Centre for
Economic
and Financial
Research
at
New Economic
School

March 2009

Portfolio Transitions and Stock Price Dynamics

Anna Obizhaeva

Working Paper No 224

CEFIR / NES Working Paper series

Portfolio Transitions and Stock Price Dynamics

Anna Obizhaeva*

This Draft: March 22, 2009

Abstract

This paper employs a proprietary data set of portfolio transitions to analyze the short run price-volume relation and its association with the long run performance of newly hired and terminated managers. Unique to our study is its focus on price dynamics that is not affected by potential endogeneity of trading decisions. In the short run, purchases of new stocks induce permanent price increases. Such price changes are especially pronounced for large orders as well as for stocks with a high degree of information asymmetry and negative past returns. In contrast, sales of legacy stocks induce only transitory price declines. In the long run, the evidence shows that institutional sponsors are able to hire managers that are, on average, more skilled than the terminated ones. The apparent benefits of portfolio transitions, however, do not exceed transaction costs.

Keywords: institutional trading, price impact, trading costs.

JEL classification: G14, G23

*Robert H. Smith School of Business, University of Maryland. This paper is a part of my MIT Thesis, and I thank Andrew Lo, Jun Pan, Stephen Ross, and especially Jiang Wang for their helpful discussions and comments. I thank Ron Kaniel and Avi Wohl, who discussed this paper at WFA 2008 and EFA 2007 Meetings. I am grateful to Ross McLellan, Simon Myrgren, and Sebastien Page for their valuable help as well as to Mark Kritzman for his kind support. The paper also benefited from comments by Doron Avramov, Gurdip Bakshi, Larry Harris, Steven Heston, Jiro Kondo, Pete Kyle, Mark Loewenstein, Nagpurnanand Prabhala, Oleg Rytchkov, Russ Wermers as well as participants of seminars at Emory, Goldman Sachs, IESE, McGill, MIT, NES, Northwestern, UIC, Maryland, and at Seattle. All errors are my own. E-mail:obizhaeva@rhsmith.umd.edu

1 Introduction

Central to the analysis of market microstructure is the process of price discovery in financial markets. Markets discover equilibrium prices by responding to buy and sell orders. Disentangling the effect of trades on prices is, however, a challenging task. A key issue is dealing with a feedback effect from prices to trades that exists because price dynamics usually affect the way market participants trade. For instance, Kyle (1985) models trading strategies as endogenous choices made by traders in response to their private information as well as past prices. This endogeneity makes it difficult to interpret the observed price-volume patterns. One could potentially account for endogeneity if there were a well specified econometric model for the joint evolution of trades and prices. However, the diverse nature of possible trading strategies poses a hurdle for this approach.

This work undertakes a different approach to handling endogeneity. It exploits a sample of portfolio transition orders with a unique property. The quantities to be traded are known *before* orders are actually executed. Portfolio transitions are economically significant transactions that involve transfers of funds from legacy portfolios to target portfolios. They are initiated by institutional sponsors wishing to replace their fund managers, rebalance their asset classes, or accommodate large cash inflows and outflows. Institutional sponsors usually delegate portfolio transitions to transition managers who become responsible for selling securities from legacy portfolios and buying securities from target portfolios. The list of orders to be executed is provided to transition managers the night before portfolio transitions begin. Exploiting this property, I study the price-volume relation following the transactions that have been carried out by a leading provider of portfolio transition services. The sample includes about 2,680 portfolio transitions corresponding to a total volume of \$630 billion traded over the period from 2001 to 2005.

The analysis of price-volume relation reveals several patterns. Both buy and sell orders affect prices. Comparing to pre-transition levels, stock prices deviate by 40 basis points upwards following buy orders and downwards following sell orders. I observe these price deviations not only after orders executed through traditional trading platforms but also after transactions on crossing networks (e.g. LiquidNet, PipeLine, Posit). These findings contradict the claim that crossing networks help to avoid execution costs related to price impact and spread. Moreover, initial price deviations are permanent after buy orders and transitory after sell orders. Thus, price dynamics for buy and sell transactions are asymmetric.

The asymmetry of price responses exposes the difference in information content of buy and sell orders. These patterns are consistent with the "smart money" hypothesis, which suggests that institutional sponsors make correct choices and hire fund managers who are, on average, more skilled than the terminated ones. Indeed, institutional sponsors employ sophisticated tools when choosing their managers (Del Guercio and Tkac (2002), Goyal and Wahal (2008), Heisler et al. (2007)). These managers usually provide institutional sponsors with any requested information and often even agree to disclose their current holdings. Based on the snapshots of portfolios during portfolio transitions, I find that the long run performance of terminated and newly hired managers is consistent with "smart money" hypothesis. Specifically, I document that target portfolios outperform legacy portfolios by 25 bps in post-transition months. The benefits of portfolio transitions, however, do not exceed trading costs. Net of trading costs, the return differentials between legacy and target portfolios are indistinguishable from zero.

The "smart money" hypothesis implies that buy orders are initiated by institutional sponsors who try to select the most skilled fund managers who, in turn, try to select the best securities for their clients. Because of this double-selection mechanism, portfolio transition purchases are most likely based on positive signals of skilled fund managers. These purchases represent particularly informative transactions. In contrast, sales of legacy securities are uninformative transactions generated by liquidations of positions of less skilled managers. This asymmetry in information content of buy and sell orders may explain the documented asymmetry in price responses induced by these orders.

Price-volume relationship exhibits patterns that are consistent with information hypothesis across various subsamples of transition orders. For instance, skilled fund managers are expected to have particularly significant information advantage when trading stocks with high degree of information asymmetry. To examine this prediction, I group orders based on the information asymmetry of corresponding securities, as proxied by the number of analysts following them, the bid-ask spread, and the probability of informed trading, and analyze price-volume relationship separately for each group. I find that for securities with high information asymmetry not only does price increase permanently following buy orders but it also continues to increase in post-transition period. The initial price deviations are especially significant for these securities as well. I document also more sizable price responses following larger (and potentially more informative) orders.

Some transition purchases may represent scaling up fund managers' current portfolios (Pollet and Wilson (2008)). Securities in these portfolios have been acquired at different times, and thus scaling up the positions that have been established long time ago may contain only "stale" information. Hasbrouck (1988, 1991) points out that only trades with "new" information content should permanently affect prices. I do not observe the trading histories of fund managers prior to portfolio transitions. However, I use past returns as the proxy for information novelty. The disclosure of information to other market participants prior to portfolio transitions would be reflected in upward price adjustment due to their trading. Therefore, low pre-transition returns indicate that positive information in buy orders is "new," or unknown to other traders. I find that permanent price deviations are large after purchases of stocks with low past returns and insignificant after purchases of stocks with high past returns. Thus, only trades with "new" information seem to induce permanent price changes. These results contribute to the literature on the relation between price impact and past returns (Chiyachantana et al. (2006) and Saar (2001)).

The price-volume relation has been analyzed in prior literature. The work on block trading (e.g., Kraus and Stoll (1972), Holthausen et al. (1987, 1990), Keim and Madhavan (1996), and Gemmill (1996)) and institutional trading (e.g., Chan and Lakonishok (1993, 1995), Keim and Madhavan (1997), Chiyachantana and Jain (2008)) often find that security prices increase permanently after buy orders and decrease temporarily after sell orders. Orders in these studies are, however, not known before the trading starts. They are reconstructed from realized trades. In the Plexus and Abel Noser data sets, for example, orders are reconstructed from trades executed during a 30-day period.

Thus, aforementioned literature has analyzed the price-volume relationship conditional on particular events. For instance, the price responses following block purchases implicitly assume several events, i.e. that orders were chosen to be executed rather than canceled, directed to upstairs market rather then downstairs market, submitted as one order rather than split over time, and also classified as buyer-initiated rather than seller-initiated transactions. Since realized trades as well as classification errors may depend on contemporaneous prices in a systematic way, conditioning on these events potentially introduces an endogeneity bias into documented price patterns. The direction and magnitude of this bias is difficult to assess (Obizhaeva (2009)). In contrast, the quantities to be traded can be precisely predicted in advance in this study. As I document asymmetric price patterns following buy and sell orders as well, my paper reinforces previous findings, among its other contributions.

This study contributes to the literature on price dynamics after trades with different trading motives. The examples include Alexander et al. (2007), Coval and Stafford (2008), and Da et al. (2008) who analyze price responses to liquidity-motivated and information-motivated trades of mutual funds, the information content of which is determined by fund inflows and outflows. Their methodology, however, potentially introduces endogeneity bias into price-volume relationship since both inflow and outflows as well as trades of mutual funds are influenced by contemporaneous price dynamics. Moreover, the authors have to use proxies for actual inflows, outflows and transaction, which they construct from fund holdings and returns. Portfolio transition data, in contrast, contains inflows and outflows as well as orders to be executed, all of which are pre-specified before the actual trading begins.

Portfolio transition orders induce price-pressure and price reversal effects also documented in other settings. The examples include the work on price responses to liquidity trading as indicated by large trading volume and order imbalances (Campbell et al. (1993), Llorente et al. (2002), Avramov et al. (2006), Chordia et al. (2002, 2005), and Chordia and Subrahmanyam (2004)) or to trades that are unlikely driven by private information (Andrade et al. (2008), Kaniel et al. (2005), and Mitchell et al. (2002)). Related are the studies on index inclusions and deletions (Garry and Goetzmann (1986), Harris and Gurel (1986), Shleifer (1986), Kaul et al. (2000), Wurgler and Zhuravskaya (2002), Chen et al. (2004), and Greenwood (2005, 2008)). My study contributes to this literature by examining the price-volume relationship for orders, the quantities to be traded for which are identified before trading in a precise manner.

As Goyal and Wahal (2008), this paper examines economic benefits of institutional sponsors' decisions to replace their fund managers. Both papers conclude that if institutional sponsors had stayed with fired fund managers, their net returns would be not less than those delivered by newly hired managers. To gauge the opportunity costs associated with these decisions, one ideally has to compare returns delivered by new managers with those potentially delivered by old managers if they had not been fired. The comparison has to begin at the exact time of portfolio transitions. Both papers, however, have limitations and compliment each other by exploiting different data sets. Goyal and Wahal (2008) observe actual returns delivered by fund managers over time. The authors are able to compare returns of new managers with returns of old managers delivered for their other clients. The benefits come, however, at a cost of a potential bias because these returns are self reported. In contrast, my analysis relies on snapshots of portfolios during portfolio transitions rather then actual returns. At the same time, the portfolio transition data has advantages in other dimensions. For instance, it contains the exact timing of transactions and the incurred trading costs. The timing is particularly important because, according to my analysis, most performance improvement occurs during transactions when informed traders profit from their superior information but reveal it to the market through trading. The data on trading costs allows to assess decisions of institutional investors after accounting for trading costs.

