Price discovery in US and Australian stock and options markets

A dissertation submitted for the Degree of Doctor of Philosophy

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Abstract

Price discovery is the timely and efficient incorporation of new information into transaction prices. In the microstructure literature price discovery has been empirically examined in three broad contexts: where price discovery occurs, how it occurs, and the informational efficiency of prices. This dissertation contributes to the literature by examining these three avenues of price discovery in the US and Australian stock and options markets in separate essays. The first essay examines whether price discovery in the US occurs primarily in stock or options markets. We use new empirical measures of price discovery and find that price discovery in the options market is approximately one third relative to the stock market. Our findings are that the options share of price discovery is between two and six times greater than has been documented in prior studies, and suggests that the options market is an important venue for informed trading, consistent with early theoretical predictions. In particular, we find that informed traders are attracted to the leverage inherent in options contracts. Our findings increase our understanding of the insider trading characteristics required to make more efficient use of regulatory resources to combat insider trading and reduce negative effects on financial markets, for example, reduced liquidity. In addition, our findings have practical implications for both option and stock market makers in managing bid ask spreads.

The second essay examines how price discovery occurs, and investigates the informational efficiency of large price changes in the Australian stock market. We find that large price changes driven by public information are permanent which is consistent with the semi-strong efficient markets hypothesis. Our findings have implications for US continuous disclosure regulation, in which similar large price changes subsequently underreact. We attribute our findings to the unique Australian information environment which reduces investor distraction which can occur due to information revelation from a number of different sources. In addition, we find that large price changes driven by private information are permanent which is consistent with the imputation of private information into fundamental value. We also find that it would be difficult to consistently profit from the overreaction in returns following large price changes driven by liquidity trading.

The third essay examines price discovery resulting from US divestiture announcements. We use both option and stock prices to disentangle the different sources of value created from divestitures, often aggregated in prior studies, into synergy gains, new information revealed about the stand-alone value of involved firms, and probability of deal success. We find that divestitures create positive synergy gains for both parties, consistent with acquirers purchasing positive synergies and sellers divesting negative synergies. The divestiture announcement reveals favorable new information about the seller's stand-alone value consistent with the undervaluation of its assets, and unfavorable new information about the acquirer's stand-alone value consistent with the friendly nature of divestiture deals. In contrast to using abnormal returns, we find that divestitures create value for the shareholders of both acquiring and selling firms. Our findings will be of interest to both managers and shareholders.

Keywords: price discovery, stock, option, informed trading, large price changes, return predictability, value, wealth, divestitures

JEL classifications: G12, G14

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List of Figures and Tables

Chapter 1. Introduction

Price discovery is an important function of financial markets and is of particular concern to financial economists monitoring the efficiency of the marketplace and various investor trading strategies (Hasbrouck, 1995; O'Hara, 2003). Lehmann (2002) defines the price discovery process as the efficient and timely incorporation of the information revealed by various investors' trading into current market prices. Price discovery has been empirically examined in the microstructure literature within three broad contexts: where price discovery occurs, how it occurs, and the informational efficiency of prices.

First, a number of studies have examined which price series or market is the first to convey new information about the fundamental value of a particular asset. For example, prior studies have examined this question for cross-listed stocks (Hasbrouck, 1995; Eun and Sabherwal, 2003), for stocks which can be traded in the derivative market, for example, options, futures and credit default swaps (Fleming et al., 1996; Chakravarty et al., 2004; Mizrach and Neely, 2008; Forte and Pena, 2009; Muravyev et al., 2013), for quotes versus trade prices (Cao et al., 2009) and for different types of traders (Anand and Subrahmanyam, 2008; Anand et al., 2011).

Second, the occurrence of price discovery has been examined from both a microstructure and an empirical perspective. Price discovery occurs due to informed trading which incorporates newly available public and private information into market prices. Informed traders' informational advantage arises from: fundamental or technical analysis, access to private or illegal inside information, knowledge of order flow, and/or using their ability to process and interpret public information. From a microstructure perspective, public information is assumed to be incorporated into market prices (Vega, 2006). Hasbrouck (1991) uses a vector autoregressive model of order flow and returns to measure the private information content of trades. In this framework, changes in the midquote can be attributed either to the trading of individuals with private information, or to quote updates made by liquidity providers in response to newly released public information. In addition, a number of empirical studies examine price discovery that occurs in anticipation of, or following, the release of public information into the marketplace, for example in the stock market via initial public offerings (Aggarwal and Conroy, 2000) and earnings announcements (Vega, 2006), or in the bond (Green, 2004) and foreign exchange markets (Evans and Lyon, 2002).

Third, the informational efficiency of prices has been examined following changes in regulation or changes in market structure using various measures including the autocorrelation of midquote returns (Hendershott and Jones, 2005), variance ratios (Lo and MacKinlay, 1988), short-term volatility (Foley and Putniņš, 2013), delay in impounding public information (Hou and Moskowitz, 2005) and predictability of midquote returns based on lagged order imbalance (Chordia et al., 2005, 2008). If prices are efficient then they will follow a random walk, not fluctuate away from fundamental value and not be predictable. Both the autocorrelation of returns and variance ratios test the random-walk requirement, short-term volatility tests the fluctuation requirement, and the delay and order imbalance measures test the predictability requirement. For example, Hendershott and Jones (2005) use the autocorrelation of midquote returns to examine the informational efficiency of exchange-traded fund prices following the removal of the display of the Island electronic communications network limit order book. Similarly, O'Hara and Ye (2011) examine the informational efficiency of prices, given the increased fragmentation of trading in the US across various platforms, using variance ratios and short-term volatility.

This dissertation focuses on all three aspects of price discovery: where price discovery occurs, how it occurs, and the informational efficiency of prices in the US and Australian stock and options markets in separate essays.

The first essay examines price discovery in the US stock and options markets. Both the theoretical and empirical literature document evidence to suggest that informed trading (or price discovery) takes place in the options market. For example, informed traders utilize the leverage inherent in options contracts to make substantial profits by trading prior to both takeover and earnings announcements (Black, 1975; Amin and Lee, 1997; Cao et al., 2005; Augustin et al., 2014). However, a number of studies using conventional price discovery metrics document that price discovery in the options market is close to 0% relative to the stock market (Chakravarty et al., 2004; Muravyev et al., 2013). We utilize a newly published metric, the information leadership share, which focuses specifically on which market is the first to impound new information. We find that price discovery in the options market is approximately one-third relative to the stock market; that is, 38.95% of new information is impounded into option prices first and then transmitted to stock prices. Our findings are between two and six times larger than documented in prior studies and suggests that the options market is an important venue for informed trading and source for price discovery, consistent with early theoretical predictions. Also consistent with theory, we find that the key determinants of price discovery (or informed trading) in the options market include the leverage of options contracts, wider spreads due to increased adverse selection risks, and the pooling of informed and uninformed traders in the options markets (Black, 1975; Glosten and Milgrom, 1985; Admati and Pfleiderer, 1988).

Our findings increase our understanding of the characteristics of insider trading strategies required to increase the efficiency of large regulatory resources in combatting insider trading, and reduce negative effects on financial markets that arise due to insider trading, for example, insider trading reduces investor confidence and participation due to a lower perceived fairness in markets, resulting in reduced liquidity (Leland, 1992). In addition, our findings have practical implications for option market makers when setting bid-ask spreads to manage adverse selection risks. Further, because option market makers delta-hedge their positions in the stock market, our findings are also informative to liquidity providers in the stock market because options market maker hedging can constitute an indirect form of informed trading.

The second essay examines how price discovery occurs and the informational efficiency of large price changes in the Australian stock market. The motivation for this essay arises from the contrasting circumstances which lead to return predictability in the US. Following large price changes, returns are found to: reverse in both the long- and short-run (De Bondt and Thaler, 1985; Park, 1995), show no return predictability (Atkins and Dyl, 1990; Cox and Peterson, 1994) and drift following large price changes driven by public information (Pritamani and Singal, 2001; Chan, 2003; Savor, 2012). We utilize the unique information environment in Australia to overcome identification issues between public information and large price changes inherent in prior US studies. The unique information environment in Australia enables the use of a primary source of data obtained from a central information dissemination platform, and the use of price sensitive information flags and trading halts that indicate the release of material information into the market. Under Regulation Fair Disclosure, information can be disclosed to the public through several channels including Form 8-K, press releases via Dow Jones Newswires or firm websites. In contrast to similar US studies, we find that large price changes are permanent when driven by public information which is consistent with the semi-strong efficient markets hypothesis (Fama, 1970). We attribute the differences in our findings to the unique Australian information environment which reduces investor distraction due to information being released from different sources and alleviates investor under-reaction to new information. Our findings have implications for the effectiveness of continuous disclosure regulation in the US.

Uniquely, we examine return predictability following other drivers of large price changes. We find that large price changes driven by private information are also permanent which is consistent with the imputation of private information into fundamental value (Hasbrouck 1991; 1995). We also observe significant reversals in returns following large price changes driven by liquidity trading which is consistent with temporary price pressure that reverses back to fundamental value (Campbell et al., 1993; Avramov et al., 2006). However, we suggest that it would be difficult to consistently profit on such return predictability after controlling for microstructure effects during our sample period.

The third essay examines price discovery resulting from US divestiture announcements. Prior studies use abnormal returns as a measure of value creation to shareholders, however, abnormal returns confound several different sources of value into essentially one number (Hietala et al., 2003). In addition, announcement date abnormal returns will understate the total value created from the acquisition as the market imputes some probability that the deal will fail, even for deals which ultimately succeed (Bhagat et al., 2005). The literature reports mixed findings as to whether divestitures create value for both acquirers and sellers of divested assets, with abnormal returns ranging between 0% and 4% (Rosenfeld, 1984; Klein, 1986; Hite et al., 1987; Sicherman and Pettway, 1992)

In addition to stock prices, we use option prices to disentangle the different sources of value creation into synergy gains, new information revealed about the stand-alone value of acquirers and sellers of divested assets, and the probability of deal success (Barraclough et al., 2013). We find that both parties achieve synergy gains from the divestiture, consistent with the acquirer purchasing assets with positive synergies or assets in which they have a comparative advantage in managing, and the seller divesting assets with negative synergies with the aim of re-focusing on core operations (Hite et al., 1987; Berger and Ofek, 1995). The divestiture announcement reveals unfavorable new information about the stand-alone value of acquiring firms consistent with divestitures being friendly deals which are associated with reduced alignment between managers and shareholders and weaker cash-flow prospects when compared to hostile transactions (Bhagat et al., 2005). In contrast, the announcement reveals favorable new information about the seller's stand-alone value consistent with the acquirer's bid representing a credible and independent signal that the seller's assets are undervalued (Klein, 1986; Hite et al., 1987). The combination of positive synergy gains and new information provides an explanation as to why abnormal returns understate total value creation and the lack of value created by divestitures as reported in the literature.

We find that the total value created from divestitures for acquirers is driven by the revelation of the transaction price in the initial announcement, the relatedness of the assets and managerial quality (Klein, 1986; Sicherman and Pettway, 1987; John and Ofek, 1995). We find similar determinants for sellers of divested assets. In addition, the financial condition of the seller is another key driver of value creation, as the sale of divested assets raises cash which increases slack, reduces the probability of default and increases firm value (Myers and Majluf, 1984; Denning, 1988; Brown et al., 1994). Our findings will be of particular interest to various stakeholders (i.e., managers and shareholders).

This dissertation proceeds as follows: Chapter 2 examines price discovery in US stock and options markets. Chapter 3 examines return predictability following different drivers of large price changes in the Australian stock market. Chapter 4 disentangles the different sources of value created by US divestitures. Chapter 5 provides concluding remarks.

Chapter 2. Price discovery in stock and options markets[1]

2.1. Introduction

The role of options markets in price discovery is at the center of an unresolved debate. Theory predicts that informed traders will be drawn to options markets due to leverage, built-in downside protection, ability to circumvent short-sale restrictions, and additional liquidity (Black, 1975; Easley et al., 1998; Chakravarty et al., 2004). Empirical research also provides some evidence of informed trading in the options markets. For example, abnormal trading volume and order imbalance in options markets can predict future stock returns (Easley et al., 1998; Pan and Poteshman, 2006; Johnson and So, 2012; Kehrle and Puhan, 2013; Hu, 2014) and is observed prior to both earnings and takeover announcements (Amin and Lee, 1997; Cao et al., 2005; Augustin et al., 2014).[2] However, a number of studies find that the share of price discovery in the options market is low relative to the stock market. Chakravarty et al. (2004) estimate that options account for about 17% of price discovery on average in US stocks between 1988 and 1992. Recently, Muravyev et al. (2013) argue that there is no economically meaningful price discovery in the options market. They find that only 6% of price discovery occurs in US options between 2003 and 2006.

The lack of consensus raises several important questions. First, do stock options make a meaningful contribution to price discovery? Second, what are the factors that affect how much price discovery occurs in the options market? Third, how has the price discovery share of the options market changed over time, in particular in response to changes in market structure? We address each of the above questions in this chapter.

There are four novel features of our empirical analysis. First, we employ a new measure of price discovery that focuses specifically on which market is the first to impound new information – the 'information leadership share' (*ILS*). Recent studies that examine price discovery measurement (Yan and Zivot, 2010; Putniņš, 2013) distinguish between two components of price discovery: (i) the relative speed at which a price reflects new information about fundamental value (permanent price changes), and (ii) the relative amount of noise in a price. While the relative amount of noise affects how informative a price is about fundamental value, it is the first component – relative speed in

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[2] Augustin et al. (2014) find abnormal options trading volume prior to 26% of their sample of US takeover announcements between 1996 and 2012, in particular in short-term out-of-the-money call options. Augustin et al. (2015) and Patel and Michayluk (2015) examine informed trading around divestiture announcements.

reflecting new information – that indicates where information enters the market. Previous empirical studies using Hasbrouck's (1995) information share (*IS*) and Gonzalo and Granger's (1995) component share (*CS*) implicitly measure a combination of the two components. The low options price discovery shares reported by such studies reflect in part the relatively lower liquidity (and thus higher noise) in the options market. In contrast, we isolate the first component and thus identify the extent to which new information is incorporated into prices via the options markets.

Second, we use a unique sample of prosecuted insider trading cases to provide a second source of evidence. We also use this unique sample to examine where insiders choose to trade on their information, and whether price discovery measures reflect the presence of informed traders. Third, we distinguish between competing determinants of price discovery in the options market including (i) liquidity, (ii) uncertainty, and (iii) leverage. This allows us to better understand what drives informed traders' choice of market. Fourth, we utilize a considerably longer sample period than previous studies. We examine price discovery in the US stock and options markets over a ten-year period from 2003 to 2013. This allows us to investigate trends in option price discovery shares, analyze the impact of market structure changes, and reconcile the differences documented in previous studies such as Chakravarty et al. (2004) and Muravyev et al. (2013).

We find that approximately one-third (38.95%) of new information is impounded into option prices first and then transmitted to stock prices. This estimate is approximately two to six times larger than previously documented. We attribute this difference to the fact that our measure of price discovery (*ILS*) isolates the relative speed at which a price reflects new information and is not affected by the relative amount of noise.

Our data on successful insider trading prosecutions (obtained from US Securities Exchange Commission litigation releases) show that insiders make extensive use of the options market, consistent with the results from price discovery shares. Further, we find that our measure of price discovery reveals the presence of informed trade (in contrast to other measures of price discovery) – the options market *ILS* is higher on days when insiders illegally trade in the options market compared to days when they trade in the stock market. In sum, our findings suggest that options markets are an important venue for informed trading and source of price discovery, consistent with the theoretical predictions of Black (1975) and Easley et al. (1998).

We find that one of the drivers of informed trading in the options market is the leverage inherent in options. Lower priced options offer greater leverage, attract more informed trade, and therefore make a larger contribution to price discovery. Evidence from insider trading prosecutions confirms that when insiders use options to trade on their information, they earn substantially larger returns on their investment.

In contrast to previous studies (e.g., Chakravarty et al., 2004), we find a positive relation between the options market's share of price discovery and the options market relative bid-ask spread (the spread in the options market scaled by the spread in the stock market). The difference between our findings and those of earlier studies arises from being able to isolate the relative speed at which information is reflected in prices as distinct from the relative noise levels. The positive relation between spreads and price discovery is consistent with an adverse selection mechanism – a relatively high level of informed trade in a given market leads to relatively high adverse selection risks in that market and a relatively large contribution to price discovery. Using tick size changes as an instrument for relative liquidity, we find no support for the liquidity hypothesis that predicts informed traders will trade where execution costs are lowest. Finally, we find a positive relation between relative trading volume and option price discovery shares, consistent with pooling of informed and uninformed traders within a market.

This chapter follows a relatively long line of research examining price discovery in stock and options markets. Early studies focus on lead-lag relations between stock and option prices, without distinguishing between permanent price changes that are due to new information and transitory price changes that are caused by mispricing or temporary order imbalances. Manaster and Rendleman (1982), Bhattacharya (1987), Anthony (1988) and Easley et al. (1998) find that option price changes and volume lead stock price changes and volume, while Stephan and Whaley (1990) and Finucane (1999) reach the opposite conclusion. More recently, Hu (2014) finds that order flow in the options market can predict the following day's stock returns, Kehrle and Puhan (2013) find that options market order flow leads stock market order flow, and Lin et al. (2013) show that option-implied volatility predicts analyst recommendations, analyst forecast revisions, and earnings surprises.

