

Information vs. Liquidity: Evidence from Portfolio Transition Trades

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This Draft: January 14, 2007

Abstract

In this paper, I study the evolution of stock prices after trades with different underlying motives. A novel data set of portfolio transitions allows me to identify trades that are most likely induced by either information-related or liquidity-related factors. My findings provide supporting evidence for a long-standing tenet of market microstructure stating that information-motivated and liquidity-motivated transactions generate different price dynamics. In fact, while information-motivated portfolio transition trades permanently shift stock prices to new levels, the temporary price pressure effects of liquidity-motivated portfolio transition trades are reversed in the following weeks. Also, the analysis of price impact and market resiliency associated with transition trades reveals interesting details of how market learns new information and accommodates liquidity shocks. Moreover, I provide trading cost estimates for institutional investors during 2001-2005.

*MIT Sloan School of Management, e-mail: obizhaeva@mit.edu. I thank Andrew Lo, Jun Pan, Steven Ross, and especially Jiang Wang for their helpful discussions and comments. I am also very 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 Jiro Kondo, Oleg Rytchkov as well as participants of the MIT Finance seminar. All errors are my own.

1 Introduction

Different stock price patterns are expected in response to trades with various information contents. Information-motivated trades shift security prices permanently to new fundamental levels. In contrast, liquidity-motivated trades bring about only temporary stock price deviations, which are expected to be promptly reversed.¹ Though being at the very heart of market microstructure, these two patterns are difficult to study. The main reason is that researchers cannot directly observe the information content of trades. In this paper, I use a unique data set of portfolio transitions to identify trades that are most likely driven by information and liquidity. This identification allows me to conduct the study of price dynamics after trades with different underlying motives; my findings confirm that information-motivated trades permanently change stock prices whereas liquidity-motivated trades affect prices only temporarily and reveal interesting facts about these patterns.

Although the portfolio transitions business is an important part of modern financial markets, my paper is one of the first academic studies to examine it.² Portfolio transitions are a sizable and expensive transferring of funds from legacy (i.e. existing) to target portfolios. These transitions are undertaken by various money management entities such as pension plans, insurance funds, endowments, and foundations. The main reasons for these transactions are strategic changes in global asset allocations, replacements of fund managers, and large cash inflows and outflows. Portfolio transitions are typically delegated to professional managers, who help execute them in a cost-efficient way. This study is based on a novel data set of transitions performed by the world's leading provider of portfolio transition services.

This data allows me to identify precisely large supply/demand shocks caused by portfolio transitions trades. More importantly and uniquely, I can differentiate informative and uninformative transactions and analyze the evolution of prices after these trades. In particular, based on the institutional details of how securities in legacy and target portfolios are selected, I argue that, on average, portfolio transition purchases are likely to be information-motivated trades whereas portfolio transition sales are liquidity-motivated trades.

¹The differential impact of these trades on return dynamics is emphasized in Wang (1994) and Llorente et al. (2002). Similar intuition underlies the empirical models of Hasbrouck (1988, 1991). Many theoretical studies analyze uninformed trading and return dynamics (e.g., Grossman and Miller (1988), De Long et al.(1990), Campbell, Grossman and Wang (1993), Wurgler and Zhuravskaya (2002), Barberis and Shleifer (2003), Chordia and Subrahmanyam (2004), Barberis, Shleifer, and Wurgler (2005), and Greenwood (2005a, 2005b), Andrade et al.(2006)). Other papers study impact of informed trading on stock prices (e.g. Glosten and Milgroom (1985), Kyle (1985), Easley and O'Hara (1987)). O'Hara (1995), Hasbrouck (1996), Madhavan (2000), Biais, Glosten and Spatt (2002), and Stoll (2003) provide excellent overviews of other related microstructure literature.

²Several recent papers have analyzed the selection and termination of investment management firms by institutional investors (Parwada and Yang (2004), Goyal and Wahal (2006)). These changes in fund management often involve portfolio transitions.

I found that transition purchases change stock prices permanently upward, and prices remain at new levels over the subsequent months. In contrast, only temporary price pressure effects are induced by transition sales, and initial price deviations are adjusted over the following weeks. Extending my analysis, I show that the permanent price changes are especially pronounced after purchases of stocks with a high degree of information asymmetry, in which informed agents have particularly substantial information advantage. Furthermore, I present the evidence that transition purchases containing new rather than stale information, as indicated by past returns, have stronger permanent effects on the stock prices. These findings provide solid support to my main conclusion that stock prices are indeed affected permanently by information-motivated portfolio transition trades and only temporarily by liquidity-motivated ones.

I also perform the detailed analysis of price patterns after portfolio transition purchases and sales, and document several interesting facts about both price impact coefficients as well as market resiliency associated with these trades. First, the price impact coefficients of transition purchases are larger than those of transition sales. Second, the dynamics of these coefficients during execution of transition buys and sells are different. Price impact is significantly lower at the beginning than at the end of buy orders, whereas it typically stays constant during execution of sell orders. Third, cross-sectional analysis shows that the price impact coefficients depend positively on proxies for information asymmetry and stocks' volatility as well as negatively on the amount of noise trading. Fourth, the analysis of dynamic properties of liquidity in response to trades shows that markets of large stocks are more resilient than markets of small stocks; liquidity of exchange-traded stocks seem to be more resilient comparing to that of Nasdaq-traded stocks. These findings are interesting details of how market learns new information, contained in transition purchases, and accommodates liquidity shocks, associated with transition sales.

Importantly, I provide estimates of institutional trading costs for the period from 2001 to 2005. First, I quantify implicit and explicit trading costs on security level for both exchange-traded and Nasdaq traded stocks as well as for alternative trading venues such as internal and external crossing networks. These results add to the work of Chan and Lakonishok (1995), Keim and Madhavan (1997), and Conrad et al. (2003) who provide trading costs estimates for 1986-1988, 1991-1993, and 1996-1998, respectively.³ Second, I make available the estimates of trading costs on portfolio transition level, and show how they depend on general transition characteristics. Interestingly, the average costs of large portfolio transitions are as low as about 30 bps.⁴

³These estimates are often used by researchers to explore the profitability of various strategies over recent decades (Wermers (2000) and Cooper, Gutierrez, and Marcum (2005)).

⁴This is much lower than the transaction costs of 0.50-5.00% assumed by Goyal and Wahal (2006) in their

My identification assumption that transition purchases are information-motivated trades and transition sales are liquidity-motivated trades is based on the double selection mechanism that underlies portfolio transitions: stocks are selected by fund managers that are in turn chosen by asset owners. First, transition trades are explicitly determined by hired and terminated fund managers, who choose the securities in target and legacy portfolios out of numerous available alternatives. Consequently, their choices may contain positive signals about stocks' perspectives. However, the existing evidence on their stock-picking skills is inconclusive (Lakonishok, Shleifer, and Vishny (1992), Coggin, Fabozzi, and Rahman (1993), Ibbotson and Kaplan (2000)). Thus, although sales of legacy portfolios do not reveal negative information about stocks, purchases of target portfolios might be uninformative as well. What further assures the informativeness of transition purchases are decisions of asset owners who hire and terminate fund managers. There is evidence that asset owners do have abilities to select skilled managers. In fact, several studies emphasize that asset owners rely on sophisticated tools during selecting fund managers.⁵ Also, Busse, Goyal, and Wahal (2006) document the predictability in performance of institutional winners portfolios for up to one year and point out that asset owners could potentially benefit from picking winners.⁶ Further evidence that supports my identification argument is the observed in my sample superior performance of target portfolios relative to that of legacy portfolios in post-transition months.

In this paper, identification of supply and demand shocks is not subject to various concerns that are frequently relevant in other studies. First, the trading intentions of transition managers are set in advance. This contrasts with other studies in which *ex ante* orders cannot be identified, and realized trades can be influenced by a variety of investment styles and order-placement strategies. Second, the trades' direction is explicitly given, whereas it is often necessary to apply heuristic and not perfectly precise algorithms for inferring a trade side.⁷ Third, the magnitude of shocks is observed; however, frequently researchers have to find instruments for actual shocks. Fourth, the execution time of trades is specified at daily frequencies; in contrast, additional assumptions about timing often have to be made. Fifth, transition trades occur at typical days and stock prices dynamics are not affected by abnormal market conditions. Sixth, a large cross-section of stocks is available for the analysis. The uniqueness of this data is apparent when it is compared to other studies of

analysis of replacement of investment managers by plan sponsors.

⁵These choices of asset owners are described in Del Guercio and Tkac (2002), Dishi, Gallagher, and Parwada (2006), Goyal and Wahal (2006), Heisler et al.(2006), and Parwada and Faff (2005).

⁶The performance persistence of institutional investment managers was also documented by Goyal and Wahal (2006), Ferson and Khang (2002), and Tonks (2005).

⁷For instance, analyzing the widely used algorithm of Lee and Ready (1991), Lee and Radhakrishna (2000) show that 40% of NYSE trades cannot be classified at all; moreover, 7% of the remaining trades are not classified correctly.

supply/demand shocks, for instance, the prominent studies of index inclusions and deletions. In these studies, researchers find instruments for the shocks based on the stock index weights and industry size, assume that all the rebalancing is done during the event, and hope that the results of tests for the stocks which undergo index deletion/addition can be extrapolated on the normal trading days.

This paper contributes to a strand of empirical literature that studies price dynamics in response to trades with different information content. Since only unsigned trading volume is usually observed, demand and supply shocks are hard to identify. To distinguish whether these shocks are informative or uninformative is an even more challenging task. However, a number of studies have succeeded in overcoming these difficulties.

My work is related to the extensive empirical literature that analyzes how markets absorb uninformative liquidity-motivated demand or supply shocks. These studies can be categorized into several groups. The first group of studies examines security prices around rare events that are believed to trigger uninformed trading. The examples are large-scale events, i.e., index inclusions and deletions (Garry and Goetzmann (1986), Harris and Gurel (1986), Shleifer (1986))⁸, or small-scale events, i.e., catastrophic events (Froot and O’Connell (1999)). The second group uses observed variables, i.e., unsigned trading volume (Campbell, Grossman and Wang (1993), Llorente et al.(2002), Avramov, Chordia and Goyal (2006)) or signed order imbalances (Chordia, Roll and Subrahmanyam (2002, 2005), Chordia and Subrahmanyam (2004)) as indicators of times with substantial liquidity trading. The third group focuses on prices after trades of particular agents who are believed to be likely uninformed. The examples include trades of margin traders (Andrade, Chang and Seasholes (2005)) or trades of individual investors (Kaniel, Saar, Titman (2005)). Finally, other studies, ones most similar to my work, investigate specific trades of market participants that are most likely not driven by private information, for instance, fire sales of fund managers (Coval and Stafford (2005)) or mergers-induced trading of arbitrageurs (Mitchell, Pulvino and Stafford (2002)). Although the majority of studies find that eventually initial price deviations are partially or completely reversed, the cases of permanent price changes or even continuations are documented as well. This inconclusive evidence can be partially explained by frequently rough identification of liquidity shocks, i.e., the magnitude of liquidity shocks is often unknown, the timing is unclear, and the absence of new information about stock fundamentals as well as no change in stock characteristics are not always unambiguous. Moreover, sometimes only a limited number of observations for a small cross-section of stocks in atypical times is available. This paper avoids most of these concerns and analyzes price responses to

⁸See also Kaul, Mehrotra and Morck (2000), Wurgler and Zhuravskaya (2002), Chen, Noronha and Singhal (2004), Greenwood (2005a, 2005b) among others.

liquidity shocks that are identified in a quite precise manner.

Less is known about the market's response to information-motivated trades. Several groups of market participants are believed to have an information advantage over the rest of the market. However, the analysis of how prices respond to their trades, while often hindered by scarcity and limitations of available data, provides only mixed evidence. For instance, previous studies of insiders' trading and managerial decisions indicate that insiders are better informed about their companies' perspectives (Jeng, Metrick, Zeckhauser (1999)); at the same time, stock prices respond only mildly to insiders' trading (Lakonishok and Lee (2001)). Professional investment managers are other market participants who are usually considered sophisticated and informed. Yet, the comprehensive analysis of the relationship between security prices and their trades at high frequencies is fairly problematic. In the U.S., institutional holdings are disclosed in SEC 13-F filings only on a quarterly basis, thus making it difficult to disentangle whether institutional trades follow past returns, induce temporary price pressure effects, or move prices permanently. At the same time, analysis of limited data at higher frequencies often show that institutional purchases are followed by permanent price increases while sales create only temporary effects. Examples include block trading (Kraus and Stoll (1972), Holthausen, Leftwich, and Mayers (1987, 1990), Keim and Madhavan (1996), Gemmill (1996)) and institutional trading (Chan and Lakonishok (1993, 1995), Keim and Madhavan (1997)). Somewhat similar patterns are documented by Campbell et al. (2005), who draw their conclusions based on both intraday TAQ and 13-F data. Given that institutional buys are believed to be more often driven by information while institutional sells are usually triggered by liquidity needs, these studies provide collaborative evidence to the main results of this paper. However, more evidence on how stock prices respond to information-motivated trades would be valuable.

The paper is structured as follows. Section 2 states and discusses the hypotheses. Section 3 describes portfolio transitions data. Section 4 explains tests and provides the evidence which supports the hypotheses. Section 5 presents the analysis of price impact and market resilience during transition trades. Section 6 provides the estimates of transaction costs. Section 7 concludes.

2 Hypotheses Development

Researchers can rarely observe motivations behind trades and, consequently, their information content. Portfolio transitions are natural large-scale experiments that allow me to examine sizable demand and supply shocks which, with a high probability, can be identified as informative or uninformative trades. Differences in information content are expected to

lead to differences in the patterns of price dynamics after these trades. In this section, I first discuss the organization of the portfolio transition industry that helps justify my main identification assumption, namely, that on average transition purchases are information-motivated trades whereas transition sales are liquidity-motivated trades. I then state my hypotheses that link transition trades and subsequent return dynamics.

2.1 Institutional Details

The current academic knowledge about portfolio transitions is fairly limited. Since my main identification arguments are based on complicated mechanisms of portfolio transition executions, I briefly discuss interesting details of this industry.

Portfolio transitions are undertaken by institutional investors, such as corporate and public pension plans, endowments, union plans, and foundations. These investors are usually referred to as asset owners. As professionals in the area of investment management, they make asset allocation decisions on behalf of investors, i.e., beneficiaries of the plans. Usually, they do not participate in the investment process directly but delegate their funds to external fund managers. Typically, an asset owner employs about 10 fund managers. Larger plans with over \$1 billion in assets might hire more than 20 fund managers. The average mandate delegated to fund managers is about \$50-100 million. Fund managers have large funds under their management and have many institutional clients. For most of their clients, they manage portfolios with essentially the same composition of securities. Interestingly, asset owners closely monitor, evaluate, and frequently reshuffle their fund managers, thus creating a fair amount of hiring and firing activity in the industry. Transferring of funds from terminated managers to newly hired managers is the most common reason for portfolio transitions. Also, transitions might be necessary when asset owners change the asset mix, deploy new cash inflows, or disburse funds.

