timely market information to hit stale quotes themselves.

Since the beginning of the century, three developments have made these questions highly topical. First, equity markets have converged towards an electronic limit order book structure, in which a large number of different financial institutions (not just designated market makers) can provide liquidity by leaving limit orders in the book. Second, low latency technologies have become available, increasing, at a cost, the ability to monitor changes in market conditions and react rapidly to them. Third, regulatory reforms before the crisis contributed to the fragmentation of markets and the development of high–frequency trading, while regulatory reforms after the crisis made proprietary trading more costly and complex for investment banks.[3] How have these developments changed the economics of liquidity supply, and the gains from trades that can be reaped in financial markets? To shed light on these issues, we empirically analyze a new dataset, with information about the orders and trades of different categories of members of Euronext, including proprietary traders and high–frequency traders.

Our data includes a time–stamped record of all orders and trades (quantities and prices) on Euronext in French stocks during 2010. Our sample period brackets the Greek crisis of the summer of 2010, enabling us to analyze how liquidity supply compares between "normal" and crisis times. Our data also includes anonymized member codes, and for each member, we know i) the quality and speed of its connection to the market, and ii) if its trades were 100% proprietary, 100% agency, or a mix of both. Using i) we identify fast traders based on direct information about their technological investment, which contrasts with indirect identification, based on trading style. Because of its huge size, and also because of some technical characteristics of the Euronext market,[4] this dataset is difficult to

[3] Correspondingly, some investment banks had to move their prop trading activities to seggregated subsidiaries, such as, e.g., Descartes Trading for Société Générale.

[4] The majority of markets refresh the limit order book at the end of the trading day, eliminating unexecuted limit orders. This is not the case in Euronext, where a limit order can be left in the book for up to one year. Consequently there are many remaining limit orders, far from the quotes. This increases the size of the dataset.

handle. At this stage, we have analyzed 23 French stocks, including 10 large caps, 9 mid caps, and 4 small caps. The size of the corresponding data exceeds 7 tera–octets.

Our first main empirical finding relates to liquidity supply. We find that proprietary traders, be they fast or slow, tend to place marketable buy orders after price declines, and marketable sell orders after price increases. Thus, we find that proprietary traders follow contrarian strategies, buying against downward price pressure, and selling against upward price pressure. This contrasts with the other traders, who tend to buy after price rises and sell after price declines, which can be interpreted as momentum trading. While the proprietary traders' contrarian strategies rely on marketable orders, they supply liquidity to the market. This is consistent with proprietary traders being better able to carry inventory risk than other traders. This might be because they commit their own capital, rather than trading on other people's behalf. This could also reflect better incentive contracts. In both cases, superior ability to carry inventory risk would stem from having more "skin in the game."

Market liquidity could be hampered if liquidity supply evaporated in times of market stress (see, e.g., Nagel 2012). Interestingly, the contrarian strategies of proprietary traders are particularly prevalent for small stocks, and during the Greek crisis. Thus, they are not "fair weather" liquidity suppliers, disappearing when the market most needs them. Moreover, the contrarian strategies of proprietary traders are on average profitable. This suggests they are able to identify when transient price pressure, possibly reflecting liquidity shocks, has driven prices away from equilibrium. In those circumstances, proprietary traders' marketable orders conduct risky arbitrage. Thus, by absorbing selling or buying pressure, they tend to stabilize the market.

Our second major empirical finding relates to adverse selection. We find that the information content of marketable orders, although significantly positive, does not significantly differ across members' categories. In particular, fast traders' marketable orders don't seem to be more informed than those of slower traders. In contrast, we find that the adverse selection cost borne by non–immediately executed limit orders is significantly lower for fast proprietary traders. On the other hand, adverse selection costs are high for fast non–proprietary traders' limit orders. This suggests that technology, in itself, is not enough to mitigate adverse selection. It is also necessary that the traders have the incentives to use the technology efficiently. Moreover, while fast proprietary traders frequently trade with non–immediately executed limit orders, slow proprietary traders only unfrequently do so. Thus, while slow proprietary traders mainly supply liquidity by placing contrarian marketable orders, fast proprietary traders also supply liquidity by placing non immediately executed limit orders. We find, however, that this second type of liquidity supply becomes much less prevalent after the crisis.

Literature: Our paper relates to the rich literature empirically analyzing algorithmic and high–frequency trading:

Hendershott, Jones and Menkveld (2011) show that liquidity provision in equity market is provided by algorithmic traders who are not officially designated as market makers.

Brogaard, Hendershott, Riordan (2014) analyze NASDAQ data, relying on a classification of traders performed by the market organizers. They find that HFTs marketable orders have information content, but not significantly more than other traders' marketable orders. They also find that HFT's orders tend to be contrarian and are on average profitable. Thus, our empirical findings complement those of Brogaard, Hendershott, Riordan (2014) in two ways:

- Our findings relative to high–frequency traders are similar to theirs, and thus speak to the robustness of their results to a different market and a different way to identify high–frequency traders.
- Our findings on proprietary traders are new, and thus provide an incremental contribution to the literature. We show that several characteristics of high-frequency traders' orders (i.e., contrarian, profitable, and marketable) are also characteristics of the slow proprietary traders' orders in our data. This suggests that these traders are able to place contrarian and profitable orders not because they have low–latency, but because they are proprietary traders.[5]

Brogaard, Hagstromer, Norden, Riordan (2014) find that the choice to colocate is followed by reduced adverse selection costs. Our results on adverse selection are in line with their findings. Our incremental contribution, here, is to emphasize that technology may not be sufficient to reduce adverse selection. Appropriate incentives to use the technology efficiently seem to be also needed.

Hendershott and Menkveld (2014) offer a state space model to identify how price pressure relates to the specialist's inventory. In a sense, the proprietary traders in our data play a similar role to the

[5] The high–frequency traders identified by NASDAQ are very likely to also be proprietary traders.

specialist in Hendershott and Menkveld (2014).[6]

Our paper is also in line with analyses of liquidity supply by market participants that are not officially designated as market makers. Franzoni and Plazzi (2014) document liquidity supply by hedge funds, classifying as liquidity supply purchases (resp. sales) at a price below (resp. above) a benchmark (e.g., the opening price or the VWAP). Nagel (2012) argues that the returns on short–term reversals can be interpreted as the returns from liquidity provision. Since, in our data, we observe the type of the market participants and the details of their orders, we can rely on more precise data to directly identify liquidity supply. Our empirical finding that proprietary traders supply liquidity with profitable contrarian trades confirm the relevance of the approch of Nagel (2012) and Franzoni and Plazzi (2014). Moreover, Nagel (2012) interprets high return on liquidity supply strategies when the VIX is high as evidence that liquidity supply is reduced at those times. Our direct evidence on liquidity supply offer some nuance on this point: On the one hand, we find that proprietary traders continued to place profitable marketable contrarian orders during the Greek crisis of the summer of 2010, so, in that sense, liquidity did not "evaporate". On the other hand, we find that the crisis triggered a drop in the placement of non–immediately executed limit orders in small caps by fast proprietary traders. Other things equal, this corresponds to a decline in liquidity supply.

The next section presents our data and summary statistics. Section 3 analyzes the placement and informational content of marketable orders. Section 4 analyzes the adverse selection costs incurred by non immediately executed limit orders. Section 5 summarizes our results and discusses policy implications.

2 Market structure, data and summary statistics

Euronext is an electronic limit order market, operating continuously for most of the stocks. Orders are submitted by the financial institutions that are members of Euronext. Members are assigned an identification code. Most institutions have a single ID code, but some choose to have up to four different codes to differentiate their activities (e.g., brokerage versus proprietary trading). Each ID

[6]Furthermore, Kirilenko, Kyle, Samadi, Tuzun (2014) find that HFTs did not cause the Flash Crash but exacerbated it. Menkveld (2013) document liquidity supply by large HFT across ChiX & Euronext.

code can have several links to the exchange. The total fee charged by Euronext to a member depends on the number of links connected to the Euronext servers, and on the capacity of each link. This capacity is named “throughput”, and indicates the maximum number of messages (order submission, cancellation or modification of an existing order) that the traders are allowed to send to the Exchange in one calendar second via this link. The throughput of each link can be 10, 25, 50, 100, 200, 250, or 500. It seems that a large throughput does not only increase the number of messages that can be sent, but also increases the speed with which they reach the market. We are able to document this empirically because, in our data, we observe (at the microsecond level) the time at which an order was sent to the market and the time at which the order was executed. We also observe the throughput of the link via which the order was sent. Marketable orders, by construction, are immediately executed. Thus, for these orders, the difference between the execution time and the submission time is an inverse measure of the speed of the connection. In Figure 1, panel A, we plot for each link, the median of this time difference against the throughput of the link. The figure illustrates that links with higher throughput tend to also have higher connection speed. Moreover, Euronext further proposes to its Members to colocate their servers close to its owns.[7] Colocation fees depend on the physical space used by the Member, and on the electricity consumption of the servers.

We obtained our data from the Autorité des Marchés Financiers (the French financial markets regulator) and Euronext. So far, we have analyzed 23 French stocks between February 2010 and August 2010. The sample includes 10 large caps (1 financial and 9 non–financial with float between 1,048 and 3,884 million euros), 9 mid caps (1 financial and 8 non financial, with float between 181 and 960 million euros), and 4 small caps (all non financial, with float between 51 and 145 million euros).

150 Euronext member IDs traded these stocks during the sample period. 28 of them only traded on their own account, and we classify them as prop traders. 37 only traded on behalf of customers and we classify them as pure brokers. 85 conducted some trades on their own account and some trades on behalf of customers. We classify them as dual traders.[8]

[7] In May 2010, Euronext servers were moved to Basildon (in the neighbourhood of London, UK). Members can choose to colocate some, all or none of their links.

[8] Actually, for each trade we observe if it was reported by the member as proprietary or agency. But we have been told by market participants that these reports can be quite noisy. To reduce the impact of such noise, we chose to classify as pure proprietary traders those reporting only proprietary trades and as pure brokers those reporting only agency trades.

As mentioned above, we observe the number of links for each member ID, and the throughput of each link. For each member ID, we compute the messaging capacity, i.e., the sum of the throughputs of all the links. As discussed above, in line of Figure 1, Panel A, messaging capacity is also correlated with speed of connection. Figure 1, Panel B, illustrates the distribution across member IDs of messaging capacities. They range between 0 and 4600. Traders with higher capacity and higher connection speed can observe changes in market conditions faster and react faster to them. We chose to classify as fast traders the 17 members with capacity above 1300 messages per second. We checked that our qualitative results were robust to changing the threshold, e.g., setting it at 800 or 1600.

Out of the 17 fast traders, 6 are proprietary traders while the 11 others are dual traders. Members' ID codes are anonymized, so we don't observe the identity of the traders, nor do we have direct information about their types. We, however, have some indirect information, unrelated to the dataset, based on which we formed conjectures. It is highly likely that the 6 fast proprietary traders are high–frequency trading "boutiques", similar to the high–frequency traders identified in the Nasdaq dataset. Moreover, it is likely that the 11 fast dual traders are, typically, European banks, sending proprietary trades as well as agency trades to the exchange via the same membership channel.

Out of the 133 slow traders, 22 are proprietary traders, 74 are dual traders, and 37 are pure brokers. Once again, because the dataset is anonymized, we have no direct information about who these members are. It is likely, however, that the 22 slow proprietary traders include proprietary trading desks of large investment banks with their own membership and possibly some hedge funds.

Combining the two criteria, we classify the members in our sample into 5 categories: fast prop–traders, slow prop–traders, fast dual traders, slow dual traders, and slow brokers. Note that no pure broker in our sample was fast. This does not mean they had absolutely no high–frequency trading technology. It is likely they also rely on algorithms, e.g., to search for best execution. Their connections to the market, however, are less advanced than that of the fast traders.

As mentioned above, our sample period brackets the Greek crisis of the summer of 2010. Figure 2 plots the evolution of the VIX volatility index during our sample period. The Vix jumps on April 23rd, when Greece asks for a bailout, and remains elevated until late June. Thus, we split our sample in three subperiods: The first period, before the crisis, is from February 23 to April 22. The second period, corresponding to the crisis, is from April 23 to June 22. The third period, after the crisis, is from June 23 to August 23.

Figure 3 depicts the number of trades per member, per stock, per day. Figure 3, Panel A, shows that fast traders (both proprietary and dual) trade more often, and rely more on non immediately executed limit orders, than slow traders. Slow proprietary traders trade less than fast traders, but more than other slow traders. Moreover, unlike fast proprietary traders, they rely mainly on marketable orders.

Panels B and C of Figure 3 show how these results vary with market capitalization and periods. Comparing Panel B (large caps) and Panel C (small and mid caps), the number of trades is much larger for the former than for the larger. Furthermore, for large caps the number of trades increases during the crisis, but the relative frequencies of marketable orders and non–immediately executed limit orders are rather stable through time. For small caps, however, the behavior of fast proprietary traders is quite different. First their trading volume does not increase during the crisis. Second, while before the crisis they frequently traded via non immediately executable limit orders, during and after the crisis they considerably reduce their reliance on this type of trade. This is an important observation, to which we come back below, when we analyze how the crisis affected adverse selection costs.