Subsequent developments in the measurement of price discovery have led to refinements of the lead-lag methodology. In particular, Hasbrouck's (1995) *IS* and Gonzalo and Granger's (1995) *CS* distinguish between permanent and transitory price changes. These models pay greater attention to permanent price changes, as they reflect new information. Chakravarty et al. (2004) are among the first to use these measures to quantify options price discovery; they calculate implied stock prices using the binomial model and measure price discovery using Hasbrouck's (1995) *IS*. They find that near-the-money options contribute 17% of total price discovery. The contribution increases with the relative liquidity of the options market and the amount of leverage. Holowczak et al. (2007) also use *IS* to measure price discovery, but instead use put-call parity to calculate the options-implied stock price. The key advantages are: put-call parity is a model-free approach, relying only on the law-of-one-price or absence of arbitrage principles; it uses observable parameters only; and it incorporates information given by both call and put prices. They find that options contribute approximately 11% of price discovery. Rourke (2013) uses the joint estimation of option-implied stock prices across different strike prices and finds that the information share of the options market is 17.49% using the *IS* metric, approximately three times larger than near-the-money options alone.

A recent study by Muravyev et al. (2013) takes a unique approach by focusing on disagreement events, that is, instances when the option-implied stock price from put-call parity is inconsistent with the actual stock price. One of the strengths of this approach is that it provides an indication of how the different prices adjust during economically meaningful price changes. They find that the disagreement events are often precipitated by stock price movements and exhibit signed option volume in the direction that eliminates the disagreement, suggesting options contribute very little to price discovery. A weakness of this approach is that their definition of disagreement events does not distinguish between permanent and transitory price changes. In support of their main conclusion, they report that the options market *IS* is 6.7% during their sample period.

This chapter builds on the convention of measuring price discovery using permanent-transitory decompositions (as exemplified by Chakravarty et al. (2004)) while incorporating important recent developments. The key methodological refinement uses *ILS* to isolate contributions to impounding new information, as distinct from a market's ability to avoid transitory price shocks. Putniņš (2013) shows that this distinction is particularly important when the markets differ in liquidity, because standard *IS* will understate the contribution of the less liquid market. We find support for this notion. To reconcile our findings with previous studies we also estimate *IS* and use subsample analysis to match the sample periods of earlier studies. These tests confirm that the considerably higher price discovery share that we attribute to the options markets follows from using a measure that is not affected by noise differences and it thereby avoids the tendency to underestimate the contribution of the less liquid market.

At the same time, we draw on the insights of Muravyev et al. (2013) to overcome some of the limitations of price discovery summary measures. Muravyev et al. (2013) emphasize the importance of assessing economic meaningfulness in addition to statistical significance. We incorporate their insight in two ways. Firstly, by drawing on a second source of evidence that is unrelated to price discovery summary measures (the insider trading prosecutions), we show that meaningful amounts of information enter the market via options. Secondly, analogous to Muravyev et al.'s (2013) use of disagreements to focus on periods when new information enters the market, we conduct tests in which we focus on days when insiders are known to trade on their private information. During these periods, significant new information is impounded into prices and we find that options play an even more important role in price discovery compared to other periods. These insights complement Muravyev et al. (2013) by considering a different set of information events, and by using a framework that distinguishes between permanent and transitory price changes. This chapter therefore bridges the approach of Muravyev et al. (2013) and the studies using permanent-transitory decompositions, while extending each of these existing approaches.

The chapter proceeds as follows: Sections 2.2 and 2.3 describe the data and methods. Section 2.4 presents the empirical results, while Section 2.5 concludes the chapter.

2.2. Data and characteristics of the sample

Our analysis makes use of two samples. The first is a sample of 36 liquid US stocks used in Muravyev et al. (2013).[3] The stocks are listed on the NYSE and NASDAQ and are selected on the basis of having the highest options trading volume in March 2003. This first sample spans the period April 17, 2003 to April 17, 2013. We focus our analysis on this sample to allow comparisons with Muravyev et al. (2013). The second sample, described in more detail in Section 2.4.2, is obtained from prosecuted cases of illegal insider trading in the US. It comprises 46 stocks during the period January 1, 1999 to August 30, 2014.

We obtain intra-day trade and quote data for both stocks and options from the *Thomson Reuters Tick History* (*TRTH*) database provided by the *Securities Industry Research Centre of Asia-Pacific* (*SIRCA*). In our calculation of price discovery measures we use the National Best Bid and Offer (NBBO) consolidated quotes in both the stock and options markets. Options quote data include the following Options Price Reporting Authority (OPRA) exchanges: AMEX, ARCA, BATS, BOX, C2, CBOE, ISE, MIAX, NASDAQ, PCX and PHLX. We use midquote prices to calculate price discovery metrics to minimize the effects of bid-ask bounce.

We apply several data cleaning procedures, including (i) filtering out negative spreads (we delete 407,438 stock-days in which spreads are negative (bid and ask quotes are crossed) for more than 5% of the trading day), and (ii) winsorizing all price discovery metrics and regression variables at the 1st and 99th percentiles. Negative spreads can indicate the market is closed or halted, in which case midquote prices, spreads and volume are not meaningful and thus we do not calculate price discovery metrics during such times.

< Table 2.1 here >

Table 2.1 Panels A and B report descriptive statistics of market characteristics in the options and stock markets, respectively. The mean time-weighted quoted bid-ask spread (in cents) in the options market is almost five times larger than in the stock market. In addition, the options market has significantly lower trading activity, 0.03% of the dollar volume and 7.26% of the number of quote updates when compared to the stock market. The combination of wider bid-ask spreads and lower trading activity indicates that in our sample, the options market has higher transaction costs and is less liquid than the stock market. The differences in liquidity and trading activity in the stock and options markets suggest that stock and options price series contain different levels of noise, which can influence measures of price discovery. The leverage in options is clearly evident from the descriptive

[3] We exclude ETFs from our sample (Muravyev et al. (2013) have three ETFs in their sample) because we focus on the issue of where private information enters the market. ETFs are often used for trading the market as a whole and thus are likely to have relatively little trading that is based on private information.

statistics; average stock prices are approximately 20 times larger in magnitude than options prices. Our simple measure of leverage has a mean of 2.53.[4]

2.3. Methodology

2.3.1. Options-implied stock price

Following Muravyev et al. (2013), we begin with the European put-call parity relation to calculate the implied stock price using options data,

$$S_t = C_t(K,T) - P_t(K,T) + PV_t(D(t,T)) + Ke^{-r(T-t)} \tag{2.1}$$

where S_t is the stock price at time t, $C_t(K,T)$ and $P_t(K,T)$ are the call and put option prices with strike price K and expiry date T, $PV_t(D(t,T))$ is the present value of cash dividends at time t, r is the continuously compounded risk-free rate of interest per annum, and $T-t$ is the time to maturity.[5] We adjust Equation (2.1) to incorporate the ability to exercise early because our sample consists of American-style options. Denoting the early exercise premium by $v_t(K,T)$, we have,

$$S_t + v_t(K,T) = C_t(K,T) - P_t(K,T) + PV_t(D(t,T)) + Ke^{-r(T-t)}. \tag{2.2}$$

We calculate $v_t(K,T)$ by first estimating the error from the put-call parity relation at every quote update,

$$\varepsilon_t = C_t(K,T) - P_t(K,T) + PV_t(D(t,T)) + Ke^{-r(T-t)} - S_t. \tag{2.3}$$

The early exercise premium is then calculated as the average error term for each stock-day,

$$v_t(K,T) = \frac{\sum_{j=1}^{N} \varepsilon_j}{N}. \tag{2.4}$$

Recognizing that we can replicate a stock position using options contracts, we can rewrite Equation (2.1) in terms of the options-implied bid price and options-implied ask price at time t:

$$Implied\ Bid_t(K,T) = C_t{}^{Bid}(K,T) - P_t{}^{Ask}(K,T) + PV_t\big(D(t,T)\big) + Ke^{-r(T-t)} - v_t(K,T) \tag{2.5}$$

[4] We calculate leverage for put and call options separately as the natural log of the ratio of the stock price to the option price (the time-weighted average midquote prices). We combine the leverage measures by taking the simple average of the two. Our measure captures the additional units of underlying exposure from an options position compared to a similar dollar investment in the stock.

[5] The continuously compounded risk-free rate of interest is obtained from *OptionMetrics*.

$$Implied\ Ask_t(K,T) = C_t^{Ask}(K,T) - P_t^{Bid}(K,T) + PV_t(D(t,T)) + Ke^{-r(T-t)} - v_t(K,T). \quad (2.6)$$

To ensure that our results are comparable to Muravyev et al. (2013) we apply the following criteria:

(a) Time to maturity (in days) is between 10 and 70 calendar days (inclusive).

(b) Options are near-the-money satisfying $\left|\ln\left(\frac{S}{K}\right)\right| \leq 6\%$.

(c) Present value of dividends with ex-dividend dates during the remaining life of the option satisfying $PV_t(D(t,T)) < \$0.05$.

(d) Bid price of option $\geq \$0.15$.

As a result, our main analysis focuses on near-the-money, short-term, liquid options. We also estimate price discovery metrics for away-from-the-money options by replacing criterion (b) with criterion (e):

(e) Options are away-from-the-money satisfying $6\% \leq \left|\ln\left(\frac{S}{K}\right)\right| \leq 18\%$.

2.3.2. Price discovery shares

Commonly used empirical measures of price discovery include Hasbrouck's (1995) *IS* and Gonzalo and Granger's (1995) *CS* metrics. *IS* decomposes the variance of innovations in the common efficient price and attributes a share of the variance to each price series. *CS* is the normalized weight of the price series in the linear combination of prices that forms the common efficient price. In essence, *IS* is a variance-weighted version of *CS*. Both *IS* and *CS* are based on a cointegrated price series that is related to one underlying asset. The parameter estimates and reduced form errors from a vector error correction model (VECM) are used to calculate *IS* and *CS*. Baillie et al. (2002) show that *IS* and *CS* metrics are complementary, rather than substitutes, in that they measure different aspects of the price discovery process.

Yan and Zivot (2010) develop a structural cointegration model in which the two price series reflect one permanent and one transitory shock. They show that for their structural model, *IS* measures relative leadership in impounding new information about the fundamental value (relative speed in reflecting the permanent shocks) and the relative avoidance of noise (relative sensitivity to the temporary shocks), while *CS* measures only the relative avoidance of noise. Yan and Zivot (2010) show that *IS* and *CS* can be combined in a way that isolates relative leadership in impounding new information.

Putniņš (2013) provides a detailed critique of the common empirical measures of price discovery. In most existing price discovery studies, the level of noise in the compared prices differs for a variety of reasons, including: differences in quoted spreads, in tick sizes, and in the conversion of derivative prices into implied prices. Putniņš (2013) shows that when the level of noise between two price series differs, *IS* and *CS* understate price discovery shares for the more noisy price series. To overcome this problem, he proposes a new price discovery metric that builds on Yan and Zivot (2010) – the Yan-Zivot-Putniņš information leadership share (*ILS*). *ILS* combines *IS* and *CS* in a way that isolates relative leadership in impounding new information and makes the measure insensitive to relative levels of noise. Thus, *ILS* can reliably attribute price discovery shares when the price series have different levels of noise. *ILS* is easy to interpret and is directly comparable to *IS* and *CS*. *ILS* takes the range [0,1] indicating the 'share' of price discovery attributable to a given price series, with values above 0.5 indicating that a price series leads price discovery (when comparing two prices). Putniņš (2013) highlights the importance of choosing and correctly interpreting the price discovery metric. In the four empirical settings used for illustration, *ILS* leads to opposite conclusions about which market dominates price discovery, compared to *IS* and *CS*.

The differences in liquidity and trading activity between the US stock and options markets suggest the level of noise in stock prices is different from that of options prices. Due to their lower liquidity, options prices are likely more susceptible to temporary shocks, and thus *IS* and *CS* likely underestimate the options market's contribution to price discovery. To overcome this issue, we use *ILS* throughout our analysis as the main measure of price discovery, and for comparability, we also report *IS* and *CS*. All three price discovery metrics are derived from a VECM of options and stock midquote prices sampled at one-second intervals. The VECM includes 200 lags (following Muravyev et al. (2013)) and is estimated separately for each stock-day:

$$\Delta p_{1,\tau} = \alpha_1\left(p_{1,\tau-1} - p_{2,\tau-1}\right) + \sum_{i=1}^{200} \gamma_i \Delta p_{1,\tau-i} + \sum_{j=1}^{200} \delta_j \Delta p_{2,\tau-j} + \varepsilon_{1,\tau} \tag{2.7a}$$

$$\Delta p_{2,\tau} = \alpha_2\left(p_{1,\tau-1} - p_{2,\tau-1}\right) + \sum_{i=1}^{200} \emptyset_i \Delta p_{1,\tau-i} + \sum_{j=1}^{200} \varphi_j \Delta p_{2,\tau-j} + \varepsilon_{2,\tau} \tag{2.7b}$$

where $p_{1,\tau}$ is the implied stock price calculated using the midquote of the implied bid (Equation (2.5)) and implied ask (Equation (2.6)) prices at one-second intervals τ, and $p_{2,\tau}$ is the midquote of the stock price at τ.[6] Following Baillie et al. (2002) we estimate the *IS* and *CS* metrics using the VECM coefficients and variance-covariance of the error-terms from Equation (2.7) for each stock-day that meets criteria (a) to (e) outlined in Section 2.3.1. The *CS* are obtained from the normalized orthogonal to the vector of error correction coefficients, $\alpha_\perp = (\gamma_1, \gamma_2)'$.[7]

$$CS_1 = \gamma_1 = \frac{\alpha_2}{\alpha_2 - \alpha_1}, \quad CS_2 = \gamma_2 = \frac{\alpha_1}{\alpha_1 - \alpha_2} \tag{2.8a}$$

[6] We use 200 lags in the VECM model so that our results are directly comparable to Muravyev et al. (2013). They find that the VECM coefficients are insignificant after 200 lags for the option price series. Chakravarty et al. (2004) use 300 lags. Similar to Hasbrouck (1995), Chakravarty et al. (2004), Holowczak et al. (2007) and Muravyev et al. (2013) we use a one-second sampling frequency. The reduced form error terms are assumed to be serially uncorrelated and contemporaneously correlated between both price series equations (Baillie et al., 2002).

[7] *CS* estimates that are negative or greater than one are truncated to zero and one, respectively. This procedure is consistent with a price discovery interpretation of the component share, in which a price series can contribute between zero and all of the price discovery for an asset, and thus its price discovery share has the range [0,1] (e.g., Harris et al., 2002).

Given the covariance matrix of the reduced form VECM error terms (Equation (2.8b)) and the Cholesky factorization, $\Omega = MM'$ (Equation (2.8c)), we calculate the *IS* in Equation (2.8d).

$$\Omega = \begin{pmatrix} \sigma_1^2 & \rho\sigma_1\sigma_2 \\ \rho\sigma_1\sigma_2 & \sigma_2^2 \end{pmatrix} \tag{2.8b}$$

$$\mathrm{M} = \begin{pmatrix} m_{11} & 0 \\ m_{12} & m_{22} \end{pmatrix} = \begin{pmatrix} \sigma_1 & 0 \\ \rho\sigma_2 & \sigma_2(1-\rho^2)^{1/2} \end{pmatrix}, \tag{2.8c}$$

$$IS_1 = \frac{(\gamma_1 m_{11}+\gamma_2 m_{12})^2}{(\gamma_1 m_{11}+\gamma_2 m_{12})^2+(\gamma_2 m_{22})^2}, \quad IS_2 = \frac{(\gamma_2 m_{22})^2}{(\gamma_1 m_{11}+\gamma_2 m_{12})^2+(\gamma_2 m_{22})^2}. \tag{2.8d}$$

Similar to Baillie et al. (2002) we estimate IS_1 and IS_2 under each of the two possible orderings in the VECM and take the average across the two orderings. Lastly, we calculate the information leadership shares, ILS_1 and ILS_2 following Putniņš (2013):

$$ILS_1 = \frac{\left|\frac{IS_1 CS_2}{IS_2 CS_1}\right|}{\left|\frac{IS_1 CS_2}{IS_2 CS_1}\right|+\left|\frac{IS_2 CS_1}{IS_1 CS_2}\right|}, \quad ILS_2 = \frac{\left|\frac{IS_2 CS_1}{IS_1 CS_2}\right|}{\left|\frac{IS_1 CS_2}{IS_2 CS_1}\right|+\left|\frac{IS_2 CS_1}{IS_1 CS_2}\right|}. \tag{2.8e}$$

We calculate price discovery metrics using prices from continuous trading, that is, between 09:45 and 15:45.[8]

2.4. Results

2.4.1. Price discovery in the stock and options markets

Table 2.2 Panels A and B report price discovery shares of the options market for near-the-money options; first ticker-by-ticker and then pooling across all stock-days during the last decade. Consistent with prior studies, the majority of new information is first reflected in stock prices before being transmitted into options prices. The mean *IS*, *CS* and *ILS* estimates of price discovery in the options market for our sample are 6.09%, 11.55% and 38.95%, respectively. The *ILS* options market price discovery share is 38.95%, which is two times larger than documented by Chakravarty et al. (2004) and six times larger than documented by Muravyev et al. (2013). This suggests options markets are an important venue for informed trading and source of price discovery, consistent with the theoretical predictions of Black (1975) and Easley et al. (1998).

< Table 2.2 here >

[8] Similar studies by Hasbrouck (1995), Chakravarty et al. (2004), Muravyev et al. (2013) and Rourke (2013) also examine price discovery during the trading day only.

The mean options price discovery shares using the *IS* and *CS* metrics are approximately three to seven times smaller than the mean *ILS* estimate for the options market. For all 36 stocks, the mean *ILS* estimate is larger than both the *IS* and *CS* metrics. These findings are consistent with evidence in Yan and Zivot (2010) and Putniņš (2013) about what each of the metrics measures. The options market, being less liquid, is more susceptible to temporary deviations of prices from their equilibrium. *IS* and *CS* in part measure this relative difference in sensitivity to temporary shocks ('noise'). Consequently, *IS* and *CS* are likely to overestimate the price discovery contribution of the (less noisy) stock market, and underestimate the contribution of the (noisier) options market. Our findings suggest the degree of underestimation in this setting is large. In contrast, *ILS* is insensitive to relative noise levels in the prices and thus provides a clearer measure of the amount of new information impounded into prices via the options market.