The paper is structured as follows. Section 2 describes the portfolio transitions data. Section 3 discusses the main findings. Section 4 extends the results for different classes of stocks and trading venues. Section 5 concludes.

2 Data

2.1 Institutional Background

Portfolio transitions are undertaken by institutional sponsors, such as corporate and public pension plans, endowments, union plans, and foundations. Making investment decisions on behalf of their beneficiaries, institutional sponsors typically do not participate in the investment processes directly but choose to delegate their funds to external fund managers. Fund managers, in turn, supervise large funds and might have several other institutional clients. As in mutual funds industry, these managers hold essentially the same portfolios for all clients. Institutional sponsors closely monitor and frequently reshuffle their fund managers. Transfers of funds from terminated managers to newly hired managers are the most common reasons for portfolio transitions. Transitions also happen during changes of asset mix, deployment of new cash inflows, or funds disbursement.

The execution of portfolio transitions is a complicated procedure. If poorly implemented, it may compromise fund annual performance. Portfolio transitions are usually outsourced to professional transition managers. The assistance of external transition manager is needed because the assignment of portfolio restructuring to either terminated or hired managers would create substantial agency problems. Moreover, while being professional money managers, both managers usually lack the expertise in large-scale portfolio rebalancing. These considerations have motivated the birth of portfolio transition management industry that transitions over \$2 trillion worth of assets annually, according to TABB Group report (2008).

A typical portfolio transition is executed along the following lines. First, the manager to be hired is informed a few days or weeks in advance about the decision of the institutional sponsor. Second, the manager to be terminated is notified a day or two before the transition that funds will be withdrawn from his management. In order to avoid the front-running concerns and to verify his actual holdings, the terminated manager is instructed to stop trading. Third, institutional sponsors selects the transition manager either through a bidding process or pre-selecting him in advance. Just before transition, this manager gets to know the list of securities of the terminated manager, which is verified by a custodian, and the "wish" list of securities of the newly hired manager. The transition manager then designs, coordinates and executes portfolio transition from legacy into target portfolios. Upon its completion, he issues a detailed post-trade report for his client.

The main goal of transition managers is to execute portfolio transitions in a cost-efficient way. Managers can split transition orders over time and use alternative trading venues, apart from traditional ones, i.e. internal and external crossing networks. Internal crossing networks are pools of liquidity generated internally either by requests of a passive investment management unit, which is affiliated with a transition company, or by orders of contemporaneously executed portfolio transitions. External crossing networks, such as POSIT, LiquidNet, or Pipeline, are financial systems that match orders without routing them to traditional markets. These networks presumably facilitate cheaper execution, which is, however, uncertain and prone to information leakage.

Several details are important for further classification of portfolio transitions. The terminated managers cannot use portfolio transitions to get rid of the stocks with negative prospects. The composition of legacy portfolios is a snapshot of their positions at the times when fund withdrawals were announced and their trading was frozen. The hired managers make their decisions without observing the composition of legacy portfolios. They have discretion to use portfolio transitions to tilt existing positions towards stocks with favorable prospects. In reality, however, they often recommend portfolios that are similar to the ones of their current clients. The institutional sponsors typically do not modify specifics of the transitions during its implementation. For instance, the transition horizon is usually pre-specified in the transition mandate.

2.2 Data Set

I use a proprietary database of portfolio transitions from a leading provider of portfolio transition services, who supervises more than 30% of transitions in the U.S. The sample includes about 2,680 portfolio transitions corresponding to a trading volume of roughly \$630 billion (\$450 billion are traded in the U. S. markets). These portfolio transitions were executed on behalf of U.S. institutions over the period from January 2001 to December 2005.

This data set is based on the actual post-transition reports prepared by transition managers for their clients.[1] For each transition, each security and each trading day, I observe the number of shares traded, the average execution price, the pre-transition benchmark price as well as the information on transaction costs. This data is given separately for each of three trading venues: traditional open markets as well as external and internal crossing networks, which were described in the previous section.

I also use the CRSP database to obtain data on stock prices, returns, volume, and shares outstanding. The sample includes common stocks (with codes 10 and 11) listed on the New York Stock Exchange, the American Stock Exchange, and NASDAQ in the period of January 2001 through December 2005. Any ADRs, REITS, or closed-end funds are excluded. I remove stocks with missing CRSP information, necessary to construct variables for the

[1] Several related studies analyze selections and termination of fund managers by US and Australian institutional investors; however, they focus on voluntary disclosed or publicly available information (Goyal and Wahal (2008), Parwada and Yang (2004), Parwada and Faff (2005), and Dishi et al. (2006)).

tests. I also exclude low-priced stocks and further check data for any typographical errors and inaccuracies.

The unique feature of portfolio transitions is that the quantities to be traded are known precisely at a specific time before the trades are actually executed. Indeed, the composition of legacy and target portfolios is fixed in transition mandates that transition managers receive the night before portfolio transitions begin. Subsequently traded quantities therefore have to add up to the quantities known beforehand. I reconstruct initial portfolio transition orders from the realized trading sequences. Since these quantities do not depend on the price dynamics unfolding during their execution, I use them to study the price-volume relationship, which is unaffected by endogeneity biases.

2.3 Portfolio Transitions Properties

Table 1 describes main features of portfolio transitions in my sample. Panel A shows that portfolio transitions are large and complicated procedures. A median transition corresponds to a trading volume of about $70 million or almost three million shares traded across 156 stocks. The largest transitions account for trading of billions of dollars across thousands of securities.

Panel B presents the distribution of transition orders across stocks with different market capitalization. I sort securities into five groups based on the stock size. The thresholds for these groups are based on equally-spaced size quintiles for the NYSE stocks. I report then the fraction of orders executed in each size group. The dominance of large stocks is apparent. While about 40% of orders is executed in large stocks, only 9% is traded in small stocks.

Portfolio transition orders are often split over several days. The execution horizon is usually negotiated between transition managers who suggest the optimal trading time as a part of their pre-trade analysis, institutional sponsors who might have additional constraints that require faster trading, and fund managers who may ask for quicker execution to minimize the blackout period during which their ability to trade might be suspended. Panel C describes the portfolio transition durations, defined as the total number of days from the first to the last trade in a given transition. The largest duration, observed in the sample, is equal to 19 days. About 50% of transitions are executed in one day, and most others are completed by the end of the week. Larger transitions are typically executed over longer periods of time; for example, the one-day transitions account only for 19% of total volume traded.[2]

[2] The duration of routine institutional orders is similar. Chan and Lakonishok (1995) show that only 50% of institutional orders or 20% of total dollar value is executed in one day (see also Keim and Madhavan (1995)).

2.4 Portfolio Transition Orders

For portfolio transitions, the quantities to be traded are fixed before their actual executions start. I first describe the magnitude of transition orders and how they are split over time. These properties are important for interpreting my findings. Since the effects of small orders on the security prices are difficult to detect statistically, I exclude them from my sample and mostly focus on transition orders, for which more than 1% of the average daily volume in the previous month is traded through open markets. This sample consists of 79,132 orders (36,544 buy and 42,588 sell orders).

Panel A of Table 2 shows that these transition orders are sizable. In absolute terms, the mean (median) size of open market transactions is about $500,000 ($150,000). In relative terms, their mean (median) size amounts to 4% (2%) of the contemporaneous trading volume. It is worth, however, noting that the magnitude of these shocks is relatively small compared to the total shares outstanding. Their average (median) value is only 3 (1.5) bps of the shares outstanding. Therefore, transition orders are large enough to induce price pressure effects, but not sizable enough to lead to significant changes of security characteristics such as degree of short sale constrains or ownership concentration.

I study the price dynamics starting with the first day of portfolio transitions. Since this dynamics might be directly affected by contemporaneously executed transition trades, it is important to understand to what extend transition orders are spread over time. For each day (relative to the starting day) and each trading venue, Panel B of Table 2 shows the average size of executed trades, normalized by the average daily volume in the previous month. Clearly, most orders are completed by the end of the week with the largest trading volume observed during the first two days. There is no contemporaneously implemented transition trades that can potentially influence price dynamics beyond one week after the first day of portfolio transitions.

3 Price Dynamics After Transition Orders

3.1 Design of Tests

I follow an event-study approach to investigate the behavior of stock prices after portfolio transitions orders. I define the risk-adjusted returns, $r_{i,t}^{adj}$. I adjust returns for their exposure to three risk factors, market value-weighted excess return, a size factor and a B/M factor, as suggested in Fama and French (1992). The composition of target and legacy portfolios might depend on the past returns; therefore, I also augment the model by the momentum factor as in Carhart (1997). For each security and each month, I estimate the factor loadings using five pre-event years of data with at least 24 monthly return observations. I also correct for potential biases due to non-synchronous trading as suggested by Dimson (1979).

For each order i and horizon T, I calculate the cumulative abnormal returns:

$$CAR_{i,T} = \sum_{t=0}^{T} r_{i,t}^{adj} \tag{1}$$

where $r_{i,t}^{adj}$ is the risk-adjusted return of the corresponding security in day t. The time evolves according to the event-time calendar with day 0 being the starting day of portfolio transitions. Horizons up to three months are considered. The use of cumulative returns rather than buy-and-hold returns is advocated by Fama (1998), who argues that the former are subjects to less severe biases, since they are less skewed at longer horizons.

Finally, for each horizon T, the cumulative average abnormal returns, CAARs, and their t-statistics are calculated following the Fama-McBeth procedure for data grouped at monthly levels. This procedure allows me to correct for the cross-sectional correlations between stock returns, which potentially might be induced either by general market dynamics or by portfolio trading. T-statistics are further adjusted with the Newey-West procedure in order to correct for potential intertemporal correlations. The number of lags is chosen by the automatic bandwidth selection procedure; results are similar, if other numbers of lags are used. I also examine the robustness of my results to the changes in estimation design. If I run pooled regressions with clustering at monthly and security levels (or only monthly level), then I obtain very similar standard errors. If I cluster standard errors at security level only, then standard errors tend to be much smaller. Thus, I report the conservative Fama-McBeth estimates of standard errors, adjusted for autocorrelation.