Figure 4 offers a graphical illustration of the frequency with which each category of traders' marketable orders hit each category of traders' limit orders. Each color corresponds to the category of the trader whose marketable order was executed. For example, the plain red bar corresponds to the marketable orders placed by fast proprietary traders. It shows that, when a fast prop trader places a marketable order, 19% of the time it hits another fast trader, 8% of the time it hits a slow prop trader, 41% of the time it hits a fast dual trader, 27% of the time it hits a slow dual trader, and 4% of the time it hits a pure broker's order. Interestingly, the frequencies are very similar for marketable orders placed by other categories of traders. So, it's not the case that fast traders "target" a certain category of trader's limit orders.

3 Marketable orders

To estimate the information content of orders in the simplest possible way, we use the percentage change from the midquote just before the trade to the midquote 2 minutes after the trade. Thus, for a trade taking place at time t, the information content is

$$\frac{M_{t+2} - M_{t^-}}{M_{t^-}} * sign_t,$$

where M_{t^-} denotes the midquote just before the trade, M_{t+2} denotes the midquote 2 minutes after the trade, and $sign_t$ takes the value 1 if the time–t marketable order is a buy order, and -1 if the time–t marketable order is a sell order.

Figure 5, Panel A, depicts the informational content of the marketable orders placed by different categories of traders. After a marketable buy (resp. sell) order placed by a fast proprietary trader, the midquote increases (resp. decreases) on average by 3.5 basis points. The informational content of the marketable orders placed by other categories of traders are not very different, ranging between 3.4 and 4.1 basis points. This suggests that the marketable orders placed by fast traders are not more informed than the marketable orders placed by other traders. Correspondingly, they don't generate more adverse selection for limit orders standing in the book.

Figure 5, Panel B, depicts how the informational content of marketable orders varies across stocks and through time.[9] It shows that, for all traders, the informational content of orders is larger for small caps and during the crisis, and remains higher after the crisis than before. Also, while, as shown in Figure 5, Panel A, fast traders' orders are, in general, not better informed than other traders' orders, during the crisis they are.

Figure 6 depicts the evolution of the midquote 5 minutes before and after the placement of a marketable order by the different categories of traders, i.e., it plots the average of

$$\frac{M_{t+h} - M_{t^-}}{M_{t^-}} * sign_t,$$

where h varies from -5 minutes to +5 minutes. Panel A shows the results for large caps, while Panel B shows the results for small caps. The two panels confirm the above discussed findings that, after the trade, the information content of marketable orders is similar for all categories of members, and is higher for small stocks. The new information in Figure 6, relative to Figure 5, is about what happens before the trade. Figure 6 shows that dual traders or brokers place marketable buy (resp. sell) orders

[9] The information content of fast prop traders' orders is larger than that of other traders for all subcases in Panel B. This does not contradict the fact that it is not higher in Panel A, because fast proprietary traders are relative more active in large cap (for which the informational content of orders is lower) than in small caps.

after price increases (resp. decreases). This is consistent with dual traders and brokers riding short–term momentum waves, or splitting orders. In stark contrast, fast proprietary traders (be they fast or slow), buy after price decreases and sell after price increases. That is, they follow contrarian strategies. Thus their marketable orders supply liquidity to the market, helping it accomodate buying or selling pressure.

Is such liquidity supply robust ? Or does this liquidity evaporate when the market really needs it, e.g., in times of crisis? To shed light on this, Figure 7 depicts the evolution of the midquote 5 minutes before and after the placement of a marketable order, similarly to Figure 6, but distinguishing between the period before the crisis (Panel A), during the crisis (Panel B) and after the crisis (Panel C). The figure shows that there are no qualitative differences across periods. During the three periods, dual traders and pure brokers buy after price rises and sell after price drops. And, during the three periods, proprietary traders buy after price drops and sell after price rises. The only difference is that, during the crisis, the magnitude of the price changes is larger. Thus, the liquidity supplied to the market by the contrarian orders of proprietary traders does not seem to evaporate during times of market stress.

Our results are consistent with those of Brogaard, Hendershott, Riordan (2014), who find that HFT's marketable orders tend to be contrarian. Indeed, the HFT firms identified by Brogaard, Hendershott, Riordan (2014) are likely to be proprietary traders. The new finding in the present study is that slow traders also place such contrarian marketable orders, when they are proprietary traders. This suggests that what enables traders to conduct such contrarian strategies is maybe not technology but the ability to trade on one's own account. That ability reduces agency conflicts between investors and traders, and thus increases the ability to carry incentory, and, correspondingly, supply liquidity to the market.

While such liquidity supply could be beneficial to the market, by accomodating liquidity shocks, one could wonder whether it is sustainable. In particular, is it profitable? To shed light on this, we computed the average profits of the marketable orders placed by the different categories of market participants. To estimate the profitability of orders in the simplest possible way, we use the percentage difference between the transaction price and the midquote 2 minutes after the trade. Thus, for a marketable order executed at time t, the profit is

$$\frac{M_{t+2} - P_t}{M_{t^-}} * sign_t,$$

where P_t denotes the transaction price, M_{t+2} denotes the midquote 2 minutes after the trade, and $sign_t$ takes the value 1 if the time–t marketable order is a buy order, and -1 if the time–t marketable order is a sell order.

Figure 8 depicts the results. Panel A of Figure 8 shows that proprietary trader's marketable orders earn positive profits: .8 bp on average for fast proprietary traders, and 1.7 bp on average for slow proprietary traders. This suggests that the ability of proprietary traders to supply liquidity with contrarian orders is sustainable, in the sense that it is profitable.[10]

Panel A of Figure 8 shows that, in contrast, the momentum riding strategies of other traders appear to be non–profitable. In particular, slow dual traders loose on average around 1.1 bp per trade, and slow brokers almost 4 bp. Thus, while these orders trade in the direction of market movement, buying before price increases and selling before declines, they are not profitable, because the spread they have to pay exceeds their informational content.

Panel B of Figure 8 shows how the profitability of marketable orders vary with the market capitalization of the traded stocks and with the crisis. Both the profits of the proprietary traders and the losses of the other traders are larger for small caps than for large caps. Furthermore, the profitability of fast proprietary traders' marketable orders increase during the crisis, while those of slow proprietary traders decrease somewhat for small caps, but remain largely positive. This is consistent with the results depicted in Figure 7: Proprietary traders continue to supply liquidity to the market via contrarian marketable orders during the crisis, and this activity continues to be profitable.

As mentioned above, the behaviour we interpret as momentum riding could in fact reflect order splitting. We can address this issue because our data contains the ID codes of market participants (anonymized of course.) If order splitting was the reason why dual traders and slow brokers bought after price rises (and sell after drops), we should see that, after a dual trader or broker placed a marketable order, the next marketable order would often be in the same direction and stemming from the same trader. To offer evidence on this point, we estimate a contingency table in the same spirit as in Biais, Hillion and Spatt (1995). Figure 9 presents the probability that, after a marketable order was placed by a given category of participant, the next marketable order is placed by the same

[10] Proprietary trades are exempted from trading fees on Euronext, so the above mentioned profitability is not eliminated by exchange fees.

participant or another one, and is the same direction or the opposite one. The figure shows that, after a marketable order was placed by a fast dual trader, the probability that the next marketable order stems from the same trader is below 10%. For slow dual traders, this probability is between 10 and 15%, for slow brokers it is between 15 and 20%. These frequencies are not very large, suggesting that order splitting is not the main driving force, and momentum trading is likely to be at play. Interestingly, after a marketable order was placed by a fast prop trader, the probability that the next marketable order stems from the same trader is very low (around 5%), while after a marketable order from a slow prop trader its is very large (above 35%). This suggests, that, at least in the case of slow prop traders, order splitting and contrarian liquidity supply coexist. Another implication from Figure 9 is that order splitting seems to be more prevalent for slow traders than for fast traders.

The overall message emerging from the above discussed findings is the following: Slow traders tend to split orders, while fast traders engage less in order splitting. Proprietary traders help the market absorb liquidity shocks by placing contrarian marketable orders, while other traders tend to consume liquidity by riding momentum waves.

4 Adverse selection costs incurred by limit orders

Limit orders left in the book are exposed to adverse selection, as analyzed, e.g., by Glosten and Milgrom (1985), Glosten (1994) and Biais, Martimort and Rochet (2000). Fast trading technology, however, enhances traders' ability to monitor market movements. This may enable them to cancel or modify stale quotes, before they receive adverse execution.

To estimate the adverse selection cost incurred by limit orders in the book, we use the percentage change from the midquote just before the trade to the midquote 2 minutes after the trade. Thus, for a trade taking place at time t, the information content is

$$\frac{M_{t+2} - M_{t^-}}{M_{t^-}} * sign_t^{\text{limit}},$$

where M_{t^-} denotes the midquote just before the trade, M_{t+2} denotes the midquote 2 minutes after the trade, and $sign_t^{\text{limit}}$ takes the value 1 if the limit order hit at time–t is a buy order, and -1 if it is a sell order. This is similar to the measure of information content illustrated in Figure 5, but, while in Figure 5 we condition on the type and direction of the aggressive marketable order, in Figure 10 we condition on the type and direction of the passive limit order (hit by a marketable order).

Figure 10, Panel A, shows that, after a limit buy (resp. sell) order left in the book by a fast proprietary trader is executed, the midquote decreases (resp. increases) on average by 2.8 basis points. The adverse selection costs of limit orders left in the book by other categories of traders are 3.1 bp for slow proprietary traders, 3.8 bp for fast dual traders, 4.1 bp for slow dual traders and 5 bp for slow brokers. Thus, the adverse selection cost is lowest for fast proprietary traders. Adverse selection costs are higher for fast non–proprietary traders. This suggests that technology, in itself, is not enough to mitigate adverse selection. It is also necessary that the traders have the incentives to use the technology efficiently.

Figure 10, Panel B, compares adverse selection costs before, during and after the crisis, and also across large and small caps. Overall, adverse selection costs are higher for small caps. They are also higher during the crisis. There are some differences between the different categories of traders:

- For non–proprietary traders, adverse selection costs increase during the crisis, and remain elevated afterwards.
- For slow proprietary traders, there is a similar pattern, except that adverse selection costs decline after the crisis.
- For fast proprietary traders, while the pattern is similar for small and mid caps, for large caps adverse selection costs remain low throughout the period, and are not higher during or after the crisis. This is consistent with the patterns depicted in Panels B and C of Figure 3: Fast proprietary traders seem to be able to control adverse selection costs for large caps during the crisis, and thus continue to supply liquidity in these stocks via limit orders. In contrast, for small and mid caps, their adverse selection costs increase and they reduce their limit order liquidity supply. This is a form of "liquidity evaporation."

Figure 11 depicts the profits earned by limit orders left in the book, estimated as

$$\frac{M_{t+2} - P_t}{M_{t^-}} * sign_t^{\text{limit}},$$

where P_t denotes the transaction price, M_{t+2} denotes the midquote 2 minutes after the trade, and $sign_t^{\text{limit}}$ takes the value 1 if the limit order hit at time–t is a buy order, and -1 if it is a sell order.

Panel A of Figure 11 shows that the limit orders of fast proprietary traders (and also those of slow dual traders) earn slightly positive profits on average. That is, for these orders, the bid–ask spread (which they earn) is slightly larger than the adverse selection cost (which they incur). In contrast, the limit orders left in the book by dual fast traders loose 3 bp per trade on average, and those of slow proprietary traders 8 bp per trade. That is, for these limit orders the adverse selection cost is so large that it exceeds the spread. This is consistent with i) our observation above that slow proprietary traders rarely use non–immediately executable orders and ii) the conjecture that they are aware that such orders would be loss making for them.

Panel B of Figure 11 shows that the profitability of non immediately executed limit orders varies considerably with capitalization and period. Both losses and profits are much lower for large caps. The most striking result is the large profitability of fast proprietary traders' limit orders in small caps during the crisis and afterwards. These are the most difficult stocks and times, for which adverse selection costs are the largest, as shown in Figurer 10, Panel B. Yet, fast proprietary traders apparently are able to earn the spread to such an extent that they more than offset these costs.

The results in Figures 10 and 11 suggest that fast proprietary traders' limit orders are less adversely selected than others, in line with the notion that fast proprietary traders monitor the market and often cancel or modify their orders before receiving adverse execution. To document this point, we computed the number of cancellations and the number of updates to less aggressive quotes for each category of trader, normalizing these numbers by the number of trades. Figure 12 shows that, for fast proprietary traders, the number of updates to less aggressive quotes is 3.7 times as large as the number of trades outside the crisis, and 4.2 times during the crisis. For cancellations, these numbers are 12.8 outside the crisis, and 15.1 during the crisis. These numbers are much larger than the corresponding numbers for fast dual traders and much, much larger than the corresponding numbers for other categories of traders. That the frequency of cancellations and modifications by fast proprietary traders is higher during the crisis, suggests that these traders exerted more effort monitoring the market and adjusting to it. The cost of this effort increased the cost of leaving limit orders in the book during the crisis.