The large difference between *ILS* and *IS* is also consistent with the results of Muravyev et al. (2013), who focus on instances of disagreement between stock and options prices and conclude that options prices typically adjust to eliminate the disagreement. A disagreement between stock and options prices could be caused by a temporary or a permanent change in prices. *ILS* focuses on the disagreements that arise due to permanent price changes, and measures which price tends to reflect those permanent price changes first. In contrast, *IS* also considers the temporary price changes and 'penalizes' a price series' price discovery share if it tends to be the one that causes disagreements via temporary shocks to its price. Therefore, disagreement events that are caused by temporary price changes drive a wedge between the *IS* and *ILS* estimates. The large difference between *IS* and *ILS* estimates suggests that many of the disagreement events studied by Muravyev et al. (2013) are likely to be caused by temporary shocks to prices.

Table 2.2 Panel C reports descriptive statistics for price discovery shares in away-from-the-money options. Using the Wilcoxon-Mann-Whitney test statistic, we find that the mean *ILS* is significantly larger for away-from-the-money options (42.58%) compared to near-the-money options (38.95%). This finding is consistent with the attraction of greater leverage in options that are cheaper to buy, that is, the leverage inherent in both out-of-the-money call and put options. Similar to Panel B, the *IS* and *CS* metrics understate price discovery in the options market relative to the *ILS* metric. In both near-the-money and away-from-the-money options, the difference between the upper and lower bounds of the *IS* estimates (*UML* in Table 2.2) is small (typically 1%–2%), suggesting the one-second sampling frequency is sufficiently fine to uniquely attribute contributions to price discovery.

Table 2.3 reports the *IS*, *CS* and *ILS* metrics year-by-year. Using the same stocks and sample period as Muravyev et al. (2013), we find almost identical results using *IS*. Specifically, the mean options *IS* is approximately 6.3% during 2003–2006.[9] In contrast, the mean options *ILS* is 42.46% during the same time period, approximately seven times larger than the *IS*. As previously explained, the differences in option price discovery shares arise because *ILS* focuses specifically on leadership in impounding new information, whereas *IS* also captures the relative amount of noise in the two price series.

< Table 2.3 here >

Table 2.3 also shows that the price discovery share of options measured using *ILS* increases from 2003 to 2007. Figure 2.1 shows that during this time period, options volume (represented by the solid black line) grew at a rate of four times the growth in stock volume (represented by the dotted line).[10] The growth in options trading volume coincided with the multi-listing of options across different exchanges from 2000, with large increases in the number of options contracts available by strike price and time-to-maturity and with the introduction of the Boston Option Exchange in 2004. The increase in options price discovery through to 2007 is consistent with increased trading volume in the options market encouraging informed traders to pool together with uninformed traders.

< Figure 2.1 here >

After 2007, the options *ILS* declines. The decline is more pronounced in medians than means, suggesting that while most stocks experience a decline, a small number go against this trend. The removal of the uptick rule on July 6, 2007 provides an explanation for the declining price discovery shares. The uptick rule restricts short selling to the following circumstances: (i) on an uptick – at a price greater than the last traded price, or (ii) on a zero-plus tick – at the last traded price if the last trade was made on an uptick. The removal of this rule makes it easier for informed traders to short sell in the stock market, which is an alternative to buying put options.

In summary, our findings suggest options markets are an important venue of informed trading and source of price discovery, consistent with theoretical predictions. We find that options contribute approximately one-third of total price discovery, significantly more than previously documented by Chakravarty et al. (2004) and Muravyev et al. (2013). The results show that the *IS* metric significantly understates the contribution of the options market to price discovery, consistent with the differences in liquidity between markets and thus susceptibility to temporary price deviations.

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[9] Muravyev et al. (2013) calculate a mean (median) option *IS* of 6.25% (2.60%) between April 17, 2003 and October 18, 2006. Using near-the-money options we calculate a mean (median) option *IS* of 6.35% (2.68%). The slight difference between the two results is due to our sample including three additional months of data and the exclusion of three ETFs.

[10] Option volume data is obtained from the *Option Clearing Corporation* (*OCC*).

2.4.2. Evidence from insider trading prosecutions

To further investigate the issue of where information first enters the market, we turn to prosecuted insider trading cases. We systematically examine all 7,061 US Securities Exchange Commission (SEC) litigation releases relating to insider trading between January 1, 1999 and August 30, 2014. From these, we identify 539 news announcements that are preceded by illegal trading on insider information (hereafter, simply 'insider trading'). The cases involve instances where the illegal trading occurs in options only, in stocks only, and in both markets.[11]

Several studies examine insider trading in the US stock market. Meulbroek (1992) uses a sample of 229 SEC litigation releases between 1980 and 1989. Cornell and Sirri (1992) and Chakravarty and McConnell (1997) examine illegal insider trades around the acquisition of Campbell-Taggart and Nestle S.A., respectively. All of these studies conclude that insider trading leads to more rapid price discovery. Subsequently, Chakravarty and McConnell (1999) re-examine the insider trades of Ivan Boesky around Carnation's takeover of Nestle S.A. and conclude there is little difference between the impact of insider and non-insider trading on price discovery.

< Table 2.4 here >

Table 2.4 reports the time-series of insider trading characteristics by year. Although in the majority of cases insider trades are executed in the stock market (382 of 539 announcements), a significant proportion of announcements (157 of 539, or 29%) involve insider(s) trading in the options market either exclusively or in addition to trading in the stock market. Closer examination of the insider trades and volumes provides further evidence that insiders often take advantage of their private information using the options market. In total, 32% of insider trades are in options (739 of 2,320). When insiders trade in both the stock and options markets, the average volume they trade in the options market is 52.14% of their total traded volume (23.64% in dollar volume terms). For all announcements, the average volume that insiders trade in the options market is 22.94% of their total traded volume (12.13% in dollar volume terms). These results suggest insiders make considerable use of options markets, consistent with our earlier evidence that options markets account for a significant share of price discovery.

The data also indicate that the leverage in options increases insiders' percentage profits. For the full sample of illegal trades, insiders that trade in the stock market earn an average of 24% on their investment, whereas insiders that trade in both the stock and options markets earn 39% (these results are not tabulated). In contrast, insiders that trade in options only earn a staggering average return of 353%.

[11] SEC litigation releases are obtained from: www.sec.gov/litigation/litreleases.shtml. Our sample contains a variety of different news announcement types including takeovers, analyst recommendation changes and earnings announcements. The majority of announcements (85%) are positive news announcements.

Do the price discovery metrics 'detect' the presence of illegal insider trading in one or the other market? To answer this question, we estimate the price discovery metrics in the days surrounding cases of prosecuted insider trading. For each news announcement that involves an insider trading prosecution, we use data for that stock, starting one month before the first insider trade and ending one month after the last insider trade. This gives us a sample of 47 news announcements in 46 stocks, with all the necessary data (total of 10,436 stock-days, of which 999 are known to have illegal insider trading).[12]

If the price discovery metrics detect the presence of insider trades, we would expect higher options price discovery shares when insiders trade in the options market only, compared to stock-days in which insiders trade in the stock market only, or in which insiders do not trade. It is difficult to make predictions for stock-days in which insiders trade in both markets because on such stock-days price discovery shares are likely to depend on the relative intensity and timing of insider trades in the two markets.

An initial, casual examination of the price discovery estimates provides support for the notion that *ILS* is impacted by insider trading in the manner predicted – the mean *ILS* for stock-days in which insider trades occur only in the options market is 2.2 percentage points (4.4%) larger than for stock-days in which insider trades occur only in the stock market (i.e., 51.8% versus 49.6%). In contrast, *IS* and *CS* means are *lower* on stock-days in which insiders trade in options compared to when they trade in stocks.[13] Thus, the initial evidence is consistent with the notion that *ILS*, not *IS* or *CS*, is positively impacted by insider trading.

To quantify statistical significance and control for potential confounding factors in our analysis of whether price discovery metrics capture insider trading, we turn to multivariate regressions. We regress price discovery metrics against three dummy variables: (i) $OptionDV_{it}$, which takes the value of one if insider trades occur in the options market only on that stock-day, (ii) $StockDV_{it}$, which takes the value of one if insider trades occur in the stock market only, and (iii) $BothDV_{it}$, which takes the value of one if insider trades occur in both the stock and options markets. We also include three exogenous control variables: (i) a dummy variable equal to one following the removal of the Grandfathering provision (DV_t^{GF}), (ii) a dummy variable equal to one following the removal of the

[12] Trades made by insiders to close out their positions are considered to be uninformed. We do not classify these trades as illegal insider trades because once the private information held by an insider is revealed to the market they are no longer considered privately informed. There are two data requirements. First, to calculate price discovery shares the stocks must have listed options. Second, to ensure our sample contains enough variation per stock (to allow stock fixed effects), we require an episode of insider trading in any given stock to contain at least six unique days on which insiders illegally trade in either market.

[13] The *IS* and *CS* is 11.7% and 16.4% (14.9% and 19.2%) on stock-days when insiders trade in the options (stock) market only.

option market-maker (OMM) exemption (DV_t^{OMM}), and (iii) a time trend variable that takes the value of one at the start of the sample period and increases by one on each subsequent trading day (TT_t).[14]

Table 2.5 reports the regression results, using IS as the price discovery metric in Model 1, CS in Model 2, and ILS in Model 3. Contrary to what is expected under the hypothesis that the price discovery shares are able to 'detect' the presence of informed trading, in Models 1 and 2 we observe negative relations between the price discovery metrics (IS and CS) and $OptionDV_{it}$. However, in Model 3 we observe a significant positive relation between the ILS of the option market and insider trading in the options market ($OptionDV_{it}$). Days in which insiders trade in the options market only have a 1.26 percentage point higher option price discovery share measured by ILS. The regression results concur with our earlier conclusion that ILS, but not IS or CS, reveals the presence of insider trading. The findings support the use of ILS as a measure of where information is first impounded into prices.

< Table 2.5 here >

There are several limitations in using the insider trading cases to validate the price discovery metrics. First, the analysis is a test of joint hypotheses: (i) that the insider trades are recognized by the market and consequently, the insider information is impounded into prices, and (ii) that the price discovery metrics can detect the market in which the information was first reflected in prices. In some cases, prices do not reveal the presence of informed traders (e.g., Collin-Dufresne and Fos, 2015) and therefore the expected relation between insider trading and price discovery metrics might be weak at best. Second, the insider trades might account for only a small fraction of the total trading and total information being impounded into prices and thus the insiders' impact on price discovery metrics could be small relative to other influential factors. Third, we only know about *detected* insider trades that resulted in legal action by the SEC. There could be other informed trades, possibly based on the same insider information, occurring in markets other than where the prosecuted insiders traded that are not captured by the litigation releases. These informed trades could impact the price discovery shares.

< Table 2.6 here >

[14] Regulation SHO was introduced on January 3, 2005 to restrict naked short-selling of stocks unless the broker could locate or make arrangements to borrow the stock and deliver to the buyer by the delivery date. If the seller does not borrow the stock in time to close out their position, the seller fails to deliver (see Putniņš, 2010). See http://www.sec.gov/news/press/2007/2007-114.htm for further details. The Grandfathering provision allows brokers to naked short-sell the underlying stock, creating fail-to-deliver positions up until the stock gets placed on a threshold list. The removal of the Grandfathering provision on October 15, 2007, may cause brokers that would have set up naked short-sell positions to instead set up synthetic short positions in the options market, resulting in increased options price discovery shares. The OMM exemption allows OMMs to hedge options positions by naked short selling the underlying stock. The removal of the OMM exemption on September 17, 2008 raised the cost of short selling for OMMs and thus might affect relative liquidity in the options market.

Muravyev et al. (2013) use disagreement events to identify times when economically meaningful information enters the market. We use an analogous approach by separately examining days during which insiders are known to trade on their inside information. On such days we know that significant new information is impounded into prices. Table 2.6 Panel A reports that the mean (median) *ILS* is 47.80% (50.23%) on days when insiders trade on their private information. These estimates are considerably higher than our unconditional estimates that consider all stock-days, reinforcing the important role that options markets play in impounding new information.

Panel B partitions the set of 999 insider trading stock-days by the number of days prior to the announcement of the insiders' information. We expect that as we approach the news announcement, informed traders are likely to trade more aggressively (e.g., Collin-Dufresne and Fos, 2015) and thus it is more likely that their trades will reveal their information closer to the news announcement. Consistent with this notion, the mean *ILS* increases from 48.49% more than 20 days before the announcement, to 50.98% as we approach the announcement, and then to 82.25% on the announcement date.

2.4.3. The determinants of price discovery in the options market

To better understand what drives informed traders to choose one market or the other we examine several competing determinants of the options price discovery share, including (i) liquidity, (ii) uncertainty, and (iii) leverage. We use one-stage OLS panel regressions in this section. To address potential endogeneity between liquidity and informed traders' choice of market (price discovery shares), the next section adopts a 2SLS instrumental variables approach, using market structure changes as instruments for liquidity. Chakravarty et al. (2004) undertake the only other examination of the competing determinants of price discovery in the stock and options markets. They use *IS* to measure price discovery. For comparability, we report our initial results using *IS*, but then turn our attention to the determinants of *ILS* as the measure of price discovery, as it provides a cleaner measure of where information is impounded first.

The liquidity hypothesis predicts that informed traders prefer to trade in the most liquid market in order to minimize the price impact of their trades and thus maximize the value of their information (Kyle, 1985; Chowdhry and Nanda, 1991). Fleming et al. (1996) examine trading costs and price discovery within stock, futures and options markets and provide evidence that price discovery will occur in the market with lower transaction costs (or the more liquid market). Chakravarty et al. (2004) measure liquidity using bid-ask spreads and trading volume in the stock and options markets. We apply a similar method and expect a negative (positive) relation between options bid-ask spreads (trading volume) and option price discovery shares, if liquidity is a key determinant of price discovery.

Capelle-Blancard (2001) models strategic interaction between traders with information about the direction of future price movements in the underlying stock (directional-informed traders) and traders informed about volatility (volatility traders). In his model, the presence of volatility traders shifts directional-informed traders from the options market into the stock market (due to wider spreads in the options market). Consistent with the model's prediction, termed the 'uncertainty hypothesis', Chakravarty et al. (2004) find weak evidence that an increased level of uncertainty (proxied by volatility in the underlying stock price) results in reduced price discovery in the options market.

Theory suggests that the leverage in options contracts will lead informed traders to trade in the options market (Black, 1975, Easley et al., 1998). Chakravarty et al. (2004) examine price discovery across different strike prices and find a higher level of price discovery in out-of-the-money options than near-the-money and in-the-money options.[15] In contrast to Chakravarty et al. (2004), our model-free approach means that we are only able to calculate price discovery for put-call pairs that have the same strike price, rather than individual put and call options. In a given pair, the price (and thus leverage) of the put option will usually be different to the price (and leverage) of the call option. Therefore, we develop a measure of leverage ($Leverage_{it}$) that is applicable to put-call pairs:

$$LeverageCall_{it} = \left(\frac{StockMQ_{it}}{CallMQ_{it}}\right) \quad (2.9a)$$

$$LeveragePut_{it} = \left(\frac{StockMQ_{it}}{PutMQ_{it}}\right) \quad (2.9b)$$

$$Leverage_{it} = LeverageCall_{it}\ \mathbf{1}_{it}^{\{r>0\}} + LeveragePut_{it}\ \mathbf{1}_{it}^{\{r<0\}} \quad (2.9c)$$

where $LeverageCall_{it}$ and $LeveragePut_{it}$ is the ratio of the stock price and the option price (prices measured as time-weighted average midquotes), and $\mathbf{1}_{it}^{\{r>0\}}$ and $\mathbf{1}_{it}^{\{r<0\}}$ are indicator variables that equal one if the daily stock return is positive or negative, respectively. If the daily stock return is positive then the $Leverage_{it}$ variable reflects the leverage inherent in the call option, and vice versa. An assumption underpinning the $Leverage_{it}$ variable is that insiders that have good (bad) news and choose to trade in the options market will buy call (put) options rather than sell put (call) options. The direction of the stock's return is a proxy for whether informed trader(s) have good or bad news. The assumption that informed traders will initially buy rather than sell options is supported by the data: in 156 of the 157 announcements in which insiders illegally trade in options, insiders buy call or buy put options as the first trade.[16] A positive relation between our leverage measure and option price discovery shares would support the leverage hypothesis.

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[15] Out-of-the-money (in-the-money) call options are defined by a strike price that is at least 5% above (below) the current stock price.
[16] We examine the first illegal option trade per announcement only, as this provides an indication as to whether the news that insiders are trading on is positive or negative news.

< Figure 2.2 here >

Informed traders in the options market might prefer particular strike prices relative to the current stock price – the degree of 'moneyness'. To test this possibility, we calculate the absolute value of the difference between the underlying stock price and strike price ($StrikeDistance_{it}$). An increase in the distance between the stock price and strike price will decrease the moneyness of the call option (if the stock price is less than the strike price) or the put option (if the stock price is greater than the strike price). Moneyness and leverage are related, but are not identical. Figure 2.2 Panel A shows that as the stock price increases relative to the strike price, the leverage of put options increases and the leverage of call options decreases. The changes in leverage are non-linear, while the changes in $StrikeDistance_{it}$ are linear. On average, as the distance between the stock price and strike price increases, the average leverage provided by each put-call parity pair increases (as represented by the solid black line). Figure 2.2 Panel B shows that regardless of whether the stock price is above or below the strike price, as the absolute value of the distance between the stock price and strike price increases ($StrikeDistance_{it}$), the average leverage provided by each put-call parity pair increases.