If an asset owner makes a decision to replace a fund manager, then a typical portfolio transition between legacy and target portfolios 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 asset owner. Second, the manager to be terminated is notified a day or two before the transition. To avoid any front-running, he is also instructed to stop any trading in his portfolio. Then, the transition manager is selected, often through a bidding process. Finally, the portfolio transition is implemented and a post-trade execution report is prepared for the asset owner.

To minimize transaction costs, transition managers can use several different trading venues. These venues include internal crossing, external crossing, and open market trad-

ing. Some trades are crossed internally against the stocks from other portfolio transition mandates or against the requests submitted by the affiliated passive investment management team. Some trades are executed through various crossing networks such as POSIT, LiquidNet, or Pipeline. These networks allow transition managers to execute their orders in a less expensive way, however, this execution is not certain and risk of information leakage exists. The rest of the orders are traded directly through the open markets.

Several details about portfolio transitions are also worth mentioning. Typically, terminated managers do not use transition to get rid of the stocks with negative information. The composition of legacy portfolios is usually fixed with the current securities in their funds. At the same time, hired managers have potentially more discretion and can choose stocks with favorable perspectives for their new clients. However, in practice, they usually recommend portfolios that are very similar to the portfolios of their current clients.

2.2 Hypotheses

In the market, the complicated relationship of returns, trades, and underlying informational structure exists. Market participants are asymmetrically informed and trade for a variety of reasons. Depending on these reasons, all trades can be broadly categorized into two groups: information-motivated trades and liquidity-motivated trades. Information-motivated trades are executed by informed market participants and thus partially reveal their private information. In contrast, liquidity-motivated trades are submitted by uninformed agents those trades do not contain information unknown to the market. The market is expected to react in different ways to the trades with different information content. On one hand, liquidity-driven trades induce temporary price pressure effects. Stock prices change in order to attract risk-averse counterparties. As liquidity providers are compensated for their services, these deviations are reversed. On the other hand, information-motivated trades shift stock prices permanently. These changes reflect new information about fundamentals, revealed by these trades. If information is only partially impounded into stock prices, then even the return continuation can be observed. This differential price reaction is emphasized by the theoretical work of Wang (1994) and Llorente et al.(2002). It also underlies the empirical models of Hasbrouck (1988, 1991).

The design of a test that can clearly identify these patterns is a challenging task, as information content behind trades is unknown to researchers. However, in case of portfolio transition trades, it can be argued that portfolio transition purchases are information-motivated trades whereas portfolio transition sales are liquidity-motivated trades. Interestingly, the underlying motives behind transition trades are determined by several market participants,

asset owners as well as hired and terminated fund managers.

Fund managers directly determine the composition of securities in legacy and target portfolios. What are the implications of their decisions for transition purchases and sales? Legacy and target portfolios are selected by hired and terminated managers for their clients and therefore their composition might potentially contain positive information about perspectives of selected stocks. This implies that transition sales do not contain any negative information, because terminated manager can not have a negative ability.⁹ However, whether transition purchases carry positive information depends on the stock picking skills of fund managers; the existing evidence on their ability to select stocks is mixed (Lakonishok, Shleifer, and Vishny (1992), Coggin, Fabozzi and Rahman (1993), Ibbotson and Kaplan (2000)).

Asset owners are the other market participants who implicitly affect the selection of stocks in target and legacy portfolios, since they decide how to reshuffle their funds between fund managers or various asset classes. The anecdotal evidence suggests that asset owners allocate a lot of their resources to evaluate and select fund managers. The level of expertise of asset owners in delegating assets to fund managers is much higher than that of retail investors choosing mutual funds. For instance, the hiring of managers includes several stages, starting with an initial screening and ending with several rounds of personal interviews. When evaluating managers, asset owners often rely on the recommendations of professional consultants who offer various advanced tools as part of their screening services. According to Del Guercio and Tkac (2002) and Heisler et al. (2006), important factors in determining asset owners' hiring and retaining decisions are managers' past performance, its consistency as well as various non-performance qualitative characteristics of managers. Interestingly, the tendency of asset owners to pick past winners might help them to benefit from persistency of performance of institutional fund managers, at least in the short-run. This short-run persistency was documented by Busse, Goyal and Wahal (2006), Goyal and Wahal (2006), Ferson and Khang (2002), and Tonks (2005).¹⁰ Consequently, asset owners choose to delegate their funds to skilled managers, and withdraw their funds from managers with no special abilities. Thus, transition purchases are informative trades and transition sales are most likely uninformative trades.

I further provide the empirical justification for my identification assumption. In fact, the portfolio transition data set gives me a unique opportunity to evaluate the choices of asset owners. More precisely, I implement the following procedure. I select 1639 two-sided

⁹Similarly, Coval and Stafford (2005) argue that fire sales of mutual fund managers are unlikely be driven by information reasons.

¹⁰These findings contrast with the well-known lack of persistence in retail mutual funds industry and can be partially explained by more sticky and lumpy capital flows of institutional investors.

transitions that represent shifts of funds between portfolios. Based on the composition of legacy and target portfolios, I compare their post-transition performances. Using the month of transitions as the starting month, I construct 1639 differences in cumulative raw returns between target and legacy portfolios for six subsequent months.

Table 1 presents the results. In the month of portfolio transition, the average difference between target and legacy portfolios is about 31 bps, reflecting price pressure effects of transition trades. These initial deviations slightly reverse in the following months. However, the average difference between portfolios remains permanently above 20 bps. These patterns are observed both for large and small portfolio transitions, but are more significant for large portfolios. These results suggest that either institutional investors, who are responsible for allocation of larger funds, are more knowledgeable and spend more resources when hiring new managers, or fund managers, who manage larger portfolios, have more ability and select better stocks. It is worth mentioning that most of the price deviations occur in the transition month, when information known to hired managers is revealed to the market. If the transition month is skipped, then no statistical difference between legacy and target portfolios is observed.¹¹ Also, the difference between the performance of legacy and target portfolios seems to be relatively small to justify the change in fund management, especially given transaction costs. At the same time, my analysis is based only on snapshots of managers' holdings during transitions, and does not take in account possible portfolio rebalancing in post-transition period.

Building on this identification assumption, I investigate abnormal returns after transition purchases (information-motivated trades) and transition sales (liquidity-motivated trades). This leads to the following hypothesis:

Hypothesis 1: *On average, transition purchases are information-motivated trades, and they permanently shift stock prices upward. At the same time, transition sales are liquidity-motivated trades, and they only temporarily affect stock prices.*

Next, extending my analysis, I discuss the particular situations when transition purchases are expected to be especially informative. My second hypothesis utilizes the observations that informed traders have a particularly substantial information advantage over other market

¹¹This evidence contradicts Goyal and Wahal (2006), who use a matched sample of firing and hiring decisions of asset owners and conclude that if asset owners had stayed with fired investment managers, their excess returns would be larger than those actually delivered by newly hired managers. However, Goyal and Wahal (2006) study the differences between the performance of hired and fired managers at longer horizons. Different results might be also attributed to the nature of data that is used in our studies. While my analysis is based on the precise information about legacy and target portfolios, Goyal and Wahal (2006) rely on the voluntarily disclosed information, public sources, and imperfect matching between hired and fired managers.

participants while trading in stocks with a high degree of information asymmetry. I claim that transition purchases of stocks with high adverse selection costs contain particularly strong signals about stocks' favorable perspectives. Thus, formally, my second test of whether markets react differently to trades with different information content states the following:

Hypothesis 2: *Transition purchases of stocks with a higher degree of information asymmetry have more information and lead to more substantial permanent price adjustments.*

By the nature of portfolio transitions, choices of purchased stocks are strictly bound to the current composition of informed agents' portfolios. Some of the stocks in these portfolios were bought recently based on new information, which has not yet been fully incorporated into stock prices; the others were acquired a long time ago based on the positive signals which have been already reflected in the stock prices. Consequently, transition purchases might contain either new or stale information. It is important to disentangle these two cases; as Hasbrouck (1988, 1991) points out, only unexpected components of trades reveal new information and have permanent effects on security prices.

Certainly, the complete history of trading by terminated and hired managers can reveal the current holdings that are most likely attributed to either stale or new information. However, this data is unavailable. To get around this problem, I suggest using recent past returns that can potentially help identify these two groups of observations. In fact, if past risk-adjusted returns are high, then either favorable information has been already revealed to all market participants or many other agents have already learned about the positive signals. In contrast, low past returns indicate that transition buys contain information that is yet unknown to the market. This observation leads to my next hypothesis, which relates buy trades to past returns and states the following:

Hypothesis 3: *Transition purchases of stocks with high past returns contain only latent information, and their permanent price impact is insignificant. In contrast, transition purchases of stocks with low past returns contain new information, and their permanent price impact is large.*

To conclude, in this section I state several hypotheses about transition trades and the different price dynamics that they are expected to generate. Next, I describe the data set of portfolio transitions and the design of my tests.

3 Data Description

3.1 Data set of Portfolio Transitions

In this study, I use a novel database of portfolio transitions, which allows me to investigate this phenomenon.¹² Data is made available by a leading portfolio transition services' provider, who supervises more than 30% of stock transitions executed in the U.S. It covers the transitions executed on behalf of institutional clients from January 2001 to December 2005. About 43 % of these clients are corporate pension plans; 35% are government/public pension funds; and the rest are endowments, foundations, mutual funds, or insurance companies. Portfolio transition transactions are fairly substantial. For example, in the year 2005 alone, the team completed more than 830 transitions totaling more than \$380 billion of assets.

The portfolio transition data set is exceptionally detailed and clean. It is constructed from the actual business reports built by transition managers for their clients on a case-by-case basis. These reports were thoroughly discussed by transition managers and their clients during portfolio transitions. As a result, this data gives a representative and reliable pictures of the actual processes. Also, the data was further checked manually to avoid any potential typographical errors and inaccuracies.

For each transition, I observe a business report. Each report contains two types of data, namely, the general information on a transition and the more detailed description of executed trades. The general information includes starting date, ending date, and the base currency of clients. Starting (ending) date denotes the day of the first (the last) transaction. Base currency is the trading currency of a client. However, at the time when this data set was constructed, mainly data on the transitions of U.S. clients was available. According to a Global Investor 2006 survey, this part corresponds to roughly 55% of all transitions facilitated by this transition team.

The information on executed trades specifies the number of shares traded, the execution price, and the price benchmarks, as well as information on transaction costs. Since the implementation shortfall methodology is used to estimate the transition efficiency, pre-trade

¹²There are several recent studies that analyze the selections and terminations of fund managers by institutional investors, which are also closely related to portfolio transitions. In comparison with this paper, other studies employ much less accurate and comprehensive data sets. Parwada and Yang (2004), Parwada and Faff (2005), and Dishi, Gallagher, and Parwada (2006) analyze data set on the allocations and withdrawals of Australian pension plan investment management mandates that is constructed based on the voluntary disclosures, public domain sources, pension plan reports, and the investigation by a team of financial reporters. Goyal and Wahal (2006) rely on the data set of hiring and firing decisions that are voluntarily disclosed by fund managers to Mercer Investment Consulting and Institutional Investor Publications, as well as electronic searches of articles published in Pensions and Investments.

price is often chosen as a benchmark. The execution prices and shares traded are provided in aggregated form; all trade records are clustered at a daily level. Moreover, they are further grouped according to the execution method. There are three different execution methods including internal crossing, external crossing, and open market trading. Thus, for each transition, each stock, each trading day and trading venue, the number of shares traded, the average execution price, and the pre-trade benchmark price are specified. Also, in-kind transactions, or assets being part of both legacy and target portfolios, are observed. Availability of these transactions allows me to reconstruct the complete legacy and target portfolios.

3.2 Supplementary Data and Filters

I use the standard CRSP and Compustat databases to get additional stock information. My sample includes ordinary common stocks (with CRSP share codes of 10 and 11) listed on the New York Stock Exchange (NYSE), the American Stock Exchange (AMEX), or NASDAQ in the period of January 2001 through December 2005. Any derivative securities, such as ADRs, REITS, or closed-end funds are excluded. Prices, returns, volume, and shares outstanding are downloaded from CRSP. The estimates of probability of information-motivated trading, PIN, are downloaded from Soeren Hvidkjaer's web site. I use unadjusted data from the Institutional Brokers Estimates System(I/B/E/S) to get the number of analysts who follow stocks.

In order to eliminate records with potential errors and unrepresentative trades, I have filtered out the transitions with obviously wrong information or typographical errors due to the storing and collecting methods. The stocks with the missing CRSP information necessary to construct variables for the tests are removed as well. Moreover, I exclude low-priced or "penny" stocks with prices below 1\$.

3.3 Facts about Portfolio Transitions

In this section, I describe the playing field and general characteristics of typical transitions analyzed in the paper. I consider 2234 U.S. portfolio transitions executed on behalf of U.S. institutions from January 2001 to December 2005. I focus on the common stocks traded in the United States. The trading volume adds up to the aggregated value of roughly \$400 billion.

Panel A of Table 2 provides a general description of the portfolio transitions in the sample of interest. It shows that these transactions represent a substantial amount of trading volume. For instance, during a median transition, about \$50 million or more than a million

shares of 133 various stocks were traded. Different values of medians and means reveal that the distribution of transition size is skewed by several large observations. In fact, some of large transitions involve several billions of dollars of trading volume. Transitions can cover numerous securities. The maximum number of stocks in a particular transition was as high as 3,669.

Panel B of Table 2 presents the distribution of transition stocks across market capitalization quintiles. Cut-offs for size groups are based on the capitalization distribution of the NYSE stocks. While about 70% of the transition dollar value is executed in large stocks, only 1.5% is traded in small stocks. The observed disproportion is the result of numerous regulatory restrictions on the investment policies of institutional investors. This disparity is less extreme for the number of different stocks across capitalization groups, since the trades in the stocks with high market capitalization tend to be larger.

Institutions often split their trades over several days to avoid large transaction costs.¹³ Similarly, portfolio transition orders might take several days to be completed. Usually, the trading horizon is the result of the negotiation between transition managers, who often suggest the optimal trading time, given the transition's complexity, and their clients, who might have additional constraints that require quicker trading.¹⁴ Panel C of Table 2 shows the distribution of transition durations, defined as the number of days between the first and the last trades in a given transition. It takes from one up to 18 days to complete a transition. About 56% of transitions are executed in one day while the majority of others is spread over the following week. If trading volume is considered, then only 26% of all volume is transacted in one day. This pattern suggests that large and complex transitions require more time to be completed and the average transition size increases with the realized execution duration. Also, there is a slight difference between the average execution time of buy and sell sides. A legacy portfolio is sold faster than a target portfolio is acquired (not reported in Table 2). This fact can be explained by the agency-based approach followed by the transition team in running transitions. Namely, transition managers do not provide any additional capital but rather finance purchases of target portfolios with the proceeds from sales of legacy portfolios.¹⁵

While total portfolio transitions may require several days to complete, individual securities can be traded much quicker. Roughly 60% and 80% of securities are executed in one day

¹³See Chan and Lakonishok(1995), Keim and Madhavan(1995) for the analysis of duration of institutional trades.