3.2 Results

Table 3 shows the cumulative average abnormal returns, or the CAARs, following portfolio transition orders. Figure 1 plots the CAARs for equally-weighed abnormal returns. Price responses exhibit several patterns. Trades certainly affect contemporaneous stock returns. During the first week, purchases lead to the 0.43%-increase in stock prices, whereas sales coincide with the 0.36%-decline. After initial price pressure effects, the price signatures are asymmetric for buy and sell orders. Sell orders induce only transitory price declines. Initial price changes reverse in several weeks. Buy orders, in contrast, move prices permanently. The gap between the CAARs after buy and sell orders remains at 0.40% at three-month horizon.[3]

Figure 2 depicts the CAARs for principle-weighted abnormal returns. In particular, the weights are equal to the sizes of open market trades, normalized by the average daily volume in the previous month. For robustness, 1% of extreme observation of weights is truncated for each month. This weighting scheme results in price deviations that are twice more pronounced than for the equally-weighted one.

Figure 3 illustrates the CAARs for abnormal returns are weighted with the market capitalization in the previous month. The price responses differ from the equally-weighted case. The initial price reaction tend to be less significant. Stock prices increase by only 0.17% for purchases of new stocks and decrease by 0.25% for sales of legacy stocks. At longer horizons, the initial price deviations disappear, and stock prices become indistinguishable from their pre-transition levels for both purchases and sales. I observe similar patterns if I do not exclude small trades from the sample, since numerous small trades do not affect security prices significantly (not reported).

The documented price pressure effects might be potentially attributed to a bid-ask bounce. Price deviations, however, are too large to be entirely explained by these effects. For stocks in the sample, the typical percentage spread is equal to 20 bps. Since the magnitude of contemporaneous price impact is approximately 40 bps for both purchases and sales, bid-ask bounce can explain only 25% of temporary price deviations (10 bps).

In summary, my analysis suggests that security prices deviate from their pre-transition levels as markets accommodate portfolio transition orders. After sales, price deviations are transitory, and prices reverse to pre-transition levels over a subsequent week. After purchases, stock prices shift to new levels permanently.

3.3 Information Hypothesis

The differences in information content of transition purchases and sales can potentially explain the asymmetry of induced price-volume relation. Indeed, trades with different trading motives are expected to trigger different price responses, as emphasized in Hasbrouck (1988, 1991), Llorente et al. (2002), and Wang (1994). On one hand, information-motivated trades reveal new information and induce a permanent price increase. If traders are risk averse and information is only partially impounded into prices, then even price continuation might follow. On the other hand, liquidity-driven transactions result in a transitory price drop, as security prices deviate to attract risk-averse liquidity providers. When the later are compen-

[3]In a two-week period prior to transitions, stocks in target (legacy) portfolios have statistically significant (insignificant) abnormal returns of 33 bps (8 bps). In a one-week period prior to transition, abnormal returns for stocks in target and legacy portfolios are both insignificant and equal to 14 bps and -1 bps, respectively.

sated for their services, the price deviations vanish. Thus, the documented price patterns reveal that buy orders seem to contain positive information whereas sell orders lack any negative information about future stocks' prospects.

Buy orders are generated by institutional sponsors who try to select the most skilled fund managers who, in turn, try to select the best securities for their clients. Several arguments suggest that this double-selection mechanism implies a particular informativeness of transition purchases. First, when choosing fund managers, institutional sponsors follow sophisticated procedures and heavily rely on recommendation of professional consultants (Del Guercio and Tkac (2002), Heisler et al. (2007)). The hiring process usually consists of several steps. It starts with initial screening, which typically involves evaluation of managers' past performance and its consistency, and ends with several rounds of personal interviews in order to evaluate qualitative characteristics of managers. Institutional investors might even ask candidates to reveal and explain their current holdings. This sophisticated selection process implies a particular relevance of the "smart money" hypothesis in institutional settings. In fact, the hiring decisions of institutional sponsors might help identify a set of managers with abilities.

Second, fund managers often can select stocks that deliver abnormal returns. Wermers (2000) summarizes the general conclusion of the literature in his comprehensive study of the mutual fund industry. He reports that funds hold stocks that outperform the market by 1.3 percent per year. If fund managers can deliver abnormal returns (even though these returns do not survive trading costs), then their trades, on average, contain information. Moreover, newly hired managers might use portfolio transitions to tilt their portfolios towards currently attractive securities. Thus, purchases of new securities during portfolio transitions are most likely based on positive signals of skilled fund managers.

Sell orders, in contrast, represent liquidation of positions of less skilled managers. The terminated managers have to hand in to transition managers the exact list of their current holdings. Even though the realized past performance of these managers might be negative, the termination of their positions will imply no particular information rather than negative information about future prospects for stocks in their portfolios.

The previous literature on institutional trading and block trading has suggested another explanation for the difference in a degree of informativeness for buy and sell orders. Institutions buy securities out of a broad universe of securities available in the market, whereas they sell the securities out of a much smaller subset of securities in their current portfolio, if short selling is costly or unavailable. Purchases, consequently, convey stronger signals than sales. For portfolio transitions, similar argument might be applied to a selection of fund managers to terminate and to hire by institutional sponsors. They, indeed, select the former among those available in the market and the later among their current fund managers.

Consistent with the information hypothesis, the equally-weighted CAARs increase permanently following transition purchases and decrease temporarily following transition sales. The value-weighted CAARs do not exhibit asymmetric patterns, because when trading larger securities, newly hired managers might have less significant information advantage over other market participants. The asymmetry of the principle-weighted CAARs is more pronounced, because this scheme puts more weight on larger and potentially more informative orders.

3.4 Long Run Performance of New Managers

I find that the short run price-volume relation and the information hypothesis are consistent with the long-run performance of newly hired and terminated fund managers. To examine whether institutional sponsors are able to choose more skilled fund managers, I analyze "round-trip" decisions of institutional sponsors, namely, portfolio transitions that include both legacy and target portfolios. The sample contains 1517 two-sided transitions.

Table 4 shows that target portfolios, on average, outperform legacy portfolios. Starting with a transition month, the cumulative returns of target portfolios are larger than those of the corresponding legacy portfolios by about 25 bps over the next six months. It is worth mentioning that this performance improvements mostly occur during portfolio transitions. Target and legacy returns do not diverge further after transition month. These price patterns imply that newly hired fund managers profit from their superior information but this information is being revealed to the market through trading. Also, my analysis shows that the performance improvement is more significant for bigger portfolio transitions. Perhaps, institutional sponsors, who are responsible for allocation of larger funds, are more knowledgeable and spend more resources when searching for fund managers.[4]

The magnitude by which target portfolios outperform legacy portfolios is statistically significant but relatively small. Assuming an annual turnover of funds is 200%, my results imply a 50 bps difference in returns delivered by more skilled and less skilled fund managers per year. Several reasons can potentially explain a small magnitude of these return differentials. Managers might have only a limited discretion in deviation from their benchmarks. They might place orders based on "stale" information rather than "new" information, as I discuss in Section 4.2. Black (1986) also points out that "because the actual return on a portfolio is a very noisy estimate of expected return, even after adjusting for returns on the market and other factors, it will be difficult to show that information traders have an edge".

[4]Tests of Section 3.2, implemented on a sub-sample of two-sided transitions, deliver results which are similar to aforementioned ones.

The documented performance improvement, however, does not survive trading costs. Panel A of Table 5 reports the realized trading costs for a sample of portfolio transitions. The typical trading cost is 11 bps for buy orders and 18 bps for sell orders. Explicit costs (fees and taxes) account for about 3 bps, implicit trading costs (price impact and bid-ask spread) account for the rest. Panel B of Table 5 shows the difference between cumulative return of legacy and target portfolios, net of realized trading costs. After adjustment for trading costs, target portfolios underperform (corresponding) legacy portfolios by 3 bps, this net return differential is not different from zero in statistical terms.

These results are broadly consistent with Goyal and Wahal (2008), who employ a manually matched sample of "round-trip" firing and hiring decisions. Comparing to their sample, portfolio transition data is more detailed in some dimensions. For instance, transition data contains exact timing of transactions and incurred trading costs. The former is particularly important because, according to my analysis, most performance improvement occurs precisely during portfolio transitions. The later allows to assess decisions of institutional investors after accounting for trading costs. The advantage of Goyal and Wahal (2008) is that the authors use actual returns delivered by fund managers rather than snapshots of legacy and target portfolios during portfolio transitions. This data allows them to analyze performance at longer horizons. The benefits come, however, at a cost of a potential bias because these returns are self reported.

3.5 Alternative Explanations

Several alternative explanations might induce the asymmetry in price responses to buy and sell orders. For instance, investors tend to mimic each others behavior. If institutional sponsors select the same managers and flock into the same security classes, or trade out currently unpopular positions, then their herding behavior might generate the pressure on security prices. This idea is formalized in Vayanos and Woolley (2009). Herding effects might be more pronounced and long-lasting for the securities being bought rather than for the ones being sold. Since investors tend to hold different portfolios, their sales might be less correlated than their purchases. Therefore, herding among institutional investors might potentially lead to asymmetric price responses following buy and sell orders.

To check a validity of herding hypothesis, I analyze autocorrelations of portfolio transitions order imbalances:

$$(OI)_{i,t+1} = \alpha + \beta \times (OI)_{i,t} + \epsilon_t \tag{2}$$

where $(OI)_{i,t}$ are the signed order imbalances of transition trades for stock i in period t, normalized by the trading volume in the previous month. I consider weekly, monthly as well as quarterly frequencies. I also split the sample into two subsamples, for which current order imbalances are positive and negative.

Table 6 presents the estimates of (2) and their Fama-McBeth standard errors. Transition orders are certainly autocorrelated at weekly frequencies. Weekly order imbalances follow by five times smaller order imbalances of the same sign. This significant autocorrelation reflects the practice of transition managers to split orders over several days. At monthly and quarterly frequencies, transition purchases are not, however, autocorrelated, whereas transition sales exhibit positive but economically insignificant autocorrelation. These results suggest that the asymmetry of price-volume relation can not be explained by the herding hypothesis.

Several other effects might potentially influence price dynamics. For instance, if no perfect substitutes are available for securities, then their excess demand and supply curves might not be flattened by risk-averse arbitrageurs. In this case, trades will induce permanent effects on security prices (Garry and Goetzmann(1986), Shleifer(1986), Kaul, Mehrotra, Morck(2000), Wurgler and Zhuravskaya(2002)). This mechanism, however, would explain the asymmetry between purchases and sales only if a hedge were more expensive for a short rather than for a long position.