Similar to Chakravarty et al. (2004), we analyze the determinants of price discovery using a panel regression with stock-day observations:

$$\frac{PD_{it}}{(1-PD_{it})} = \alpha + \beta_1 Spread_{it} + \beta_2 Volume_{it} + \beta_3 Volatility_{it} + \beta_4 Leverage_{it} + StrikeDistance_{it} + \varepsilon_{it} \tag{2.10}$$

where PD_{it} is the price discovery share of the options market for stock i on day t, $Spread_{it}$ is the ratio of the time-weighted average quoted bid-ask spread in the options market to that of the stock market, $Volume_{it}$ is the ratio of options market traded dollar volume to that of the stock market, and $Volatility_{it}$ is the standard deviation of one-minute midquote stock returns.[17] All variables are expressed in natural log form.

< Table 2.7 here >

Table 2.7 reports regression results. For comparison with Chakravarty et al. (2004), Model 1 uses *IS* as the measure of price discovery and includes near-the-money options only. Consistent with Chakravarty et al. (2004) we find a significant negative relation between the options market *IS* and

[17] We use quoted bid-ask spreads in cents because we compare the liquidity of stocks and options related to the same underlying asset at the same point in time, rather than cross-sectional or time-series comparisons in which a measure that is scaled by the price of the security might be preferred.

relative bid-ask spreads.[18] Chakravarty et al. (2004) interpret this result as support for the liquidity hypothesis – wider options spreads discourage informed trading in the options market, which reduces the options market's contribution to price discovery. However, given the recent evidence that *IS* also measures the relative avoidance of noise (Yan and Zivot, 2010; Putniņš, 2013), an alternative explanation for this result is that higher liquidity (narrower spreads) is associated with fewer temporary deviations from equilibrium prices (less noise). To eliminate this possibility, subsequent regression models use *ILS*.

In Models 3 to 10, we use ILS as the measure of price discovery and include both near-the-money and away-from-the-money options in our panel regression model.[19] In contrast to the results in Models 1 and 2, the relation between the options market's contribution to price discovery using *ILS* and its spread (relative to that of the stock market) is positive and highly statistically significant. In terms of economic meaningfulness, Model 3 shows that a 1% increase in the option market's relative bid-ask spread is associated with a 1.76% increase in relative option price discovery share.[20] This finding is consistent with an adverse selection mechanism – higher levels of informed trading in the options market leads to wider options market spreads (e.g., Glosten and Milgrom, 1985) and greater price discovery in the options market.

Model 3 also shows a significant and positive relation between traded dollar volume in the options market (relative to stock market dollar volume) and options market price discovery. This result is consistent with informed traders attempting to hide their trades amongst those of uninformed traders (Admati and Pfleiderer, 1988; Chowdhry and Nanda, 1991). In a 'pooling' equilibrium, an increase in the proportion of uninformed agents that trade in the options market causes informed traders to also increase their trading activity in the options market, which increases the options market's contribution to price discovery. The coefficient of 0.17 on the $Volume_{it}$ variable in Model 3 implies that a 1% increase in the ratio of options volume to stock volume is associated with a 0.17% increase in the ratio of options price discovery share to stock price discovery share (recall that all variables are in log form). The coefficient of $Volatility_{it}$ is statistically indistinguishable from zero, providing no support for the uncertainty hypothesis.

Model 4 examines the impact of leverage ($Leverage_{it}$) and moneyness ($StrikeDistance_{it}$). We find a significant positive relation between option price discovery shares and both $Leverage_{it}$ and $StrikeDistance_{it}$. A 1% increase in option leverage is associated with a 0.27% increase in option price discovery. A 1% increase in the absolute distance between the stock and strike price is associated with a 0.36% increase in option price discovery. Our findings are consistent with Black

[18] Model 2 also shows a significant negative relation between options market *CS* and relative bid-ask spreads.

[19] We obtain similar results if we include near-the-money options only.

[20] For example, our dependent variable is $ln\left(\frac{PD_{it}}{(1-PD_{it})}\right)$ and the independent variable is $ln\left(\frac{Spread_{option,it}}{Spread_{stock,it}}\right)$. A 1% increase in $\left(\frac{Spread_{option,it}}{Spread_{stock,it}}\right)$ would cause $\left(\frac{PD_{it}}{(1-PD_{it})}\right)$ to increase by $e^{1.76\ln(1.01)} = 1.0176$ or 1.76%.

(1975) and Easley et al. (1998) who predict that informed traders use away-from-the-money options to take advantage of their private information and are attracted to the options market by the ability to leverage up their returns. They are also consistent with the empirical findings of Augustin et al. (2014).

We include dummy variables in Model 5 for two exogenous regulation changes arising from exceptions to Regulation SHO: (i) removal of the Grandfathering provision (${DV_t}^{GF}$), and (ii) removal of the OMM exemption. These regulation changes are described in the previous section. By restricting naked short selling, the Grandfathering provision might cause brokers who would otherwise have naked short sold a stock to instead set up a synthetic short position in the options market, resulting in increased options price discovery shares. The economic model proposed by Stratman and Welborn (2013) suggests that the removal of the OMM exemption raises the cost of short selling for OMMs as they incur borrowing costs and have to close out their fail-to-deliver positions. As a result, OMMs might widen the bid-ask spread to be compensated for the increased cost of short-selling, resulting in decreased option price discovery shares. The results in Table 2.7 support these predictions. The removal of the Grandfathering provision coincides with an increase in option price discovery shares, consistent with increased use of synthetic short positions in the options market. The OMM exemption coincides with a decrease in option price discovery consistent with reduced liquidity in the options market. Our results are robust to stock and date fixed effects applied in Models 6 and 7.

Leverage is determined by how cheap an option is compared to the underlying stock price, which in turn is a function of several factors such as the strike price (or $StrikeDistance_{it}$), implied volatility and time to maturity. Some of these factors might influence trading decisions and thus price discovery for reasons other than leverage. To examine this possibility, we repeat our analysis replacing $Leverage_{it}$ with the set of factors that influence leverage. The relations between these various factors and leverage are as follows: decreased expected future stock price volatility and/or lower time-to-maturity decreases options prices (because there is a lower probability that the option will expire in-the-money), increasing leverage. Consequently, we expect a negative relation between option price discovery shares and implied volatility/time-to-maturity. We define $ImpVol_{it}$ as the implied volatility that makes the market price of the call and put options consistent with Black-Scholes options prices. To allow for non-linearity in time to maturity, we define a set of dummy variables, DV_{it}^{a-b}, that equal one if there is between a and b days (inclusive) until the expiration of the options contract.

The regression results in (Model 8) indicate that both $ImpVol_{it}$ and $StrikeDistance_{it}$ have the expected negative and positive relations with option price discovery shares, respectively. A 1% increase in implied volatility is associated with a 1.21% decrease in option price discovery shares. In contrast, coefficients on the time-to-maturity dummy variables are mainly statistically indistinguishable from zero. Again, our results are largely robust when stock and date fixed effects are applied in Models 9 and 10.

2.4.4. Evidence from changes in market structure

Price discovery and liquidity can be co-determined by the informed trader's choice of market. For instance, if informed traders choose to trade in the options market for exogenous reasons, perhaps more stringent regulatory oversight in the stock market, then this will increase the share of price discovery occurring in the options market and it might also cause a deterioration of liquidity in the options market as options market liquidity providers protect themselves from increased adverse selection risks (e.g., Glosten and Milgrom, 1985; Kyle, 1985).

To address this potential endogeneity between liquidity and price discovery, we use the reduction in the options market tick size as an instrumental variable for relative liquidity. Our measure of relative liquidity is $Spread_{it}$, the ratio of the time-weighted average quoted bid-ask spreads in the options market to that of the stock market. Under the Penny Pilot program, tick sizes for OPRA options exchanges were reduced from \$0.05 and \$0.10 for options with prices less than and greater than \$3 respectively, to \$0.01 and \$0.05 for options with prices less than and greater than \$3 respectively (Battalio et al., 2004). The reduction in tick sizes occurred in a staggered manner on different dates for different options classes. In total, 29 of 36 stocks in our sample experienced a reduction in tick size on seven separate dates between February 2007 and August 2010. Our instrumental variable is a dummy variable that takes the value of one when the options tick size is reduced (${DV_{it}}^{Tick}$).[21] This change in market structure should cause a decrease in the options market bid-ask spread due to the removal of a binding constraint on the width of the spread (Harris, 1999). Under the liquidity hypothesis, this exogenous increase in options market liquidity should result in increased price discovery in the options market as it becomes relatively cheaper to trade in the options market (Chowdhry and Nanda, 1991; Fleming et al., 1996). To be a valid instrument, the reduction in options market tick sizes should not directly affect option price discovery shares other than through changes in relative liquidity. While this is likely to be true when using *ILS* as the measure of price discovery, it may be violated when using *IS* due to the sensitivity of *IS* to differences in noise. For this reason, we only analyze *ILS* using the tick size instrumental variable.

We use this exogenous event as an instrumental variable in a two stage least squares (2SLS) regression model. In the first stage (Equation (2.11)), we regress $Spread_{it}$ on the instrumental variable and a set of control variables:

$$Spread_{it} = \alpha + \beta_1 {DV_{it}}^{Tick} + \textstyle\sum_j \gamma_j \, Control_{j,it} + \varepsilon_{it} \tag{2.11}$$

$$\frac{PD_{it}}{(1-PD_{it})} = \alpha + \beta_1 \widehat{Spread}_{it} + \textstyle\sum_j \gamma_j \, Control_{j,it} + \varepsilon_{it}. \tag{2.12}$$

[21] Seven stocks in our sample changed ticker, merged or delisted prior to the reduction in tick sizes.

In the second stage (Equation (2.12)), we regress the options price discovery share on fitted values of relative bid-ask spreads ($\widehat{Spread}_{it}$) obtained from the first stage and the same set of control variables as used in the first stage. The control variables include combinations of the variables used in the previous section, namely, $Leverage_{it}$, $StrikeDistance_{it}$, $ImpVol_{it}$, DV_{it}^{0-9}, DV_{it}^{10-19}, DV_{it}^{20-29} and DV_{it}^{30-39}. In addition, we apply stock and date fixed effects separately.

The first stage regression results presented in Table 2.8 show a significant reduction in options market spreads (relative to stock market spreads) after the reduction in tick size. Option market spreads decrease by between 0.72% and 0.95%. Furthermore, we observe a significant negative (positive) relation between $Spread_{it}$ and $Volume_{it}$ ($Volatility_{it}$ or $ImpVol_{it}$) consistent with the microstructure literature. Bound et al. (1995) argue that instruments with F-statistics of around one may be weak. The F-statistics for our instrumental variable are all in the range of 37,910 to 65,461, indicating the instrument is strong.[22]

< Table 2.8 here >

Table 2.9 reports results from the second stage regressions. In Models 1-6 we observe a positive relation between relative bid-ask spreads ($\widehat{Spread}_{it}$) and options price discovery shares. The coefficient on relative spread is not substantially different in magnitude to the one-stage OLS results in Table 2.7, although, using stock fixed effects, the coefficient of relative spread falls by almost one percentage point to 0.79%. Given that the coefficient of $\widehat{Spread}_{it}$ is positive, the 2SLS instrumental variables regressions do not find any evidence in support of the liquidity hypothesis, contrary to Chakravarty et al. (2004).

< Table 2.9 here >

Also, consistent with the OLS results reported in Table 2.7, we continue to observe a positive and significant relation between option price discovery shares and $Volume_{it}$, $Leverage_{it}$ and $StrikeDistance_{it}$, consistent with increased price discovery in the options market being associated with the pooling of uninformed and informed traders in the options market and the leverage advantage inherent in away-from-the-money options.

[22] For example, $F = \frac{(SSR_R - SSR_{UR})/q}{SSR_{UR}/(n-k-1)} = \frac{(141{,}775-69{,}305)/5}{69{,}305/(313{,}016-5-1)} = 65{,}461$. The F-statistics calculated from our model are heavily influenced by the number of stock-day observations (n) spanning over ten years in our sample period.

2.5. Conclusion

This chapter sheds new light on the contribution of stock and options markets to price discovery. We present several novel findings. We document that the options market contributes approximately one-third (38.95%) of the price discovery in US stocks during the past decade. Our estimates make use of the information leadership share (*ILS*) which focuses on the speed at which a price series reflects new information about fundamental value. Our estimate of option price discovery shares is approximately two to six times larger in magnitude than documented in previous studies (e.g., Chakravarty et al., 2004; Muravyev et al., 2013). The difference compared to previous studies arises from our focus on measuring leadership in impounding new information, and not measuring the relative noise in prices or susceptibility to temporary shocks. Furthermore, drawing on insights from Muravyev et al. (2013), we conduct tests in which we focus on days during which insiders are known to have been trading illegally on their inside information. During such times economically meaningful information enters the market and we find that options play an even more important role in price discovery than during other times.

Our findings using price discovery shares are supported by evidence from a unique dataset of prosecuted insider trading. We find that 29% of insider trading cases, 32% of insider trades, and between 12% and 52% of the amount invested illegally by insiders, occur in the options market. We also find that our measure of price discovery (*ILS*) reveals the presence of informed trade (in contrast to other measures of price discovery), since the options market *ILS* is higher on days when insiders trade in the options market compared to days when they trade in the stock market. In sum, our findings show that options markets are an important venue for informed trading and an important source of price discovery.

Consistent with theoretical predictions we find that one of the drivers of informed trading in the options market is the leverage inherent in options. Lower priced options offer greater leverage, attract more informed trade, and therefore make a larger contribution to price discovery. Evidence from insider trading prosecutions confirms that when insiders use options to trade on their information, they earn substantially larger returns on their investments.

In contrast to previous studies, we find a positive relation between the option market's share of price discovery and the options market relative bid-ask spread (the bid-ask spread in the options market scaled by the bid-ask spread in the stock market). The difference compared to earlier studies again arises from focusing on where information is first reflected in prices rather than relative noise levels. The positive relation between bid-ask spreads and price discovery is consistent with an adverse selection mechanism – a relatively high level of informed trade in a given market leads to relatively high adverse selection risks in that market and gives that market a relatively large contribution to price discovery. Using tick size changes as an instrument for liquidity, we find no support for the liquidity hypothesis that predicts informed traders will trade where execution costs are lowest. Finally, we find a positive relation between relative trading volume and option price discovery shares consistent with pooling of informed and uninformed traders within a particular market.

Our findings have a number of implications. Illegal insider trading is associated with substantial costs, including (i) the substantial regulatory resources used in lawmaking, monitoring, and enforcement of insider trading rules (e.g., in 2014 the US SEC spent approximately $531 million in combating insider trading (SEC, 2013)), and (ii) negative effects on financial markets such as damaged investor confidence in the fairness of markets, which can reduce investor participation, harming liquidity (Leland, 1992). A better understanding of the characteristics of insider trading strategies can help to make the use of regulatory resources devoted to insider trading more efficient and reduce the negative effects of insider trading. Our findings contribute to this understanding by characterizing in which markets informed agents/insiders choose to trade. Given the significant share of price discovery stemming from options, regulators should not ignore options markets in their surveillance activities.

Our findings also have practical implications for option market makers when setting bid-ask spreads to manage adverse selection risks. Further, because option market makers delta-hedge their positions in the stock market, our findings are also informative to liquidity providers in the stock market because options market maker hedging trades can constitute an indirect form of informed trading.

Figure 2.1. Option and stock volume through time

This figure shows the total option contract volume reported by the *OCC* and total stock volume obtained from *CRSP* in millions between 2003 and 2013.