¹⁴Often institutional investors ask for quicker execution because they want to minimize the blackout period during which the ability to trade is temporarily suspended.

¹⁵When quick turnaround are necessary or when costs must be known in advance, principle-based approach can be used. The entire portfolio is sold to a broker who takes all risks of selling stocks for a fixed pre-determined price.

and two days correspondingly. About 97% are traded in less than a week. In fact, portfolio transition trades are executed more quickly than routine institutional strategies.¹⁶

To summarize, portfolio transitions are large and complicated transactions. A typical size of a transition is about \$50 million. It involves more than 100 stocks, most of which are large ones. Transition trades are spread over different trading venues and over time. It requires from one to 18 days to run a transition. On the stock level, about 60% of securities are traded in one day and 97% are executed over the first week.

3.4 Facts about Transition Orders

In this section, I discuss the characteristics of transition orders in individual securities and how they are split over time into component trades. Panel A of Table 3 presents summary statistics for the size of transition orders. All statistics are calculated from the pooled data. Transition purchases and sales have similar characteristics. Their average size is about \$600,000, from which about \$125,000 are common for legacy and target portfolios and transferred as in-kind transactions, about \$120,000 are traded through open market, \$180,000 are crossed externally and \$165,000 are crossed internally. Apparently, these significant values are influenced by some large orders, since the corresponding median values are much lower. Interestingly, these orders represent only insignificant fraction of shares outstanding. On average, total transition buy and sell orders are about than 1.5 bps of shares outstanding. Moreover, open market trades represent only 0.5 bps of shares outstanding. For comparison, according to NYSE data, the average annual turnover in 2005 was above 100%, which roughly corresponds to 40 bps of average daily turnover. Also, on average, transition orders add up to about 3% of trading volume. However, its median is only 0.05%.

In my study, I often discuss the sample of transition orders during whose execution more than 1% of average daily volume was traded through open market trading, since the impact of these trades on prices is more easily detectable. Panel B of Table 3 shows their summary statistics. These orders represent, on average, about 5.5 bps of shares outstanding and more than 10% of average daily volume. At the same time, the median value of these transition orders are much less significant: roughly 2.8% of average daily volume and 1.5 bps of shares outstanding, most of which is executed through open market trading.

Transition orders are frequently split over several days. Table 4 presents information on the distribution of trades over time. For each day relative to the starting day of transition

¹⁶For example, acknowledging a usual practice of splitting institutional orders, Chan and Lakonishok (1995) reconstruct an ex ante institutional order looking at trading packages, or a sequence of trades which is followed by a 5-day period when a manager stays out of the market. They show that only about 20% of the value of institutional trading is executed in one day; meanwhile trade packages, which take four and more days to complete, account for about a half of all institutional trades.

and trading venue, Table 4 exhibits the average trade size normalized by the average daily volume. Clearly, most of transition trades are executed during the first week, and especially first two days.

4 Event Study

In this section, I test my hypotheses by looking at the behavior of stock prices after substantial portfolio transition trades. I show that these trades create significant price pressure effects. Moreover, stock price dynamics exhibit different patterns after transition purchases and sales. After purchases, security prices are shifted permanently and remain high at a new equilibrium level during the subsequent months. After sales, security prices decline only temporarily and revert to their prior level over the following weeks. This evidence supports my hypothesis: on the whole, transition purchases represent information-motivated trades, which permanently shift stock prices, whereas sales are more often liquidity-driven trades, which induce only temporary effects. I also discuss why alternative explanations of the documented patterns are less plausible.

4.1 Design of Tests

I implement the event study approach to investigate the stock prices dynamics triggered by portfolio transitions trades. First, I define the risk-adjusted returns $r_{i,t}^{adj}$. The specification of a correct model for risk-adjustment is always problematic. I adjust returns for their exposure to the standard three risk-factors of Fama and French (1992). The composition of target and legacy portfolios can potentially depend on the past returns of stocks. Therefore I augment my model by the momentum factor as suggested by 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. To correct for potential biases occurring because of non-synchronous trading, I apply a standard methodology suggested by Dimson (1979). In particular, I regress contemporaneous monthly excess stock returns on the contemporaneous market value-weighted excess return, a size factor, and a B/M factor with their lags. The size factor is a return on a portfolio that is long in small stocks and short in large stocks. The B/M factor is a return on a portfolio that is long in stocks with high B/M and short in stocks with low B/M. Sensitivity to a factor is a sum of coefficients on the factor and its lagged value.

Second, I calculate the cumulative abnormal returns CARs as the following:

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

where $r_{i,t}^{adj}$ is the risk-adjusted return of stock i at day t and T is a horizon. Both short-term horizons, such as several days and weeks, as well as longer horizons such as one, two, and 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 is subject to less severe biases.

Third, for each horizon T , cumulative average abnormal returns, CAARs, and their t -statistics are calculated following the standard Fama-McBeth procedure for the data grouped at monthly levels. This procedure allows one to correct for the cross-sectional correlations between stock returns. The interdependence might occur since the analyzed transactions involve portfolio trading, and contemporaneously traded stocks might share similar characteristics. For example, institutions might withdraw funds from their small stock portfolios or stocks of firms from the same industry. T -statistics are further adjusted with the Newey-West procedure to correct for intertemporal correlations. The number of lags is chosen by the automatic bandwidth selection procedure.¹⁷

My first hypothesis emphasizes the distinctive patterns of CAARs after transition purchases and sales. For purchases, CAARs are expected to be shifted upward during the event and then remain significantly positive at longer horizons. For sales, CAARs are predicted to deviate downward during the event but then reverse and become insignificant at longer horizons. The results presented below support my hypothesis.

4.2 Results

4.2.1 Test of Hypothesis 1

I consider abnormal returns after large transition orders during which more than 1% of average daily volume was traded through the open markets, since their effects of security prices can be more easily detected. Figure 1 plots the cumulative average abnormal returns, CAARs; returns are weighted equally. Panel A of Table 5 quantifies the results. Horizons up to three months are considered. Two main patterns are observed. First, the trades certainly affect the contemporaneous stock returns. Large transition purchases are accompanied by increases in stock prices whereas large transition sales coincide with price reduction. On

¹⁷Results are similar if other numbers of lags are used.

average, during the first week the prices of the bought and sold stocks deviate from the pre-trade level by as much as 0.43% for buys and -0.41% for sales. Second, there is a surprising asymmetry in stock price dynamics following buy and sell trades at longer horizons. On average, the sales of stocks from legacy portfolios only temporarily shift prices; the initial price drop gradually reverses and completely disappears in several weeks. This dynamics resembles a signature of temporary price pressure effects. In contrast, the purchases of stocks from target portfolios permanently shift prices by 0.36% to the new fundamental level. This finding is consistent with my hypothesis about the different information content of transition purchases and sales.

Figure 3 depicts the cumulative average abnormal returns for principle-weighted returns, or, to be more precise, for returns weighted with magnitude of open market trades normalized by average daily volume in the previous month. This weighting scheme gives more weight to potentially more informative purchases. It leads to much stronger evidence on the information component contained in transition buys. For instance, the principle-weighted CAARs are roughly 50 bps in three months after portfolio transitions.

Panel B of Table 5 presents the estimates of cumulative average abnormal returns when all returns are weighted with stock market capitalizations in the previous month. Figure 2 graphically illustrates the results. We observe that price responses for the value-weighted case are different from the equally-weighted one. First, the initial price reaction is less significant. The stock price increases by only 0.21% for the stocks acquired as part of target portfolios. At the same time, it decreases by 0.14% for the stocks sold as part of legacy portfolios. Second, at longer horizons, no asymmetry between prices of sold and purchased stocks is observed. After the initial price change, the average price reverses and over the next several weeks eventually comes back to the original pre-transition level. The difference between the results for the equally-weighted and value-weighted schemas implies that the price dynamics are far from being homogeneous across stocks.

Figure 4 presents average price responses to the sample of all transition orders without restriction to only orders with large open market trades. Again, although the temporary price deviations are observed, the difference between sold and bought stocks at longer horizons is insignificant. These patterns are observed because there are a lot of small trades that do not affect security prices.

Interestingly, the price pressure effects, created by the trades of a particular market participant rather than a segment of investors, might cause a substantial price impact not only on daily but also on weekly frequencies. This impact is especially surprising, since these trades represent relatively small fraction of contemporaneously traded volume. This fact implies that observed intensive trading and high daily volume can be largely attributed

to the trades of noise traders, who do not eliminate effects of one-sided order imbalances on securities prices. This finding is in contrast with Chordia, Roll and Subrahmanyam (2005) who document the result that even the aggregated intraday order imbalances are usually accommodated within the subsequent hour.

The evidence of long-lasting price pressure caused by portfolio transition sales is related to a number of studies of institutional trades. For example, Coval and Stafford (2005) have documented that mutual fund sales/purchases that are triggered by flows in and out of the fund create patterns of price pressure that do not vanish for several quarters. Jin and Scherbina (2006) point out that sell-offs of recently hired fund managers might significantly affect the market and result in substantial underperformance of the inherited losers relative to other momentum losers for three months following the managerial change. Also, the observed long-lasting effects are partially consistent with Subrahmanyam (2006), who shows that order imbalances constructed from the intraday data might affect stock returns for up to two months.¹⁸ One of the suggested explanations for these long-lasting effects might be the inventory control effects, which are most likely to be found at the horizons longer than a day or even a week.

In summary, I provide strong empirical evidence that supports *Hypothesis 1*, i.e., large portfolio transition purchases are informative and induce permanent effects on the prices, whereas uninformative sales generate temporary price pressure effects.

4.2.2 Alternative Explanations of Buy/Sell Asymmetry

Here I discuss other effects that accompany the transition trades and might change the follow-up stock price dynamics. I argue that these changes are less plausible explanations for the observed buy/sell asymmetry than the primary informational hypothesis.

First, if no perfect substitutes are available, then stock excess demand and supply curves will not be flattened by risk-averse arbitrageurs and transition trades will have permanent effects on the prices (see among others Garry and Goetzmann(1986), Shleifer(1986), Kaul, Mehrotra, Morck(2000), Wurgler and Zhuravskaya(2002)). However, it is difficult to explain asymmetry between purchases and sales, unless it is harder to find a hedge for a short rather than for a long position. Hence, the substitution hypothesis cannot explain the documented buy/sell asymmetry.

A second explanation might be that transition trades might change the composition of investors who hold the security. Large purchases increase the institutional ownership. Boehmer and Kelley (2005) show that stocks with greater institutional ownership are priced

¹⁸However, Mitchell, Pulvino and Stafford (2002) describe the impact of the merger arbitrageurs' trades on the stock prices; however, their price pressure effects are relatively short-lived.

more efficiently. Two mechanisms can be triggered. The increase in the number of institutions that hold the stock might increase the number of analysts following it and might induce competition among the strategic informed traders. Both effects enhance efficiency, decrease the future trading costs, and shift the stock price up following the transition purchases. Also, large purchases might create block holders who will closely monitor the firm and contribute to the increase of its value. However, I believe that the transition trades analyzed in this study are fairly insignificant to trigger these effects. Table 3 shows that the average value of order traded through open market is about 3 bps of shares outstanding. At the same time, Boehmer and Kelley (2005) find the effect on the proxies for market efficiency while analyzing much larger 60-bp changes in the institutional holdings. Also, it is not clear why the opposite effects for the transition sales are not observed. Hence, the institutional ownership hypothesis is unlikely to explain the documented buy/sell asymmetry.

Finally, another explanation is that large transition trades might change the severity of short-sale constraints. Purchases make the ownership more concentrated. Additionally, the analyzed institutional investors are by and large reluctant to engage in short selling. These two mechanisms can aggravate the short-sale constraints. Miller (1977) notes that prices of constrained stocks may be inflated beyond fundamental levels since only beliefs of optimistic investors are incorporated. Analyzing the dynamic markets, Duffie, Garleanu and Pedersen (2002) show that prices of constrained stocks can be even higher than the marginal valuation of the most optimistic investors, if they take into account the potential profit to be made by lending these stocks in the future. Thus, the change in the severity of short-sale constraints can explain the permanent price impact asymmetry after transition buys and sells. However, I believe that the transition trades are too small to make this explanation plausible.

In summary, the study of stock prices around the transition trades shows that the contemporaneous stock prices do deviate from the pre-trade levels. On average, during the transition sells, stock prices change temporarily and reverse to the original level over the next several weeks; during the transition buys, stock prices shift to new levels permanently. These patterns clearly support my primary hypothesis that the distinctive price dynamics following transition buys and sells are explained by the difference in their information content.

4.2.3 Test of Hypothesis 2

My second hypothesis states that transition purchases in stocks with high risk of adverse selection are in particular informative and result in more significant permanent price changes. To test this hypothesis, I consider separately transition trades in stocks with high and low information asymmetry and then investigate the cumulative average abnormal returns after

these trades.

The information asymmetry of individual stocks is not directly observed. There is no agreement on how to define its best proxy. For robustness, I use several measures suggested by the previous literature. In the previous section, I analyzed effects on the price dynamics of market capitalization that can be used as a proxy for information asymmetry. In fact, large stocks are expected to be subjects to information asymmetry to a much less extent than small stocks. Empirical literature provides evidence consistent with this assumption. For instance, Lo and McKinlay (1990) find that stock prices of the stocks with smaller capitalization do not follow random walks, which would be expected for the securities with no significant informed trading. My analysis of equally and value weighted returns in Table 5 shows that permanent price impact is more pronounced after trades in small stocks. In this section, I focus on other proxies of information asymmetry.

My first proxy for information asymmetry is the number of analysts who are following a stock. I construct this proxy based on the monthly number of analysts who provided I/B/E/S with end-of-fiscal-year earnings forecast. Brennan and Subrahmanaym (1995) and Easley, O'Hara and Paperman (1998) show that the greater number of investment analysts, being a proxy for the number of individuals producing information about a firm, is associated with the lower adverse selection costs of trading in the stock. Also, the initiations of analyst coverage improve liquidity. The large number of analysts following stocks enhances transparency regarding their perspectives. Hence, market participants who are trading these stocks face low risk of asymmetric information.

My second measure of information asymmetry is the percentage spread. This proxy reflects the assessment of market makers of how probable trading against informed traders is. Stocks with higher information asymmetry tend to have larger percentage spread.