Transition trades might also change the composition of investors who hold securities: large purchases increase the institutional ownership of acquired securities. Boehmer and Kelley (2007) show that stocks with greater institutional ownership are priced more efficiently. Indeed, the increase in the number of institutions that hold stocks might increase the number of analysts following them and therefore induce the competition among informed traders. Transition purchases might, consequently, enhance efficiency and, decreasing the future trading costs, shift security prices upwards. Moreover, large purchases might create block holders who tend to monitor firms more closely and thus contribute to the increase of their value. I believe, however, that transition orders are not large enough to trigger these effects. For example, Boehmer and Kelley (2007) detect the improvement in market efficiency after changes in institutional ownership of the magnitude as large as 60 bps of shares outstanding. In comparison, the average size of portfolio transition orders is only 4 bps (Table 2). It is also unclear why the opposite effects would not be observed for transition sales.

Finally, portfolio transition purchases might aggravate the short-sale constraints, since large purchases make the ownership more concentrated and since institutional sponsors are usually reluctant to be engaged into short selling. Miller (1977) points out that the prices of constrained stocks may be inflated because they reflect exclusively the beliefs of optimistic investors. Thus, the change in the severity of short-sale constraints can explain permanent price changes after buy orders but not transitory price change after sell orders. Also, transition orders are too small to make these effects significant.

4 Cross-Sectional Results

4.1 Price Dynamics and Information Asymmetry

When trading in stocks with a high degree of information asymmetry, informed traders have particularly significant advantage over other market participants. These trades therefore might induce larger permanent price adjustments. I next examine how price-volume relation varies across stocks with a different degree of information asymmetry. Since this stock characteristic is unobservable and there is no agreement on how to define its best proxy, I use several proxies.

The first proxy is $ANUM$, the number of analysts who follow stocks or, in other words, produce information about firms. In particular, I use the number of analysts who provide I/B/E/S with their end-of-fiscal-year forecasts of earnings. Analysts following a stock alleviate the information asymmetry about its prospects. Trading in stocks with greater number of analysts therefore is associated with lower adverse selection costs. The second measure of information asymmetry is $SPREAD$, the percentage spread. This proxy reflects the likelihood of trading against informed traders from the perspectives of market participants. Stocks with higher information asymmetry tend to have wider percentage spread. The third measure of information asymmetry is PIN, the probability of information-motivated trading, which is constructed following the algorithm of Easley et al.(1996). Larger PIN reveals a higher degree of information asymmetry. Easley et al.(1996), for example, show that PIN is closely related to the spread which is, in turn, tightly linked to the adverse selection costs of trading. Based on these proxies, I sort portfolio transition orders into three groups and analyze their price-volume relations. The "Low" group includes bottom tercile and the "High" group includes top tercile of orders with the lowest and the highest degrees of information asymmetry, respectively.

It is worth acknowledging that $ANUM$, $SPREAD$, and PIN are only noisy proxies for unobserved information asymmetry. For example, Boehmer et al. (2006) show that inaccuracies in trade classification might lead to the biased estimates of PIN. The number of analysts $ANUM$ is frequently unidentified for the stocks with potentially high information asymmetry, since analysts do not regularly report on them. The effective spread $SPREAD$ represents only one aspect of liquidity along with price impact and resilience. Moreover, the exact functional form of cross-sectional relation between these measures and a degree of asymmetry is unknown. Regardless of the proxy employed, I observe qualitatively similar price-volume relations.

Reported in Table 7, the CAARs following transactions in “Low” and “High” groups provide additional insights on price dynamics after portfolio transition orders. The initial price pressure effects tend to be more pronounced for stocks with greater adverse selection risk. The consequent price dynamics notably differ between groups for buy orders. For buy orders from “Low” group, initial price changes are transitory. For buy orders from “High” group, in contrast, initial price deviations are permanent. Moreover, they are followed up by further price increase in post-transition period. For example, the CAARs are 53 bps, 61 bps, and 101 bps at one week, one month and two months horizons, respectively, for orders in “High” group, when I use $ANUM$ as a proxy for the degree of information asymmetry. At the same time, the corresponding CAARs for orders in “Low” group are not (statistically) different from zero.

Proxies for information asymmetry are highly correlated with market capitalization. Smaller stocks typically have larger spreads and higher PIN as well as fewer analysts following them. For example, the correlation between PIN and stock size is -0.60 in my sample. To disentangle effects of information asymmetry from those of stock size, I use a double-sorting procedure. Each month, observations are first sorted into three groups based on their stock capitalization and then, within each size group, they are further clustered into two subgroups according to their information asymmetry. Tables 8 presents the results for securities sorted on size and $ANUM$. Permanent price impact is the largest for stocks with lowest market capitalization and lowest $ANUM$. Similar patterns prevail if other proxies are considered (not reported). I skip reporting the CAARs after transition sales, since they are not statistically different from zero at long horizons. To summarize, documetned price patterns for orders in stocks with different degree of information asymmetry are consistent with the information hypothesis.

4.2 Price Dynamics and Past Returns

Hasbourck (1988, 1991) emphasizes that if trades contain different types of information, then price responses to these trades should be different. Trades with “new” information should induce permanent price shifts, as the market learns about this information. In contrast, trades with “stale” information should not affect security prices significantly, as they do not bring new evidence into the marketplace. I next analyze how information novelty influences the price-volume relation.

Information content of transition purchases might be "new" or "stale". Indeed, although newly hired fund managers can potentially use portfolio transitions to tilt their current positions towards better securities, they often recommend portfolios that are similar to portfolios of their existing clients. Securities in these portfolios have been bought by fund managers at different times. Some stocks have been acquired very recently, and favorable information about their prospects has not been yet fully incorporated into security prices. Buy orders that mimic these stocks contain "new" information. Other stocks have been acquired into funds long time ago, and positive signals about these stocks have been already impounded into security prices. Buy orders that mimic those might reflect "stale" information.

A complete trading history of newly hired managers would unable me to differentiate these cases. Since I do not observe the identity of fund managers, however, I cannot match portfolio transitions data to that on institutional holdings. Instead, I suggest to use risk-adjusted past returns to identify observations with "new" and "stale" information. Low past returns might indicate the novelty of information behind transition purchases, whereas high past returns might reveal its obsoleteness.

The logic behind this identification argument is as follows. If traders get information about stock's positive prospects, they begin acquiring this security into their portfolios. As they walk up a demand curve, stock price increases (Kyle (1985)). At early stages of their trading, most information is still "new" and average past returns are not particularly high. Therefore, price signatures following their early trades will exhibit large permanent price changes. At later stages of their trading, most information is already "stale" and past returns are high. Therefore, price signatures following their last trades will exhibit only small permanent price changes.

Table 9 shows how post-transition price dynamics depends on pre-transition returns. I report the CAARs for stocks grouped based on their risk-adjusted returns in pre-transition quarters, $R^{adj}_{-3m,-1d}$.[5] The "Low" group includes bottom tercile of stocks with negative risk-adjusted past returns, and the "High" group includes top tercile of stocks with positive risk-adjusted past returns. For the stocks in "Low" group, buy orders induce significant permanent change. For instance, the CAARs are as high as 1.61% and 1.47% in two and three months after portfolio transitions. For the stocks in "High" group, buy orders trigger only transitory price changes, and prices revert to pre-transition levels over subsequent weeks. These patterns are consistent with the hypothesis that portfolio transition purchases can potentially contain both "new" and "stale" information, which might be identified by low and high realized returns in pre-transition months, respectively.

[5]Results are qualitatively similar, if raw returns or returns over past six months are considered.

4.3 Price Dynamics and Trading Venues

Transition managers use various trading platforms. Securities that are common to both legacy and target portfolios are transferred as in-kind transactions. Other securities are traded in conventional markets. The rest are executed in "dark pools" of liquidity such as internal and external crossing networks. In previous sections, I have studies the price dynamics following transition trades executed through conventional markets. In this section, I complement my study with the analysis of how security prices evolve following orders executed through other trading venues as well as after in-kind transactions.

I consider three sets of orders: orders that are executed entirely as internal crosses (39,639 orders), orders that are executed entirely as external crosses (59,944 orders), and orders that are transferred entirely as in-kind transactions (27,449 orders). I exclude small orders from the sample and focus on orders that account for at least 1% of the average trading volume in the previous month, since the effects of small orders are typically insignificant.

Table 10 shows the CAARs after orders executed entirely through internal crossing networks (Panel A), external crossing networks (Panel B) and as in-kind transactions (Panel C). As expected, there is no statistically significant initial price pressure during in-kind transactions and internal crosses, since these orders are executed internally. At the same time, crosses on external crossing networks induce significant price pressure. On average, price increases by 20 bps on buy orders and decreases by 30 bps on sell orders. Although these price deviations are twofold smaller than those following open market trades, they are still statistically significant. Price pressure effects after crosses on external networks are inconsistent with the belief that these networks do not have any price discovery mechanisms embedded and, consequently, help to avoid trading costs associated with bid-ask spread and price impact. These results are, however, in a line with frequent complaints of practitioners who frequently mention that external crossing networks are not effective in eliminating information leakage.

At longer horizons, the CAARs are insignificant for both purchases and sales regardless of execution methods. These transactions typically involve large stocks, in which newly hired managers do not have significant information advantage. Perhaps, these transactions also reflect common benchmarks rather than managers' bets on individual securities.

5 Conclusion

This paper studies how financial markets incorporate information and accommodate liquidity shocks. In particular, I examine how security prices respond to portfolio transition orders.

Unique to my study is its focus on orders that are known before their actual execution. Since the quantities to be traded are not influences by contemporaneous price dynamics, this analysis allows me to examine price-volume relationship which is not affected by potential endogeneity of trading.

Portfolio transition orders affect security prices. Following buy and sell orders executed at traditional exchanges, security prices deviate by about 40 bps from their pre-transition levels. These deviations are especially pronounced for large orders and for stocks with a high degree of information asymmetry. I also document price deviations following crosses at external crossing networks. These price patterns contradict the claim that these crossing networks do not have a price discovery mechanism embedded and that they help to avoid any trading costs related to price pressure. Finally, security prices do remain, on average, unchanged following crosses at internal crossing networks and in-kind transactions.

After initial price changes, the price dynamics exhibit asymmetric patterns for buy and sell orders. Buy orders induce permanent price increase and even price continuation for stocks with a high degree of information asymmetry. Sell orders, in contrast, affect security price only temporarily. This asymmetric patterns of the short run price-volume relation are consistent with the difference in the long run performance of terminated and newly hired fund managers. Indeed, target portfolios outperform legacy portfolios in post-transition months. Transition purchases, consequently, represent informative purchases of stocks selected by more skilled fund managers, whereas transition sales are uninformative liquidations of positions of less skilled managers.