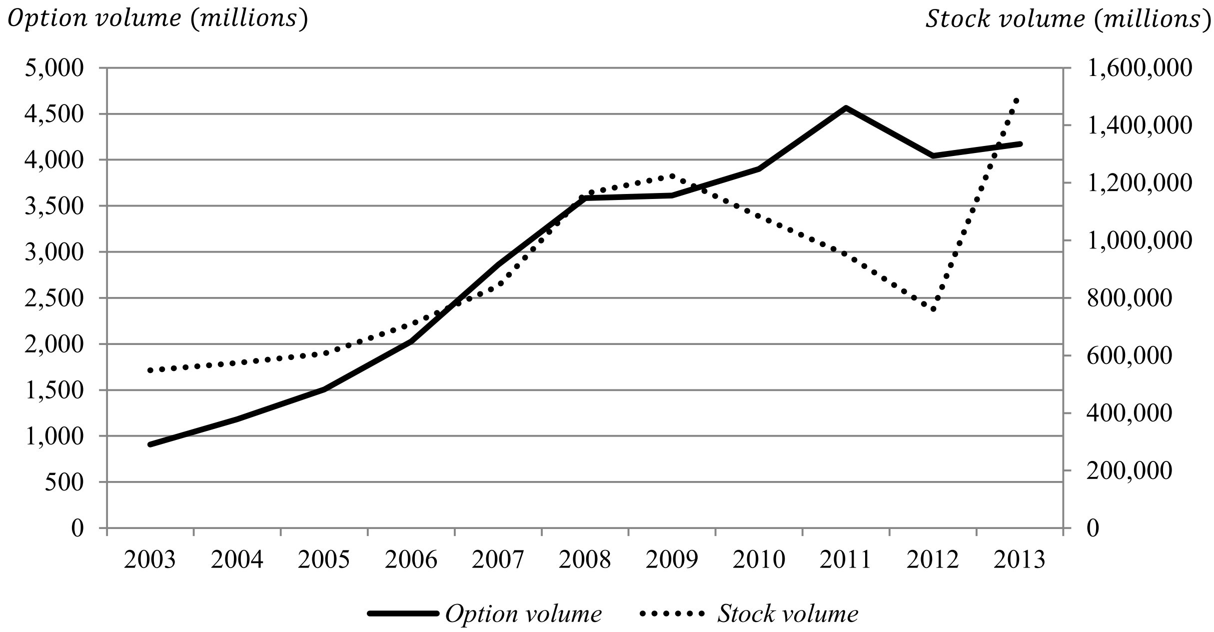
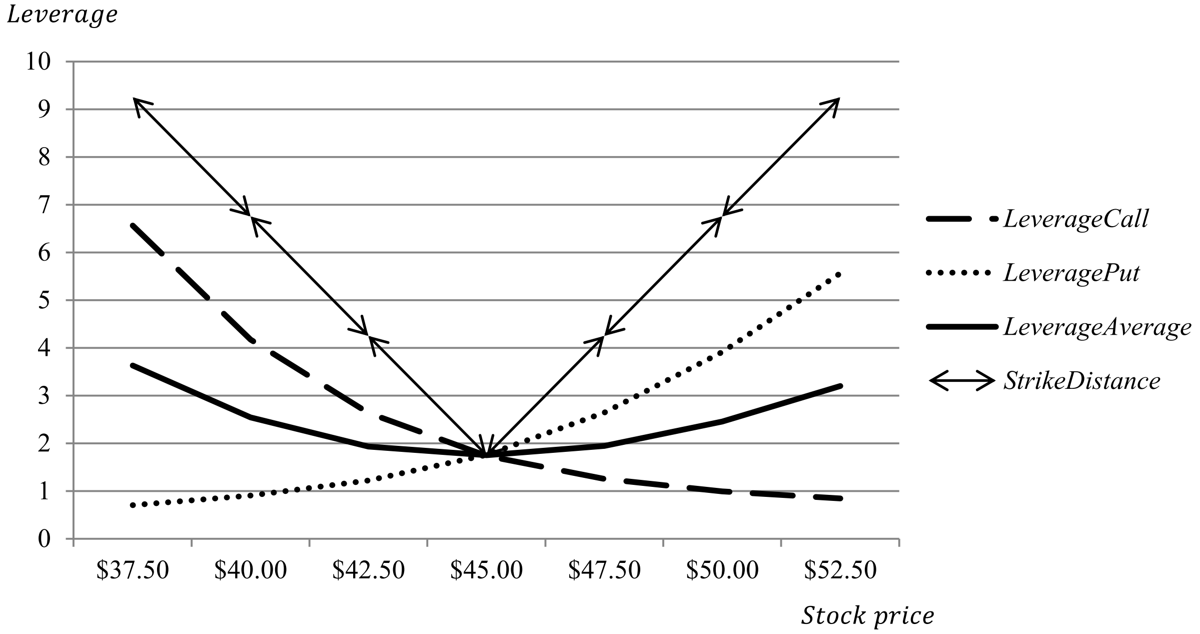


Figure 2.2. Leverage versus moneyness

Panel A shows the relation between the leverage in call and put options compared to a stock (vertical axis) for different stock prices (horizontal axis). $LeverageCall$ is the natural log of the ratio of the stock price to the call option price, $LeveragePut$ is the natural log of the ratio of the stock price to the put option price, $LeverageAverage$ is the average of $LeverageCall$ and $LeveragePut$, and $StrikeDistance_{it}$ is the absolute value of the difference between the underlying stock price and strike price. We calculate the call and put option prices using the Black-Scholes model with the following inputs: strike price $(K) = 45$, risk-free rate $(r) = 2\%$, time-to-maturity $(T) = 0.05$ years, volatility $(\sigma) = 20\%$. Panel B shows the relation between the leverage in call and put options compared to a stock (vertical axis) and $StrikeDistance_{it}$ (horizontal axis).

Panel A: Leverage versus stock price



Panel B: Leverage versus moneyness

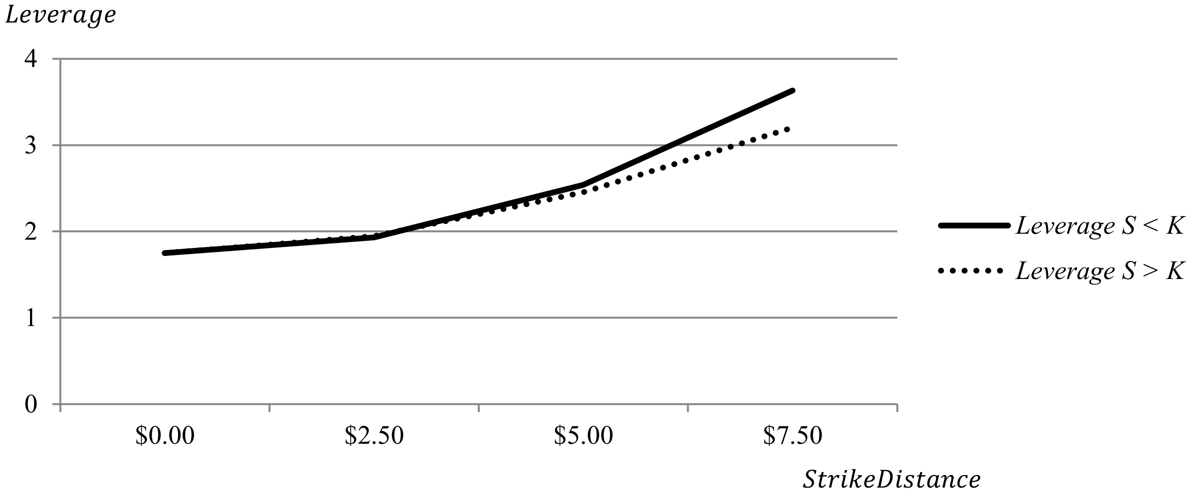


Table 2.1. Descriptive statistics

This table reports descriptive statistics for our sample of 36 stocks between April 17, 2003 and April 17, 2013. $Spread$ is the daily time-weighted average quoted bid-ask spread in cents, $Volume$ is the daily traded dollar volume in units of \$1,000, $Quotes$ is the daily number of NBBO quote changes, $Price$ is the daily time-weighted average midquote price, $Volatility$ is the daily standard deviation of one-minute midquote returns in the stock market multiplied by 10^5, and $Leverage$ is the natural log of the ratio of the stock price and options price (prices are time-weighted average midquotes).

Panel A: Options market					
	$Spread$	$Volume$	$Quotes$	$Price$	$Leverage$
Mean	0.09	209	573	2.74	2.53
Median	0.07	39	480	1.32	2.49
Std. Dev.	0.10	461	407	4.46	0.62
Panel B: Stock market					
	$Spread$	$Volume$	$Quotes$	$Price$	$Volatility$
Mean	0.02	654,427	7,890	54.79	8.80
Median	0.01	456,529	4.251	37.11	6.81
Std. Dev.	0.02	595,402	9,471	52.60	55.13

Table 2.2. Options market price discovery shares

This table reports options market price discovery shares for our sample of 36 stocks between April 17, 2003 and April 17, 2013. The price discovery shares are: (i) Hasbrouck (1995) information share (IS), (ii) Gonzalo-Granger (1995) component share (CS), and (iii) Yan-Zivot-Putniņš (2013) information leadership share (ILS). All price discovery metrics are expressed as percentages (range 0-100%). UML is the difference between the upper and lower bound estimates for IS. Panel A reports means by ticker for near-the-money options. Panels B and C report pooled sample descriptive statistics for near-the-money and away-from-the-money options, respectively. N is the number of stock-day observations. When a stock changes ticker, is acquired or is de-listed, it is removed from our sample, resulting in different N for different tickers. The following stocks changed tickers or merged during the sample period: AOL, CPN, MWD, SBC and NXTL. There are approximately 2,520 trading days in ten years but it is possible for each ticker to have more than 2,520 observations if more than one put-call pair per stock-day meets the criteria outlined in Section 2.3.1.

Panel A: Near-the-money options, means by ticker

$Ticker$	N	IS	CS	ILS	UML	$Ticker$	N	IS	CS	ILS	UML
AIG	11,425	6.11	13.19	38.38	0.87	HD	8,056	6.10	12.83	34.63	0.76
AMAT	5,585	5.06	9.66	40.68	1.03	IBM	11,247	7.04	12.07	41.75	0.75
AMGN	11,257	4.23	8.04	48.79	0.97	INTC	6,398	8.70	16.48	30.78	1.02
AMR	3,977	5.90	11.22	41.48	0.94	JPM	13,056	6.02	13.29	31.70	0.80
AMZN	17,744	3.07	8.19	43.06	0.99	KLAC	10,892	3.63	6.33	52.10	0.76
AOL	253	10.17	13.52	41.27	2.05	MMM	9,249	4.74	8.02	50.26	0.76
BMY	6,288	5.37	13.44	31.67	0.80	MO	6,961	7.37	11.14	46.27	0.99
BRCM	11,248	2.94	7.49	45.74	0.73	MSFT	9,103	9.27	15.18	39.23	0.89
C	10,591	5.58	12.66	30.80	0.96	MWD	1,003	4.87	9.08	37.75	2.02
COF	12,353	3.57	7.89	46.61	0.65	NXTL	1,061	4.37	7.15	45.01	1.04
CPN	337	12.70	13.33	54.24	0.76	ORCL	9,774	5.00	12.01	34.82	0.71
CSCO	8,293	9.12	17.20	31.14	0.79	PFE	5,545	7.58	15.27	29.83	0.85
DELL	6,998	4.27	10.19	37.39	0.88	QCOM	9,319	3.40	9.28	38.45	0.95
EBAY	11,875	3.43	8.94	40.01	0.95	QLGC	4,765	5.43	9.17	45.26	1.23
EMC	8,643	6.72	14.80	29.35	0.95	SBC	644	6.82	11.02	36.70	1.09
F	3,964	9.00	17.42	30.11	1.01	TYC	8,576	7.60	13.68	43.77	0.58
GE	6,825	9.95	16.68	34.42	1.08	XLNX	6,901	4.61	9.58	44.11	0.66
GM	7,472	4.90	11.02	37.17	0.84	XOM	8,632	4.74	9.42	43.46	0.78

Panel B: Near-the-money options, pooled sample descriptive statistics

	N	IS	CS	ILS	UML
Mean	7,675	6.09	11.55	38.95	0.94
Median	8,175	5.50	11.18	39.00	0.89
Std. Dev.	3,976	10.65	14.93	45.64	1.31

Panel C: Away-from-the-money options, pooled sample descriptive statistics

	N	IS	CS	ILS	UML
Mean	12,130	6.90	11.03	42.58	0.81
Median	12,523	6.50	11.00	42.31	0.72
Std. Dev.	6,216	12.63	16.52	46.32	1.22

Table 2.3. Options market price discovery shares through time

This table reports the mean, median and standard deviation of options market price discovery shares for our sample of 36 stocks by year between April 17, 2003 and April 17, 2013. The price discovery shares are: (i) Hasbrouck (1995) information share (IS), (ii) Gonzalo-Granger (1995) component share (CS), and (iii) Yan-Zivot-Putniņš (2013) information leadership share (ILS). All price discovery metrics are expressed as percentages (range 0-100%).

Panel A: Hasbrouck (1995) *IS* metric											
$Year$	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013
Mean	8.92	6.82	5.82	5.12	4.10	7.06	3.74	4.80	5.72	5.77	6.65
Median	3.99	2.83	2.53	2.01	1.56	1.15	1.31	1.62	1.63	1.92	2.34
Std. Dev.	13.25	10.94	8.82	9.20	7.25	18.53	7.50	9.26	11.90	11.08	11.08
Panel B: Gonzalo-Granger (1995) *CS* metric											
$Year$	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013
Mean	12.25	10.67	9.37	7.34	7.25	11.93	9.46	11.43	12.12	12.35	13.20
Median	9.12	7.90	5.75	2.28	1.28	3.45	5.31	6.85	5.96	7.44	8.63
Std. Dev.	14.05	12.17	12.22	11.13	10.97	20.85	12.03	14.21	16.94	16.13	15.97
Panel C: Yan-Zivot-Putniņš (2013) *ILS* metric											
$Year$	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013
Mean	37.62	37.74	43.18	51.30	50.10	44.97	39.52	38.18	40.88	38.01	37.87
Median	21.63	16.40	20.84	29.43	22.38	7.02	5.29	5.13	5.72	6.11	7.57
Std. Dev.	36.97	40.34	41.53	44.33	47.22	47.70	46.63	46.10	46.84	45.63	44.93

Table 2.4. Characteristics of insider trading prosecuted by the SEC

This table reports insider trading characteristics for 539 announcements in which insiders were successfully prosecuted for illegal trading in the stock, options, or both markets between January 1, 1999 and August 30, 2014. $Year$ indicates the year in which the offending conduct occurred. N_{Stock}, $N_{Options}$, and N_{Both} is the number of announcements in which insiders traded in the stock market only, in the options market only, and in both the stock and options markets, respectively. N_{Total} is the sum of N_{Stock}, $N_{Options}$, and N_{Both}. $Stock\ Trades$ ($Option\ Trades$) is the number of insider trades in the stock (options) market. $Total\ Trades$ is the sum of $Stock\ Trades$ and $Option\ Trades$. $Option\ Trade\ Ratio$ is the ratio of insider options trades to total insider trades each year. $Option\ Volume\ Ratio$ is the ratio of insider options volume to total insider volume, with All referring to all announcements and $Both$ referring to announcements in which insiders trade in both the stock and options markets. Options volume is calculated as contract size multiplied by number of contracts. $Option\ \$Volume\ Ratio$ is similarly defined, except that it uses traded dollar volume rather than share volume. All of the volume and value ratios are calculated for each announcement and then averaged across all announcements each year.

$Year$	N_{Stock}	$N_{Options}$	N_{Both}	N_{Total}	$Stock\ Trades$	$Option\ Trades$	$Total\ Trades$	$Option\ Trade\ Ratio$ (%)	$Option\ Volume\ Ratio, All$ (%)	$Option\ Volume\ Ratio, Both$ (%)	$Option\ \$Volume\ Ratio, All$ (%)	$Option\ \$Volume\ Ratio, Both$ (%)
1999	1	0	1	2	2	1	3	33.33	46.67	93.33	-	-
2000	4	0	0	4	7	0	7	-	-	-	-	-
2001	7	0	3	10	11	9	20	45.00	20.79	69.29	-	-
2002	14	0	3	17	90	4	94	4.26	2.87	16.29	-	-
2003	33	0	3	36	128	19	147	12.93	4.03	48.32	2.71	25.32
2004	23	0	5	28	114	56	170	32.94	15.12	61.62	0.01	0.05
2005	77	1	25	103	280	107	387	27.65	12.93	44.73	3.19	7.76
2006	37	7	11	55	118	67	185	36.22	27.16	65.54	14.51	26.15
2007	39	3	22	64	220	118	338	34.91	24.58	43.38	13.9	16.7
2008	46	2	16	64	210	90	300	30.00	19.14	41.44	25.56	49.53
2009	47	2	10	59	168	70	238	29.41	16.25	49.46	4.88	5.82
2010	32	5	12	49	121	75	196	38.27	36.27	64.48	23.12	29.06
2011	18	5	10	33	87	44	131	33.59	44.82	70.32	13.67	1.68
2012	4	5	4	13	25	72	97	74.23	66.43	65.72	18.55	14.91
2013	0	2	0	2	0	7	7	100.00	100.00	-	100.00	-
Total	382	32	125	539	1,581	739	2,320	31.85	22.94	52.14	12.13	23.64

Table 2.5. Options market price discovery around SEC insider trading prosecutions

This table reports coefficient estimates of the determinants of price discovery from the following regression using stock-day observations:

$$\frac{PD_{it}}{(1-PD_{it})} = \alpha + \beta_1 OptionDV_{it} + \beta_2 StockDV_{it} + \beta_3 BothDV_{it} + \sum_{j=1}^{3} \gamma_j \, Controls_{j,it} + \varepsilon_{it}$$

PD_{it} is the price discovery share of the options market for stock i on day t using the Hasbrouck (1995) information share (IS_{it}) in Model 1, Gonzalo-Granger (1995) component share (CS_{it}) in Model 2, and Yan-Zivot-Putniņš (2013) information leadership share (ILS_{it}) in Model 3. $OptionDV_{it}$ is a dummy variable equal to one if insiders illegally trade in the options market only, $StockDV_{it}$ is a dummy variable equal to one if insiders illegally trade in the stock market only, and $BothDV_{it}$ is a dummy variable equal to one if insiders illegally trade in both the stock and options markets. $Controls_j$ consists of the following exogenous control variables: ${DV_t}^{GF}$ is a dummy variable equal to one following the removal of the Grandfathering provision, ${DV_t}^{OMM}$ is a dummy variable equal to one following the removal of the option market-maker (OMM) exemption, and TT_t is a time-trend variable. The dependent variable is in natural log form. The sample comprises 46 stocks (47 news announcements) in which insiders were successfully prosecuted for illegal trading between January 1, 1999 and August 30, 2014. For each announcement we take one month before the first insider trade, one month after the last insider trade, and all stock-days in between to give a sample that includes days with and without illegal insider trades. Standard errors are clustered both by stock and date and *t*-statistics are reported in parentheses. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels.