My third measure of information asymmetry is the probability of information-motivated trading, PIN, built based on the structural sequential model of Easley and O'Hara (1987, 1992). Easley et al. (1996) suggest how to estimate this measure on intraday trade data. The higher is the probability of information-motivated trading, the larger is the degree of information asymmetry to be expected. Consistent with this hypothesis, Easley et al. (1996) show that PIN is closely related to spread, which is often linked to the adverse selection costs of trading.

The suggested measures are only the noisy proxies for unobserved information asymmetry. They are far from being perfect. Indeed, the strength and the exact functional form of their cross-sectional relation with the degree of asymmetry are unknown. Moreover, there are other concerns. For instance, recently Boehmer et al. (2006) showed that inaccuracies in trade classification lead to downward biased PIN. As for the number of analysts, it is

frequently not identified for the stocks with potentially high information asymmetry, since these stocks are not regularly followed by analysts. Despite these issues, I use these proxies to test whether permanent price impact is more significant after transition purchases of the stocks with high degree of information asymmetry.

To examine how the price dynamics induced by transition trades depend on information asymmetry, I slightly modify event study tests, described in section 4.1. Each month, observations are additionally sorted into three groups based on the information asymmetry proxies.

Table 6 shows the results for the groups with low and high information asymmetry. For all three proxies, such as the number of analysts following stocks, the percentage spread and the probability of information-motivated trading, similar patterns are observed. First, the price signatures following transition buys differ for the stocks with high and low degrees of asymmetry. For the former, the initial price impact is more significant, and the price is shifted permanently to the new level. For the later, only temporary price deviations are observed. Second, regardless of the degree of information asymmetry, the stock prices tend to come back to the pre-transition levels after transition sales.

The number of analysts, percentage spread and probability of information-trading are closely related to the stocks' market capitalization. The correlation between the probability of information-motivated trading and stock size is about -0.60. Also, fewer analysts are expected to follow smaller stocks, and larger spreads in their markets are typically observed. In order to clearly disentangle the dependence of price dynamics on either the number of analysts, percentage spread, or the probability of information-motivated trading from the size effect, I apply the double-sorting procedure. Each month observations are sorted into three groups based on corresponding stock capitalization. Within each capitalization group, all observations are further split into two sets according to the degree of information asymmetry. I test whether the patterns of permanent price impact for stocks with low and high proxies of information asymmetry differ within size groups.

Table 7 presents the results for the double-sorting procedure on the stock size and the number of analysts, ANUM. They confirm that ANUM is directly linked to the long-run price dynamics even after controlling for stock capitalization. Indeed, as expected, the transactions in smaller stocks permanently affect the stock prices, whereas the transactions in larger stocks cause only temporarily price deviations. The second sorting on ANUM highlights that the permanent price impact is particularly significant after large transition purchases in the stocks with fewer analysts. For instance, two and three months after transitions, the average returns of roughly 0.77% and 1.24% for small stocks tracked by many analysts are statistically indistinguishable from zero. At the same time, for the same months, the returns

of about 2.25% and 3.28% for small stocks with low ANUM are significant at 5% and 10% levels, respectively. Similar patterns are observed for medium-size stocks. The results for sell transition trades are not presented. As before, returns following transition sells are not statistically different from zero at longer horizons.

In Table 8 the results for the double sorting on the stock size and the percentage spread are reported. They imply that the percentage spread is related to the stock price dynamics even after controlling for stock capitalization. Indeed, transition purchases in small stocks with large percentage spread cause permanent shifts in stock prices. At the same time, transition purchases in small stocks with small spread bring about much less significant price deviations. Table 9 reveals similar patterns for the probability of informed trading as a proxy for information asymmetry.

The analysis of this section indicates that transition buys in the stocks, traditionally considered as being prone to high risk of information asymmetry, are followed by a significant and permanent upward shift in prices. These effects are observed regardless of the employed proxy for information asymmetry. Therefore, the documented evidence is consistent with the hypothesis that the average transition buy order is more informative if executed in stocks with high adverse selection risk.

4.2.4 Test of Hypothesis 3

In this section, I test my third hypothesis, according to which purchases of stocks with larger abnormal past returns bring less information into the market and, consequently, have less significant permanent effects on stock prices. The opposite is expected to hold for stocks with lower abnormal past returns.

To test this claim, I implement the methodology described before but sort all observations into two groups based on the risk-adjusted past returns $R_{-3m,0}^{adj}$ in the previous three months. Group "Low" includes stocks with the bottom 33% of risk-adjusted past returns. Group "High" includes stocks with the top 33% of risk-adjusted past returns. Then, estimates of cumulative abnormal returns for both groups are calculated following the Fama-McBeth procedure.¹⁹

Table 10 shows that, in fact, permanent effects of transition buy orders are much more significant for stock with low past returns than for stocks with high past returns. For stocks with low past returns, abnormal returns are as high as 1.16% and 1.10% in two and three months after transition purchases, respectively. At the same time, for groups of stocks with high past returns, the effects of transition purchases are short-lived and stock prices revert

¹⁹If groups with positive and negative risk-adjusted returns are considered instead, the results are qualitatively similar.

to their pre-transition levels over the following weeks. These results are consistent with the intuition of Hasbrouck (1988, 1991) that only unanticipated trades reveal new information and shift security prices permanently.

Also, the analysis of transition sales uncovers interesting patterns. Although cumulative average abnormal returns for both stock groups are insignificant in the long run, the short-run market's responses are very different. Sales of stocks with low past returns have almost no significant effects on the stock prices. In contrast, price pressure effects of sales of stocks with high past returns last for about a month.

These intriguing patterns can be partially explained by the arguments discussed in Saar (2001); he develops a model that shows that information content of trades is the result of the trading strategies of informed agents that might depend on past prices. In his model, agents are bound by diversification and short-sale constraints. Being short-sale constrained, they typically cannot sell stocks even if negative signals about the stock's perspectives are received. Therefore, sales are usually submitted by noise traders, their information content is low, and their price impact is insignificant in contrast to that of buys. However, a long run-up in the stock price implies that informed agents have bought this stock and are not bound by short-sale constraints anymore. In these cases, if negative signals are observed, their current stock holdings allow them to sell securities and the magnitude of adverse selection costs in sales increases.²⁰ These arguments can apply to the temporary price responses, if the market cannot ex ante distinguish between information-motivated and liquidity-motivated trades.

5 Price Impact and Market Resiliency

In this section, I provide more detailed analysis of price dynamics during executions of portfolio transition orders. I focus on static and dynamic aspects of market liquidity such as price impact and market resiliency. More precisely, I investigate how price impact coefficients of consequent trades change during execution of transition, how these coefficients differ for purchases and sales, and what stocks' characteristics explain cross-sectional variations in liquidity measures.

5.1 Definition of Price Impact Coefficients

The issue of how to define the price impact coefficient is a complicated one. Previous literature has suggested a number of possible specifications. My first measure is closely

²⁰Empirical study by Chiyachantana et al.(2006) provides corroborative evidence for dependence of permanent price impact on past prices.

related to the one suggested by Breen et al. (2002).²¹ For each order in portfolio transition, the price impact coefficient is defined as the return stated in percent over the trade size,

$$PI_1 = \frac{100(P_{exec}/P_{bch} - 1)}{TrSize} \quad (2)$$

where $TrSize$ is the signed number of shares executed in the open market (multiplied by 1000) and normalized by shares outstanding in the previous month, P_{bch} is a pre-trade benchmark price for a stock in the given transition, P_{exec} is the volume-weighted average execution price of the component trades executed in the open market. Only open market trades are considered. This specification is inspired by the measure of information asymmetry first introduced by Kyle (1985) and defined as the price change over the trade size. Scaled rather than absolute values are used to make these measures more meaningful cross-sectionally: this scaling assures the proper price impact specification for the stocks with the same market capitalization but different number of shares outstanding. For further discussion of this specification see Breen et al. (2002).²²

Temporary price impact functions are often found to be concave. This functional form is suggested among others by Almgren et al. (2005), Hasbrouck (1991), Hausman, Lo, and MacKinlay (1992), and Keim and Madhavan (1996). Several factors might contribute to mitigating transaction costs of large orders. Among them is the ability of block traders to credibly signal the liquidity-motivated motives behind their large trades. Another channel might be the potential leakage of information while large orders are being 'shopped'. Also, since trades can place their orders strategically, most of large costly orders will be split into the smaller ones to be traded over the time (Bertsimas and Lo (1998)). Additionally, large costly orders can be strategically directed to external crossing networks. All these issues are relevant for the portfolio transition orders and can potentially introduce non-linearity into their realized price impact estimates.

To address the problem of non-linearity, I slightly modify my first specification (2) and define the second measure of price impact as:

$$PI_2 = \frac{100(P_{exec}/P_{bch} - 1)}{i TrSize^{1/2}} \quad (3)$$

where i is 1 for transition buy orders and -1 for transition sell orders. The choice of the

²¹This specification is also related to the measures used in Korajczyk and Sadka (2004) and Keim and Madhavan (1997).

²²Following Keim and Madhavan (1997), Conrad et al. (2003) among others, I do not adjust (2) for risk. Slightly positive average market return over 2001-2005 might induce bias into price impact of purchases upwards and price impact of sales downwards. However, these biases are too small to drive the presented results.

square-root function was motivated by the popular Barra's price impact model which is often used by practitioners. Next, I analyze how price impact coefficients defined in (2) and (3) differs for transition buy and sell orders.²³

5.2 Asymmetry of Price Impact for Buys and Sells

Similar to documented asymmetry in the price responses, there is also the asymmetry in the price impact coefficients of transition buy and sell orders. Table 11 shows means and medians of associated with these orders price impact coefficients. Regardless of price impact specification, the percentage price changes during buy orders are significantly larger than those during sell orders. Similar results are observed for stocks from most of market capitalization groups. This asymmetry might reflect more substantial information content of transition buys than that of transition sales.

Also, Table 11 highlights the dependence of price impact magnitude on market capitalization. Interestingly, if estimated for various capitalization groups, price impact tend to exhibit u-shaped patterns: it is particularly significant for large and small stocks. Previous literature has documented that small stocks are typically subjects to high degree of information asymmetry, and experience significant price impact (Hasbrouck (1991)). High price impact of trades in stocks with large market capitalization is more surprising. Large stocks are closely followed by many market participants. Therefore, liquidation or acquisition of large positions in these stocks is quickly revealed to other traders who can try to manipulate the market and, consequently, increase the total price impact of transition trades. This mechanism is consistent with the results documented in Section 5.4. Another potential explanation is that many market participants follow similar trading patterns when trading in large stocks. This contemporaneous trading in the same direction can amplify price impact as well.²⁴

To summarize, the analysis of transition trades reveals the asymmetry in price impacts of transition purchases and sales. Price impact of transition purchases is higher than that of transition sales. Moreover, average price impact of trades varies with capitalization quintiles. Interestingly, trades in large and small stocks tend to induce more significant price impact than trades in medium stocks.

²³To avoid the influence of extreme values in (2) and (3), I replace the values above 95th quintiles by 95th quintiles.

²⁴Other factor that contributes to these patterns is measuring the price impact coefficients per unit of net turnover; the size of a trade which represents a given percent turnover increases with firms' size, and, mechanically, leads to the positive relation between size and price impact (Breen et al. (2002)).

5.3 Cross-Sectional Results

Data on portfolio transitions gives an opportunity to investigate the differences in liquidity measures across large cross-section of stocks. Here I mostly focus on how prices react to transition sales, which can be considered being uninformed liquidity shocks. However, for completeness I present the results for transition purchases as well. To be more precise, I implement the Fama-McBeth regression analysis to examine which of stock characteristics influence the observed price impact of transition orders, as defined in (2) and (3). Next, I briefly discuss the explanatory variables.

Price impact of trades depends on market participants' beliefs about the degree of adverse selection risk. Price impact is expected to be larger for stocks that are subjects to more significant information asymmetry. As its proxies, I use market capitalization, number of analysts who follow the stocks, and percentage spread. Another factor that can influence the magnitude of price impact is the amount of noise trading; the more active noise traders are, the lower price impact is (Kyle (1985)). A good proxy for noise trading is stocks' monthly turnover (Campbell et al. (1993)). Also, if counterparties of transition managers are risk averse, then they require execution prices that properly compensate them for holding additional risk of suboptimal portfolios. The riskier stocks are, the more costly it is to get liquidity in their markets. Therefore, price impact might depend on stocks' volatility. I run the Fama-McBeth regressions of price impacts on these explanatory variables taken as of the month before transitions. All observations are grouped at monthly levels.

Table 12 shows the results for exchange-traded and Nasdaq-traded stocks. In general, price impacts of transition sales depend on the proxies of information asymmetry: coefficients for the number of analysts are significantly negative, whereas coefficients for the percentage spread are positive in most cases. Also, the negative relation between price impact and amount of noise trading is observed. Additionally, trades in more volatile stocks tend to have larger price impact. However, with a few exceptions, no statistically significant relation between price impact of transition purchases and explanatory variables is found. This fact might be explained by more complex mechanism of how new information is incorporated into prices.

5.4 Price Impact during Transition Execution

Theoretical literature has long been recognized that traders often split their orders to minimize transaction costs and described the complicated dynamic relation between orders and returns (Kyle (1985), Vayanos (1999, 2001)). The analysis of price impact dynamics for the consecutive trades in trading packages might reveal both how market learns new informa-

tion and how market accommodates liquidity shocks. However, so far empirical literature has mostly focused on the analysis of individual trades (Chan and Lakonishok (1993), Kraus and Stoll (1972), Keim and Madhavan (1996)). A few empirical studies examine total effect of trading 'packages' (Chan and Lakonishok (1995), Keim and Madhavan (1997)). Yet, the dynamics of price impact over the course of trading packages has not been examined. To fill this gap, I study the evolution of price impact induced by the sequence of portfolio transition trades that constitute transition orders.

According to identification assumption, portfolio transitions purchases contain private information. If transition buy orders are split over several days, then as more and more trades are executed, market learns about informed trading. Moreover, this learning is expected to occur quicker in larger stocks. Consequently, the price impact coefficients of transition trades are most probably increasing from the beginning to the end of transition purchases execution. This increase is more pronounced during purchases of large stocks.

According to identification assumption, transition sales do not carry new information, and, consequently, different dynamics of price impact coefficients are expected. These price dynamics in response to large uninformative trades of institutional investors was modeled in Vayanos (2001).²⁵ Despite of the absence of private information about stocks' future payoffs, he points out the curious form of information asymmetry. In fact, institutional traders have informational advantage over other market participants, since they know that their large orders will be executed and that future stock prices will change adversely. For example, if a pension fund liquidates its position in a given stock due to exogenous reasons, it has private information about the future drop in the stock prices. This information is similar to information of an insider who observes the negative signal about future payoffs. Interestingly, if a trader does not manipulate the market, the model predicts the decreasing over time price impact, as market maker learns about the large trader's intentions and unexpected order flows decrease.