This paper provides a novel evidence on the investment strategies of institutional sponsors and their fund managers. The behavior of these market participants has remained largely unexplored, mostly due to the scarcity and limitations of available data. Both the extent of assets under their jurisdiction and their social importance, however, place them among key players in financial markets. Institutional sponsors make, on average, correct decisions when choosing their fund managers and undertaking portfolio transitions. The benefits of portfolio transitions, however, do not survive trading costs.

References

Alexander, Gordon, Gjergji Cici, and Scott Gibson, 2007, Does motivation matter when assessing trade performance? An analysis of mutual funds, *Review of Financial Studies* 20, 125–150.

Andrade, Sandro, Charles Chang and Mark Seasholes, 2008, Trading imbalances, predictable reversals and cross-stock effects, *Journal of Financial Economics* 88, 406–423.

Avramov, Doron, Tarun Chordia, and Amit Goyal, 2006, Liquidity and autocorrelations in individual stock returns, *Journal of Finance* 61, 2365–2394.

Black, Fischer, 1986, Noise, *Journal of Finance* 41, 529–543.

Boehmer, Ekkehart, Joachim Grammig, and Erik Theissen, 2006, Estimating the probability of informed trading - Does trade misclassification matter?, *Journal of Financial Markets* 10, 26–47.

Boehmer, Ekkehart, and Eric Kelley, 2007, Institutional investors and the informational efficiency of prices, *Working Paper.*

Cahart, Mark, 1997, On persistence in mutual fund performance, *Journal of Finance* 52, 57-82.

Campbell, John, Sanford, Grossman, and Jiang Wang, 1993, Trading volume and serial correlation in stock returns, *Quarterly Journal of Economics* 108, 905–939.

Chan, Louis, and Josef Lakonishok, 1993, Institutional trades and intra-day stock price behavior, *Journal of Financial Economics* 33, 173–199.

Chan, Louis, and Josef Lakonishok, 1995, The behavior of stock prices around institutional trades, *Journal of Finance* 50, 1147–1174.

Chen, Honghui, Gregory Noronha, and Vijay Singhal, 2004, The price response to S&P 500 Index additions and deletions: evidence of asymmetry and a new explanation, *Journal of Finance* 59, 1901-1929.

Chiyachantana, Chiraphol, Pankaj Jain, Christine Jiang, and Robert Wood, 2006, Price history and asymmetry in the impact of institutional trades, *Working paper.*

Chiyachantana, Chiraphol, and Pankaj Jain, 2008, The opportunity cost of inaction in financial markets: An analysis of institutional decisions and trades, *Working paper.*

Chordia, Tarun, Richard Roll, and Avanidhar Subrahmanyam, 2002, Order imbalance, liquidity, and market returns, *Journal of Financial Economics* 65, 111–130.

Chordia, Tarun, Richard Roll, and Avanidhar Subrahmanyam, 2005, Evidence on the Speed of Convergence to Market Efficiency, *Journal of Financial Economics* 76, 271–292.

Chordia, Tarun and Avanidhar Subrahmanyam, 2004, Order imbalance and individual stock returns: theory and evidence, *Journal of Financial Economics* 72, 485–518.

Coval, Joshua, and Erik Stafford, 2007, Asset fire sales (and purchases) in equity markets, *Journal of Financial Economics* 86, 479–512.

Da, Zhi, Pengjie Gao, and Ravi Jagannathan, 2008, When does a mutual fund's trade reveal its skill?, *NBER Working Paper* No. 13625.

Del Guercio, Diane, and Paula Tkac, 2002, The determinants of the flow of funds of managed portfolios: Mutual funds versus pension funds, *Journal of Financial and Quantitative Analysis* 37, 523–557.

Dimson, Elroy, 1979, Risk measurement when shares are subject to infrequent trading, *Journal of Financial Economics* 5, 263–278.

Dishi, Elor, David Gallagher, and Jerry Parwada, 2006, Institutional investment flows and fund manager turnover: Evidence from pension plan mandate, *Working Paper*.

Easley, David, Nick Kiefer, Maureen O'Hara, Maureen, and Joseph Paperman, 1996, Liquidity, information, and infrequently traded stocks, *Journal of Finance* 51, 1405–1436.

Fama, Eugene, 1998, Market efficiency, long-term returns, and behavioral finance, *Journal of Financial Economics* 49, 283–306.

Fama, Eugene, and Kenneth French, 1992, The cross–section of expected stock returns, *Journal of Finance* 47, 427–465.

Fama, Eugene, and James MacBeth, 1973, Risk, return, and equilibrium: empirical tests, *Journal of Political Economy* 81, 607–636.

Froot, Kenneth, and Paul O'Connell, 1999, The pricing of US catastrophe reinsurance, *The Financing of Catastrophe Risk*, 195–232.

Garry, Mark, and William Goetzmann, 1986, Does delisting from the S&P 500 affect stock price? *Financial Analysts Journal* 42, 64-69.

Gemmill, Gordon, 1996, Transparency and liquidity: A study of block trades in the London Stock Exchange under different publication rules, *Journal of Finance* 51, 1765–1790.

Goyal, Amit, and Sunil Wahal, 2008, The selection and termination of investment management firms by plan sponsors, *Journal of Finance* 63, 1805–1847.

Greenwood, Robin, 2005, Short- and long-term demand curves for stocks: theory and evidence on the dynamics of arbitrage, *Journal of Financial Economics* 75, 607–649.

Greenwood, Robin, 2008, Excess comovement of stock returns: Evidence from cross-sectional variation in Nikkei 225 weights, *Review of Financial Studies* 21, 1153–1186.

Harris, Lawrence, and Eitan Gurel, 1986, Price and volume effects associated with changes in the SP500: New evidence for the existence of price pressure, *Journal of Finance* 41, 851-60.

Hasbrouck, Joel, 1988, Trades, quotes, and information, *Journal of Financial Economics* 22, 229–252.

Hasbrouck, Joel, 1991, Measuring the information content of stock trades, *Journal of Finance* 46, 179–207.

Heisler, Jeffrey, Christopher Knittel, John Neumann, and Scott Stewart, 2007, Why do institutional plan sponsors fire their investment managers? *The Journal of Business and Economic Studies* 13, 88–116.

Holthausen, Robert, Richard Leftwich, and David Mayers, 1987, The effect of large block transactions on security prices: A cross-sectional analysis, *Journal of Financial Economics* 19, 237–67.

Holthausen, Robert, Richard Leftwich, and David Mayers, 1990, Large-block transactions, the speed of response, and temporary and permanent stock-price effects, *Journal of Financial Economics* 26, 71–95.

Kaniel, Ron, Gideon Saar, and Sheridan Titman, 2004, Individual investor sentiment and stock returns, *Working paper, Duke University.*

Kaul, Aditya, Vikas, Mehorta, and Randall Morck, 2000, Demand curves for stocks do slope down: New evidence from an index weights adjustment, *Journal of Finance* 55, 893-912.

Keim, Donald, and Madhavan, Ananth, 1995, Anatomy of the trading process empirical evidence on the behavior of institutional traders, *Journal of Financial Economics* 37, 371–398.

Keim, Donald, and Ananth Madhaven, 1996, The upstairs market for large-block transactions: Analysis and measurement of price effects, *Review of Financial Studies* 9, 1–36.

Keim, Donald, and Ananth Madhavan, 1997, Transactions costs and investment style: an inter-exchange analysis of institutional equity trades, *Journal of Financial Economics* 46, 265–292.

Kraus, Alan, and Hans Stoll, 1972, Price impacts of block trading on the New York Stock Exchange, *Journal of Finance* 27, 569–588.

Lakonishok, Josef, and Inmoo Lee, 2001, Are insider trades informative?, *Review of Financial Studies* 14, 79–111.

Lakonishok, Josef, Andrei Shleifer, and Robert Vishny, 1992, The structure and performance of the money management industry, *Brookings Papers: Microeconomics*, 339–391.

Llorente, Guillermo, Roni Michaely, Gideon Saar, and Jiang Wang, 2002, Dynamic volume-return relation of individual stocks, *Review of Financial Studies* 15, 1005–1047.

Lo, Andrew, and Craig MacKinlay, 1988, Stock market prices do not follow random walks: Evidence from a simple specification test, *Review of Financial Studies* 1, 41–66.

Miller, Edward, 1977, Risk, uncertainty, and divergence of opinion, *Journal of Finance* 32, 1151-1168.

Mitchell, Mark, Todd Pulvino, and Erik Stafford, 2004, Price pressure around mergers, *Journal of Finance* 59, 31–63.

Obizhaeva, Anna, 2009, Price impact and spread: Bias-free estimates from portfolio transition data, *University of Maryland Working paper.*

O'Hara Maureen, 1997, Market Microstructure Theory.

Parwada, Jerry, and Wenling Joey Yang, 2004, Stock market effects of institutional investment flows: Evidence from Australian pension plan mandate changes, *Working Paper.*

Parwada, Jerry, and Robert Faff, 2005, Pension plan investment management mandates: An empirical analysis of manager selection, *Journal of Financial Services Research*, 77–98.

Perold, Andre, 1988, The implementation shortfall: Paper vs. reality, *Journal of Portfolio Management* 14, 4–9.

Pollet, Joshua, and Mungo Wilson, 2008, How does size affect mutual fund behavior?, *Journal of Finance* 63, 2941 – 2969 .

Saar, Gideon, 2001, Price impact asymmetry of block trades: An institutional trading explanation, *Review of Financial Studies* 14, 1153–1181.

Shleifer, Andrei, 1986, Do demand curves for stocks slope down? *Journal of Finance* 41, 579-590.

Subrahmanyam, Avanidhar, 2006, Lagged order flows and returns: A longer-term perspective, *Working Paper.*

TABB Group Report, 2008, The optimal transition: Mitigating risk and minimizing market impact.

Vayanos, Dimitri, and Paul Woolley, 2009, An institutional theory of momentum and reversal, *LSE Working Paper.*

Wang, Jiang, 1994, A Model of Competitive Stock Trading Volume, *Journal of Political Economy* 102, 127–168.

Wermers, Russ, 2000, Mutual fund performance: An empirical decomposition into stock-picking talent, style, transactions costs, and expenses, *The Journal of Finance* 55, 1655–1695.

Wurgler, Jeffrey, and Ekaterina Zhuravskaya, 2002, Does arbitrage flatten demand curves for stocks?, *Journal of Business* 75, 583–608.