	IS_{it} Model 1	CS_{it} Model 2	ILS_{it} Model 3
$Intercept$	-0.69 (-0.20)	-11.06 (-2.98)***	21.12 (5.38)***
$OptionDV_{it}$	-0.35 (-1.77)*	-0.98 (-2.51)**	1.26 (2.20)**
$StockDV_{it}$	-0.12 (-0.87)	-0.23 (-0.56)	0.22 (0.24)
$BothDV_{it}$	0.62 (2.51)**	1.15 (1.26)	-0.84 (-0.56)
${DV_t}^{GF}$	-0.34 (-7.98)***	4.66 (89.03)***	-10.09 (-115.94)***
${DV_t}^{OMM}$	0.46 (8.16)***	1.59 (26.85)***	-2.39 (-45.34)***
TT_t	-0.00 (-0.70)	0.00 (0.11)	-0.00 (-1.45)
R^2 (%)	9.28	7.61	5.02
Fixed effects	Stock	Stock	Stock

Table 2.6. Options market price discovery shares on stock-days that have illegal insider trading

This table reports options market price discovery shares for 999 stock-days (in 46 stocks and 47 unique announcements) that are known to have illegal insider trading. The sample comprises insider trading prosecuted by the SEC between January 1, 1999 and August 30, 2014. The price discovery shares are: (i) Hasbrouck (1995) information share (IS), (ii) Gonzalo-Granger (1995) component share (CS), and (iii) Yan-Zivot-Putniņš (2013) information leadership share (ILS). All price discovery metrics are expressed as percentages (range 0-100%). Panel A reports descriptive statistics across all 999 stock-days. Panel B partitions the insider trading stock-days by the number of days prior to the announcement of the insiders' information ($DaysToAnnouncement$). N is the number of stock-day observations.

Panel A: Pooled descriptive statistics				
	N	IS	CS	ILS
Mean	999	14.60	18.88	47.80
Median	999	9.25	12.97	50.23
Std. Dev.	999	13.37	14.80	13.68
Panel B: Mean price discovery shares by days to announcement (day 0)				
$DaysToAnnouncement$	N	IS	CS	ILS
< -20	317	12.15	17.40	48.49
-20 to -1	665	13.87	18.48	50.98
0	17	29.22	17.65	82.35

Table 2.7. Determinants of price discovery shares

This table reports the coefficient estimates of the determinants of price discovery from the following regression using stock-day observations:

$$\frac{PD_{it}}{(1-PD_{it})} = \alpha + \beta_1 Spread_{it} + \beta_2 Volume_{it} + \beta_3 Volatility_{it} + \beta_4 Leverage_{it} + \sum_j \gamma_j \, Determinants_{j,it} + \varepsilon_{it}$$

PD_{it} is the price discovery share of the options market for stock i on day t using the Hasbrouck (1995) information share (IS_{it}) in Model 1, Gonzalo-Granger (1995) component share (CS_{it}) in Model 2, and Yan-Zivot-Putniņš (2013) information leadership share (ILS_{it}) in Models 3 to 10. $Spread_{it}$ is the ratio of the time-weighted average quoted bid-ask spread in the options market to that of the stock market, $Volume_{it}$ is the ratio of options market traded dollar volume to that of the stock market, $Volatility_{it}$ is the standard deviation of one-minute midquote returns in the stock market, $Leverage_{it}$ is the ratio of the stock price to that of the call option price (if the daily stock return is positive) or to that of the put option price (if the daily stock return is negative). $Determinants_j$ consists of option-level determinants of leverage and market structure control variables: $StrikeDistance_{it}$ is the absolute value of the difference between the underlying stock price and strike price, $ImpVol_{it}$ is the implied volatility using the Black-Scholes model, DV_{it}^{a-b} is a dummy variable equal to one if the time to expiry is between a and b days (inclusive) (options with expiry between 40 and 70 days are the base case), ${DV_t}^{GF}$ is a dummy variable equal to one following the removal of the Grandfathering provision, and ${DV_t}^{OMM}$ is a dummy variable equal to one following the removal of the option market-maker exemption. All variables are in natural log form (except dummy variables). Panel A examines the same determinants of price discovery as Chakravarty et al. (2004). Panel B examines the determinants of ILS_{it}. The sample comprises 36 stocks during the period April 17, 2003 and April 17, 2013. Standard errors are clustered both by stock and date and *t*-statistics are reported in parentheses. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels.

Panel A: Chakravarty et al. (2004) framework

	IS_{it} Model 1	CS_{it} Model 2	ILS_{it} Model 3
$Intercept$	-8.05 (-10.43)***	-8.43 (-8.71)***	0.87 (0.84)
$Spread_{it}$	-0.18 (-2.63)***	-0.85 (-5.38)***	1.76 (8.64)***
$Volume_{it}$	-0.02 (-0.84)	-0.11 (-5.61)***	0.17 (5.42)***
$Volatility_{it}$	-0.51 (-4.89)***	-0.36 (-2.73)***	-0.18 (-1.21)
R^2 (%)	1.88	1.62	1.63
Fixed Effects	None	None	None

Table 2.7. Determinants of price discovery shares (Continued)

Panel B: Determinants of Yan-Zivot-Putniņš ILS_{it} metric							
	ILS_{it} Model 4	ILS_{it} Model 5	ILS_{it} Model 6	ILS_{it} Model 7	ILS_{it} Model 8	ILS_{it} Model 9	ILS_{it} Model 10
$Intercept$	2.62 (2.35)**	1.60 (1.33)	2.56 (1.69)*	0.18 (1.33)	3.49 (5.96)***	2.97 (5.16)***	0.19 (1.33)
$Spread_{it}$	1.66 (9.58)***	1.68 (8.99)***	1.26 (7.70)***	1.68 (8.21)***	1.69 (9.60)***	1.29 (8.27)***	1.72 (8.44)***
$Volume_{it}$	0.22 (6.08)***	0.22 (5.57)***	0.15 (4.49)***	0.20 (4.95)***	0.24 (6.53)***	0.18 (4.88)***	0.22 (5.96)***
$Volatility_{it}$	0.08 (0.44)	-0.02 (-0.11)	0.08 (0.48)	0.27 (0.63)			
$Leverage_{it}$	0.27 (3.33)***	0.29 (3.35)***	0.14 (1.66)*	0.23 (2.34)**			
$Strike\ Distance_{it}$	0.36 (4.94)***	0.36 (4.76)***	0.26 (7.75)***	0.33 (4.72)***	0.36 (4.72)***	0.27 (7.49)***	0.33 (4.55)***
$ImpVol_{it}$					-1.21 (-2.18)**	-0.95 (-1.85)*	-1.12 (-1.12)
DV_{it}^{0-9}					0.20 (0.94)	0.02 (0.09)	0.26 (1.29)
DV_{it}^{10-19}					0.10 (0.74)	-0.09 (-0.62)	0.04 (0.33)
DV_{it}^{20-29}					-0.19 (-1.68)*	-0.33 (-2.95)***	-0.14 (-1.23)
DV_{it}^{30-39}					-0.05 (-0.50)	-0.09 (-0.95)	0.05 (0.52)
${DV_t}^{GF}$		1.02 (4.02)***	1.10 (3.77)***	0.46 (2.48)**		1.23 (4.14)***	0.47 (2.32)**
${DV_t}^{OMM}$		-0.79 (-3.24)***	-0.81 (-3.50)***	-0.57 (-2.63)***		-0.85 (-3.54)***	-0.55 (-2.56)***
R^2 (%)	1.93	1.98	2.86	1.68	1.95	2.88	1.68
Fixed Effects	None	None	Stock	Date	None	Stock	Date

Table 2.8. First stage IV regressions of liquidity

This table reports coefficient estimates from the first stage of an instrumental variables regression. The reduction in the minimum tick size for options as a result of the Penny Pilot Program is used as an instrument for the level of relative liquidity in the options and stock markets ($Spread_{it}$):

$$Spread_{it} = \alpha + \beta_1 DV_{it}{}^{Tick} + \sum_j \gamma_j\, Control_{j,it} + \varepsilon_{it}$$

$Spread_{it}$ is the ratio of the time-weighted average quoted bid-ask spread in the options market to that of the stock market, and $DV_{it}{}^{Tick}$ is a dummy variable equal to one after the reduction in minimum tick size. The control variables include: $Volume_{it}$ is the ratio of options market traded dollar volume to that of the stock market, $Volatility_{it}$ is the standard deviation of one-minute midquote returns in the stock market, $Leverage_{it}$ is the ratio of the stock price to that of the call option price (if the daily stock return is positive) or to that of the put option price (if the daily stock return is negative), $StrikeDistance_{it}$ is the absolute value of the difference between the underlying stock price and the strike price, $ImpVol_{it}$ is the implied volatility from the Black-Scholes model, and DV_{it}^{a-b} is a dummy variable equal to one if the time to expiry is between a and b days (inclusive) (options with expiry between 40 and 70 days are the base case). All variables are in natural log form (except dummy variables). The sample comprises 36 stocks during the period April 17, 2003 and April 17, 2013. Standard errors are clustered both by stock and date and *t*-statistics are reported in parentheses. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels.

	$Spread_{it}$ Model 1	$Spread_{it}$ Model 2	$Spread_{it}$ Model 3	$Spread_{it}$ Model 4	$Spread_{it}$ Model 5	$Spread_{it}$ Model 6
$Intercept$	1.57 (3.20)***	2.22 (9.69)***	-0.05 (-0.98)	0.12 (0.45)	0.64 (4.96)***	-0.08 (-1.55)
$DV_{it}{}^{Tick}$	-0.90 (-12.94)***	-0.73 (-9.68)***	-0.95 (-14.31)***	-0.89 (-12.64)***	-0.72 (-9.37)***	-0.95 (-15.10)***
$Volume_{it}$	-0.12 (-6.27)***	-0.09 (-11.75)***	-0.12 (-5.52)***	-0.12 (-6.22)***	-0.09 (-10.98)***	-0.12 (-5.27)***
$Volatility_{it}$	0.12 (2.48)**	0.14 (5.75)***	0.08 (0.65)			
$Leverage_{it}$	-0.13 (-4.51)***	-0.14 (-9.92)***	-0.13 (-6.20)***			
$StrikeDistance_{it}$	0.10 (2.06)**	0.12 (6.94)***	0.10 (2.21)**	0.10 (2.03)**	0.12 (6.71)***	0.10 (2.16)**
$ImpVol_{it}$				0.81 (4.65)***	0.92 (9.47)***	0.77 (2.60)***
DV_{it}^{0-9}				-0.20 (-3.29)***	-0.20 (-8.47)***	-0.19 (-5.69)***
DV_{it}^{10-19}				-0.16 (-5.01)***	-0.20 (-10.39)***	-0.15 (-6.51)***
DV_{it}^{20-29}				-0.10 (-4.16)***	-0.13 (-8.75)***	-0.11 (-4.96)***
DV_{it}^{30-39}				-0.02 (-1.91)*	-0.05 (-5.38)***	-0.04 (-2.76)***
R^2 (%)	51.12	64.14	48.08	51.88	65.03	49.20
Fixed effects	None	Stock	Date	None	Stock	Date

Table 2.9. Second stage IV regressions of the impact of liquidity on price discovery

This table reports coefficient estimates from the second stage of an instrumental variables regression:

$$\frac{PD_{it}}{(1-PD_{it})} = \alpha + \beta_1 \widehat{Spread}_{it} + \sum_j \gamma_j \, Control_{j,it} + \varepsilon_{it}$$

PD_{it} is the price discovery share of the options market for stock i on day t using the Yan-Zivot-Putniņš (2013) information leadership share (ILS_{it}), and $\widehat{Spread}_{it}$ is the fitted value of the ratio of time-weighted average quoted bid-ask spread in the options market to that of stock market (obtained from the first-stage regression). The control variables include: $Volume_{it}$ is the ratio of options market dollar volume to that of the stock market, $Volatility_{it}$ is the standard deviation of one-minute midquote returns in the stock market, $Leverage_{it}$ is the ratio of stock price to that of the call option price (if the daily stock return is positive) or to that of the put option price (if the daily stock return is negative), $StrikeDistance_{it}$ is the absolute value of the difference between the underlying stock price and the strike price, $ImpVol_{it}$ is the implied volatility from the Black-Scholes model, and DV_{it}^{a-b} is a dummy variable equal to one if the time to expiry is between a and b days (inclusive) (options with expiry between 40 and 70 days are the base case). All variables are in natural log form (except dummy variables). The sample comprises 36 stocks during the period April 17, 2003 and April 17, 2013. Standard errors are clustered both by stock and date and *t*-statistics are reported in parentheses. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels.

	ILS_{it} Model 1	ILS_{it} Model 2	ILS_{it} Model 3	ILS_{it} Model 4	ILS_{it} Model 5	ILS_{it} Model 6
$Intercept$	2.46	4.72	0.13	3.50	3.36	0.18
	(1.48)	(3.01)***	(0.86)	(4.36)***	(5.19)***	(1.24)
$\widehat{Spread}_{it}$	1.72	0.79	2.04	1.74	0.79	2.09
	(4.92)***	(2.18)**	(5.19)***	(4.84)**	(2.17)**	(5.18)***
$Volume_{it}$	0.22	0.12	0.25	0.25	0.14	0.28
	(3.72)***	(2.37)**	(3.34)***	(3.93)***	(2.84)***	(3.67)***
$Volatility_{it}$	0.06	0.28	0.20			
	(0.27)	(1.70)*	(0.42)			
$Leverage_{it}$	0.28	0.07	0.27			
	(2.87)***	(0.72)	(2.38)**			
$StrikeDistance_{it}$	0.35	0.33	0.30	0.35	0.33	0.30
	(4.64)***	(7.22)***	(3.92)***	(4.74)***	(7.17)***	(4.00)***
$ImpVol_{it}$				-1.30	-0.10	-1.42
				(-1.74)*	(-0.21)	(-1.17)
DV_{it}^{0-9}				0.23	-0.10	0.35
				(1.05)	(-0.48)	(1.50)
DV_{it}^{10-19}				0.12	-0.18	0.08
				(0.76)	(-1.07)	(0.62)
DV_{it}^{20-29}				-0.18	-0.40	-0.12
				(-1.36)	(-3.05)***	(-0.94)
DV_{it}^{30-39}				-0.04	-0.11	0.07
				(-0.48)	(-1.12)	(0.65)
R^2 (%)	1.14	2.39	1.05	1.15	2.40	1.05
Fixed effects	None	Stock	Date	None	Stock	Date

Chapter 3. Return predictability following different drivers of large price changes[23]

3.1. Introduction

There is contrasting evidence regarding the circumstances which lead to the under- and overreaction of returns following large price changes in US markets. De Bondt and Thaler (1985) were one of the first to suggest that investors overreact as returns significantly reverse in the three- to five-year period following portfolio formation. A number of studies also document that returns exhibit reversal in the shorter term, specifically in the 20 days following large price changes (Bremer and Sweeney, 1991; Park, 1995; Bremer et al., 1997; Pham et al., 2009).[24] In contrast, several studies reject the overreaction hypothesis developed by De Bondt and Thaler (1985). Brown et al. (1988) find evidence to support their uncertain information hypothesis (UIH), while Atkins and Dyl (1990) and Cox and Peterson (1994) document that the reversal in returns is non-existent after controlling for the bid ask bounce, market illiquidity and transaction costs.[25]

More recently, several US studies have examined the impact of public information upon the subsequent patterns in returns following large price changes (Pritamani and Singal, 2001; Chan, 2003; Savor, 2012). These studies find that returns underreact following large price changes driven by public information, inconsistent with Fama's (1970) semi-strong efficient markets hypothesis. In addition, these studies find that returns overreact following large price changes which do not correspond with the release of public information.

In this chapter we utilize the unique information environment in Australia to examine return predictability following large price changes. Large price changes may occur for a number of reasons including: the release of public information, investor sentiment, liquidity trading and private information. We investigate return predictability following large price changes to examine whether the under-/overreaction phenomenon differs between countries and whether any differences can be attributed to the dispersed nature of the information environment in the US. In addition to examining the impact of public information, we extend the literature by simultaneously looking at return predictability following other drivers of large price changes including liquidity trading and private information.

[23] We thank Henk Berkman, Paul Brockman, Carole Comerton-Forde, Douglas Foster, Narasimhan Jegadeesh, Talis Putnins, Tom Smith, Terry Walter, four anonymous referees, participants at the Behavioural Finance and Capital Markets Conference 2013 (Adelaide), Securities Industry Research Centre of Asia-Pacific Limited Young Researcher Workshop 2013 (Sydney), Financial Research Network Conference 2013 (Sydney), Financial Management Conference 2013 (Paris) and European Financial Management Association Doctoral Student Consortium 2015 (Venice).

[24] Bremer et al. (1997) examine Nikkei 300 listed stocks and Pham et al. (2009) examine Australian Securities Exchange 100 listed stocks.

[25] The UIH predicts that regardless of the sign of the large price change, firm risk and expected return will increase and will result in subsequent drift (or under-reaction) in returns.

Using the Australian market to examine return predictability following large price changes is advantageous for several reasons. First, in contrast to the secondary sources of US data used by Pritamani and Singal (2001) and Chan (2003), all public firm-specific information is centrally disseminated from a primary source – the Australian Securities Exchange (ASX).[26] Under ASX Listing Rule 3.1, all listed firms are required to immediately disclose all material information to the ASX and thus to the public. In comparison, Regulation Fair Disclosure ensures information is fairly disseminated, but does not necessarily require the immediate disclosure of information.[27] Information can be disclosed to the public through a variety of channels including firm websites, press releases or by Form 8-K which allows between one and four business days before filing for each type of announcement.[28] The precise timing of announcements upon one centralized platform in Australia allows us to accurately identify when public information is released and widely disseminated so that we can cleanly associate public information with large price changes.

Second, there is a special category of ASX announcements that identifies those announcements that contain price sensitive material information. This classification allows us to overcome another shortcoming of Pritamani and Singal (2001) and Chan (2003) in which the authors cannot be certain that a particular news item contains material information about a firm's fundamental value.