To empirically investigate the dynamics of price impact patterns, I study the average price impact of individual trades in transition orders. More precisely, for each transition order, all open market trades are grouped into two sets: trades that are executed during the first half of transition and trades that are executed during the second half of transitions.²⁶ Then, for each transition order, the average price impacts of the first and second halves are calculated. Price impact coefficients of component trades are defined as in (2) and (3), but as P_{bch} the close price in the previous to a trade day is used. Afterwards, the means and

²⁵See also Vayanos(1999) for similar analysis of the market without noise traders.

²⁶For instance, if transition order is executed in four days, then trades of the first two days belong to the first group and trades in the last four days belong to the second group.

medians of their pairwise differences (if available) are estimated. Table 13 shows the results along with p-values of t-tests and Wilcoxon signed-rank tests, respectively.

For transition buy orders, on average, price impact of the trades in their first half is significantly smaller than price impact of the trades in their second half. This finding is consistent with the hypothesis that as trading strategy unfolds and market absorbs more and more trades, market participants learn about informative trading. This learning is reflected in the increasing price impact coefficients, those changes are especially significant for larger stocks. At the same time, results for transition sales are very different. No distinctive patterns in their price impact dynamics are observed, and the effects described in Vayanos (1999, 2001) are not found in the data. These findings are robust to different price impact specifications. They are observed for both exchange-traded stocks and Nasdaq-traded stocks.

So, during execution of transition purchases price impact of subsequent trades increases as more trades are placed into the market. This shows that market does learn about informed trading. At the same time, during execution of transition sales, price impact of subsequent trades remains constant.

5.5 Market Resiliency

Dynamic aspect of liquidity is characterized by market resiliency. Resiliency is the speed with which supply and demand rebuild themselves after being temporarily depleted by trades. Although there are less empirical studies on market resiliency than that on price impacts and spread (Dong, Kempf, and Yadav (2006)), dynamic properties of liquidity are crucial in determining the trading strategies of market participants and, potentially, asset prices (Obizhaeva and Wang (2006)). Next, I examine how market resiliency differs across stocks with different market capitalization and across exchanges.

Being uninformative shocks, transition sales provide the opportunity to analyze market resiliency. I split observations into five groups according to firms' market capitalization. Then, for each group of orders, I estimate the average initial price deviation as the cumulative abnormal return from the beginning of transition to the last open market trade in transition orders. These deviations represent the contemporaneous reactions to the supply shocks. As these shocks are uninformative, they trigger temporary price deviations, and eventually stock prices revert to pre-transition levels. To determine market resiliency, for each group, I first calculate average price responses that are lined up with the last open market trade in transition orders; then, resiliency is defined as a half-life of these price responses.

For each size group, Table 14 reports the magnitude of initial price deviation and its half-life (in days). Typical half-life of price responses to supply shocks is about 3 days

for exchange-traded stocks and 8 days for Nasdaq-traded securities. Interestingly, half-life tends to increase as market capitalization decreases. This finding implies that markets of larger stocks are more resilient, and liquidity shocks dissipate more quickly. These patterns might be attributed to stronger competitions among market participants and lower degree of information asymmetry for larger stocks.

Numerous studies suggest that execution costs on Nasdaq are significantly greater than those on the NYSE. For instance, market makers post wider spread and smaller depth. Results in Table 14 show that market resiliency of exchange-traded securities is also higher than that of Nasdaq stocks, even after controlling for size. Liquidity shocks take more time to be accommodated on Nasdaq than on the NYSE. Several reasons could explain these patterns. First, it might take more time for Nasdaq dealers to learn information content of transition orders, since these orders can be executed through several dealers who cannot see the order flows of each other. At the same time, the NYSE specialists operate in centralized markets and are better informed about current situation in their stocks' market. Second, inventory concerns might be more important for dealer markets rather than for auction markets. In fact, on Nasdaq, large transition orders are simultaneously executed with several dealers. Consequently, the easiness to undo accumulated inventory position will be aggravated by similar intentions of other dealers. At the same time, on the NYSE, liquidity can be partially provided by other limit orders rather than specialist. The difference in resiliency suggests that NYSE specialists might be more efficient in providing liquidity than Nasdaq market makers, not only in terms of its price, quantity but also in terms of its time aspects.²⁷

The main finding of this section is that market resiliency increases with market capitalization. Moreover, resiliency of exchange-traded stocks tends to be higher than that of Nasdaq-traded stocks.

6 Trading Cost Analysis

I also analyze the magnitude of transaction costs for a sample of portfolio transition trades.²⁸ I update the estimates of institutional trading costs for individual securities for the period from 2001 to 2005 and make available the estimates of total costs for portfolio transitions. To measure execution transaction costs, I follow the implementation shortfall method used

²⁷For exchange-traded stocks, liquidity shocks are accommodated at a constant speed. At the same time, for Nasdaq-traded stock, accommodation of shocks is non-linear, i.e., prices remain at new levels for several days and then quickly converge to pre-transition levels.

²⁸In this section, I extend the trading cost analysis of portfolio transitions that is discussed in Kritzman, Myrgren and Page (2006).

in the previous literature (Perold (1988), Keim and Madhavan (1997), Conrad et al. (2003)). Total execution costs is a sum of implicit and explicit trading costs, defined as:

$$\textit{Implicit Cost} = P_{exec}/P_{bch} - 1 \tag{4}$$

$$\textit{Explicit Cost} = C_t/P_{bch} \tag{5}$$

where P_{bch} is the pre-trade benchmark price for the stock in the given transition, P_{exec} is the volume-weighted average execution price of the component trades executed in the open market, and C_t is the volume-weighted commissions and security fees per share. Costs are calculated not on trade level but rather on order level. This approach is similar to the one implemented in Keim and Madhavan (1995, 1997) and Conrad et al. (2003) as well as the trade-packages approach of Chan and Lakonishok (1995, 1997).²⁹

Panel A of Table 15 shows means and medians of trading costs, based on all transition trades. For exchange-traded stocks, the average round-way cost is about 35 bps, whereas for Nasdaq-traded securities, it is roughly 58 bps. The median values of trading costs correspond to slightly lower values of 22 bps and 44 bps, respectively.

However, the correct trading cost analysis of individual trading venues (internal crossing, external crossing, or open market trading) is problematic. The first reason is the difficulty of attributing the cost to particular trading mechanisms during multiple-mechanisms orders.³⁰ For instance, even though crossings have insignificant effects on security prices, the implicit cost of external crossing trades can be biased upwards by preceding open market trades. This issue can be addressed by examining trading costs of single-mechanism orders. The second reason is the strategic trading of transition managers. In fact, execution of portfolio transitions is a challenging task. Transition managers endogenously choose between executing trades through different market venues. These choices depend on the securities' characteristics, current market conditions and the time left till the end of transitions. For example, despite its high trading costs, transition managers might buy an illiquid security through open market trading, if its price has recently decreased relative to a benchmark price. Also, if stock is illiquid and expensive to trade in open markets, transition managers might prefer to send their orders to the crossing networks. However, execution of their orders there is uncertain. Waiting increases opportunity costs and information leakage, consequently implying non-linear dependence of the choice between trading venues on liquidity.

²⁹The implicit cost for transition sales is measured as the negative of (4).

³⁰As defined in Conrad et al. (2003), multiple-mechanisms orders are the ones executed through several trading venues, and single-mechanism orders are the ones executed through a single trading venue.

Thus, endogenous switching regressions, similar to the ones adapted in Keim and Madhavan (1997) and Conrad et al. (2003), can be implemented. I leave these questions for the future research and conclude this paper with a rough analysis of trading costs.

Panel B of Table 15 reports estimates of trading costs that are based only on open market trades. Additionally, the results for a subset of trades with positive implicit costs are shown, as only in these cases transition managers were, in fact, demanding liquidity rather than providing it. The average total round-trip cost of open market trades is about 46 bps for exchange-traded stocks and 73 bps for Nasdaq-traded stocks. If trades with positive price impact are considered, then these values become higher than 2.00%. This observation implies that the real cost of market liquidity can be much higher than the traditionally reported estimates that does not take in account strategic order placement.

Panel C of Table 15 shows estimates of average trading costs for transition orders that are executed either through internal or external crossings but not through open markets. I examine this sample of orders to address the concern that contemporaneous market trades can induce bias into costs estimates of crossing networks. Trading costs for internal and external crossing networks are reported separately. Explicit costs of external crossings are similar to those of open market trades. However, their implicit costs are much lower, yet, being positive as well. This fact is intriguing, since most of crossing networks execute orders at prices that are obtained from primary markets in order to avoid price impact of large trades. Positive implicit costs can be explained, if current market design of networks still leaves room for market manipulation. Another reason can be endogenous choice of transition managers between trading venues: they tend to send orders to crossing networks for stocks which prices have recently moved adversely relative to the benchmarks. These choices might results in, on average, positive implicit costs of external crossings. Internal crossing trades have no explicit costs and their implicit costs are much lower than those of other trading venues. These cost differentials vividly highlight that availability of large pool of internal liquidity can substantially reduce portfolio transition costs.

Following Keim and Madhavan (1997), I also estimate a regression model to analyze the various factors affecting trading costs and update results of previous literature for 2001-2005 sample period. The dependent variable is the total trading costs in percent. The set of explanatory variables includes Nasdaq dummy, the trade size defined as the order size (multiplied by 10^4) over shares outstanding in percent, $TrSize$, the logarithm of market capitalization in thousands of dollars, $LN\ Cap$, and the price inverse, $InvPrc$. Results for transition purchases and sales are presented in Panel A of Table 16. Only open market trades are considered. Although the R^2 is quite low, most coefficients are statistically significant. As in Keim and Madhavan (1997), trading costs depend positively on the trade size and the

price inverse, and negatively on market capitalization. The coefficients on Nasdaq dummy are positive and significant.

Next, I investigate transaction costs on portfolio transition level. I apply regression analysis to examine the relation between total transition costs (in percents) and various transition characteristics. I consider purchases of target and sales of legacy portfolios separately.³¹ The explanatory variables are based on the ones defined in the previous paragraph. I use the average trade sizes in transitions, $\text{Avg}(\text{TrSize})$, the average logarithm of market capitalization in thousands of dollars, $\text{Avg}(\text{Ln Cap})$, dummy for purchases of target portfolios, Buy , and the logarithm of transition duration (in days).

Panel B of Table 16 shows the results. First, executions of portfolio transitions are cheaper than previously assumed (Goyal and Wahal (2006)). Their average round-trip execution cost is about 34 bps of the total dollar trading volume. At the same time, some transitions are more expensive to execute. These are large transitions in small stocks that typically require longer execution periods. Overall, inexpensiveness of portfolio transitions might be explained by availability of alternative trading venues (such as internal and external crossing networks) that significantly reduce their cost.

7 Conclusion

The main goal of this paper is to investigate how the market learns new information and how it accommodates liquidity shocks. Unique data set of portfolio transition trades allows me to identify information-motivated and liquidity-motivated trades. More precisely, I argue that transition purchases contain private information, whereas transition sales are uninformative. Analysis of price dynamics triggered by these transactions reveals that the market responses differently to trades with different underlying motives. Information-motivated trades permanently shift prices. These permanent changes are especially pronounced after large trades, trades in stocks with high degree of information asymmetry, and trade that reflect new rather than stale information. At the same time, liquidity-motivated trades induce only temporary price pressure effects that reverse in the following weeks.

Extending my analysis, I examine the price impact and market resiliency associated with portfolio transitions. I document that price impact coefficients of transition purchases are statistically larger than those of transition sales. Moreover, price impact of component trades in transition purchases increases, as more trades are placed into the market, and the market learns about informed trading. At the same time price impact of subsequent

³¹These portfolios include positions that are common for both legacy and target portfolios and reflected in in-kind transactions.

trades in transition sales remains constant. I also perform cross-sectional analysis of price impacts and market resiliency, and investigate what determines these measures of liquidity and how they differ across exchanges. All these findings offer new glimpse into how the market incorporates information and accommodates liquidity shocks.

This paper contributes to our understanding of the elusive concept of market liquidity. To know more about liquidity is especially important in light of the recently growing evidence that both liquidity and liquidity risk affect asset prices (Amihud, Mendelson and Pedersen (2005)). This implies interesting directions for the future research. Since data on portfolio transitions trades covers large universe of stocks, it allows to investigate whether liquidity helps explain cross-sectional variation in expected returns. In fact, liquidity for both traditional and alternative trading systems (i.e. crossing networks) can be quantified. Also, various aspects of liquidity such as spread, price impact, and market resiliency can be extracted. Then, the effects of liquidity on asset prices can be tested.

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Table 1: Identification Assumption: Target vs. Legacy Portfolios

Horizon	All Transitions		Large Transitions		Small Transitions	
	Δ	t-stat	Δ	t-stat	Δ	t-stat
Month 0	0.31**	(4.58)	0.30**	(4.33)	0.33**	(2.77)
Month 1	0.25**	(2.65)	0.27**	(2.82)	0.23	(1.40)
Month 2	0.22 [†]	(1.78)	0.29*	(2.45)	0.15	(0.71)
Month 3	0.21	(1.45)	0.22	(1.60)	0.19	(0.78)
Month 4	0.26	(1.51)	0.22	(1.46)	0.29	(0.96)
Month 5	0.20	(1.00)	0.24	(1.40)	0.17	(0.46)
Month 6	0.25	(1.18)	0.26	(1.47)	0.24	(0.64)
# Obs	1639		819		820	

Table 1 shows the average difference between cumulative raw returns of target and legacy portfolios for two-sided transitions, Δ . Returns are cumulated starting the month of portfolio transitions. Six subsequent months are considered. Estimated for all two-sided transitions are presented; also, results for small and large transitions are shown separately. Small and large transitions are defined based on the size of legacy and target portfolios. The threshold is about \$100 million. 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 2: Summary Statistics for Portfolio Transitions

<i>Panel A: Transitions, Summary Statistics</i>				<i>Panel B: Cap Quintiles</i>		
	<u>\$Volume (000)</u>	<u>#Shares (000)</u>	<u>#Stocks</u>	<u>Cap Qnt</u>	<u>\$Volume</u>	<u>#Stocks</u>
Mean	184,504	6,048	268	1(Small)	1.46%	8.60%
Median	53,359	1,837	133	2	5.17%	14.30%
25th	16,597	548	65	3	9.28%	16.97%
75th	149,513	5,152	314	4	14.29%	20.66%
Max	24336,138	881,040	3669	5(Large)	69.80%	39.46%
StDev	641,957	22,076	378			

Panel C: Split over Time

Duration	Total Transitions		Stock Trades, \$Volume	
	<u>#Trans</u>	<u>\$Volume</u>	<u>Buy</u>	<u>Sell</u>
1 day	55.71%	25.66%	60.59%	61.56%
2 days	18.70%	18.98%	20.35%	19.73%
3 days	10.22%	16.68%	9.75%	9.09%
4 days	5.51%	8.76%	3.88%	3.95%
5 days	3.12%	7.70%	2.43%	2.69%
6–10 days	5.63%	18.41%	2.97%	2.83%
11–18 days	1.12%	3.82%	0.03%	0.15%

Table 2 presents general information on the portfolio transitions: summary statistics in Panel A, distribution of transition trades across different capitalization quintiles in Panel B, distribution of transition trades across time in Panel C. Panel A shows average, median, standard deviation, maximum value and minimum value for the dollar volume (in thousands), the number of shares traded (in thousands) and the number of different 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. The duration is shown for the transition trades in individual stocks as well. Capitalization thresholds are calculated based on NYSE stock capitalization quintiles. The sample ranges from January 2001 to December 2005.