5 Conclusion and policy implications

We analyze a unique dataset enabling us to observe, in addition to time stamped orders and trades on Euronext, the number of messages per second traders can exchange with the market, and whether they are prop traders. Our sample period, in 2010, brackets the Greek crisis of the summer of 2010.

We find that proprietary traders, be they fast or slow, tend to place marketable buy orders after price drops, and marketable sell orders after price increases. And, after they have bought, the market tends to recover, while, after they have sold, the market tends to retreat. This is consistent with proprietary traders helping the market accomodate liquidity shocks, and thus reducing transient deviation from efficient pricing. Moreover, we find that this liquidity supply remains available during the crisis. In that sense, liquidity supply by proprietary traders does not evaporate when it is most needed.

We also find that the limit orders of fast proprietary traders (but not other fast traders) incur lower adverse selection costs than the limit orders of other traders. Our results suggest that fast proprietary traders supply liquidity to the market via contrarian marketable orders and non–immediately executed limit orders, while slow proprietary traders supply liquidity only via contrarian marketable orders. The crisis, however, triggered a decline the in the placement of non–immediately executable for small and mid caps by fast proprietary traders. In that sense, some liquidity "evaporated."

Our empirical findings suggest that current regulatory reforms might have unintended negative consequences:

- Under MIFID 2, trading venues will be required to cap the ratio of the number of messages to the number of trades by participant. This might be counterproductive, as our findings suggest that fast proprietary traders rely on numerous cancellations and updates to reduce the adverse selection cost incurred by their limit orders. Capping the percentage of cancellations and updates could increase the adverse selection costs incurred by limit orders left in the book, and thus deter the provision of liquidity by these orders. This could be harmful for market liquidity, especially at times of market stresss, when the need to modify and cancel orders is particularly acute.

- In this context, new banking regulations, making it more difficult and costly for banks to engage in proprietary trading, might also reduce market liquidity.

References

Biais, B., J. Hombert and P. O. Weill, 2014, "Equilibrium Pricing and Trading Volume under Preference Uncertainty," *Review of Economic Studies.*

Biais, B., P. Hillion, and C. Spatt, 1995, "An Empirical Analysis of the Limit Order Book and the Order Flow in the Paris Bourse," *Journal of Finance*, 50, 1655-1689.

Biais, B., D. Martimort, and J. Rochet, 2000, "Competing Mechanisms in a Common Value Environment," *Econometrica*, 68, 799-838.

Brogaard, J., T. Hendershott and R. Riordan, 2014, "High-Frequency Trading and Price Discovery," *Review of Financial Studies*, 27, 2267-2306.

Brogaard, J., B. Hagströmer, L. Nordén, and R. Riordan, 2014, "Trading fast and slow: colocation and market quality," Working paper, University of Stockholm.

Franzoni, F. and A. Plazzi, 2014, "What constrains liquidity provision? Evidence from hedge fund trades." Working paper, Swiss Finance Institute.

Glosten, L., 1994, "Is the Electronic Open Limit Order Book Inevitable?" *Journal of Finance*, 49, 1127-1161.

Glosten, L., and P. Milgrom, 1985, "Bid, Ask and Transaction Prices in a Specialist Market with Heterogeneously Informed Traders," *Journal of Financial Economics*, 14, 71-100.

Gromb, D. and D. Vayanos, 2010, "Limits of Arbitrage: The State of the Theory", NBER Working paper No. 15821.

Gromb, D. and D. Vayanos, 2002, "Equilibrium and Welfare in Markets with Financially Constrained Arbitrageurs," *Journal of Financial Economics* 66, 361-407.

Gromb, D. and D. Vayanos, 2015, "The Dynamics of Financially Constrained Arbitrage", Working paper, LSE.

Grossman, S., and M. Miller, 1987, "Liquidity and market structure," Journal of Finance, 617–633.

Hendershott, T., C. Jones and A. Menkveld, 2011, "Does algorithmic trading improve liquidity?" *Journal of Finance*, 66, 1–33.

Ho, T., and H. Stoll, 1983, "The Dynamics of Dealer Markets Under Competition," *Journal of Finance*, 38, 1053-1074.

Ho, T., and H. Stoll, 1981, "Optimal Dealer Pricing Under Transactions and Return Uncertainty," *Journal of Financial Economics*, 9, 47-73.

Nagel, S., 2012, "Evaporating Liquidity," *Review of Financial Studies*, 25, 2005–2039.

Shleifer, A., and R. Vishny, 1997, "The limits of arbitrage," *Journal of Finance*, 52, 37–55.

Weill, P.O., 2007, "Leaning against the Wind," *Review of Economic Studies*, 74, 1329–1354.