Third, also under ASX Listing Rule 3.1, the ASX issues price queries when there is a large price change that does not correspond with the dissemination of an official ASX announcement. We use ASX price queries that coincide with and/or follow large price changes to create a cleaner sample of price events that are not explained by other public information sources (not captured by our proxy or previous studies' proxies for public information), but likely driven by private information. Our analysis of return predictability following different drivers of large price changes sheds further light on the price discovery process and has practical implications for regulatory bodies concerned about the presence of informed trading.

In this chapter we show that public and private information as well as liquidity trading drive large price changes. We find that 2,840 of 6,641 (or 43%) of our sample of large price changes can be explained by the release of ASX announcements. Using several trading and liquidity measures we confirm that liquidity trading is associated with 3,383 large price changes. In addition, the abnormal behavior of adverse selection costs prior to a sample of large price changes that are not accompanied by public information, and which coincide with or are followed by an ASX price query, provide evidence of private information driving large price changes.

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[26] The secondary sources for public information used in these US studies were obtained from the Dow Jones Interactive Publications Library which consists of the following sources: The Wall Street Journal, Associated Press Newswires, The Chicago Tribune, The Globe and Mail, Gannett News Service, The Los Angeles Times, The New York Times, The Washington Post, USA Today and Dow Jones Newswires.

[27] Sidhu et al. (2008) find that Regulation Fair Disclosure has reduced the number of disclosures made in the US.

[28] See http://www.sec.gov/answers/form8k.htm for a list of material corporate events which must be filed using Form 8-K.

Our panel regression analysis of large price events on post-event cumulative abnormal returns provides evidence of permanent price changes for large information-based price events (or price events that coincide with the release of ASX announcements). We obtain similar findings for ASX announcements which contain price sensitive information. Our results suggest that ASX announcements efficiently incorporate information into prices consistent with Fama's (1970) semi-strong efficient markets hypothesis. We also find that large price changes that are preceded by abnormal adverse selection costs and generate ASX price queries, are also permanent, consistent with the imputation of private information into fundamental value (Hasbrouck 1991; 1995). In contrast, we observe significant reversal (or overreaction) in returns following large no-information-based price changes (or price events which do not coincide with the release of ASX announcements). This finding is consistent with liquidity trading which creates temporary price pressure that reverts to fundamental value (Campbell et al., 1993; Avramov et al., 2006).

After controlling for microstructure factors, we err on the cautious side and suggest that it would be difficult for investors to consistently profit from the overreaction in returns following large price changes driven by liquidity trading. In addition, the subsequent reversal in returns is around 1.5 times larger when calculated using unadjusted closing prices rather than adjusted closing prices. As a result, we suggest that prior US studies which document annualized returns using unadjusted closing prices should be interpreted with care.

This chapter is most similar to the examinations of short-run return predictability following large price changes in the presence and absence of public information conducted by Pritamani and Singal, (2001), Chan (2003) and Savor (2012). Pritamani and Singal (2001) examine patterns in daily returns for 1.5% of the universe of stocks listed on the NYSE and AMEX between 1990 and 1992 after a variety of information signals including: large price changes, increases in trading volume, and the dissemination of public information. They suggest that the prior literature does not simultaneously examine the magnitude, precision and dissemination of an information signal. To address this gap in the literature large price changes are used to represent the magnitude of the information signal, increases in volume are used to represent the precision of the information signal and public information (obtained from the Dow Jones Interactive Publications Library) is used to represent the dissemination of the information signal. For large positive (negative) price changes that simultaneously correspond with increases in volume and the release of public information, the authors document cumulative abnormal returns (CAR) of 2% (-1.68%) in the following 20 day period. Further using unadjusted closing prices, a trading strategy which consists of taking a long (short) position in stocks which exhibit large positive (negative) information-based price changes accompanied by an increase in volume is found to earn significant annualized abnormal returns of 12-18%.[29]

[29] Large price events are excluded when there is a stock split, stock dividend or equity issue in the previous 60 trading days.

Chan (2003) documents drift in monthly returns following news events (price events accompanied by the release of public information) and reversal in returns following no-news events between 1980 and 2000. Similar to Pritamani and Singal (2001), news data is obtained from the Dow Jones Interactive Publications Library. Both studies determine whether news is classified as a positive or negative price event based on the market reaction to the news story. In addition, Chan (2003) uses the headline of the news story as an additional determinant of the sign of a price event. An issue with interpretation using this methodology is that a number of news and no-news events may be misclassified as some news stories may not contain any material information about the fundamental value of a firm.

Savor (2012) provides the most comprehensive study of return predictability following 166,470 large price changes between 1995 and 2009. Unlike Pritamani and Singal (2001) and Chan (2003), analyst recommendations are used as a proxy for public information. The benefit of using analyst recommendations is that large price events are likely to be supplemented with an analyst report, recommendations provide a view on how individuals (or analysts) form expectations about asset values and constitute an intuitive method to determine whether public information can be classified as positive or negative news. Savor (2012) finds that when an analyst recommendation is made in the three-day window around a large price change, returns exhibit drift following large information-based price events and reversal following large no-information-based price events over a five- to forty-day post-event horizon. Using unadjusted closing prices, a trading strategy that consists of a long (short) position in information winners (information losers) and a long (short) position in no-information losers (no-information winners) is found to earn significant abnormal annualized returns of 36%.

A notable difference between our findings and prior US studies is that we find permanent large information-based price changes rather than subsequent drift (or under-reaction) in returns. In particular, this result can be attributed to several unique features of the Australian information environment, including a central information dissemination platform, price sensitive flags, and the use of trading halts that reduce investor distraction to information revelation from several different sources and make it easier for investors to determine the value of information (Hirshleifer et al., 2009). Our findings suggest there is an increased level of informational efficiency of prices in Australia that will be of interest to regulators in other jurisdictions.

The remainder of this chapter is organized as follows: Sections 3.2, 3.3 and 3.4 explain the institutional details of the Australian market, the data and methodology employed, respectively. In Section 3.5 we present our analysis of the drivers of large price changes and subsequent patterns in returns. Section 3.6 concludes the chapter.

3.2. Institutional details of the Australian market

3.2.1. Exchange details and market structure

The ASX is the tenth-largest exchange in the world with a market capitalization of approximately \$1.5 trillion Australian dollars and provides a secondary market to over 2,000 stocks.[30] In contrast to major US quote-driven or hybrid markets, the ASX is a continuous order-driven market and operates as a fully-automated stock exchange (SEATS). In 2011 the Australian equity market became fragmented with the introduction of another exchange, Chi-X. From May 2013 all ASX-listed stocks became available for trade on Chi-X and by January 2014 Chi-X had a 10.15% market share of the trading of Australian stocks (Aitken et al., 2015). Opening prices for ASX-listed stocks are determined in alphabetical order via an opening call auction between 10:00 and 10:09, and normal trading hours occur between 10:09 and 16:00. In contrast, Chi-X does not open via an auction process and normal trading hours are from 10:00 to 16:00. During normal trading hours trade execution occurs according to a price/time priority.

3.2.2. ASX continuous disclosure rules

Continuous disclosure requirements for ASX-listed firms are stated in Rule 3.1: "*once an entity is or becomes aware of any information concerning it that a reasonable person would expect to have a material effect on the price or value of the entity's securities, the entity must immediately tell the ASX that information*". The immediate disclosure of information to the ASX means *promptly without delay* rather than *instantaneously*. If the market is closed, it is sufficient for a firm to disclose information prior to the opening on the next trading day. If the market is open then the firm is required to disclose information to the ASX promptly and without delay, otherwise the firm can request a trading halt. A trading halt gives the firm time to provide material information to the ASX which reduces information asymmetries between traders and prevents a false market.[31] A maximum two-day period is permitted for a trading halt, otherwise a voluntary suspension of the security might be required. In addition, all firms must receive acknowledgement from the ASX that such information has been released to the market before informing other parties.[32]

Another feature of the Australian information structure is that the ASX will report whether a particular announcement contains price sensitive or material information about the fundamental value of the firm. Examples of material information include asset acquisitions and disposals, takeover bids, discovery of minerals, changes in credit ratings or differences between actual and expected earnings. Examples of non-material information include changes in substantial holdings, the top 20

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[30] See http://www.asx.com.au/about/corporate-overview.htm for further details.

[31] A false market is a situation in which incomplete or incorrect information results in the mispricing of a security.

[32] See http://www.asx.com.au/documents/rules/abridged-continuous-disclosure-guide-clean-copy.pdf for further details of ASX continuous disclosure rules described in this section.

shareholders and option holders, addendums to annual reports or presentations, results of general meetings and changes to directors' interests.

The main objective of the enforcement of Rule 3.1 is to ensure that the ASX provides a central platform for collation and the release of material and non-material information required for an efficient, fair and fully informed marketplace. In contrast to the US, material information can be disclosed via various avenues including: a firm's website, news streams like Bloomberg and Reuters and via Form 8-K.

Listing Rule 3.1A describes a number of exceptions (which are referred to as carve-out provisions) in which a firm does not have to disclose information to the ASX. These include instances when releasing the information is a breach of law, or when it is incomplete, insufficiently definite, for internal management only, a trade secret or is confidential in the ASX's eyes. In addition, Listing Rules 3.2 to 3.19 allows firms a predetermined number of trading days to be compliant with continuous disclosure regulation. For example:

- Rule 3.4 – requires the acquirer to disclose the takeover bid, the consideration offered and details regarding the top 20 shareholders within ten trading days following the offer period.
- Rule 3.10A – requires a firm to disclose that restricted securities will be released within ten trading days before the escrow period ends.
- Rule 3.11 – requires a firm to disclose changes to options on the underlying stock including changes to the strike price and number of shares controlled by each option at least five trading days before the effective date.
- Rule 3.12 – requires a firm to disclose details regarding the auction of forfeited shares in no-liability firms within ten trading days before the auction.
- Rule 3.13 – requires a firm to disclose if directors will be elected at a meeting at least five trading days before the nominations ballot is confirmed.
- Rule 3.15 – requires a firm to disclose whether it will set up or cease operating in Australia at least 20 trading days before the event date.
- Rule 3.19 – requires a firm to disclose interests or changes in interests of a director within five trading days of such events.

The ASX has a number of enforcement procedures for Listing Rule 3.1. First, each listed firm has a listings adviser who liaises and monitors the continuous disclosure of each firm. Each listing adviser will review a number of news sources including local and national newspapers, investor forums, chat sites and analyst reports to see whether a firm is compliant with Listing Rule 3.1.

Second, if there is abnormal trading in a security which does not correspond with the release of an ASX announcement, the ASX will issue a price query letter to the firm. The price query letter will ask four questions:

1. Is the entity aware of any information concerning it that has not been announced to the market which, if known by some in the market, could explain the recent trading in its securities?
2. If the answer to question 1 is "yes":
   a. Is the entity relying on Listing Rule 3.1A not to announce that information under Listing Rule 3.1? Please note that the recent trading in the entity's securities would suggest to ASX that such information may have ceased to be confidential and therefore the entity may no longer be able to rely on Listing Rule 3.1A. Accordingly, if the answer to this question is "yes", you need to contact us immediately to discuss the situation.
   b. Can an announcement be made immediately? Please note, if the answer to this question is "no", you need to contact us immediately to discuss requesting a trading halt.
   c. If an announcement cannot be made immediately, why not and when is it expected that an announcement will be made?
3. If the answer to question 1 is "no", is there any other explanation that the entity may have for recent trading in its securities?
4. Please confirm that the entity is in compliance with the Listing Rules and, in particular, Listing Rule 3.1.

The firm in question usually has to respond to the ASX during the same trading day if the market is open or before trading begins on the next trading day. The price query letter and the firm's response will be released concurrently by the ASX.

Third, the ASX will issue an awareness letter if it is unsure whether a firm has disclosed material information promptly and without delay to the ASX. This letter is similar to the price query letter and the ASX will release concurrently the letter and the firm's response. In addition, the ASX will investigate third-party claims about a firm's failure to promptly disclose material information to the ASX or request further information from a firm to provide a more in-depth and accurate ASX announcement.

If a firm violates its continuous disclosure obligations then the ASX will refer a particular case to the Australian Securities Investment Commission (ASIC) who will issue a penalty. Before referral to ASIC, the ASX must determine whether a firm failed to disclose material information in a timely fashion. In order to determine whether such information is material, the ASX will look at the price reaction of the security relative to the market when the information was eventually released to the public. The ASX will take into account the market capitalization, the beta and normal bid-ask spread of the firm, as well as examine abnormal trading volume prior to, during and after the announcement. Generally, a price change of more than 5% will be a sufficient sign that the information that was not promptly disclosed to the ASX was in fact material.

The violation of Listing Rule 3.1 can result in a criminal penalty of up to $110,000 and financial services civil penalty of up to $1,000,000. If found guilty each firm may have to compensate parties who were misinformed due to the firm's breach of Listing Rule 3.1. Other sanctions for firms that do not comply with Listing Rule 3.1 include suspension from trading of the security until the market is fully informed or until the security becomes delisted.

The following case studies of Rio Tinto and Commonwealth Bank highlight the immediacy in which firms are expected to disclose information to the ASX and the financial ramifications for violating Listing Rule 3.1. On July 12, 2007 by 2:30 pm, Rio Tinto had knowledge that its takeover bid for Alcan was successful and news of this deal was reported by the Dow Jones Newswires. Rio Tinto did not disclose such information which was no longer deemed to be confidential by the ASX and did not immediately request a trading halt (and did not do so until 3:42 pm). For breaching ASX Listing Rule 3.1 Rio Tinto was fined $100,000.

On November 23, 2008, the Commonwealth Bank announced that the full year loan impairment expense (LIE) ratio was expected to be between 40 and 50 basis points; however, by 3:00 pm on December 16, 2008, ASIC had reason to believe that the LIE ratio was expected to be 60 basis points. The Commonwealth Bank did not disclose such material information to the ASX until 7:14 pm on the same date, and as a result was fined $100,000 for breaching ASX Listing Rule 3.1.[33]

3.3. Data

This chapter examines large price changes for firms included in the ASX 200 index during the period January 1, 1996 to June 30, 2011.[34] Our sample consists of 428 unique firms. The selection of firms listed on the ASX 200 is applied with the aim of examining a sample of larger firms not subject to microstructure issues such as non-synchronous trading and the bid ask bounce (Scholes and Williams, 1977; Blume and Stambaugh, 1983). Similar to Pritamani and Singal (2001), we delete large price changes which occur within 20 days of each other as this confounds the interpretation of the subsequent patterns in returns.[35] Daily and intraday price, trade and quote, volume and liquidity data are obtained from the *Thomson Reuters Tick History* (*TRTH*) database provided by *Securities*

[33] For more details regarding the Rio Tinto case see http://asic.gov.au/about-asic/media-centre/find-a-media-release/2008-releases/08-117-rio-tinto-complies-with-asic-infringement-notice/. Promina Group Limited committed a similar infringement, see http://asic.gov.au/about-asic/media-centre/find-a-media-release/2007-releases/07-69-promina-pays-100000-fine/ for further details. For more details regarding the Commonwealth Bank case see http://asic.gov.au/about-asic/media-centre/find-a-media-release/2009-releases/09-199mr-commonwealth-bank-pays-100-000-penalty/.

[34] From May 2011 all ASX-listed stocks became available for trade on the Chi-X. Our sample period is largely free from this change in market structure.

[35] Our main results hold if we do not apply this constraint (see Panels A and B in Table A3.1 of the Appendix). In addition, our main results also hold if we delete firms which delist or become bankrupt from the ASX during our sample period and if a stock does not trade in at least 200 of 252 trading days around the large price change (see Panels C and D in Table A3.1 of the Appendix).

Industry Research Centre of Asia-Pacific Limited (*SIRCA*).[36] ASX announcement data containing the date, time, type, and price-sensitive flag is obtained from the *Core Research Database* developed by *SIRCA*. We obtain analyst recommendation data from the *Institutional Broker's Estimate System* (*IBES*).

3.4. Methodology

3.4.1. Large price changes

Following the approach used by Savor (2012) large price changes are identified in the following manner: as a starting point we calculate the daily return for each firm as the percentage change in unadjusted daily closing prices. We define a large price change as one which occurs when the absolute value of the daily return (R_{it}) minus the return ($\widehat{R_{it}}$) predicted by the Fama and French (1993) three factors supplemented with the Carhart (1997) momentum factor, is greater than 10%.[37]

$$\left|R_{it} - \widehat{R_{it}}\right| > 10\% \tag{3.1}$$

Savor (2012) justifies using a 10% threshold to filter out large price changes which cannot be attributed to changes in fundamental value or investor sentiment.[38] In support of this threshold, "*if information appears to the ASX to have moved the market price of the entity's securities (relative to prices in the market generally or in the entity's sector) by roughly 10% or more, the ASX will generally regard that as confirmation that the information was market sensitive and therefore a potential breach of Listing Rule 3.1 and section 674 to the Australian Securities Investment Commission*."[39] Abnormal returns are calculated using the following Fama and French (1993) three factor plus the Carhart momentum (1997) factor model:

$$R_{i,t} - R_{f,t} = \alpha + B_{i,m}\left(R_{m,t} - R_{f,t}\right) + B_{i,SMB}SMB_t + B_{i,HML}HML_t + B_{i,MOM}MOM_t + u_{i,t} \tag{3.2}$$

where $R_{i,t}$ is the daily return of each firm using the percentage change in unadjusted daily closing prices, $R_{m,t}$ is the market return which we proxy using the daily All Ordinaries Accumulation Index

[36] Our sample period begins on January 1, 1996 as this is the earliest date with which we can reliably obtain daily closing price data from the *TRTH* database. We use the *Share Price & Price Relative* (*SPPR*) database provided by *SIRCA* to account for firms which change their ticker code over time.