Table 3: Summary Statistics for Portfolio Transition Orders

		Buy			Sell			In-Kind
		OMT	EC	IC	OMT	EC	IC	
\$ Volume (000)	Mean	111.20	183.83	169.12	120.30	182.92	163.62	123.96
	Median	0.00	13.36	3.60	0.00	8.85	4.44	0.00
# Shrs (000)	Mean	4.16	6.52	5.44	4.40	6.43	5.23	3.67
	Median	0.00	0.50	0.10	0.00	0.40	0.20	0.00
# Shrs/ADV (%)	Mean	1.02	1.29	0.75	1.17	1.83	0.85	0.33
	Median	0.00	0.04	0.01	0.00	0.01	0.01	0.00
# Shrs/ShrOut (bp)	Mean	0.47	0.61	0.38	0.51	0.70	0.42	0.15
	Median	0.00	0.03	0.01	0.00	0.03	0.01	0.00

		Buy			Sell			In-Kind
		OMT	EC	IC	OMT	EC	IC	
\$ Volume (000)	Mean	512.37	208.57	219.52	529.08	242.49	207.69	105.12
	Median	150.80	0.00	0.00	150.22	0.00	0.00	0.00
# Shrs (000)	Mean	20.55	9.42	8.38	21.15	10.29	7.68	3.40
	Median	7.33	0.00	0.00	7.50	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/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

Table 3 presents summary statistics on portfolio transition orders and their distribution over various trading venues: open market (OMT), external crossing (EC) and internal crossing (IC). Panel A presents the statistics for all portfolio transition orders. Panel B shows the statistics for transition orders during whose execution more than 1% of average daily volume was traded through open market trading. For transition trades, the means and medians of the following 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. Results for buy, sell and in-kind transactions are presented separately. All statistics are calculated based on pooled data from January 2001 to December 2005.

Table 4: Distribution of Portfolio Transition Orders over Time

		0d	1d	2d	3d	4d	5d	6–11d	>11d	All
<i>Panel A: All Portfolio Transition Orders</i>										
Buy	OMT	0.16	0.37	0.22	0.11	0.08	0.04	0.04	0.00	1.02
	EC	0.28	0.49	0.24	0.12	0.08	0.04	0.03	0.01	1.29
	IC	0.16	0.29	0.15	0.07	0.05	0.01	0.02	0.00	0.75
Sell	OMT	0.23	0.34	0.22	0.13	0.09	0.05	0.09	0.02	1.17
	EC	0.36	0.51	0.32	0.22	0.19	0.07	0.11	0.05	1.83
	IC	0.25	0.30	0.13	0.07	0.04	0.02	0.03	0.01	0.85
<i>Panel B: Portfolio Transition Orders with OMT Trades > 1% ADV</i>										
		0d	1d	2d	3d	4d	5d	6–11d	>11d	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

Table 4 presents the distribution of the portfolio transition orders over time. Panel A presents the statistics for all portfolio transition orders. Panel B shows the statistics for transition orders during whose execution more than 1% of average daily volume was traded through open market trading. For each day relative to starting day of transition (0d), table exhibits the average trade size normalized by the average daily volume, ADV, in the previous month (in percents). Open market trades (OMT), external crossing trades (EC), and internal crossing (IC) trades are considered separately. All statistics are calculated based on the pooled data from January 2001 to December 2005.

Table 5: Cumulative Average Abnormal Returns, CAARs

Panel A: Stocks Weighted Equally, EW

	Time Horizon T							
	0d	1d	2d	1w	2w	1m	2m	3m
Buy	0.23** (4.86)	0.37** (7.39)	0.45** (8.34)	0.43** (6.70)	0.27* (2.55)	0.35 [†] (1.87)	0.27 (1.17)	0.36 (0.83)
Sell	-0.19** (-3.86)	-0.39** (-5.50)	-0.43** (-7.19)	-0.41** (-7.36)	-0.22* (-2.36)	-0.08 (-0.42)	-0.25 (-1.14)	0.05 (0.15)
Δ	0.42** (4.87)	0.75** (6.66)	0.88** (9.82)	0.84** (9.28)	0.49** (4.20)	0.43** (2.82)	0.53* (2.44)	0.31 (1.24)

Panel B: Stocks Weighted by Market Capitalization, VW

	Time Horizon T							
	0d	1d	2d	1w	2w	1m	2m	3m
Buy	0.04 (1.63)	0.09** (2.81)	0.08 (1.32)	0.21** (4.81)	0.11 (1.06)	0.05 (0.33)	-0.14 (-1.04)	0.15 (0.41)
Sell	-0.11** (-4.88)	-0.21** (-5.90)	-0.23** (-9.56)	-0.14 [†] (-1.91)	0.17 (1.16)	0.02 (0.09)	-0.15 (-0.52)	-0.08 (-0.19)
Δ	0.15 (3.69)**	0.31 (6.35)**	0.32 (5.08)**	0.35 (4.07)**	-0.05 (-0.24)	0.01 (0.06)	-0.03 (-0.11)	0.17 (0.42)

Table 5 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. 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: CAARs for Stocks with Different Degrees of Information Asymmetry

<i>Panel A: Groups by Number of Analysts, ANUM</i>							
	0d	1d	1w	2w	1m	2m	3m
Buy Low	0.33** (4.16)	0.52** (6.09)	0.59** (4.70)	0.53** (3.27)	0.58 [†] (1.88)	1.08* (2.46)	0.91 [†] (1.68)
High	0.14** (4.11)	0.20** (5.00)	0.21** (2.75)	0.14 (0.78)	-0.11 (-0.49)	-0.38 (-1.64)	-0.40 (-0.88)
Sell Low	-0.23** (-3.36)	-0.45** (-3.98)	-0.40** (-2.72)	-0.02 (-0.14)	0.19 (0.71)	0.11 (0.27)	0.35 (0.75)
High	-0.13** (-3.04)	-0.25** (-4.87)	-0.28* (-2.64)	-0.18 (-0.73)	-0.29 (-0.72)	-0.31 (-0.63)	-0.14 (-0.20)

<i>Panel B: Groups by Percentage Spread, SPREAD</i>							
	0d	1d	1w	2w	1m	2m	3m
Buy Low	0.10** (3.89)	0.11** (2.74)	0.14 (1.52)	-0.02 (-0.14)	-0.22 (-0.91)	-0.19 (-0.63)	-0.40 (-0.94)
High	0.40** (3.74)	0.68** (4.78)	0.87** (3.67)	0.76* (2.30)	0.76* (2.26)	1.04 [†] (1.79)	1.03 (1.05)
Sell Low	-0.12** (-4.10)	-0.25** (-5.99)	-0.30** (-3.41)	-0.17 (-0.92)	-0.35 (-1.08)	-0.67 (-1.59)	-0.80 (-1.65)
High	-0.27** (-3.10)	-0.67** (-4.02)	-0.48** (-5.25)	-0.11 (-0.84)	0.73 (1.62)	0.76 (1.40)	0.87 (1.20)

<i>Panel C: Groups by Probability of Informed Trading, PIN</i>							
	0d	1d	1w	2w	1m	2m	3m
Buy Low	0.07 (1.62)	0.12** (2.77)	0.12 (0.98)	0.34* (2.11)	0.32 (1.52)	0.12 (0.42)	0.28 (0.64)
High	0.31** (5.22)	0.47** (5.78)	0.61** (4.02)	0.73** (4.09)	0.71** (2.91)	0.93** (2.94)	0.55 (1.13)
Sell Low	-0.06 (-1.43)	-0.14** (-3.12)	-0.07 (-0.87)	0.07 (0.47)	0.10 (0.50)	0.06 (0.03)	0.29 (0.32)
High	-0.21** (-3.45)	-0.49** (-5.50)	-0.49** (-3.97)	-0.09 (-0.71)	-0.04 (-0.25)	0.04 (-0.24)	0.44 (0.50)

Table 6 shows the cumulative average abnormal returns, $CAAR_T$, following transition trades for the stock with different degrees of information asymmetry. In Panel A stocks are sorted based on the number of analysts following them. In Panel B stocks are sorted based on their percentage spread. Panel C presents results for stocks sorted by their probability of informed trading, PIN. The "Low" group includes stocks with bottom 33% of ranked stocks. The "High" group includes stocks with 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 and presented in parentheses. Returns are adjusted for risk with the 4-factor model. 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: CAARs for Transition Buys, Double-Sort on Size and Number of Analysts

<i>Panel A: Small Size Stocks</i>							
	Time Horizon T						
	0d	1d	1w	2w	1m	2m	3m
Low ANUM	0.44** (4.03)	0.70** (5.26)	0.58* (2.47)	0.73 [†] (1.83)	1.27* (2.10)	2.25* (2.12)	3.28* (2.11)
High ANUM	0.32** (4.00)	0.52** (4.61)	0.78** (3.31)	0.71* (2.17)	0.78* (2.10)	0.77 (0.92)	1.24 (0.75)

<i>Panel B: Medium Size Stocks</i>							
	Time Horizon T						
	0d	1d	1w	2w	1m	2m	3m
Low ANUM	0.26** (4.93)	0.41** (5.95)	0.77** (7.02)	0.80** (4.60)	0.95** (3.55)	0.79 [†] (1.98)	0.13 (0.16)
High ANUM	0.17** (2.77)	0.22* (2.12)	0.31** (3.91)	0.53* (2.18)	0.41 (1.25)	-0.54 (-0.96)	-0.37 (-0.33)

<i>Panel C: Large Size Stocks</i>							
	Time Horizon T						
	0d	1d	1w	2w	1m	2m	3m
Low ANUM	0.09* (2.41)	0.15* (2.65)	0.05 (0.27)	-0.38 (-1.52)	-0.42 (-1.09)	-0.40 (-0.72)	-0.30 (-0.33)
High ANUM	0.05 (1.51)	0.14 [†] (2.00)	0.20* (2.25)	0.13 (0.76)	0.05 (0.24)	0.14 (0.34)	0.75 (0.85)

Table 7 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. 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: CAARs for Transition Buys, Double-Sort on Size and Spread

<i>Panel A: Small Size Stocks</i>							
	Time Horizon T						
	0d	1d	1w	2w	1m	2m	3m
Low SPREAD	0.27** (3.81)	0.42** (3.83)	0.55* (2.49)	0.41 [†] (1.91)	0.59 [†] (1.79)	0.95 [†] (2.00)	0.83 (1.01)
High SPREAD	0.49** (3.14)	0.86** (3.92)	0.98* (2.54)	1.08* (2.01)	1.40* (2.08)	2.25 [†] (1.78)	4.67 [†] (1.94)

<i>Panel B: Medium Size Stocks</i>							
	Time Horizon T						
	0d	1d	1w	2w	1m	2m	3m
Low SPREAD	0.19** (4.32)	0.20** (3.91)	0.36** (3.59)	0.35* (3.24)	0.16 (0.65)	-0.18 (-0.70)	0.03 (0.04)
High SPREAD	0.28** (3.25)	0.50** (4.27)	0.77** (4.74)	1.03** (3.94)	1.11** (2.82)	0.19 (0.23)	-0.09 (-0.06)

<i>Panel C: Large Size Stocks</i>							
	Time Horizon T						
	0d	1d	1w	2w	1m	2m	3m
Low SPREAD	0.01 (0.07)	0.05 (1.45)	0.09 (0.81)	-0.06 (-0.43)	-0.20 (-1.05)	-0.08 (-0.19)	-0.13 (-0.19)
High SPREAD	0.14** (5.03)	0.25** (4.64)	0.18 (0.93)	-0.29 (-1.20)	-0.12 (-0.42)	-0.38 (-0.84)	0.01 (0.01)

Table 9 shows the cumulative average abnormal returns, $CAAR_T$, following transition buys for the stocks sorted by their market capitalization and their percentage spread, SPREAD. 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 SPREAD into two groups, "Low SPREAD" and "High SPREAD". 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. 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: CAARs for Transition Buys, Double-Sort on Size and PIN

Panel A: Small Size Stocks

	Time Horizon T						
	0d	1d	1w	2w	1m	2m	3m
Low PIN	0.39** (2.87)	0.61** (3.63)	0.88** (3.30)	1.33* (2.66)	1.75** (2.76)	1.83 [†] (1.73)	1.68 (0.86)
High PIN	0.41** (4.01)	0.58** (4.62)	0.67* (2.33)	0.73 (1.47)	0.92 (1.48)	2.20* (2.30)	3.44* (2.01)

Panel B: Medium Size Stocks

	Time Horizon T						
	0d	1d	1w	2w	1m	2m	3m
Low PIN	0.06 (0.77)	0.07 (0.74)	0.21* (2.05)	0.10 (0.36)	-0.07 (-0.17)	-0.44 (-0.67)	0.43 (0.36)
High PIN	0.18** (3.73)	0.30** (2.98)	0.26 (1.62)	0.36 [†] (1.81)	0.15 (0.47)	0.24 (0.41)	-1.25 (-1.31)

Panel C: Large Size Stocks

	Time Horizon T						
	0d	1d	1w	2w	1m	2m	3m
Low PIN	0.03 (0.74)	0.05 (1.04)	0.10 (0.76)	0.30 (1.36)	0.31 (1.15)	0.47 (0.99)	0.67 (0.71)
High PIN	0.01 (0.34)	0.09 (1.39)	0.04 (0.26)	-0.18 (-0.62)	-0.28 (-0.78)	0.19 (0.34)	0.83 (0.79)

Table 9 shows the cumulative average abnormal returns, $CAAR_T$, following transition buys for the stocks sorted by their market capitalization and the probability of informed trading, PIN. 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 PIN into two groups, "Low PIN" and "High PIN". The estimates of CAARs are calculated following the Fama-McBeth procedure. T-statistics adjusted with the Newey-West methodology and presented in parentheses. Returns are adjusted for risk with the 4-factor model. 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: CAARs and Past Returns

		Time Horizon T						
		0d	1d	1w	2w	1m	2m	3m
Buy	Low $R_{-3m,0}^{adj}$	0.34** (5.29)	0.48** (5.06)	0.64** (4.46)	0.65** (3.42)	0.92** (2.73)	1.16* (2.17)	1.10 (1.40)
	High $R_{-3m,0}^{adj}$	0.14* (2.38)	0.28** (3.55)	0.15 (1.49)	-0.14 (-0.81)	-0.54 (-1.66)	-0.48 (-1.14)	-0.13 (-0.20)
Sell	Low $R_{-3m,0}^{adj}$	-0.18** (-3.00)	-0.41* (-3.18)	-0.32 (-2.35)	0.21 (1.04)	0.57 (1.48)	0.51 (0.95)	0.92 (1.12)
	High $R_{-3m,0}^{adj}$	-0.21** (-2.74)	-0.48** (-4.48)	-0.56** (-4.63)	-0.39† (-1.77)	-0.42 (-1.60)	-0.68 (-1.25)	-0.69 (-0.98)

Table 10 shows 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 $R_{-3m,0}^{adj}$ in the previous three months. The "Low" group includes stocks with bottom 33% of ranked stocks. The "High" group includes stocks with top 33% of ranked stocks. 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. The sample ranges from January 2001 to December 2005.