Figure 1, Panel A: Connection speed plotted against throughput

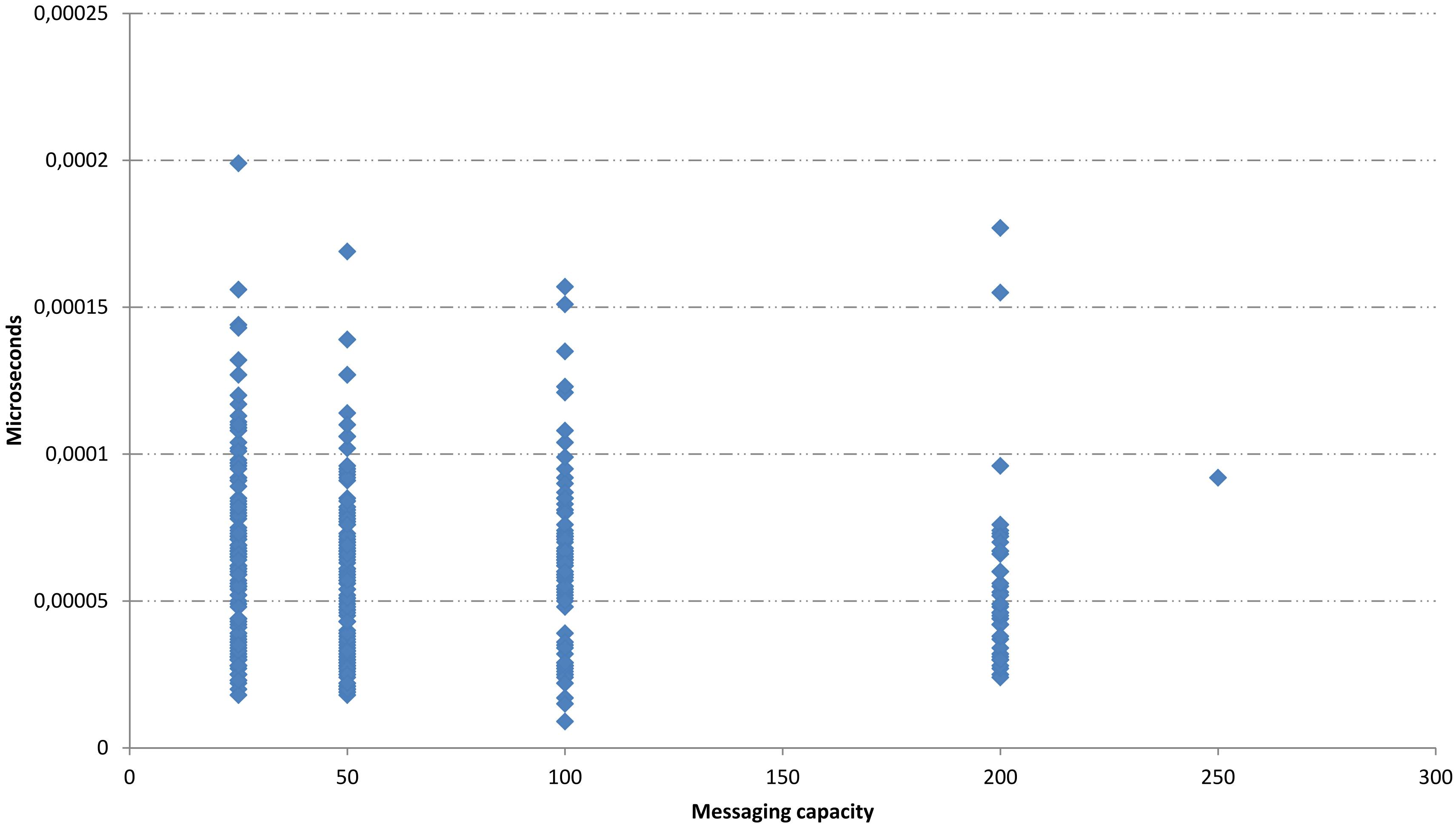


Figure 1, Panel B: Distribution of trading capacity across members

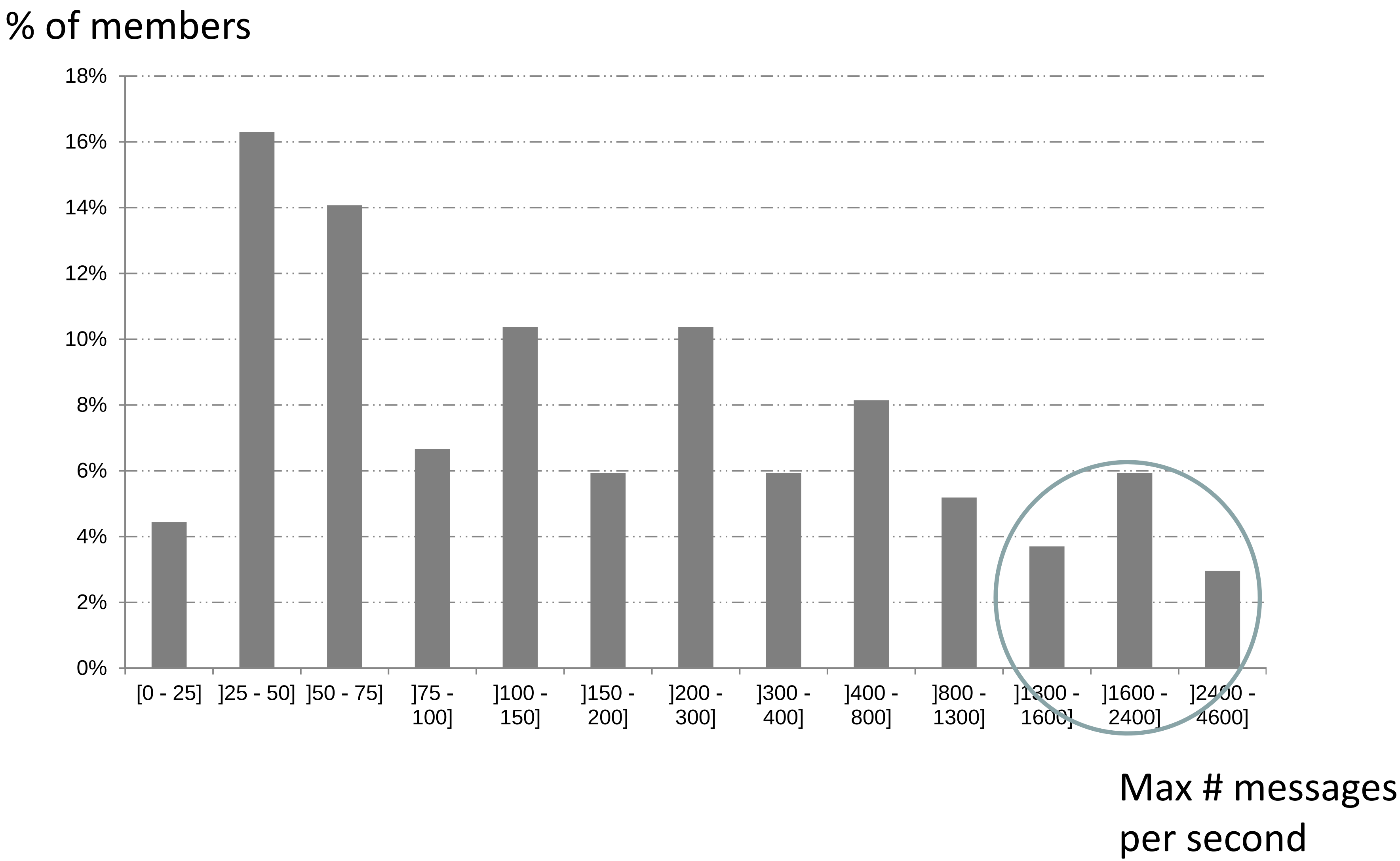


Figure 2: VIX during the sample period

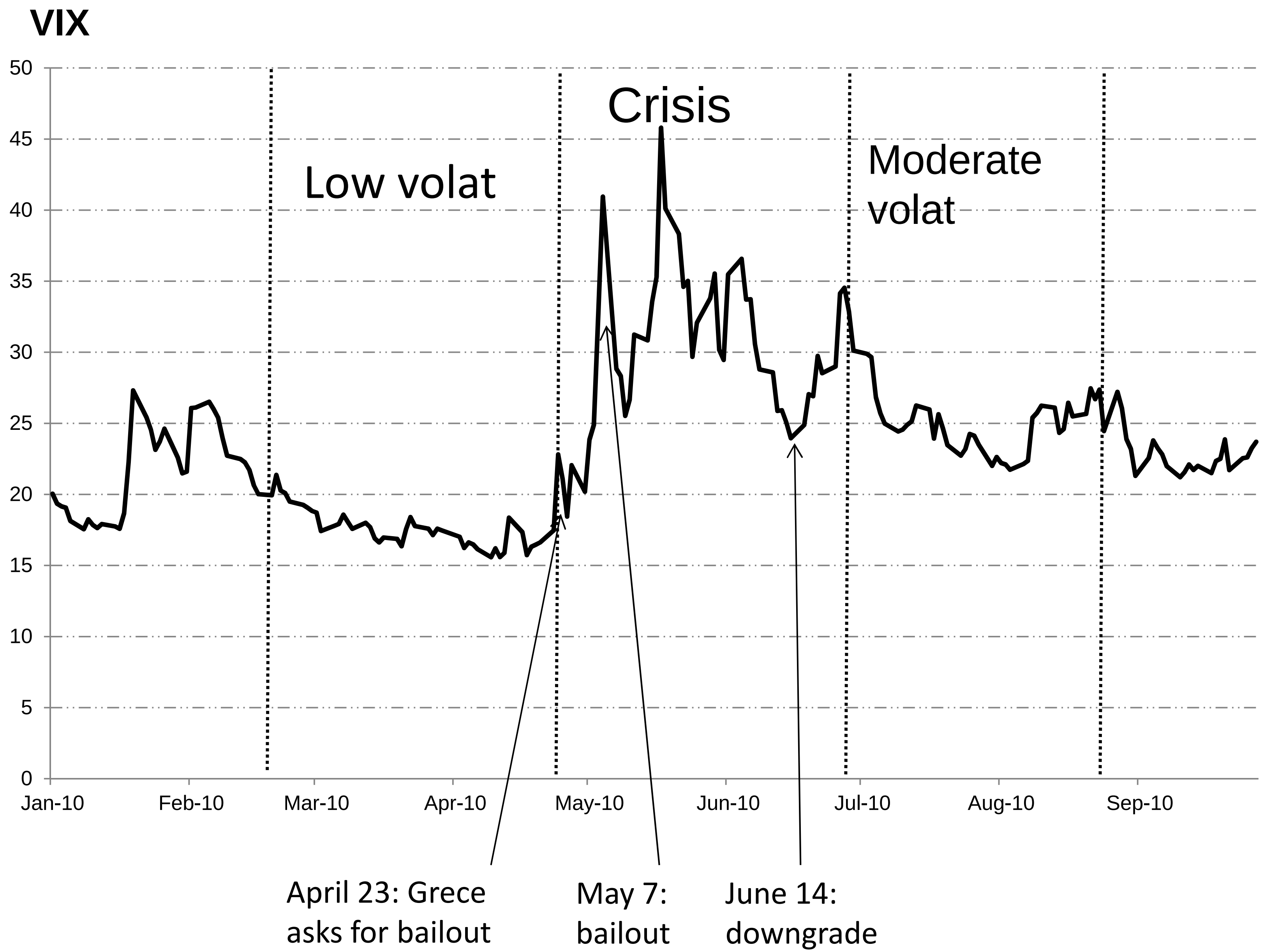


Figure 3, Panel A: Number of trades per member, stock and day

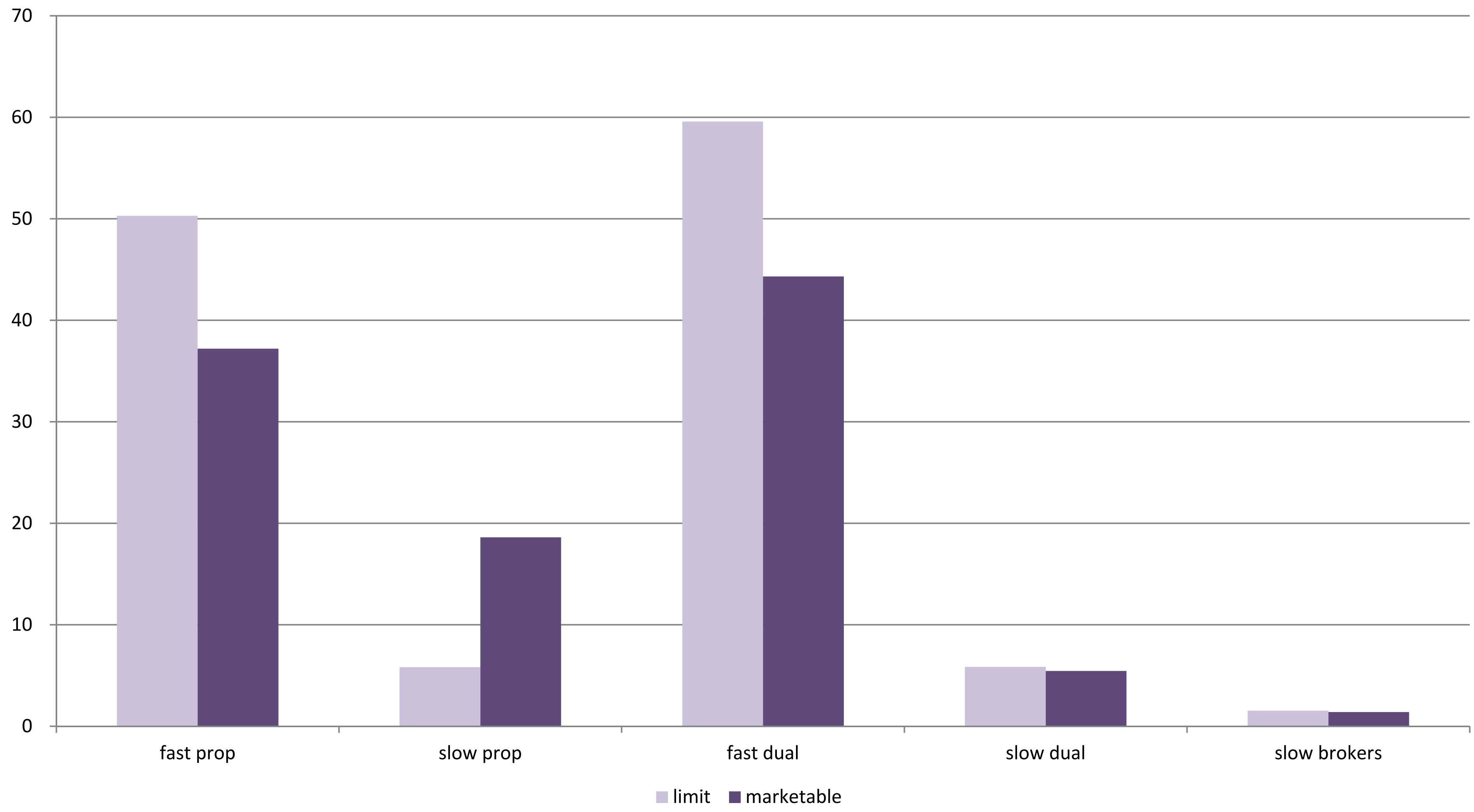


Figure 3, Panel B: Number of trades per member, stock and day – Large caps by period

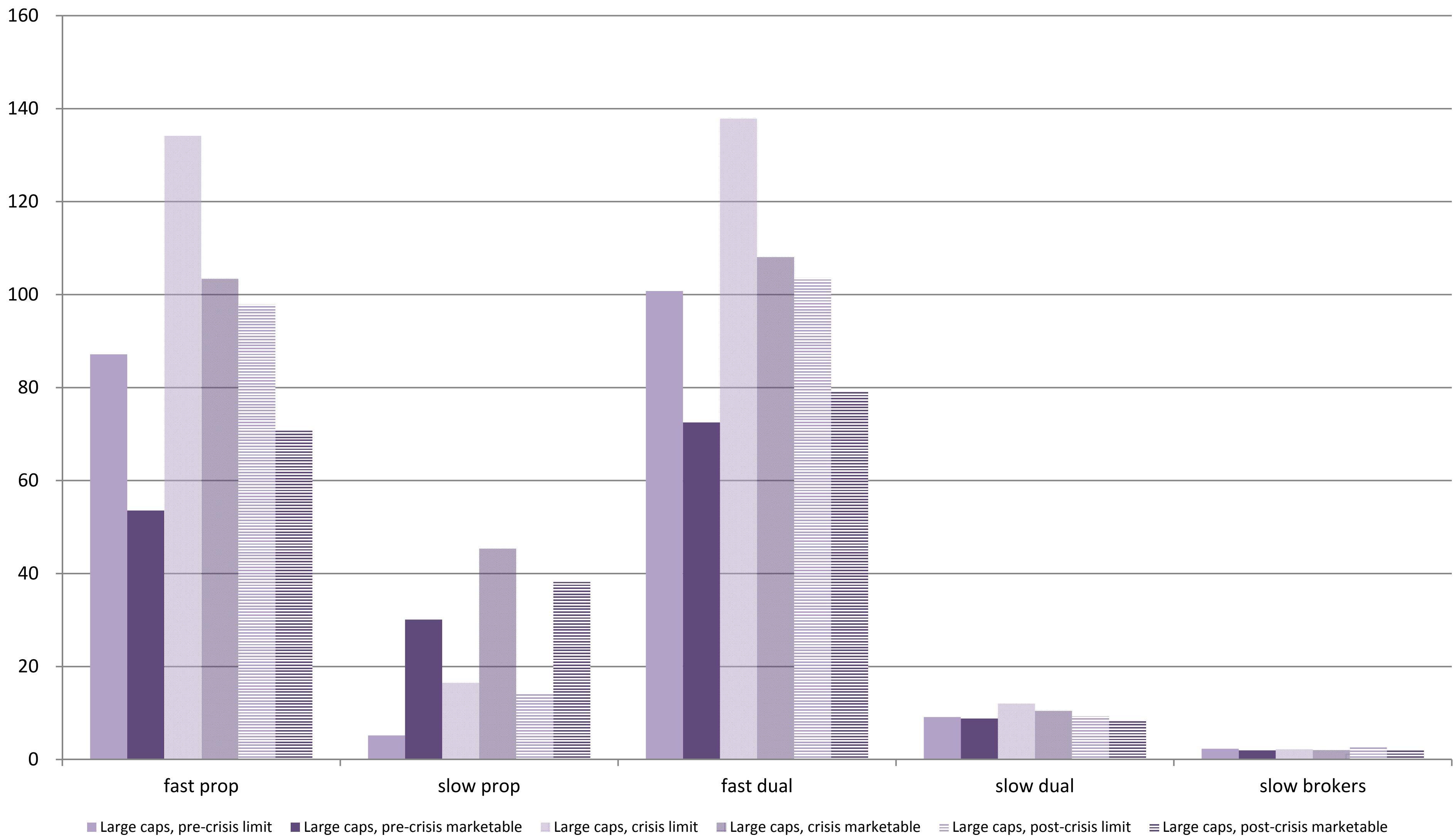


Figure 3, Panel C: Number of trades per member, stock and day – Small and mid caps by period