Table 1: Descriptive Statistics for Portfolio Transitions

Panel A: Summary Statistics for Transitions

	$Volume (000)	#Shares (000)	#Stocks
Mean	234,232	16,545	310
Median	68,688	2,747	156
25th	22,391	826	78
75th	189,280	8,208	390
Max	36083,859	2773,048	4,042

Panel B: Split over Capitalization Quintiles

Cap Qnt	$Volume	#Stocks
1(Small)	1.51%	8.84%
2	5.16%	14.90%
3	9.35%	17.93%
4	15.14%	21.88%
5(Large)	68.84%	36.45%

Panel C: Split over Time

Duration	#Trans	$Volume
1 day	46.19%	18.75%
2 days	20.39%	17.46%
3 days	11.73%	15.92%
4 days	6.95%	10.16%
5 days	4.82%	9.94%
6–10 days	7.62%	21.93%
11–19 days	2.32%	5.85%

This table presents general information on the portfolio transitions: summary statistics in Panel A, distribution of transition trades across different capitalization quintiles in Panel B, and distribution of transition trades across time in Panel C. Panel A shows average, median, and maximum value for the dollar volume (in thousands), the number of shares traded (in thousands) and the number of stocks in transitions. Panel B shows the distribution of the dollar volume and the number of stocks in transitions across different capitalization groups. Panel C presents the duration of transitions and their dollar volume (in-kind transactions are excluded). Capitalization thresholds are calculated based on the capitalization quintiles of NYSE stock in 2003. The sample ranges from January 2001 to December 2005.

Table 2: Portfolio Transition Orders with Open Market Trades

Panel A: Summary Statistics of Transition Orders

		Buy			Sell			In-Kind
		OMT	EC	IC	OMT	EC	IC	-
$ Volume (000)	Mean	512	209	220	529	242	208	105
	Median	151	0	0	150	0	0	0
# Shrs (000)	Mean	215	92	8	21	10	8	3
	Median	7	0	0	8	0	0	0
# Shrs/ShrOut (bp)	Mean	2.89	1.46	1.07	3.18	1.85	1.09	0.28
	Median	1.51	0.00	0.00	1.46	0.00	0.00	0.00
# Shrs/ADV (%)	Mean	6.96	3.56	2.39	8.11	5.60	2.59	0.61
	Median	2.83	0.00	0.00	2.67	0.00	0.00	0.00
# Shrs/Vol (%)	Mean	3.58	1.08	0.79	3.74	1.20	0.90	0.00
	Median	1.72	0.00	0.00	1.70	0.00	0.00	0.00

Panel B: Distribution of Transition Orders over Time

		Time Horizon T								
		0d	1d	2d	3d	4d	1w	2w	>2w	All
Buy	OMT	1.06	2.43	1.53	0.77	0.56	0.26	0.32	0.04	6.96
	EC	0.68	1.07	0.67	0.42	0.32	0.16	0.20	0.04	3.56
	IC	0.37	0.67	0.51	0.38	0.25	0.07	0.14	0.01	2.39
Sell	OMT	1.50	2.21	1.54	0.96	0.66	0.39	0.69	0.15	8.11
	EC	0.82	1.11	0.91	0.79	0.65	0.34	0.61	0.37	5.60
	IC	0.52	0.78	0.46	0.31	0.22	0.11	0.13	0.07	2.59
	In-Kind	0.61								0.61

The table presents descriptive statistics for portfolio transition orders. Panel A shows summary statistics on portfolio transition orders and their distribution over various trading venues. The means and medians of the following order characteristics are reported: the dollar value (in thousands), the number of shares (in thousands), the number of shares as a fraction of shares outstanding (in bps), the number of shares as a fraction of average daily volume (ADV) in the previous month and as a fraction of contemporaneous trading volume (Vol). Panel B shows the distribution of the portfolio transition orders over time. For each day relative to starting day of transition ("0d"), table exhibits the average trade size normalized by the average daily volume in the previous month (in percents). Results for different trading venues are presented: open market trading (OMT), external crossing (EC) and internal crossing (IC) as well as in-kind transactions (In-Kind). Small orders (orders with less than 1% of average daily volume traded through the market) are excluded from the sample. All statistics are calculated based on pooled data from January 2001 to December 2005.

Table 3: The CAARs after Transition Purchases and Sales

Panel A: Stocks Weighted Equally, EW

	Time Horizon T						
	0d	1d	1w	2w	1m	2m	3m
Buy	0.22**	0.35**	0.43**	0.30**	0.42*	0.41†	0.52
	(4.97)	(7.49)	(7.08)	(2.78)	(2.41)	(1.75)	(1.19)
Sell	-0.18**	-0.39**	-0.36**	-0.10	0.02	-0.10	0.12
	(-3.94)	(-5.32)	(-6.69)	(-0.95)	(0.09)	(-0.44)	(0.38)
Δ	0.41**	0.75**	0.82**	0.43**	0.44**	0.56*	0.39
	(4.58)	(6.60)	(8.51)	(3.70)	(2.67)	(2.51)	(1.46)

Panel B: Stocks Weighted by Market Capitalization, VW

	Time Horizon T						
	0d	1d	1w	2w	1m	2m	3m
Buy	0.03	0.07†	0.17*	0.00	0.03	-0.02	0.30
	(0.95)	(1.99)	(2.03)	(-0.03)	(0.28)	(-0.13)	(0.93)
Sell	-0.13**	-0.25**	-0.25**	0.02	-0.07	-0.08	-0.07
	(-5.46)	(-8.43)	(-3.24)	(0.19)	(-0.43)	(-0.30)	(-0.15)
Δ	0.17**	0.34**	0.45**	0.03	0.12	0.08	0.35
	(5.88)	(16.28)	(7.74)	(0.21)	(0.57)	(0.34)	(1.02)

This table presents the cumulative average abnormal returns, $CAAR_T$, for the acquired (Buy) and sold (Sell) stocks for various horizons T starting the event day 0 and up to three months. Returns are adjusted with the 4-factor model, which includes three Fama-French factors and the momentum factor. Estimates are calculated using the Fama-McBeth method for data grouped at monthly frequencies. Equally-weighted and value-weighted schemas are considered. T-statistics are adjusted with the Newey-West procedure and presented in parentheses. Small orders (orders with less than 1% of average daily volume traded through the market) are excluded from the sample. The sample ranges from January 2001 to December 2005. **is significance at 1% level, *is significance at 5% level, †is significance at 10% level.

Table 4: Cumulative Returns on Target and Legacy Portfolios

Panel A: Two-Sided Portfolio Transitions

Months	0	1	2	3	4	5	6
Sell	0.40	1.31	1.93	2.87	3.52	4.14	4.71
Buy	0.64	1.47	2.10	3.04	3.69	4.36	4.98
Δ	0.24**	0.16*	0.17*	0.17†	0.18†	0.21*	0.26*
	(4.64)	(2.28)	(2.04)	(1.75)	(1.71)	(1.91)	(2.18)

Panel B: Large Two-Sided Portfolio Transitions

Months	0	1	2	3	4	5	6
Sell	0.47	1.36	2.19	3.15	3.64	4.36	4.90
Buy	0.73	1.52	2.46	3.39	3.93	4.76	5.46
Δ	0.26**	0.16†	0.27*	0.25†	0.29*	0.41**	0.56**
	(3.91)	(1.71)	(2.54)	(1.91)	(2.01)	(2.65)	(3.41)

Panel C: Small Two-Sided Portfolio Transitions

Months	0	1	2	3	4	5	6
Sell	0.34	1.27	1.71	2.65	3.41	3.96	4.55
Buy	0.57	1.43	1.80	2.76	3.50	4.03	4.58
Δ	0.22**	0.16	0.09	0.11	0.09	0.06	0.02
	(2.91)	(1.57)	(0.70)	(0.77)	(0.60)	(0.37)	(0.14)

Panel A shows the average cumulative returns of target and legacy portfolios for 1517 two-sided portfolio transitions (that include both legacy and target portfolios). Returns are cumulated starting the month of portfolio transitions. Six subsequent months are considered. Δ is the difference between the returns of legacy and target portfolios in post-transition period. Panel B presents Δ for large and small portfolio transitions. Small and large transitions are defined based on the total size of legacy and target portfolios. The threshold is about \$100 million. I exclude 47 two-sided transitions in which the legacy portfolios are ten times larger or smaller than the target ones. T-statistics are presented in parentheses. The sample ranges from January 2001 to December 2005. **is significance at 1% level, *is significance at 5% level, †is significance at 10% level.

Table 5: Trading Costs

Panel A: Implicit and Explicit Trading Costs (in %)

			Quintiles				
		Mean	10th	25th	50th	75th	90th
Sell	Expl	0.03	0.01	0.02	0.03	0.05	0.07
	Impl	0.14	-1.40	-0.59	0.08	0.80	1.76
	Total	0.18	-1.37	-0.57	0.11	0.84	1.80
Buy	Expl	0.03	0.00	0.01	0.03	0.05	0.08
	Impl	0.11	-1.45	-0.54	0.15	0.83	1.65
	Total	0.14	-1.41	-0.50	0.18	0.87	1.68

Panel C: Returns Net Trading Costs

Months	0	1	2	3	4	5	6
Δ	0.24**	0.16*	0.17*	0.17†	0.18†	0.21*	0.26*
	(4.64)	(2.28)	(2.04)	(1.75)	(1.71)	(1.91)	(2.18)
Net Δ	-0.09	-0.16*	-0.15†	-0.13	-0.13	-0.09	-0.03
	(-1.63)	(-2.12)	(-1.76)	(-1.34)	(-1.23)	(-0.78)	(-0.29)

This table shows the trading costs incurred by institutional sponsors during portfolio transitions. Panel A reports the average values and quintiles of explicit and implicit trading costs (in %) for legacy and target portfolios. Panel B reports the difference between returns of target and legacy portfolios for two-sided portfolio transitions. Δ is the difference between the returns of legacy and target portfolios in post-transition period. Net Δ is return differential adjusted for trading costs. Returns are cumulated starting the month of portfolio transitions. Six subsequent months are considered. T-statistics are presented in parentheses. The sample ranges from January 2001 to December 2005.**is significance at 1% level, *is significance at 5% level, †is significance at 10% level.