Table 11: Price Impact Coefficients of Transition Orders

		Cap Quintiles					
		1 (Small)	2	3	4	5 (Large)	All
NYSE/AMEX	Buy	8.74 [2.36]	6.63 [1.79]	7.23 [1.49]	15.30 [3.02]	16.26 [5.14]	13.38 [2.74]
	Sell	10.15 [3.48]	5.30 [1.54]	4.11 [0.81]	0.98 [0.68]	3.62 [1.57]	3.45 [1.29]
	t(B-S)	(-0.58)	(0.79)	(2.09)	(9.97)	(9.24)	(12.63)
NASDAQ	Buy	8.63 [2.35]	6.98 [1.71]	10.69 [1.85]	13.85 [2.89]	20.21 [5.62]	11.29 [2.17]
	Sell	9.35 [3.49]	7.28 [1.90]	5.35 [1.00]	3.34 [1.06]	-2.03 [-0.70]	5.13 [1.67]
	t(B-S)	(-0.49)	(-0.23)	(3.14)	(4.08)	(6.80)	(6.92)

		Cap Quintiles					
		1 (Small)	2	3	4	5 (Large)	All
NYSE/AMEX	Buy	1.79 [1.21]	1.14 [0.80]	0.96 [0.55]	1.54 [0.80]	1.42 [0.93]	1.36 [0.81]
	Sell	1.99 [1.77]	0.86 [0.78]	0.46 [0.36]	0.21 [0.21]	0.31 [0.30]	0.42 [0.41]
	t(B-S)	(-0.73)	(1.57)	(3.64)	(10.92)	(10.57)	(14.61)
NASDAQ	Buy	1.85 [1.23]	1.14 [0.76]	1.33 [0.71]	1.45 [0.82]	1.67 [0.96]	1.44 [0.88]
	Sell	1.92 [1.67]	1.13 [0.89]	0.65 [0.45]	0.39 [0.34]	-0.11 [-0.15]	0.86 [0.73]
	t(B-S)	(-0.35)	(0.07)	(4.10)	(4.75)	(6.93)	(6.98)

Table 11 shows the means and medians (in parentheses) of price impact coefficients for different capitalization groups. Two models of price impact coefficients are considered. In the first model, price impact coefficient PI_1 is defined as $(P_{exec}/P_{bch} - 1)/TrSize$ in percent, where P_{exec} is the average price of all executed open market trades in the transition order, P_{bch} is the pre-trade benchmark, and $TrSize$ is the number of shares executed in the market (multiplied by 10^4) and normalized by shares outstanding in the previous month. In the second model, PI_2 , square root of trade size is used in denominator. Capitalization thresholds are calculated based on NYSE stock capitalization quintiles. The sample ranges from January 2001 to December 2005.

Table 12: Cross-Sectional Analysis of Price Impact Coefficients

<i>Panel A: NYSE/AMEX Stocks</i>								
	Price Impact Coefficient: PI_1				Price Impact Coefficient: PI_2			
	Buy		Sell		Buy		Sell	
	coef	t-stat	coef	t-stat	coef	t-stat	coef	t-stat
const	-2.99	(-0.25)	-15.74	(-1.39)	1.04	(0.94)	-0.37	(-0.41)
LN Cap	1.59	(1.18)	3.14*	(2.04)	0.00	(0.02)	0.15	(1.28)
ANUM	0.17	(0.73)	-0.48**	(-4.31)	0.02	(1.10)	-0.04**	(-5.49)
LN Turn	0.49	(0.07)	-22.56*	(-2.10)	-0.64	(-1.07)	-1.86*	(-2.19)
StDev	-12.58	(-0.11)	213.68 [†]	(1.86)	-1.48	(-0.14)	23.07*	(2.20)
SPREAD	-0.20	(-0.57)	-0.12	(-0.32)	0.03	(0.83)	0.01	(0.15)
Avg R^2	0.02		0.02		0.02		0.02	
# Obs	76,027		91,242		76,027		91,242	

<i>Panel B: NASDAQ Stocks</i>								
	Price Impact Coefficient: PI_1				Price Impact Coefficient: PI_2			
	Buy		Sell		Buy		Sell	
	coef	t-stat	coef	t-stat	coef	t-stat	coef	t-stat
const	-2.36	(-0.16)	6.99	(0.98)	1.71	(1.32)	2.28*	(2.25)
LN Cap	1.75	(0.97)	1.10	(1.07)	-0.08	(-0.50)	-0.10	(-1.10)
ANUM	0.18	(0.79)	-0.61**	(-3.10)	0.03	(1.39)	-0.04**	(-3.40)
LN Turn	-3.33	(-0.81)	-8.15*	(-2.20)	-0.43	(-0.98)	-0.17	(-0.16)
StDev	-45.19	(-0.44)	31.11	(0.47)	-3.13	(-0.27)	1.68	(0.26)
SPREAD	0.75**	(2.85)	0.25	(1.24)	0.09**	(3.41)	0.05**	(2.67)
Avg R^2	0.04		0.03		0.03		0.03	
# Obs	41,005		50,936		41,005		50,936	

Table 12 shows the regression analysis of price impact coefficients for exchange-traded (Panel A) and Nasdaq (Panel B) stocks. Two models are considered. In the first model, price impact coefficient PI_1 is defined as $(P_{exec}/P_{bch} - 1)/TrSize$ in percent, where P_{exec} is the average price of all executed open market trades in the transition order, P_{bch} is the pre-trade benchmark, and $TrSize$ is the number of shares executed in the market (multiplied by 10^4) and normalized by shares outstanding in the previous month. In the second model, square root of trade size is used in denominator. These measures are regressed on the stock characteristics: LN Cap, the logarithm of capitalization (in thousands), the number of analysts following stocks, ANUM, the logarithm of turnover, LN Turn, the standard deviation of daily returns, StDev, and the percentage spread, SPREAD. The estimated are calculated following the Fama-McBeth procedure for data grouped at a monthly level. T-statistics are adjusted with the Newey-West procedure and presented in parentheses. **is significance at 1% level, *is significance at 5% level, [†]is significance at 10% level.

Table 13: Evolution of Price Impact Coefficients during Transition Execution

<i>Panel A: Difference in Price Impact Coefficients PI_1 of the First and Second Halves</i>					
		Buy: $\Delta = PI_{1,FH} - PI_{1,SH}$		Sell: $\Delta = PI_{1,FH} - PI_{1,SH}$	
	Cap Qnt	Mean[Δ]	Median[Δ]	Mean[Δ]	Median[Δ]
NYSE/AMEX	1 (Small)	-10.59 (0.00)	-4.94 (0.00)	-2.91 (0.32)	-1.05 (0.94)
	2	-4.63 (0.02)	-2.82 (0.02)	-0.62 (0.73)	0.30 (0.83)
	3	-3.20 (0.12)	-1.79 (0.41)	1.55 (0.37)	0.45 (0.07)
	4	-20.93 (0.00)	-6.77 (0.00)	6.08 (0.01)	0.56 (0.01)
	5 (Large)	-8.16 (0.01)	-9.25 (0.00)	1.55 (0.51)	-0.87 (0.12)
NASDAQ	1 (Small)	-8.13 (0.00)	-2.32 (0.00)	-2.45 (0.16)	-0.91 (0.66)
	2	-6.52 (0.00)	-1.87 (0.00)	-4.78 (0.00)	-1.16 (0.15)
	3	-11.23 (0.00)	-3.04 (0.01)	-1.69 (0.41)	-0.13 (0.39)
	4	-27.72 (0.00)	-8.31 (0.01)	4.27 (0.20)	-2.08 (0.59)
	5 (Large)	-12.92 (0.06)	-6.77 (0.07)	2.04 (0.71)	0.20 (0.66)
<i>Panel B: Difference in Price Impact Coefficients PI_2 of the First and Second Halves</i>					
		Buy: $\Delta = PI_{2,FH} - PI_{2,SH}$		Sell: $\Delta = PI_{2,FH} - PI_{2,SH}$	
	Cap Qnt	Mean[Δ]	Median[Δ]	Mean[Δ]	Median[Δ]
NYSE/AMEX	1 (Small)	-1.86 (0.00)	-2.01 (0.00)	-0.65 (0.10)	-0.67 (0.12)
	2	-0.99 (0.00)	-0.97 (0.00)	-0.11 (0.63)	-0.07 (0.87)
	3	-0.65 (0.00)	-0.57 (0.01)	0.37 (0.06)	0.08 (0.05)
	4	-2.55 (0.00)	-1.84 (0.00)	0.24 (0.26)	0.04 (0.96)
	5 (Large)	-0.82 (0.00)	-1.35 (0.00)	-0.02 (0.92)	-0.20 (0.04)
NASDAQ	1 (Small)	-1.38 (0.00)	-1.00 (0.00)	-0.60 (0.01)	-0.71 (0.02)
	2	-1.02 (0.00)	-0.76 (0.00)	-0.64 (0.00)	-0.57 (0.02)
	3	-1.32 (0.00)	-1.16 (0.00)	-0.39 (0.11)	0.11 (0.06)
	4	-2.96 (0.00)	-2.27 (0.00)	-0.25 (0.50)	-0.79 (0.22)
	5 (Large)	-0.84 (0.24)	-1.55 (0.15)	0.35 (0.53)	-0.35 (0.68)

Table 13 shows the differences between price impact coefficients during the first ($PI_{i,FH}$) and second ($PI_{i,SH}$) halves of transitions. Means and medians of pairwise differences between price impacts in the first and second halves along with p-values of t-tests and Wilcoxon signed-rank tests are presented. Two specifications of price impacts coefficients are considered. In the first model, price impact coefficient PI_1 is defined as $(P_{exec}/P_{bch} - 1)/TrSize$ in percent, where P_{exec} is the average price of executed open market trades in the transition order, P_{bch} is the close price in the day before trade, and $TrSize$ is the number of shares executed in the market (multiplied by 10^4) and normalized by shares outstanding in the previous month. In the second model, PI_2 , square root of trade size is used in denominator. P-values are presented in parentheses. The sample ranges from January 2001 to December 2005.

Table 14: Market Resiliency after Portfolio Transition Orders

<i>Panel A: All Portfolio Transition Sell Orders with OMT Trades</i>						
Cap Qnt	NYSE/AMEX			NASDAQ		
	Ret_{exec}	Half Life	N	Ret_{exec}	Half Life	N
1 (Small)	-0.59	8	3,151	-0.45	9	9,330
2	-0.29	8	7,859	-0.27	6	12,964
3	-0.17	3	14,374	-0.16	10	11,121
4	-0.13	3	21,429	-0.16	8	7,600
5 (Large)	-0.08	2	42,479	-0.03	8	8,139
All	-0.13	3	89,292	-0.20	8	49,154

<i>Panel B: Portfolio Transition Orders with OMT Trades > 1% ADV</i>						
Cap Qnt	NYSE/AMEX			NASDAQ		
	Ret_{exec}	Half Life	N	Ret_{exec}	Half Life	N
1 (Small)	-0.68	8	2,110	-0.53	7	5,572
2	-0.43	7	3,827	-0.41	5	5,395
3	-0.29	3	5,002	-0.31	7	3,171
4	-0.24	3	4,698	-0.28	7	1,265
5 (Large)	-0.26	4	3,928	-0.43	7	437
All	-0.32	5	19,565	-0.41	7	15,840

Table 14 shows the market resiliency after open market transition sales, measured by half-life of price responses. Transition orders are grouped according to the stocks' capitalization. Starting with the first day after the last market trade in the order, the average responses for each group are calculated. Their half-lives are reported. Also, the average execution returns of orders, Ret_{exec} , defined as the cumulative return from the beginning of transition to the last market trade, are presented. The exchange-traded and Nasdaq-traded stocks are considered separately. Capitalization thresholds are estimated based on NYSE stock capitalization quintiles. The sample ranges from January 2001 to December 2005.

Table 15: Transaction Costs Based on Portfolio Transition Trades

NYSE/AMEX					NASDAQ				
<i>Panel A: All Portfolio Transition Orders</i>									
		Implicit	Explicit	Total	N	Implicit	Explicit	Total	N
Buy		0.17 [0.09]	0.04 [0.03]	0.21 [0.12]	265,373	0.26 [0.16]	0.06 [0.05]	0.31 [0.22]	128,664
Sell		0.10 [0.05]	0.04 [0.04]	0.14 [0.10]	301,915	0.21 [0.16]	0.06 [0.06]	0.27 [0.22]	158,723
<i>Panel B: Only Open Market Trades</i>									
		Implicit	Explicit	Total	N	Implicit	Explicit	Total	N
All	Buy	0.20 [0.13]	0.07 [0.06]	0.27 [0.19]	75,828	0.29 [0.21]	0.10 [0.08]	0.39 [0.29]	40,957
	Sell	0.11 [0.06]	0.08 [0.06]	0.19 [0.13]	91,091	0.23 [0.17]	0.11 [0.09]	0.34 [0.26]	50,797
$PI > 0$	Buy	1.33 [1.09]	0.09 [0.07]	1.42 [1.17]	42,338	1.33 [1.09]	0.09 [0.07]	1.42 [1.17]	22,621
	Sell	1.34 [1.09]	0.09 [0.07]	1.42 [1.17]	46,385	1.36 [1.12]	0.09 [0.07]	1.44 [1.20]	27,549
<i>Panel C: Portfolio Transition Orders, not Executed through Open Market</i>									
		Implicit	Explicit	Total	N	Implicit	Explicit	Total	N
EC	Buy	0.13 [0.08]	0.07 [0.06]	0.21 [0.15]	58,209	0.11 [0.06]	0.07 [0.06]	0.18 [0.13]	27,127
	Sell	0.13 [0.09]	0.07 [0.06]	0.20 [0.16]	59,295	0.14 [0.10]	0.07 [0.06]	0.21 [0.17]	32,299
IC	Buy	0.10 [0.00]	0.00 [0.00]	0.10 [0.00]	46,242	0.13 [0.05]	0.00 [0.00]	0.14 [0.05]	21,532
	Sell	0.10 [0.02]	0.00 [0.00]	0.10 [0.02]	45,409	0.09 [0.00]	0.00 [0.00]	0.09 [0.00]	27,316

Table 15 shows the means and medians (in parantheses) of implicit and explicit transaction costs for portfolio transition orders. Implicit trading cost is defined as $(P_{exec}/P_{bch} - 1)$, where P_{exec} is the average price of all executed trades in the transition order, P_{bch} is the pre-trade benchmark price. Explicit trading cost is defined as $(Commissions + Secfee)/(Shares * P_{bch})$. Costs are reported in percent. In Panel A, all orders are considered. In Panel B, only open market trades are included. All market trades as well as market trades that demanded liquidity (with positive implicit cost, $PI > 0$) are analyzed. In Panel C, only portfolio transition orders are included that are not executed through open market trading. Results for external crossing (EC) and internal crossing (IC) are presented separately. The sample ranges from January 2001 to December 2005.