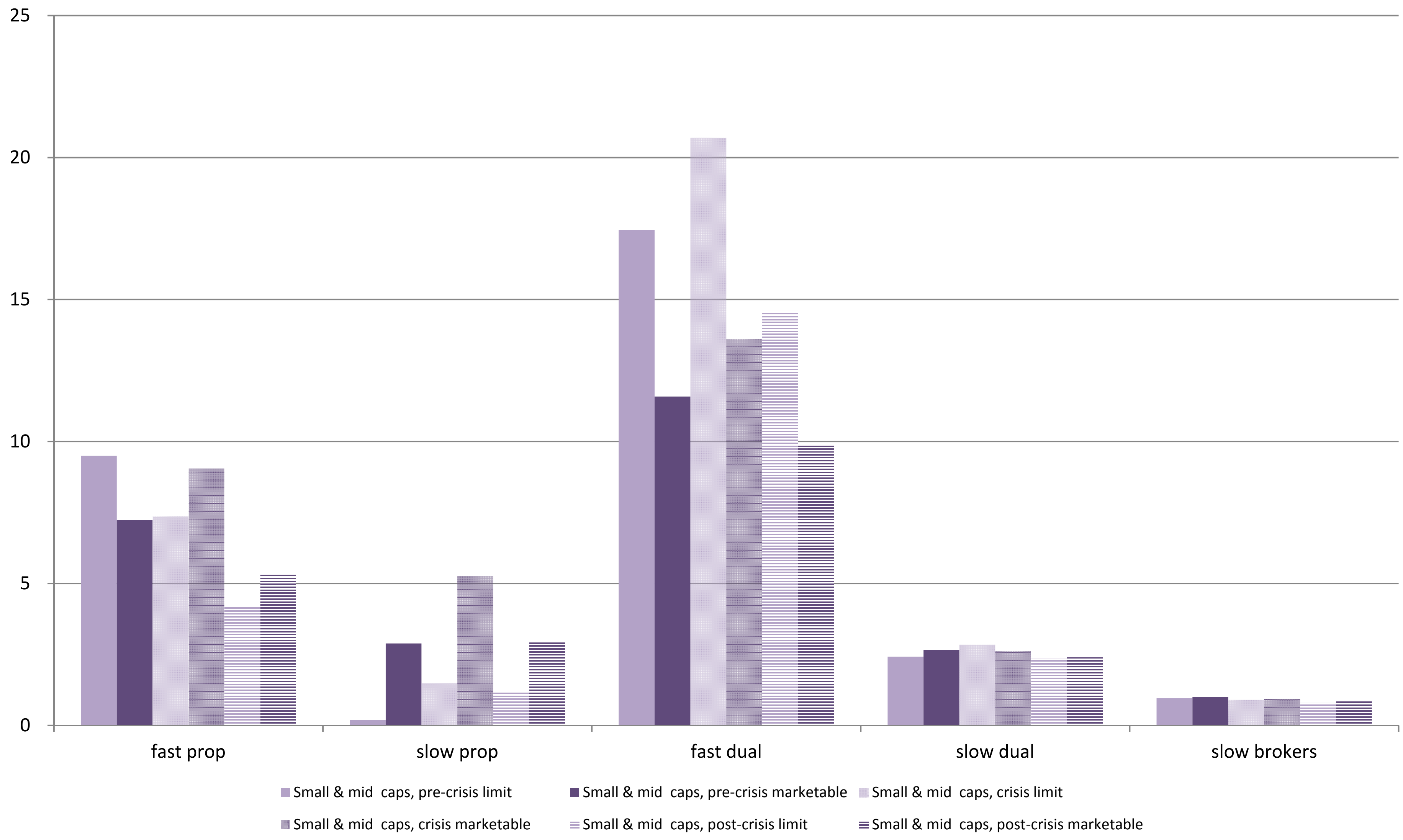
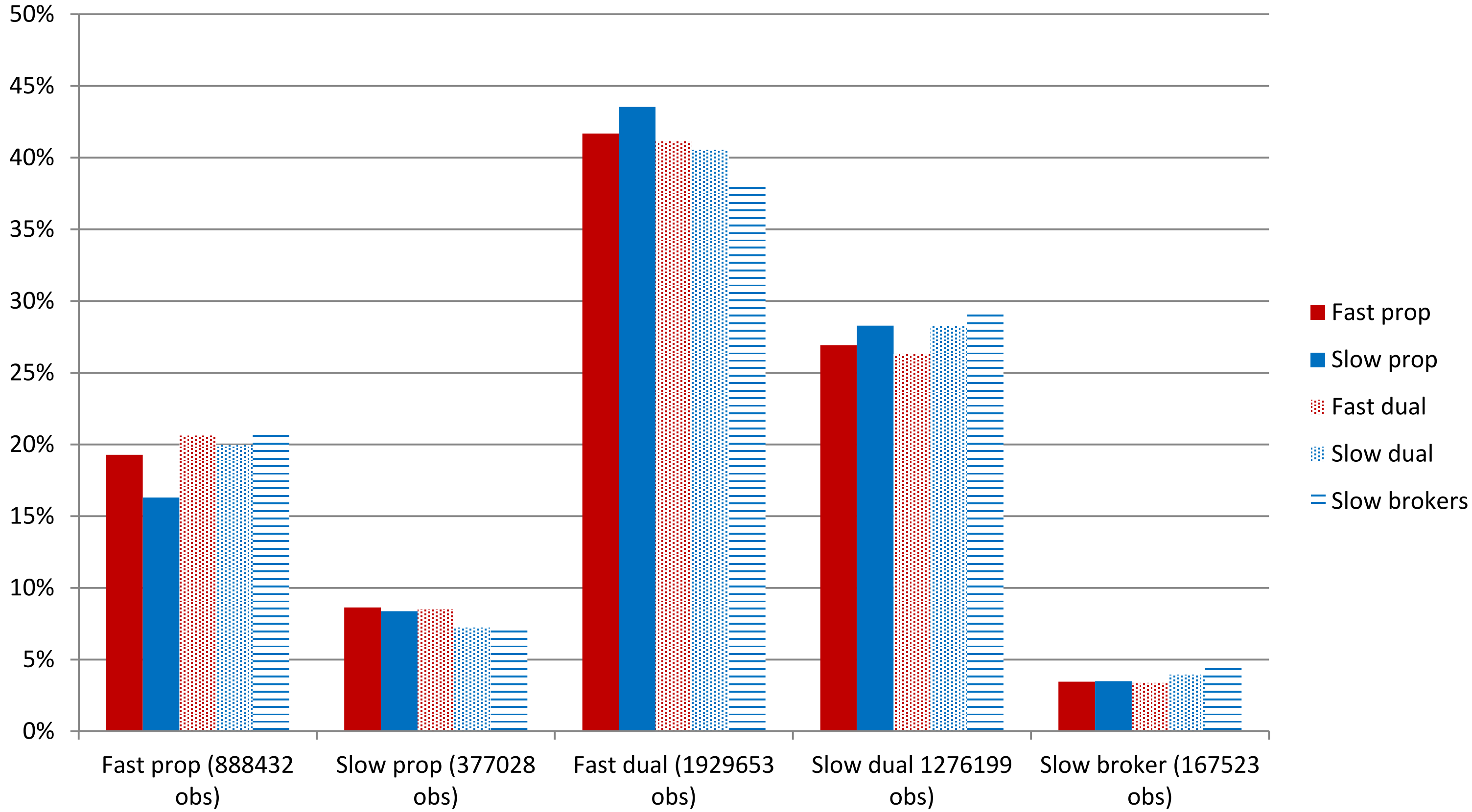


Figure 4: Who trades with whom?



Who placed the marketable order

Who placed the limit order that got hit

Figure 5, Panel A: Average information content of marketable orders

$(M_{t+2min} – M_{t-})/(M_{t-}) * (\text{sign of marketable order}) * 100$

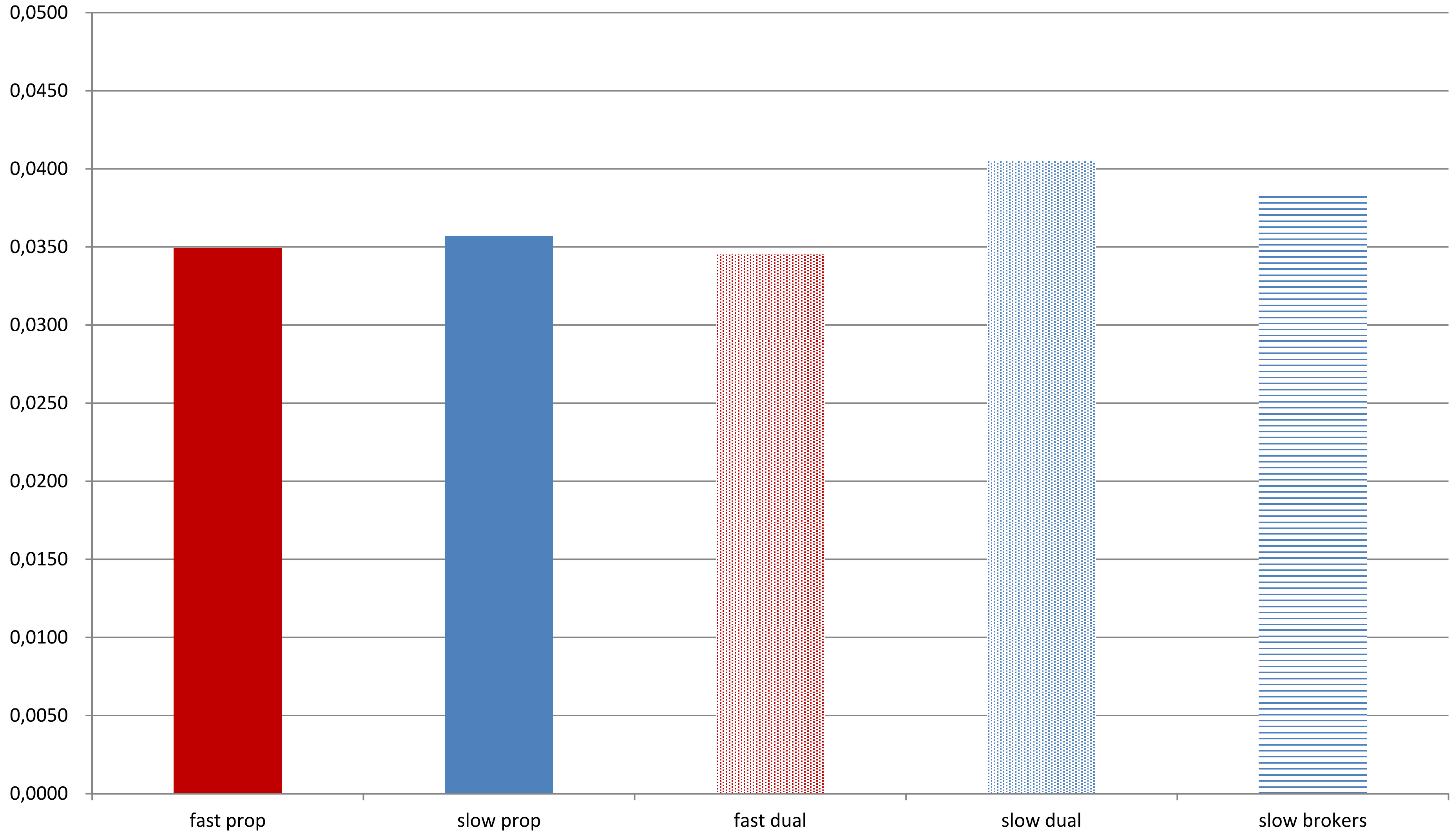


Figure 5, Panel B: How does the information content of marketable orders vary?