Table 6: Herding in Portfolio Transitions

Panel A: All Sample

	Buy			Sell		
	Weekly	Monthly	Quarterly	Weekly	Monthly	Quarterly
α	0.04**	-0.02	-0.02	-0.11**	-0.06**	-0.07**
	(0.02)	(0.02)	(0.01)	(0.03)	(0.02)	(0.02)
β	0.18**	-0.06	-0.08	0.22**	0.08**	0.03*
	(0.03)	(0.05)	(0.07)	(0.03)	(0.03)	(0.01)

Panel B: Sample with Small Orders Excluded

	Buy			Sell		
	Weekly	Monthly	Quarterly	Weekly	Monthly	Quarterly
α	0.14**	-0.03	-0.02†	-0.36**	-0.03	-0.05**
	(0.05)	(0.04)	(0.01)	(0.08)	(0.04)	(0.02)
β	0.25**	0.05	-0.04	0.22**	0.11*	0.05**
	(0.05)	(0.07)	(0.08)	(0.05)	(0.04)	(0.02)

This table shows the estimates of cross-sectional regression $(OI)_{i,t+1} = \alpha + \beta(OI)_{i,t} + \epsilon_t$, where $(OI)_{i,t}$ is the signed order imbalances of stock i in period t. Results are presented for weekly, monthly and quarterly horizons. In Panel A, all transactions are included in construction of order imbalances variables. In Panel B, the small orders are excluded from the sample (orders with less than 1% of average daily volume traded through open markets). The sample is further split into two groups "Buy" and "Sell" with positive and negative order imbalances $OI_{i,t}$. The estimates are calculated using the Fama-McBeth procedure. The standard errors are presented in parentheses. The sample ranges from January 2001 to December 2005. **is significance at 1% level, *is significance at 5% level, †is significance at 10% level.

Table 7: The CAARs and Degree of Information Asymmetry

Panel A: Groups by Number of Analysts, ANUM

		0d	1d	1w	2w	1m	2m	3m
Buy	Low	0.32**	0.52**	0.53**	0.54**	0.61*	1.12**	1.01†
		(4.20)	(6.30)	(3.55)	(4.23)	(2.01)	(2.67)	(1.89)
	High	0.13**	0.21**	0.22**	0.18	-0.01	-0.15	-0.10
		(4.20)	(5.54)	(2.98)	(1.02)	(-0.02)	(-0.56)	(-0.21)
Sell	Low	-0.22**	-0.42**	-0.35*	-0.06	0.11	0.00	0.17
		(-3.34)	(-3.83)	(-2.41)	(0.14)	(0.97)	(0.44)	(1.01)
	High	-0.13**	-0.26**	-0.25**	-0.13	-0.17	-0.07	0.15
		(-3.16)	(-5.35)	(-3.27)	(-0.40)	(-0.19)	(0.02)	(0.35)

Panel B: Groups by Percentage Spread, SPREAD

		0d	1d	1w	2w	1m	2m	3m
Buy	Low	0.13**	0.20**	0.30*	0.12	0.01	-0.06	-0.02
		(4.44)	(7.55)	(2.35)	(0.78)	(0.07)	(-0.20)	(-0.06)
	High	0.39**	0.69**	0.76**	0.79**	0.81*	1.31*	1.32
		(3.86)	(4.73)	(3.39)	(3.23)	(2.22)	(2.43)	(1.47)
Sell	Low	-0.13**	-0.28**	-0.32**	-0.13	-0.20	-0.23	-0.25
		(-3.36)	(-5.37)	(-4.99)	(-0.40)	(-0.78)	(-0.66)	(-0.80)
	High	-0.26**	-0.61**	-0.58**	-0.10	0.45†	0.52	0.60
		(-3.22)	(-4.13)	(-4.97)	(-0.33)	(1.80)	(1.15)	(1.44)

Panel C: Groups by Probability of Informed Trading, PIN

		0d	1d	1w	2w	1m	2m	3m
Buy	Low	0.05	0.09†	0.09	0.36*	0.41†	0.19	0.39
		(1.26)	(1.95)	(0.67)	(2.19)	(1.79)	(0.62)	(0.94)
	High	0.29**	0.47**	0.62**	0.74**	0.74**	1.01**	0.67
		(5.09)	(6.07)	(4.80)	(3.96)	(2.99)	(3.42)	(1.46)
Sell	Low	-0.07	-0.14**	-0.04	0.09	0.16	0.14	0.49
		(-1.57)	(-3.99)	(-0.44)	(0.86)	(1.12)	(0.69)	(0.91)
	High	-0.20**	-0.49**	-0.50**	0.00	0.08	0.30	0.83
		(-3.56)	(-5.44)	(-3.77)	(-0.19)	(0.18)	(0.29)	(1.09)

This table shows the cumulative average abnormal returns, $CAAR_T$, following transition trades for the stock with different degrees of information asymmetry. In Panel A, B and C stocks are sorted by the number of analysts following them, their percentage spread, and their probability of informed trading, PIN, respectively. The "Low" ("High") group includes stocks with bottom (top) 33% of ranked stocks. The estimates of CAARs are calculated following the Fama-McBeth procedure. T-statistics are adjusted with the Newey-West methodology (in parentheses). Returns are adjusted for risk with the 4-factor model. Small orders (orders with less than 1% of average daily volume traded through the market) are excluded from the sample. The sample ranges from January 2001 to December 2005.**is significance at 1% level, *is significance at 5% level, †is significance at 10% level.

Table 8: The CAARs: Purchases, Sort on Capitalization and $ANUM$

Panel A: Small Size Stocks

	Time Horizon T						
	0d	1d	1w	2w	1m	2m	3m
Low ANUM	0.45**	0.72**	0.76**	0.89*	1.19*	1.96**	2.21*
	(3.78)	(5.26)	(3.38)	(2.33)	(2.62)	(2.70)	(2.20)
High ANUM	0.30**	0.50**	0.89**	0.85*	0.72*	0.73	0.42
	(3.45)	(4.00)	(3.55)	(2.17)	(2.11)	(1.02)	(0.40)

Panel B: Medium Size Stocks

	Time Horizon T						
	0d	1d	1w	2w	1m	2m	3m
Low ANUM	0.25**	0.40**	0.73**	0.69**	0.85**	0.87**	0.79
	(4.96)	(5.98)	(7.26)	(7.83)	(5.40)	(3.54)	(1.55)
High ANUM	0.15*	0.16*	0.27**	0.48*	0.53	0.15	0.10
	(2.48)	(2.11)	(2.80)	(2.35)	(1.56)	(0.29)	(0.14)

Panel C: Large Size Stocks

	Time Horizon T						
	0d	1d	1w	2w	1m	2m	3m
Low ANUM	0.09*	0.13*	0.10	-0.25	-0.21	-0.11	0.02
	(2.33)	(2.23)	(0.92)	(-1.01)	(-0.78)	(-0.31)	(0.05)
High ANUM	0.04	0.13*	0.18	0.13	-0.01	0.14	0.41
	(1.16)	(2.13)	(1.53)	(1.57)	(-0.04)	(0.39)	(0.75)

This table shows the cumulative average abnormal returns, $CAAR_T$, following transition buys for the stocks sorted by their market capitalization and the number of analysts following them, ANUM. Returns for small stocks are presented in Panel A, for medium size stocks in Panel B, and for large stocks in Panel C. Inside each size group, stocks are sorted by ANUM into two groups, "Low ANUM" and "High ANUM". The estimates of CAARs are calculated following the Fama-McBeth procedure. T-statistics are adjusted with the Newey-West methodology and presented in parentheses. Returns are adjusted for risk with the 4-factor model. Small orders (orders with less than 1% of average daily volume traded through the market) are excluded from the sample. The sample ranges from January 2001 to December 2005.**is significance at 1% level, *is significance at 5% level, †is significance at 10% level.

Table 9: The CAARs and Past Returns

Panel A: Transition Purchases

	Time Horizon T						
	0d	1d	1w	2w	1m	2m	3m
Low $R^{adj}_{-3m,-1d}$	0.37**	0.59**	0.87**	0.95**	1.22**	1.61*	1.47
	(4.95)	(4.91)	(4.58)	(3.38)	(3.04)	(2.15)	(1.59)
High $R^{adj}_{-3m,-1d}$	0.10†	0.24**	0.22	0.14	0.06	0.35	0.36
	(1.79)	(2.79)	(1.58)	(0.66)	(0.23)	(1.07)	(0.53)

Panel B: Transition Sales

	Time Horizon T						
	0d	1d	1w	2w	1m	2m	3m
Low $R^{adj}_{-3m,-1d}$	-0.17*	-0.44**	-0.24	0.26	0.79†	0.98	1.33
	(-2.27)	(-2.72)	(-1.42)	(1.03)	(1.77)	(1.35)	(1.33)
High $R^{adj}_{-3m,-1d}$	-0.20*	-0.50**	-0.60**	-0.19	-0.02	-0.22	-0.01
	(-2.42)	(-4.32)	(-4.37)	(-1.32)	(-0.23)	(-0.93)	(-0.39)

This table shows the cumulative average abnormal returns, CAARs, following transition trades for stock grouped by their past returns. Stocks are sorted into two groups based on their risk-adjusted past returns $R^{adj}_{-3m,-1d}$ in the previous three months. The "Low" group includes stocks with bottom 33% of ranked stocks that have negative past returns. The "High" group includes stocks with top 33% of ranked stocks that have positive past returns. Purchases and sales are considered in Panel A and B, respectively. The estimates are calculated following the Fama-McBeth procedure. T-statistics are adjusted with the Newey-West methodology and presented in parentheses. Returns are adjusted for risk with the 4-factor model. Small orders (orders with less than 1% of average daily volume traded through the market) are excluded from the sample. The sample ranges from January 2001 to December 2005.**is significance at 1% level, *is significance at 5% level, †is significance at 10% level.