Table 16: Regression Analysis of Total Trading Costs

<i>Panel A: Regression Analysis of Transaction Costs, Securities Level</i>							
		Const	NASDAQ	TrSize	Ln Cap	InvPrc	Adj R2
Buy	coef	0.699	0.024	3.050	-0.033	1.340	0.01
	(SE)	(0.052)	(0.011)	(0.240)	(0.003)	(0.099)	
Sell	coef	0.759	0.027	2.813	-0.042	1.386	0.02
	(SE)	(0.048)	(0.010)	(0.313)	(0.003)	(0.078)	
All	coef	0.748	0.024	2.876	-0.039	1.357	0.01
	(SE)	(0.036)	(0.007)	(0.224)	(0.002)	(0.061)	

<i>Panel B: Regression Analysis of Transaction Costs, Transition Level</i>							
		Const	Avg (TrSize)	Avg(Ln Cap)	Buy	Ln Dur	Adj R2
Model 1	coef	0.767	1.189	-0.045	0.102	0.057	0.03
	(SE)	(0.176)	(0.314)	(0.011)	(0.026)	(0.024)	
Model 2	coef	0.912	1.446	-0.052	0.103		0.03
	(SE)	(0.168)	(0.333)	(0.010)	(0.026)		
Model 3	coef	0.120			0.107		0.01
	(SE)	(0.017)			(0.026)		

Table 16 presented the estimated coefficients of the regression model of total transaction costs on the set of variables. In Panel A, total trading costs (in percent) for individual securities in portfolio transitions are regressed on dummy variable for Nasdaq stocks, *TrSize*, the order size over shares outstanding in percent, LN Cap, the logarithm of market capitalization in thousands of dollars, and *InvPrc*, the inverse of stock price. Only open market trades are included. In Panel B, total transaction costs of portfolio transitions (in percent) are regressed on the average trade size in individual securities in the transition, *Avg(TrSize)*, the average logarithm of market capitalization in thousands of dollars, *Buy*, dummy for purchases of target portfolios, and the logarithm of portfolio duration. Standard errors are heteroscedasticity-consistent estimates. They are presented in parentheses. The sample ranges from January 2001 to December 2005.

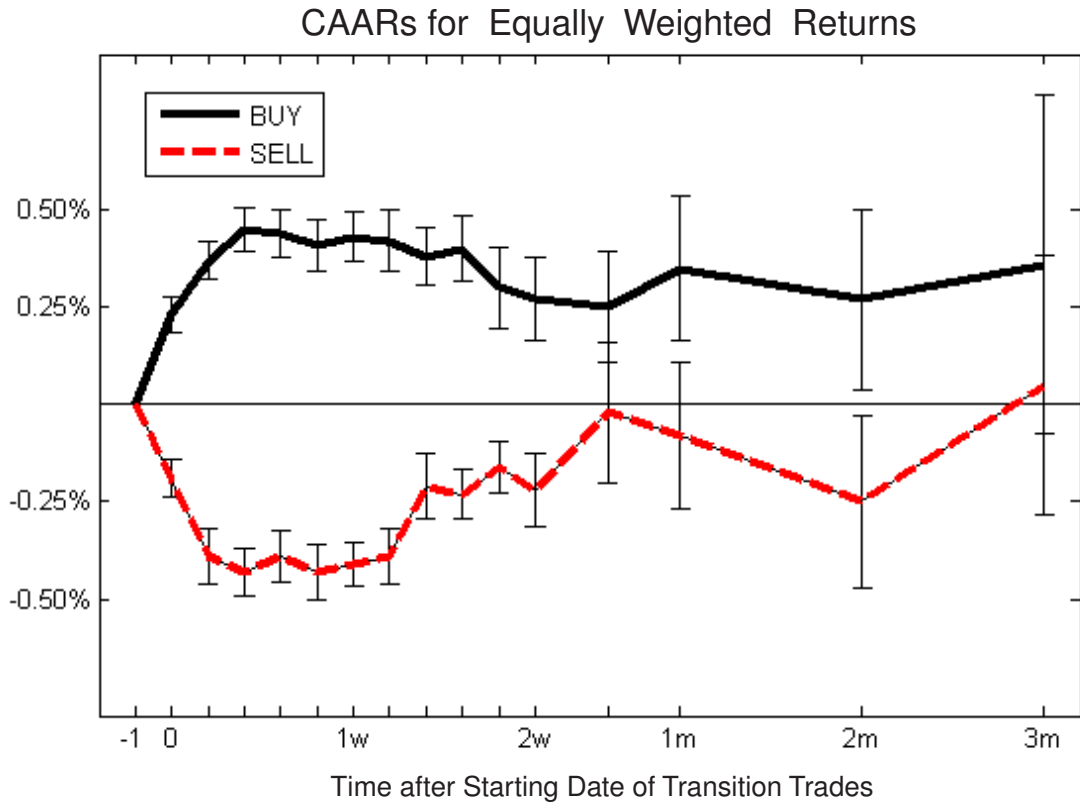


Figure 1: Price Response to Large Transition Trades, Equally-Weighted Case

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. The sample ranges from January 2001 to December 2005.

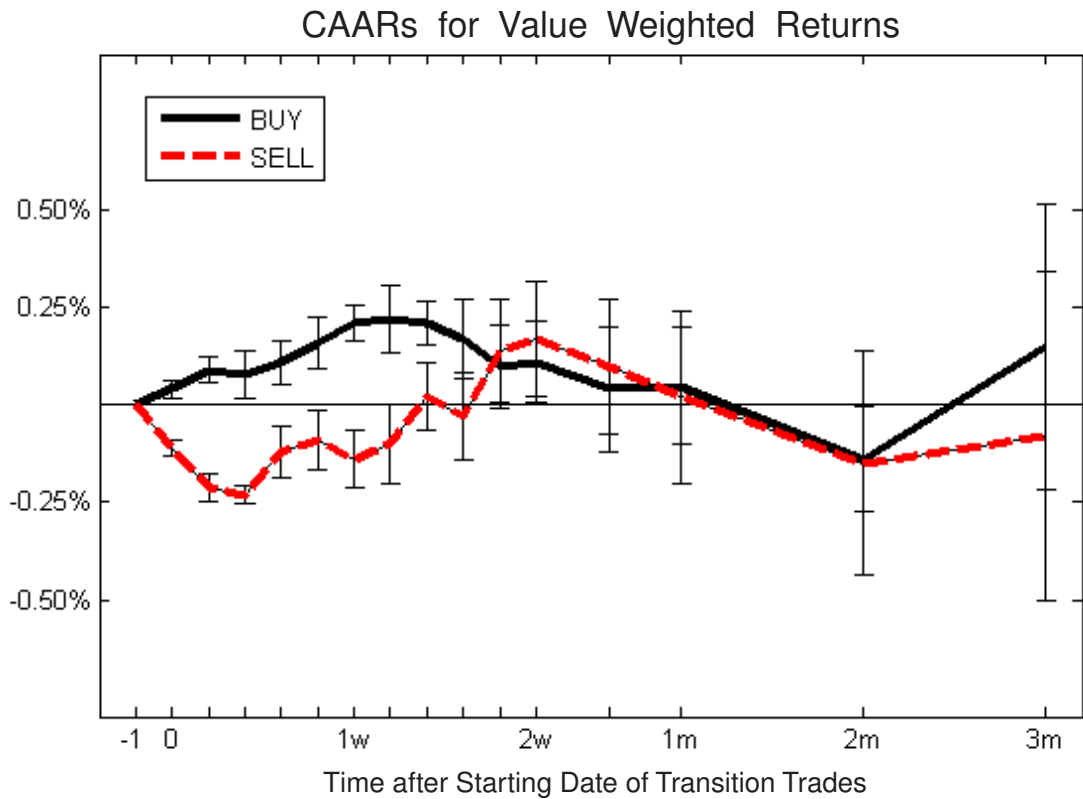


Figure 2: Price Response to Large Transition Trades, Value-Weighted Case

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. The sample ranges from January 2001 to December 2005.

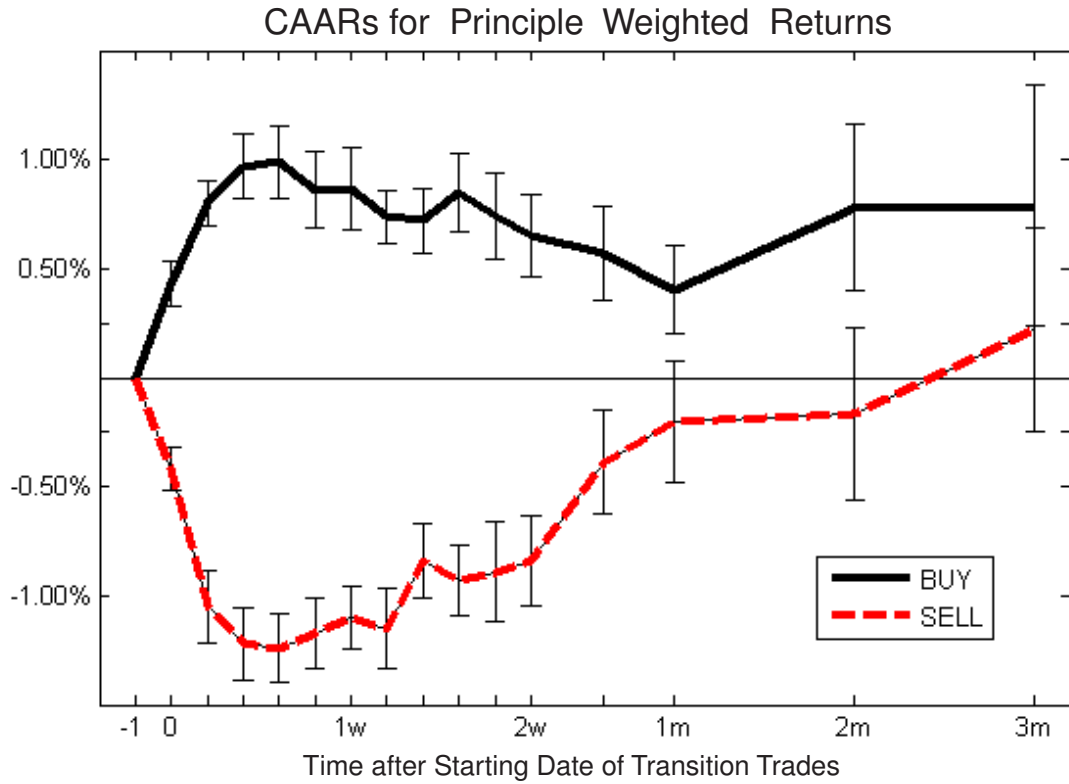


Figure 3: Price Response to Large Transition Trades, Principle-Weighted Case

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. Principle-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. The sample ranges from January 2001 to December 2005.

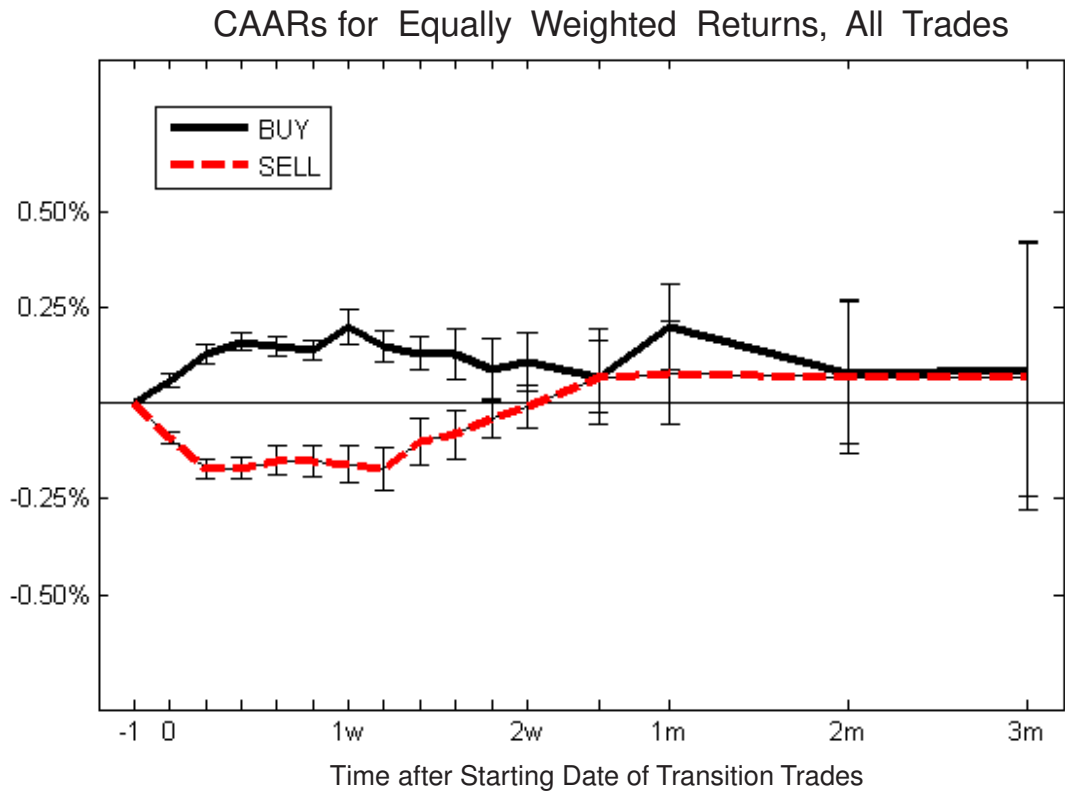


Figure 4: Price Response to All Transition Trades, Equally-Weighted Case

Figure shows the cumulative average abnormal returns (in percents), $CAAR_T$, following portfolio transition buys and sells. All transition trades are included. 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. The sample ranges from January 2001 to December 2005.