$(M_{t+2min} - M_{t-})/(M_{t-})$ * (sign of marketable order) * 100

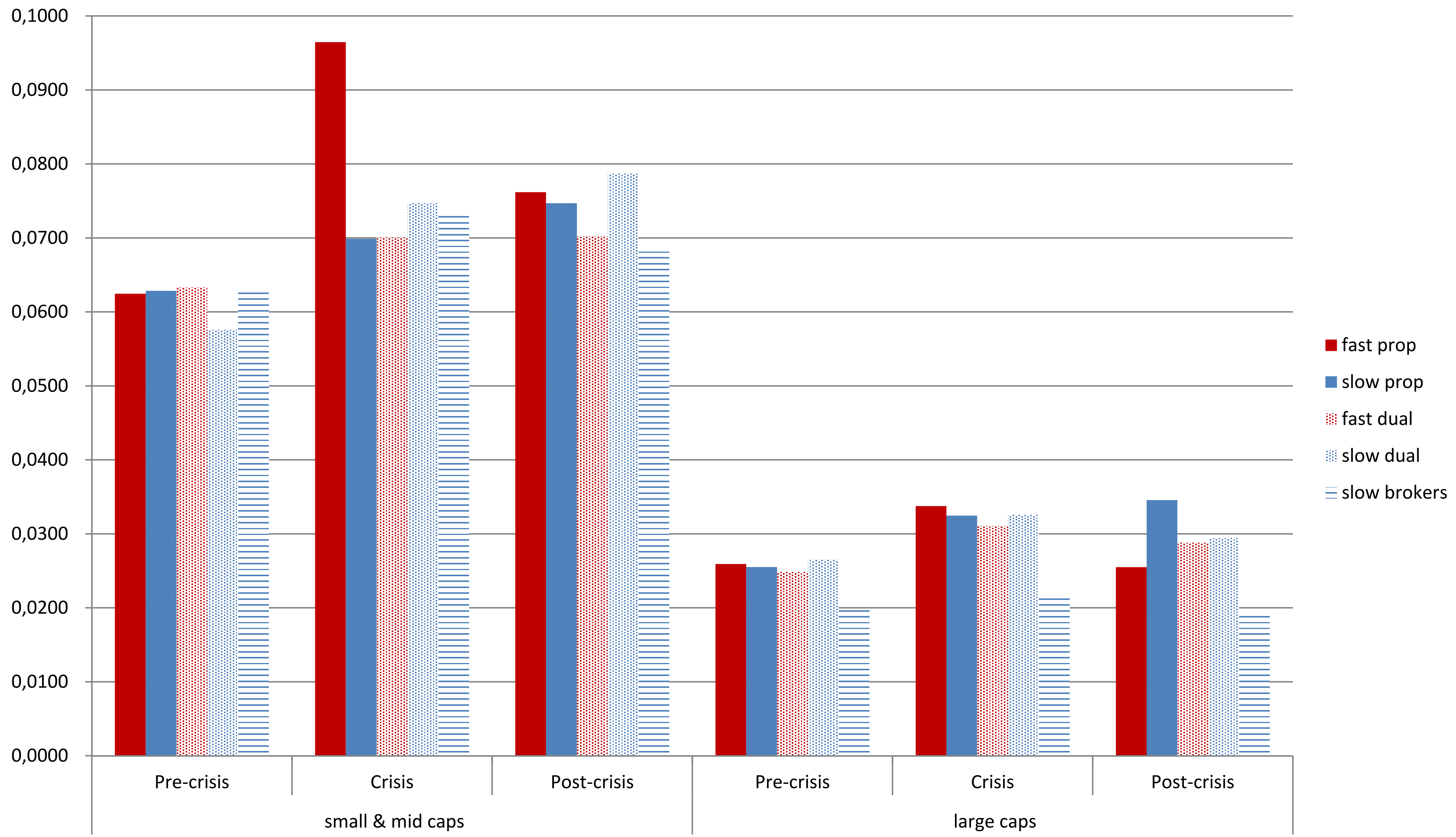
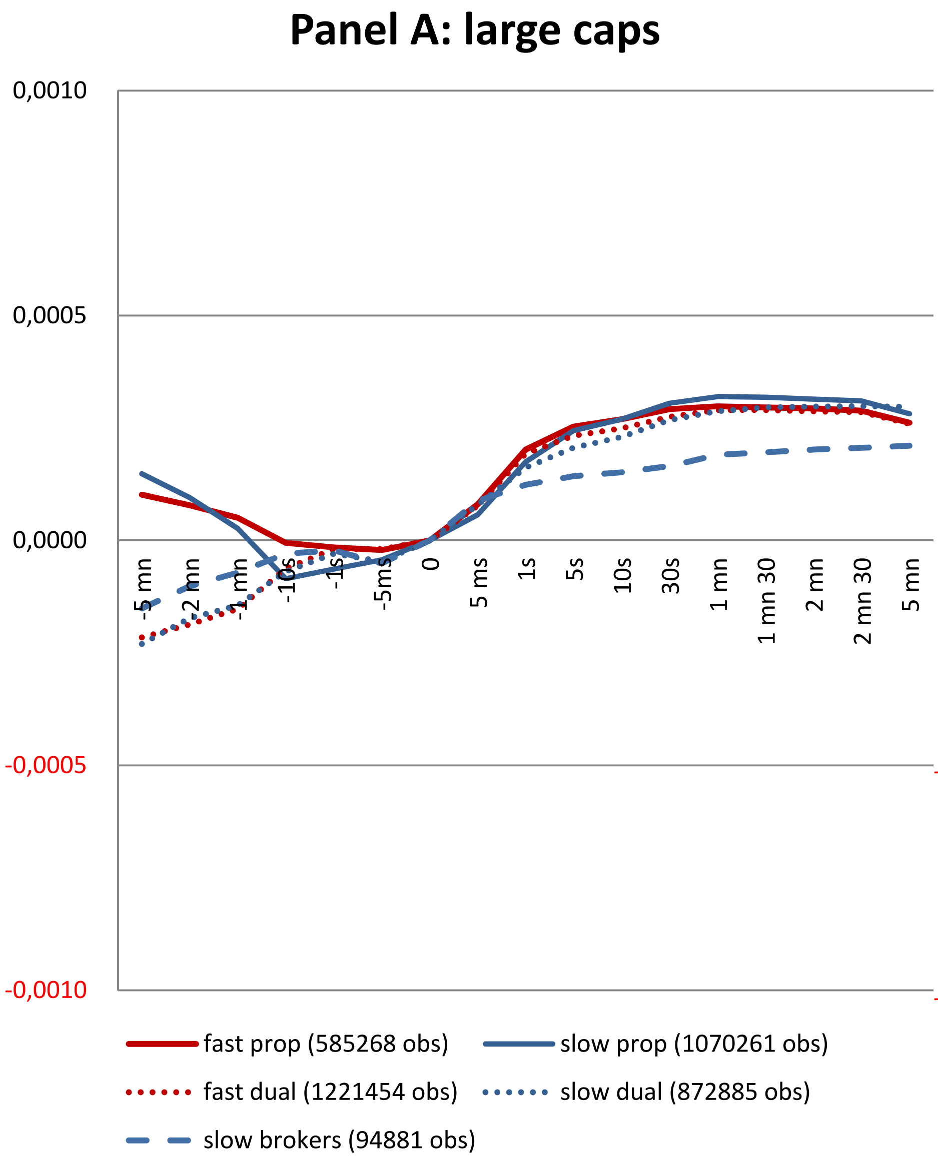