Table 10: The CAARs and Different Trading Venues

Panel A: Internal Crosses

	Time Horizon T						
	0d	1d	1w	2w	1m	2m	3m
Buy	-0.06	0.01	0.28	0.06	-0.21	0.06	0.49
	(-0.92)	(0.08)	(1.32)	(0.17)	(-0.35)	(0.08)	(0.41)
Sell	-0.01	0.05	0.15	1.03	0.81	0.46	0.79
	(-0.09)	(0.45)	(0.74)	(1.37)	(1.15)	(0.42)	(0.52)
Δ	-0.05	-0.04	0.14	-0.84	-1.00	-0.37	-0.31
	(-0.65)	(-0.23)	(0.58)	(-1.49)	(-1.63)	(-0.35)	(-0.24)

Panel B: External Crosses

	Time Horizon T						
	0d	1d	1w	2w	1m	2m	3m
Buy	0.14*	0.29**	0.33*	0.23	0.36	0.04	-0.14
	(2.22)	(4.06)	(2.51)	(1.10)	(1.32)	(0.10)	(-0.27)
Sell	-0.14**	-0.20**	-0.04	-0.01	-0.16	-0.26	-0.06
	(-3.19)	(-3.84)	(-0.20)	(-0.04)	(-0.47)	(-0.49)	(-0.10)
Δ	0.27**	0.48**	0.37	0.24	0.52	0.30	-0.09
	(3.72)	(6.88)	(1.50)	(0.61)	(1.15)	(0.46)	(-0.17)

Panel C: In-kind Transactions

	Time Horizon T						
	0d	1d	1w	2w	1m	2m	3m
In-Kind	0.02	0.02	0.06	0.22	0.12	0.21	0.23
	(0.56)	(0.47)	(0.44)	(1.32)	(0.40)	(0.47)	(0.43)

This table shows the cumulative average abnormal returns, CAARs, following transition orders executed though different trading venues. In Panel A, the orders executed entirely through internal crossing networks are included. In Panel B, the orders executed entirely through external crossing network are considered. In Panel C, the orders entirely transferred as in-kind transactions are included. Purchases and sales are considered separately. The estimates are calculated following the Fama-McBeth procedure. T-statistics are adjusted with the Newey-West methodology (in parentheses). Returns are adjusted for risk with the 4-factor model. Small orders (orders with less than 1% of average daily volume traded through the market) are excluded from the sample. The sample ranges from January 2001 to December 2005. ** is significance at 1% level, * is significance at 5% level, † is significance at 10% level.

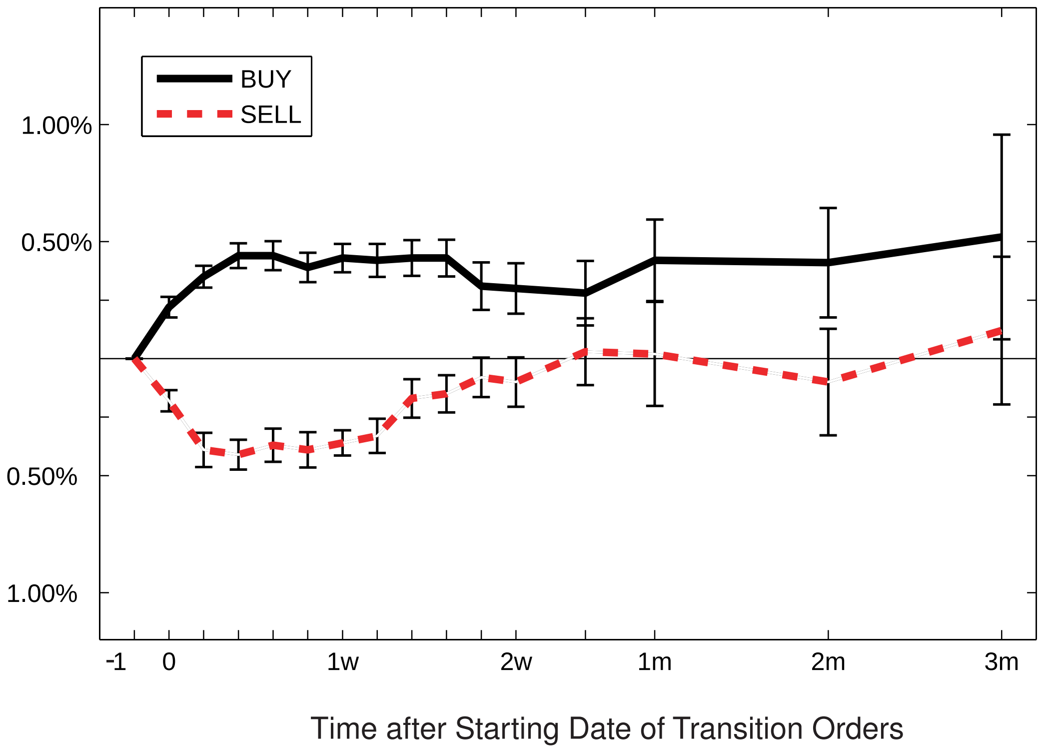

Figure 1: Price Response to Transition Orders, Equally-Weighted Case

Figure shows the cumulative average abnormal returns (in percents), $CAAR_T$, following large portfolio transition buys and sells. The day 0 is the starting date of transition trades. Horizons T up to three months are considered. Equally-weighted returns are calculated. Means and standard errors are calculated using the Fama-McBeth procedure for observations grouped at monthly level. Standard errors are shown as error bars. Small orders (orders with less than 1% of average daily volume traded through the market) are excluded from the sample. The sample ranges from January 2001 to December 2005.

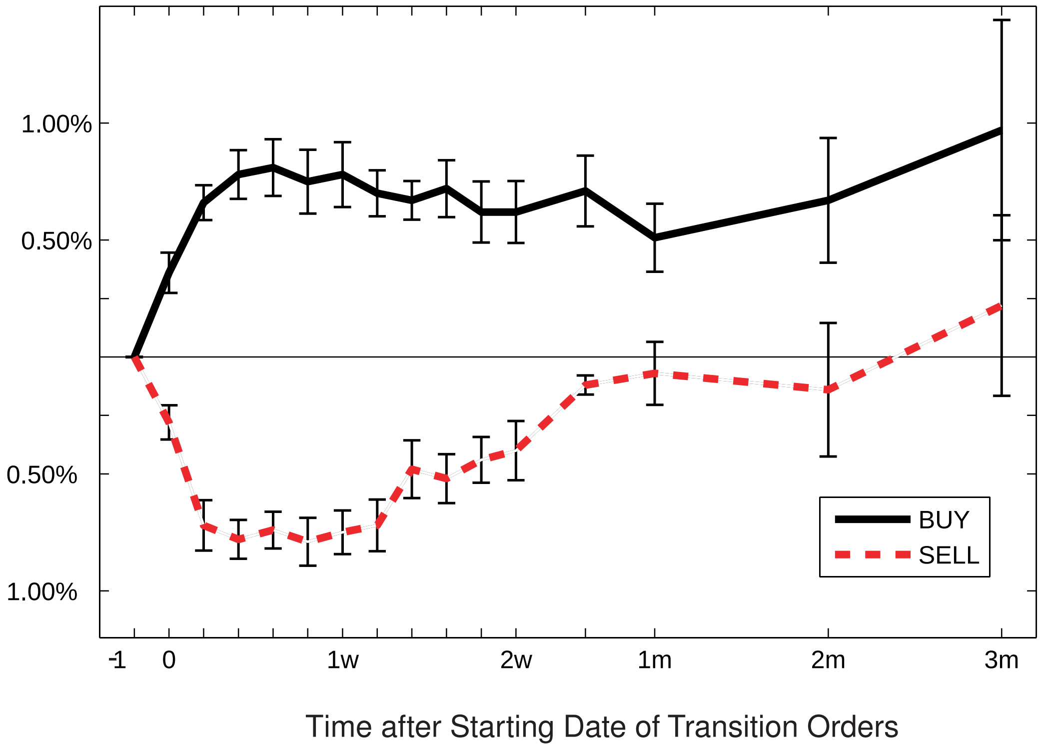

Figure 2: Price Response to Transition Orders, Principal-Weighted Case

Figure shows the cumulative average abnormal returns (in percents), $CAAR_T$, following large portfolio transition buys and sells. The day 0 is the starting date of transition trades. Horizons T up to three months are considered. Principal-weighted returns are calculated; namely, observations are weighted by the size of trades normalized by average daily volume in the previous month. Means and standard errors are calculated using the Fama-McBeth procedure for observations grouped at monthly level. Standard errors are shown as error bars. Small orders (orders with less than 1% of average daily volume traded through the market) are excluded from the sample. The sample ranges from January 2001 to December 2005.

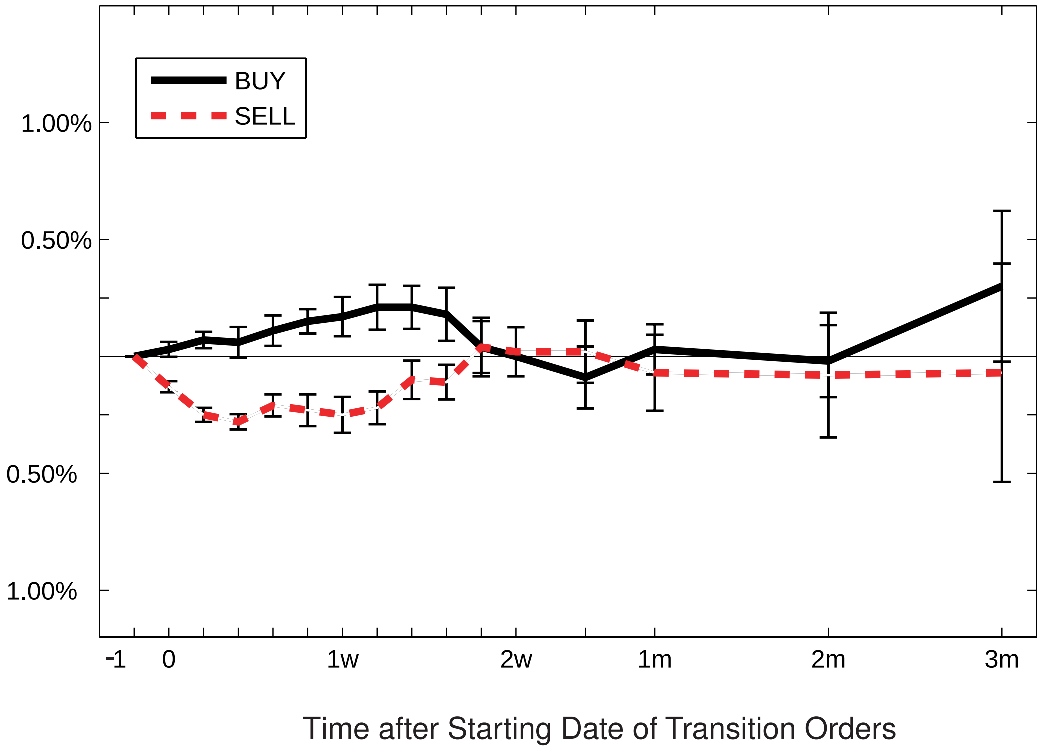

Figure 3: Price Response to Transition Orders, Value-Weighted Case

Figure shows the cumulative average abnormal returns (in percents), $CAAR_T$, following large portfolio transition buys and sells. The day 0 is the starting date of transition trades. Horizons T up to three months are considered. Value-weighted returns are calculated. Means and standard errors are calculated using the Fama-McBeth procedure for observations grouped at monthly level. Standard errors are shown as error bars. Small orders (orders with less than 1% of average daily volume traded through the market) are excluded from the sample. The sample ranges from January 2001 to December 2005.