Figure 6: The midquote around marketable order executions



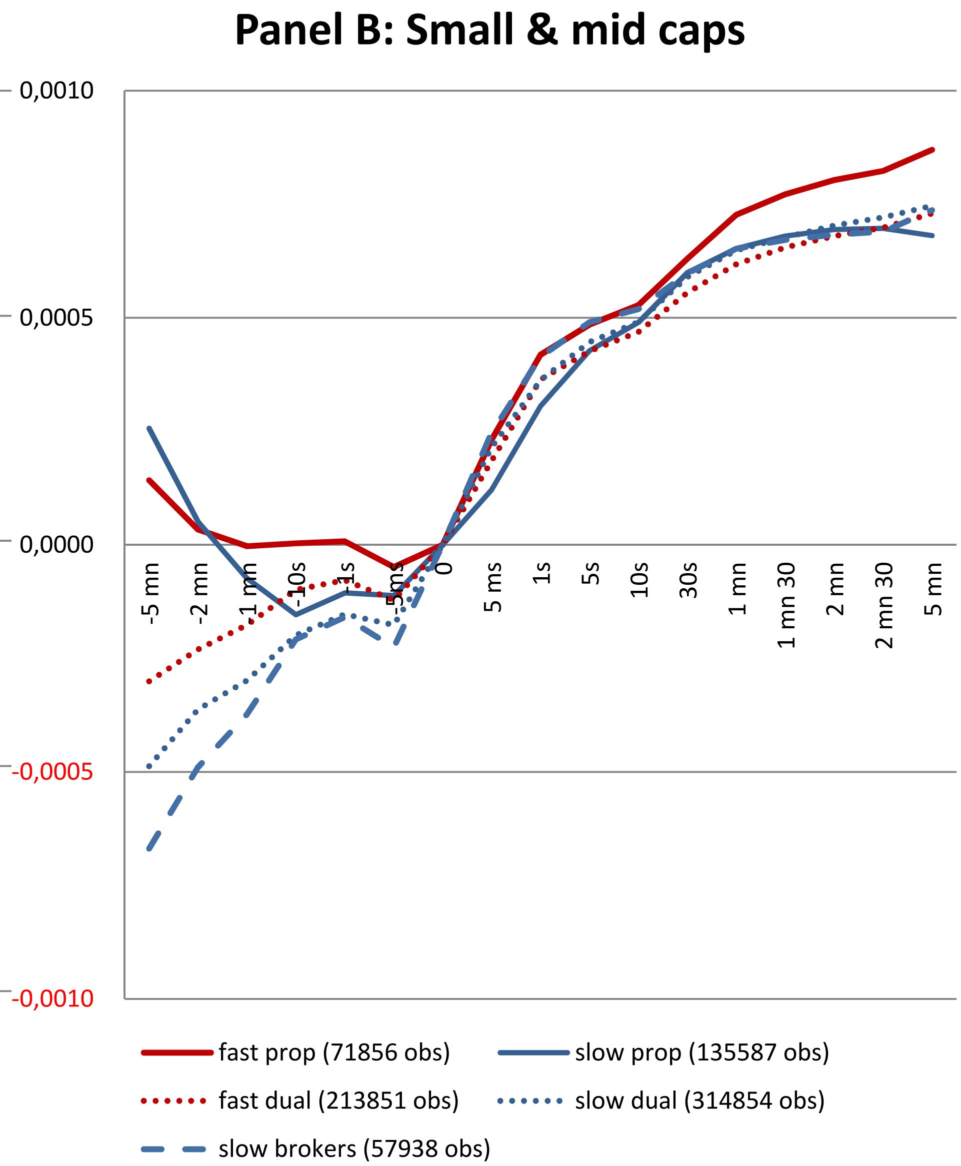


Figure 7: Momentum and contrarian marketable orders during crisis

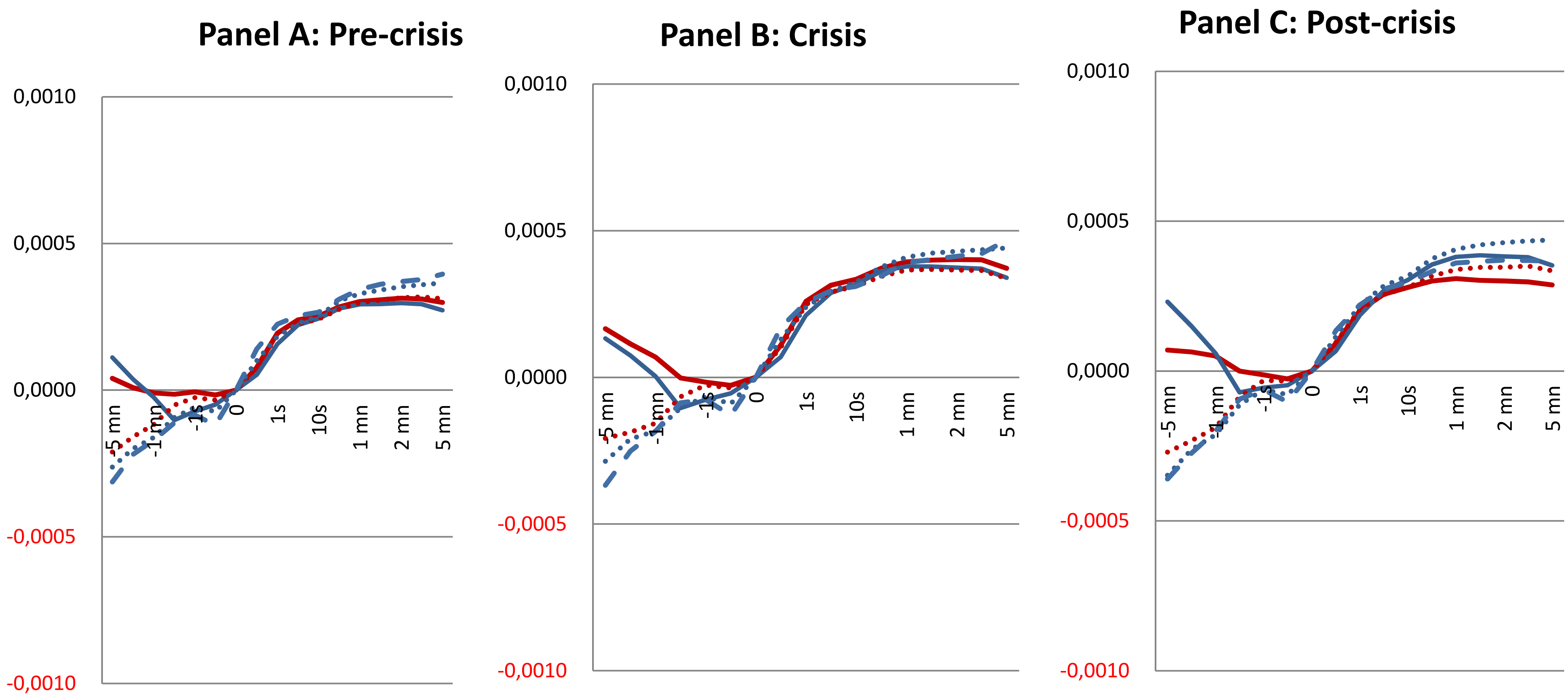


Figure 8, Panel A: Marketable orders' profits

$(M_{t+2min} - P_t)/(M_{t-})$ * (sign of marketable order) * 100

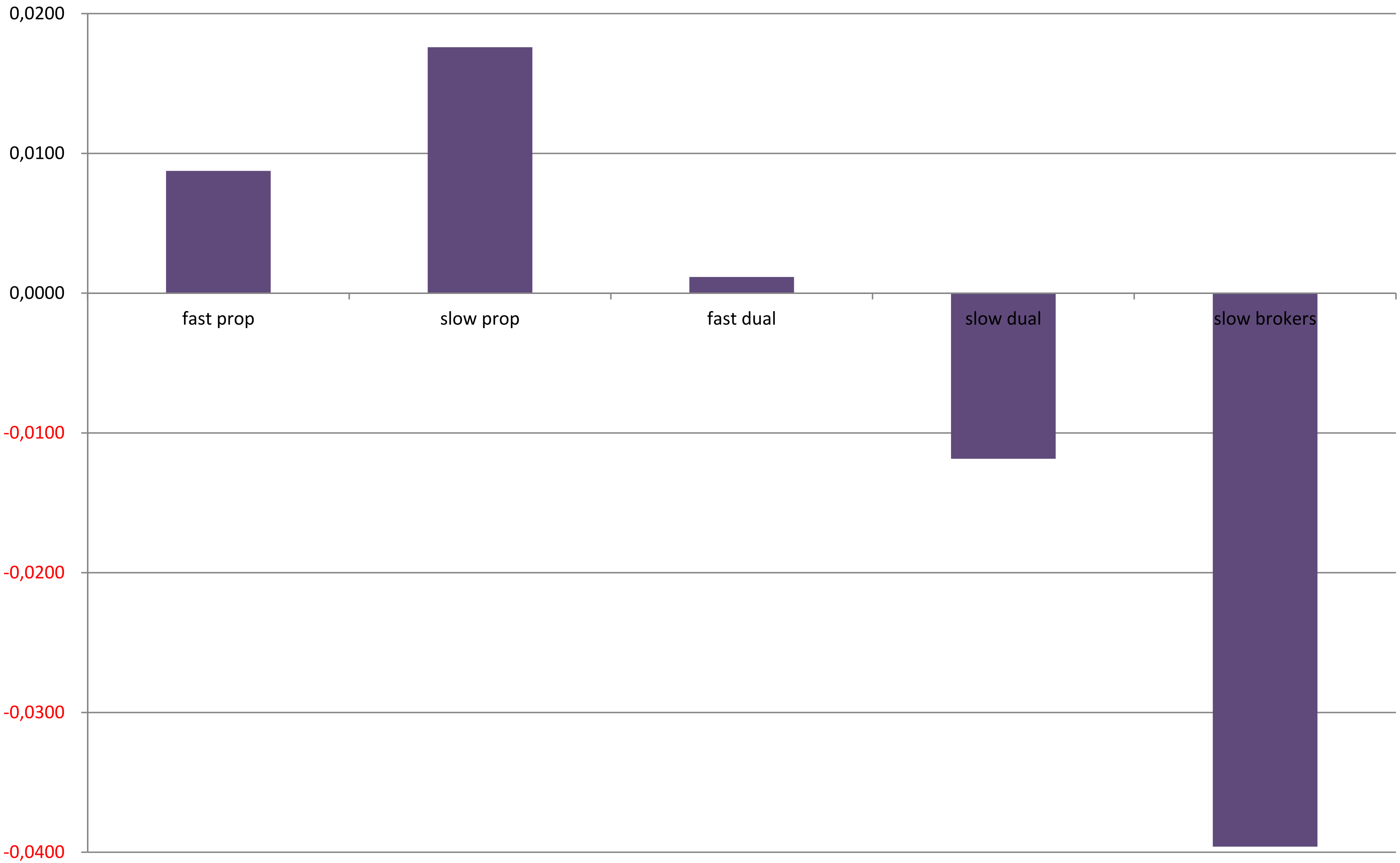


Figure 8, Panel B: Marketable orders' profits by periods and by capitalization

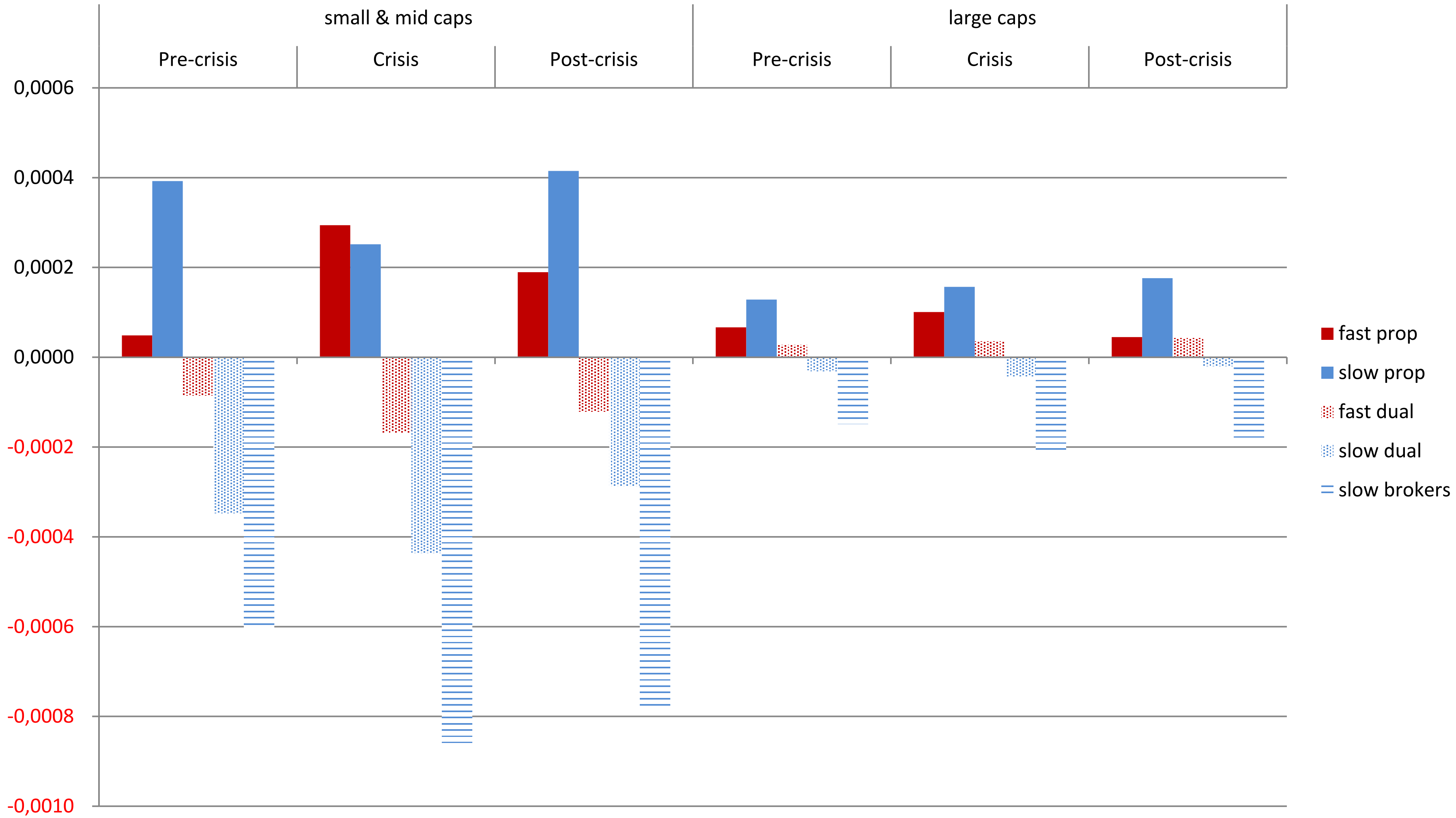


Figure 9:
Prob(marketable order *n* | marketable order *n-1*)

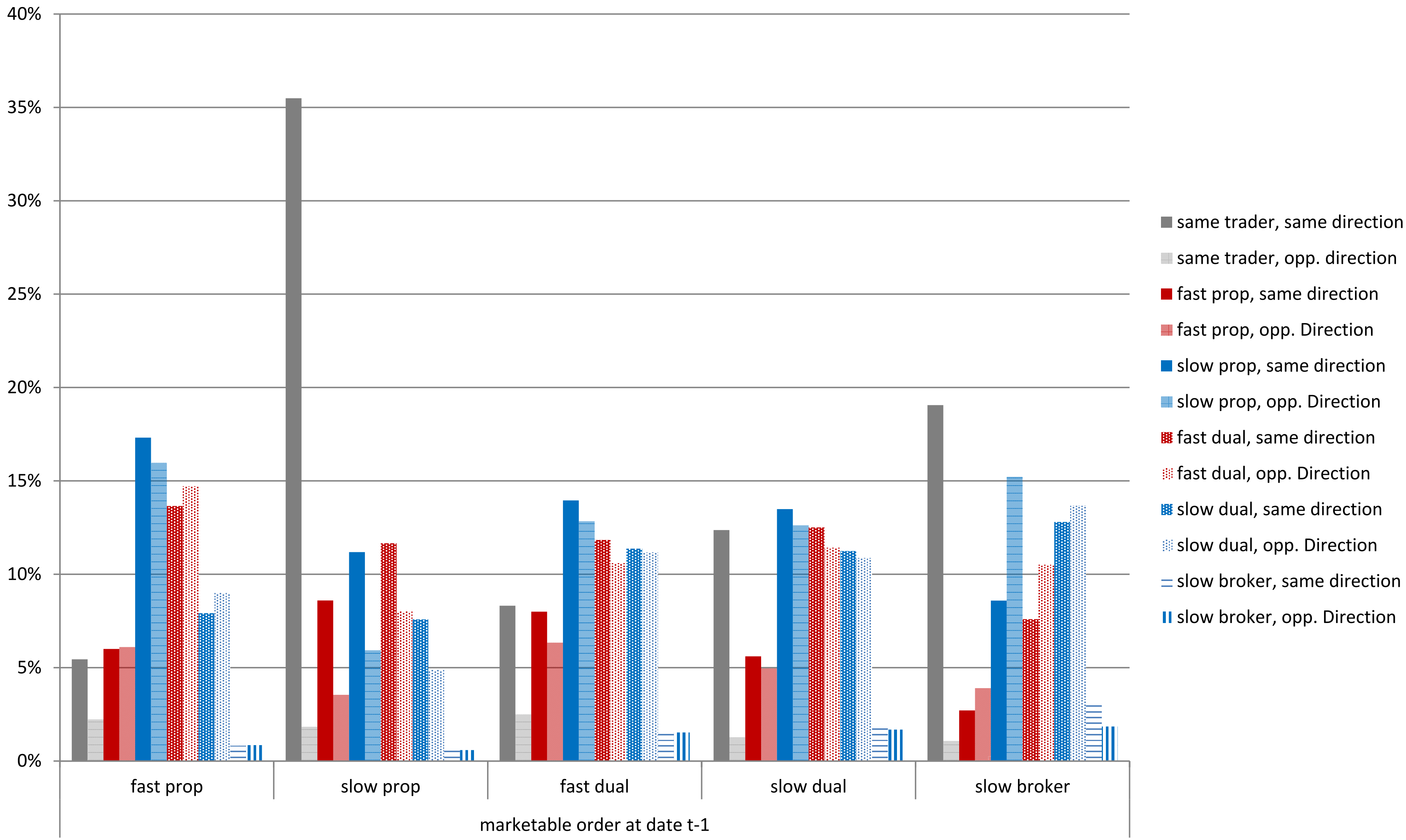


Figure 10,panel A: Adverse selection cost for (non immediately executed) limit orders

$(M_{t+2min} - M_{t-})/(M_{t-})$ * (sign of limit order) *100

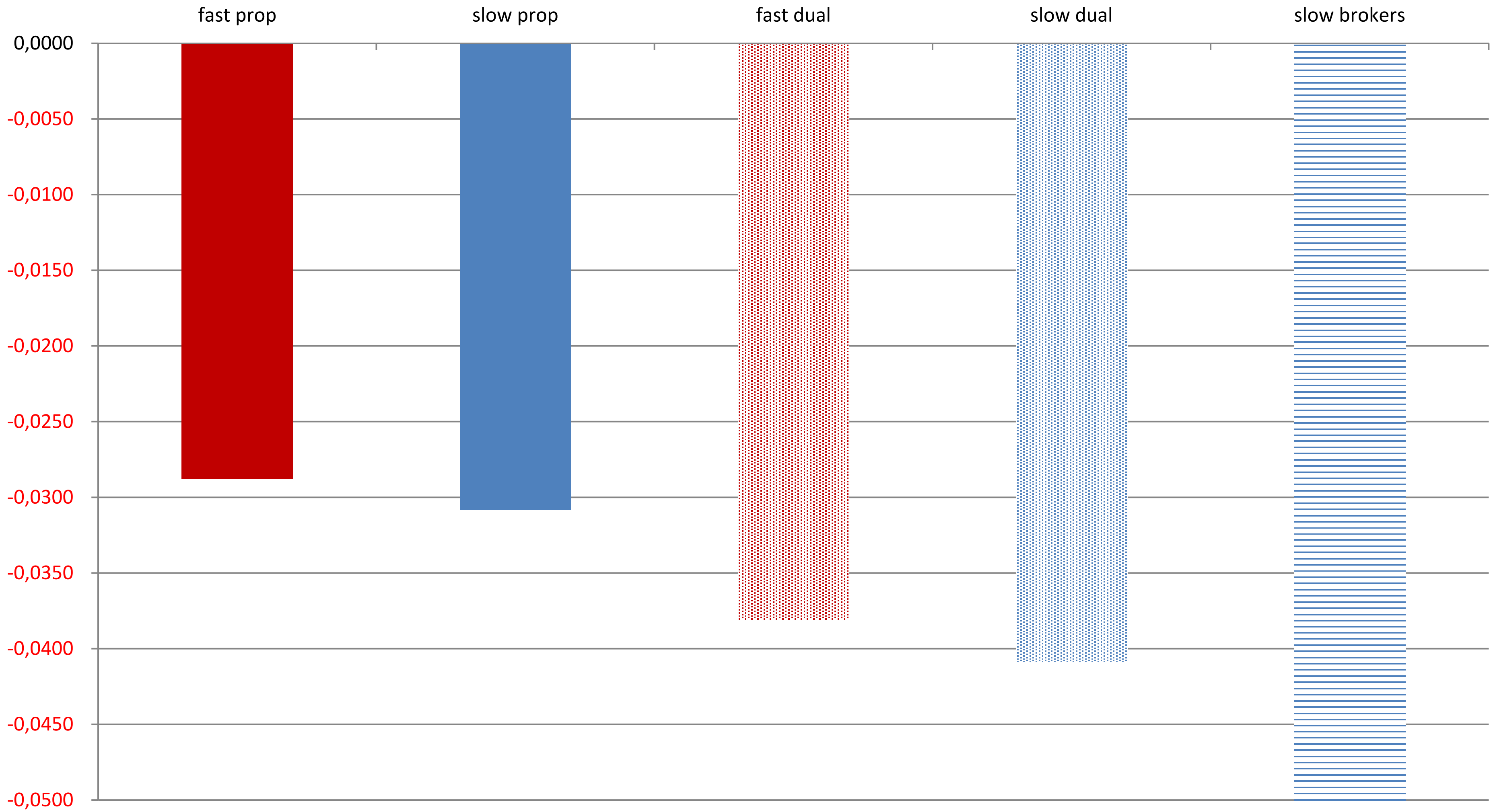


Figure 10, Panel B: Adverse selection cost during crisis

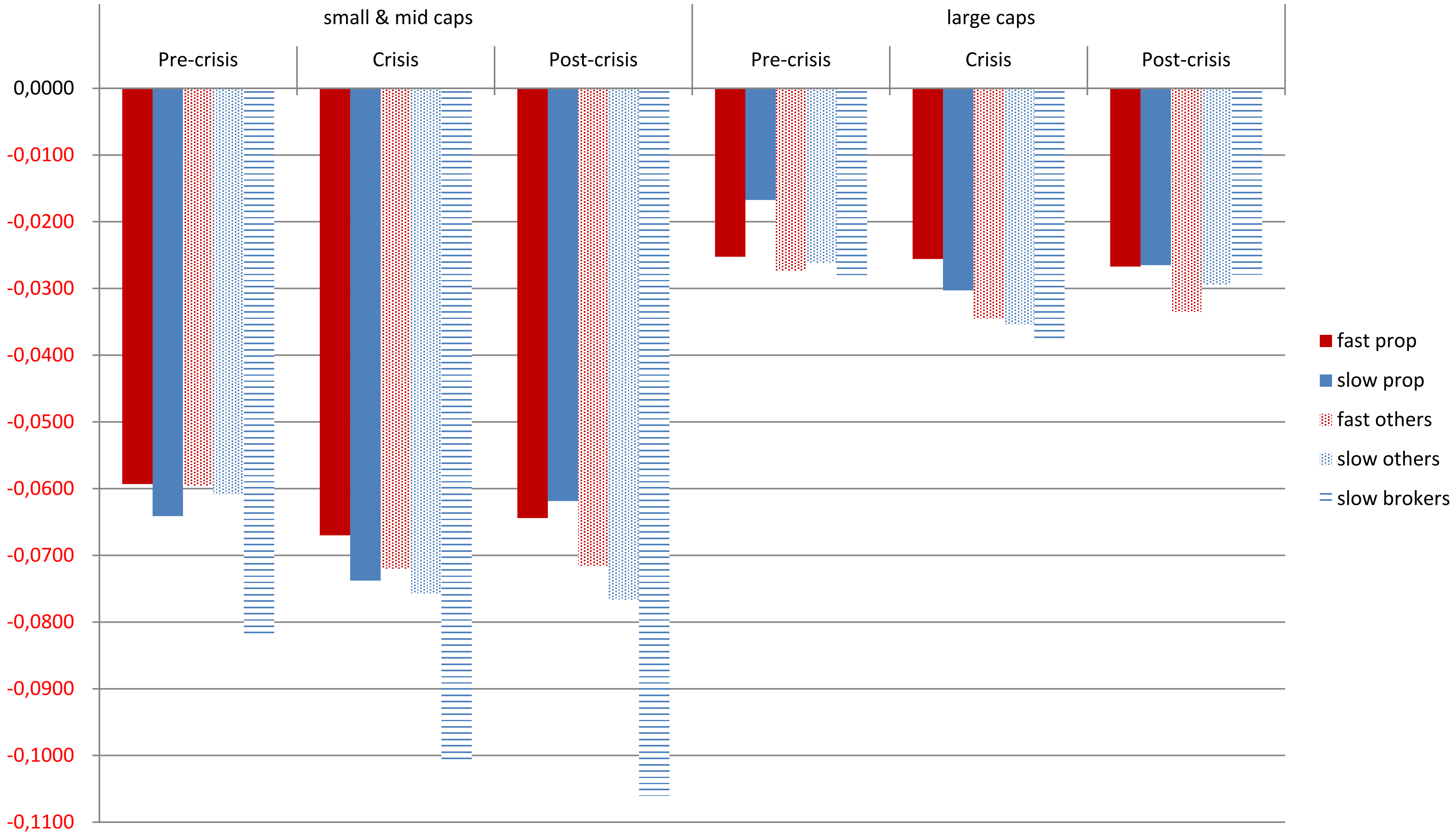


Figure 11, Panel A: Profits of limit orders

$(M_{t+2min} – P_t)/(M_{t-})$ * (sign of limit order) * 100

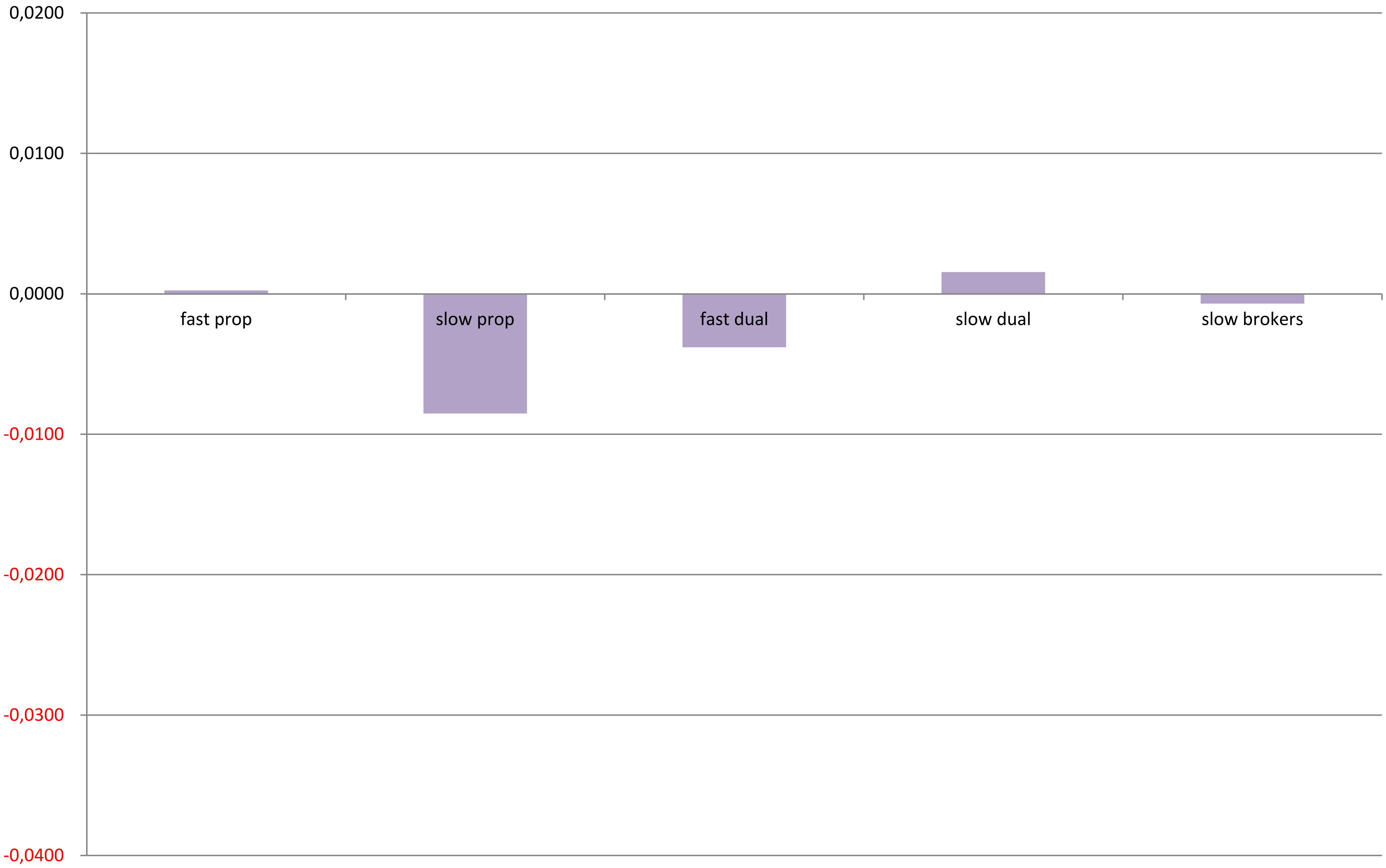


Figure 11, Panel B: Profits of limit orders by capitalization and period

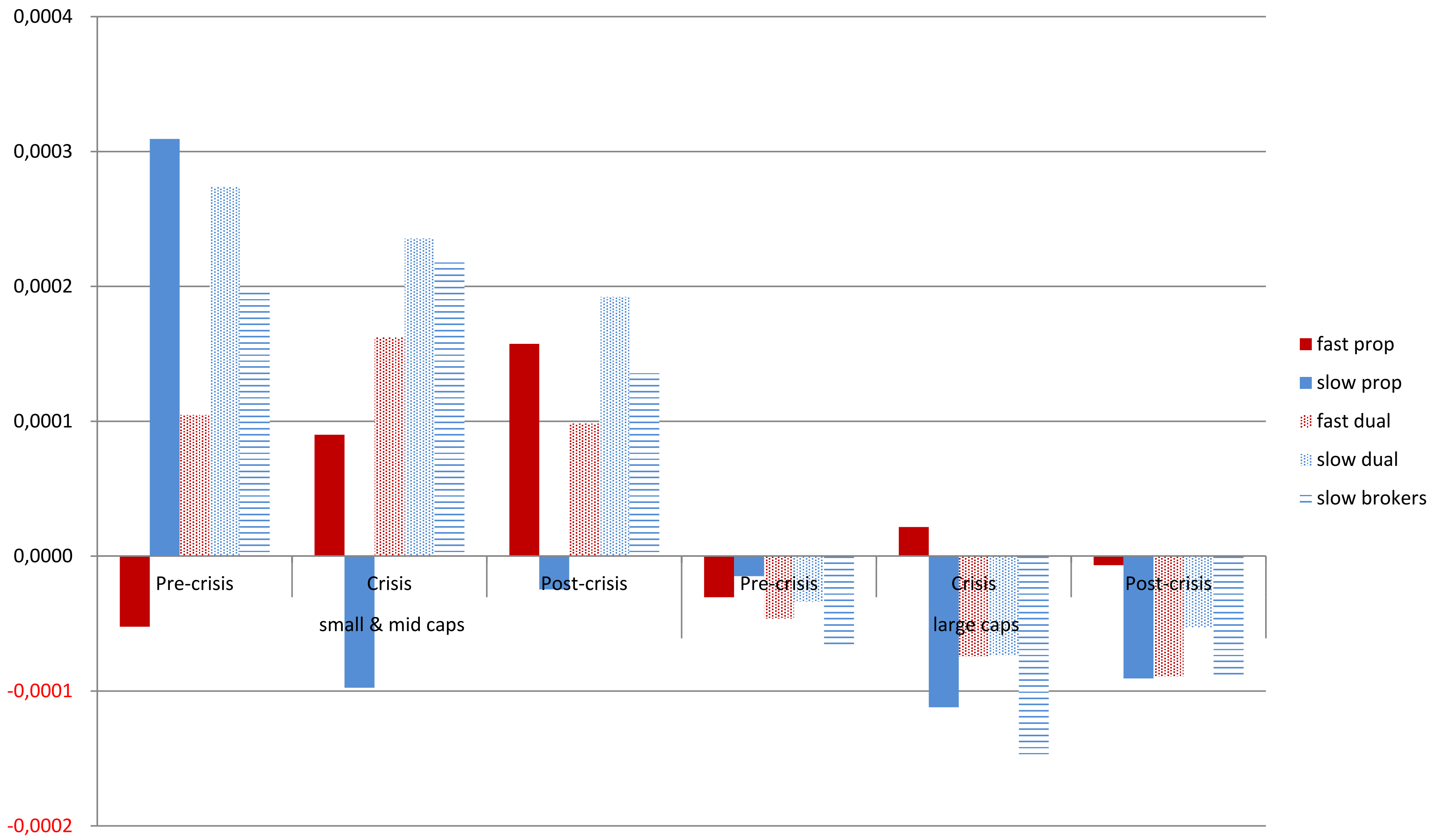


Figure 12: # of cancellations & # of updates to less agressive/# of trades