[37] Atkins and Dyl (1990), Bremer and Sweeney (1991), Cox and Peterson (1994), Park (1995) and Bremer et al. (1997) use similar definitions.

[38] Our main findings hold if we use a lower threshold of 7.5% to define a large price change (see Panels E and F in Table A3.1 of the Appendix).

[39] See http://www.asx.com.au/documents/rules/gn08_continuous_disclosure.pdf for further details.

(XAO) and $R_{f,t}$ is the risk free rate which we proxy using the 90-day bank bill rate.[40] The size (SMB_t) and book-to-market (HML_t) factors are constructed in a similar vein to Fama and French (1993) by ranking firms yearly and forming six intersecting value-weighted portfolios on a daily basis.[41] The daily size (value) factor is calculated by subtracting a portfolio of small (high book to market) firms from a portfolio of large (low book to market) firms. The Carhart (1997) momentum (MOM_t) factor is constructed by ranking firms monthly into three equally-weighted portfolios depending on the performance over the past six months. The daily momentum factor is calculated by subtracting a momentum portfolio from a contrarian portfolio. Portfolio returns are calculated using the buy-and-hold decomposition method documented in Liu and Strong (2008). These authors show that portfolio returns calculated using the commonly used rebalanced method contain bias, lead to spurious size and momentum factors, and are not realistic due to significant transaction costs. For a value-weighted portfolio the weights are updated on a daily basis depending on the market capitalization of each firm. For an equal-weighted portfolio the weight of each firm within the portfolio is a weighted average of the past returns for each firm relative to the past returns of each firm within the portfolio. The model in Equation (3.2) is estimated over a contemporaneous 255 trading day window starting 31 days prior to the large price change (-31 to +224). We use the same contemporaneous beta estimation window and methodology as Savor (2012) so that our results are directly comparable.[42] We also remove large price changes from our sample which contain less than 30 observations during the estimation window. After estimating beta coefficients in Equation (3.2) we calculate abnormal returns using Equation (3.3),

$$AR_{i,t} = (R_{i,t} - R_{f,t}) - [B_{i,m}(R_{m,t} - R_{f,t}) + B_{i,SMB}SMB_t + B_{i,HML}HML_t + B_{i,MOM}MOM_t]. \quad (3.3)$$

The full sample contains 6,641 large price changes using a 10% threshold. For our main analysis we divide the full sample into two subsamples, i) large information-based price changes – at least one ASX announcement is released in the -1 to 0 day event window around a large price change, and ii) large no-information-based price changes – there is no firm specific ASX announcement released in the -1 to 0 day event window around a large price change.[43]

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[40] The XAO consists of the largest 500 ASX listed firms and includes the re-investment of dividends. The use of the XAO as a proxy for market returns is reasonable as the top 200 ASX stocks contained within our sample make up approximately 91% of the total market capitalization of the XAO. Daily 90-day bank bill rates are obtained from the *Reserve Bank of Australia* (*RBA*) website.

[41] We calculate the book value and market value of each firm listed on the ASX between 1990 and 2011 using data from the *SPPR* and *Aspect Huntley* databases.

[42] Our main results hold if we use a more conventional beta estimation period of -244 to -6 days prior to the large price change (Brown and Warner, 1985) or if we use the market model to calculate abnormal returns (see Panels G to J in Table A3.1 of the Appendix).

[43] Savor (2012) defines a large information-based price change if at least one analyst recommendation occurs in the -1 to +1 day event window around a large price change. Our main results hold if we use a similar definition, suggesting that our findings are not idiosyncratic to the Australian market (see Panels K and L in Table A3.1 of

3.4.2. Liquidity trading and private information

Previous studies including Pritamani and Singal (2001), Chan (2003) and Savor (2012) suggest other drivers of large price changes. In this chapter we uniquely examine return predictability following liquidity trading and private information. We define liquidity trading as a driver of large price changes when there is abnormal non-informational trading volume combined with abnormal illiquidity on the day of a large price change that does not coincide with the release of at least one ASX announcement (Campbell et al., 1993; Avramov et al., 2006). In addition, if large no-information-based price changes are explained by liquidity trading, then we expect to observe return reversal over the post-event horizon as liquidity trading creates temporary price pressure that subsequently reverts to fundamental value (Campbell et al, 1993, Avramov et al, 2006).

Our methodology to examine whether liquidity trading and private information drive large price events is similar to the approach employed by Lee et al. (1993) who examine spreads, depth and volume around earnings announcements.[44] They calculate various liquidity measures at half hourly intervals -2 to +2 days around earnings announcements. The abnormal behavior of various liquidity measures is determined by comparing event period values to control period values. For each half hour interval within the event period, the control period for the same half hourly interval for each firm consists of 300 previous observations (controlling for the time of day).

In this chapter we implement a similar approach, the event period for each large price change is a five day period, that is, two days prior (-2) to the large price change, the day of a large price change (0) and two days following (+2) the large price change. Using intraday data we calculate several trading and liquidity measures at hourly intervals during the trading day.[45] The control period is a five week period starting 30 days before (-30) and ending six days before (-6) the large price event. As a result, the control period value for each hourly interval within the event window consists of 25 observations and in this way our methodology controls for time-of-day effects.[46] To determine the abnormal behavior of each measure we calculate t-statistics on the difference between average control period values and event period values, using each firm as its own control, and averaging the values across the sample number of firms for each of the 30 hourly intervals within the event period.

Similar to Chordia et al. (2002), we examine the following trading activity measures to determine whether liquidity trading drives large price events: $Order\ Imbalance$ which is the difference

the Appendix). An advantage of ASX announcement data is that we have an official time stamp for when the announcement was released into the market. Our main results hold if we define a large information-based price change if we use a more restrictive event window requiring at least one ASX announcement after trading hours on day -1 or on the day of the large price change (see Panels M and N in Table A3.1 of the Appendix).

[44] Bugeja et al. (2015) apply a similar methodology in their examination of informed trading around takeover announcements.

[45] We delete trades at the open and close of each trading day as the opening and closing transactions are determined by a call auction.

[46] We restrict our control period to five weeks due to the sheer size of the intraday trade and quote data.

between buyer initiated and seller initiated trades, and $Volume$ which is the total number of shares traded. For each trading measure we calculate the total for each firm during each hourly interval during the trading day. An advantage of using ASX data is that we have access to data which details whether a trade is buyer or seller initiated. We do not need to sign trades using the Lee and Ready (1991) algorithm commonly used in the literature and we are able to determine the trade initiator without error.[47]

Lee et al. (1993) decompose liquidity into a price component measured by the spread and a quantity component measured by depth. In addition, we examine the following time-weighted spread and depth liquidity measures at the best prices to determine whether liquidity trading drives large price events: $Quoted\ Spread$ is the difference between the ask price and bid price, $Relative\ Quoted\ Spread$ is the $Quoted\ Spread$ weighted by the midpoint price, $Effective\ Spread$ is the absolute difference between the transaction price and midpoint price multiplied by two, $Relative\ Effective\ Spread$ is the $Effective\ Spread$ weighted by the share price, $Depth$ is the sum of ask depth and bid depth, and $Amihud\ Illiquidity$ is the absolute value of daily returns divided by daily dollar volume multiplied by 10^6. For each of the time-weighted liquidity measures we delete observations in which the bid price is greater than the ask price and if the bid, ask or transaction price are negative.[48] If liquidity trading drives large price changes we expect to observe abnormally increased levels of volume and illiquidity proxied by the Amihud (2002) illiquidity measure, widened spreads and reduced depth.

As a proxy for private information we calculate the adverse selection component of the bid ask spread using the Lin et al. (1995) spread decomposition model. Previous research conducted by Van Ness et al. (2001) suggests that spread component estimates are more realistic when using the Lin et al. (1995) decomposition model when compared to other models developed by Glosten and Harris (1988) and Huang and Stoll (1997). It is important to note that the Australian market is an order driven market in which prices are determined by demand and supply forces. Glosten (1994), Aitken and Frino (1996) and Brockman and Chung (1999) provide evidence to suggest that the bid ask spread within order driven markets is similar in nature and function to spreads within quote driven markets.[49]

We estimate adverse selection costs (α) using Equation (3.4), where Q_t represents the midpoint price at time *t* and P_t represents the transaction price at time *t*.

$$Q_{t+1} - Q_t = \alpha(P_t - Q_t) + \varepsilon_{t+1} \tag{3.4}$$

[47] This detailed buyer- and seller-initiated trade data is only available following October 1, 2006.
[48] Data required to calculate time-weighted depth is available after December 16, 2001.
[49] Copeland and Galai (1983) document that widened (narrow) spreads suggest an increase (decrease) in information asymmetry between investors.

The LHS of Equation (3.4) represents the quote revision and α represents the quote revision due to adverse selection costs in response to trades as a fraction of the half-signed effective spread $(P_t - Q_t)$. Consistent with Lin et al. (1995) we use the natural logarithm of the midpoint price and transaction price and exclude opening transactions. To ensure reliable estimates we calculate a daily measure of adverse selection costs and require at least 30 trades per day.

3.5. Results

We first present evidence of the different drivers of large price changes before examining return predictability following large price changes.

3.5.1. Drivers of large price changes

Table 3.1 Panel A reports the time-series of large price changes after accounting for the Fama and French (1993) three factors and the Carhart (1997) momentum factor. The sample period consists of the Internet bubble in the years leading up to 2000 and the global subprime debt crisis beginning in 2008. These periods correspond with an increase in the number of large price events. Overall, there are a large number of price events within each year during the sample period, with the number of large price events falling after 2009. In total 2,840 (or 43%) of 6,641 large price changes are accompanied by the release of at least one ASX announcement confirming that our proxy for public information is a key driver of large price changes. We also observe that the ratio of large information-based price changes to large no-information-based price changes increases from 37% in 1996 to 162% in 2011 which shows that public information has become a more dominant driver of large price changes over time.

< Table 3.1 here >

Panel B reports the ratio of large information-based price changes to large no-information-based price changes for different levels of stock liquidity measured using the daily Amihud (2002) illiquidity measure. For the lowest level of illiquidity (between 0 and 0.5) the ratio of large information to no-information-based events peaks at 131%. As the level of illiquidity increases (100+) this ratio declines to 22%. In a relative sense, we observe that a greater proportion of large no-information-based price events occur in illiquid stocks which is consistent with liquidity trading being a key driver of such price events.

Table 3.2 documents the magnitude of large price changes for the full sample, and for large information-based and large no-information-based price event subsamples.[50] On the day of a large

[50] We winsorize the top and bottom 5% of the distribution of large price changes and cumulative abnormal returns five, ten, twenty and forty days following the event date to ensure our results are not driven by outliers.

price change the magnitude of large positive and negative price events is similar for the information and no-information subsamples, at approximately 15%. In our sample there is almost twice the number of large positive price events when compared to large negative price events. However, the ratio of large information-based to large no-information-based price events is similar (approximately 75%) for both large positive and negative price events.

In total, 3,801 (or 57%) of the large price change events are not accompanied by the release of at least one ASX announcement (these are defined as large no-information-based price changes) which suggest that there exist other drivers of large price events, for example, liquidity trading, private information or other sources of public information not captured by ASX announcements.

< Table 3.2 here >

In this chapter we uniquely examine return predictability following liquidity trading and private information. We examine the abnormal behavior of several trading and liquidity measures in the five day event window around large price changes not accompanied by public information or price queries made by the ASX to distinguish between large price changes driven by liquidity trading and private information. Table 3.3 reports significant increases in trading volume on the days of large no-information-based price changes. In addition, order imbalance, time-weighted quoted spreads, effective spreads and the Amihud (2002) illiquidity measure are abnormally elevated indicating increased illiquidity on the day of the large no-information-based price change.[51] The combination of increased trading volume with increased illiquidity is consistent with liquidity trading driving large no-information-based price changes.

< Table 3.3 here >

We also observe that order imbalance is significantly elevated on day 0. Chordia et al. (2002) suggest that order imbalance can be random (i.e., uninformed) or it can occur as a result of private or public information, however, either case results in reduced liquidity. If the observed order imbalance is measuring private or public information (rather than being random) we could expect significantly increased order imbalance in the two days prior to the event date. Our results show that order imbalance is insignificant during this time horizon.[52] In the following subsections we examine the subsequent patterns in returns to shed further light on whether the observed order imbalance is uninformed or informed. Specifically in Section 3.5.2, we should expect insignificant patterns in returns (or permanent price changes) following large no-information-based price changes if order

[51] Table A3.2 also shows increased illiquidity as time-weighted relative quoted spreads and relative effective spreads (bid-depth) are significantly larger (lower) on day 0.
[52] Similarly, abnormal adverse selection costs are insignificant during the same time horizon.

imbalance is capturing private information. Another explanation for the observed order imbalance could be due to other sources of public information that are not captured by ASX announcements. In Section 3.5.3 we examine other sources of public information as potential drivers of large price changes and again expect insignificant subsequent patterns in returns following these price events if order imbalance is capturing public information.

We examine the same trading and liquidity measures on a sample of large no-information-based price changes that coincide with (are followed by) an ASX price query on day 0 (day +1) to determine whether private information is also a key driver of large price changes (Marsden and Poskitt, 2009). The ASX will issue a price query if the stock price of a firm abnormally changes without the dissemination of information to the marketplace. As a result, this creates a cleaner subsample of large no-information-based price changes not explained by ASX announcements, but by private information.

< Table 3.4 here >

Table 3.4 documents similar findings to Table 3.3, that is, the abnormal behavior of order imbalance, volume, and quoted and effective spreads on the day of the large price change. In contrast to the results within Table 3.3, we observe abnormal increases in order imbalance, volume and adverse selection costs in the two days preceding our sample of 418 large price events. If we examine large no-information-based price changes which coincide with an ASX price query on day 0 only (146 of 418 large price events), we also observe significantly elevated (lower) levels of relative quoted and effective spreads (bid depth) in the two days preceding (on) the event date. Further, for large no-information-based price changes followed by an ASX price query on day +1 only (272 of 418 large price events), we also observe significant levels of adverse selection costs on day 0. The behavior of our trading and liquidity measures provides evidence in support of private information driving large price changes.[53]

3.5.2. Return predictability following different drivers of large price changes

In the previous section we presented evidence which supports public information, liquidity trading and private information as key drivers of large price changes. To further validate these findings, and consistent with the semi-strong efficient markets hypothesis, we expect there to be insignificant patterns in abnormal returns following large price changes driven by public information. Similarly, for large price changes driven by private information we also expect no subsequent patterns in returns as private information becomes incorporated into fundamental value. In contrast, following

[53] We show in Table A3.3 of the Appendix that the abnormal behavior of our trading, liquidity and adverse selection measures are statistically significant in explaining large no-information-based price changes.

large price changes driven by liquidity trading, we expect significant reversal in returns as temporary price pressure reverts back toward fundamental value.

Table 3.2 presents descriptive statistics for subsequent patterns in returns following large positive and negative information-based and no-information-based price changes. Following large positive price events we observe negative post-event CARs which decrease (increase) over time in Panel B (D), and are larger in magnitude for the large no-information-based events. We observe a similar pattern when comparing the subsequent patterns in returns following large negative information to no-information-based price changes. A difference is that the subsequent patterns in returns change sign 20 days following the large negative information-based price events. Overall, large no-information-based price events have a larger post-event reaction than information-based price events, indicating that the release of ASX announcements is a key determinant of the post-event CARs.

In a similar manner to Savor (2012) we examine return predictability following large price events using the following OLS regression model:

$$CAR_{1,n} = Intercept + \beta_1(AR_0) + \beta_2(AR_0 x\ DV) + \beta_3(SIZE) + \beta_4(\mathrm{BM}) + \beta_5(VOL) + \beta_6(MOM) + \beta_7(AR_0 x\ VOL) + \varepsilon \tag{3.5}$$

The dependent variable $CAR_{1,n}$ represents the sum of the abnormal returns over *n* trading days after the large price change after controlling for the Fama and French (1993) three factors and the Carhart (1997) momentum factor. We introduce an interaction term $(AR_0\ x\ DV)$ within Equation (3.5) which is equal to one if there are zero ASX announcements made in the -1 to 0 day window around a large price change. We focus our analysis on the abnormal return on the day of a large price change (AR_0) and the interaction term $(AR_0\ x\ DV)$. The AR_0 coefficient documents the magnitude of the drift or reversal following large information-based price events and the interaction term $(AR_0\ x\ DV)$ represents the additional magnitude of the post-event CARs following large no-information-based price events. In addition, several control variables are included within the model. Fama and French (1993), Carhart (1997) and Lee and Swaminathan (2000) document evidence that size, book to market, momentum and volume explain returns. We also introduce an interaction term $(AR_0\ x\ VOL)$ between event day returns and volume, as volume enhances momentum returns (Lee and Swaminathan, 2000; Pritamani and Singal, 2001; Savor, 2012). In the subsequent analysis we apply clustered standard errors by stock and by date as each large price change may violate the assumption of independent observations.[54]

The results for the full sample are reported in Table 3.5 Panel A. Following large information-based price changes we observe that returns significantly reverse (or investors overreact) by a

[54] Our main results hold if we use stock fixed effects, date fixed effects or both stock and date fixed effects (see Panels O to T in Table A3.1 of the Appendix).

maximum of 6.2% before reducing to 3.1% from five to forty days following the event date. Following large no-information-based price changes returns significantly reverse by 23.3% (6.2% + 17.1%) and increase to 28.8% (3.1% + 25.7%) over the same post-event horizon. The interaction term is significant across all post-event horizons indicating that there is a significant difference between patterns in returns following large information- and no-information-based price events. In addition, the book-to-market control variable is significantly negative indicating that lower book-to-market firms (or growth firms) have larger post-event CARs.

A key advantage of examining ASX announcement data when compared to similar US studies is that we can determine which announcements are classified as price sensitive announcements, that is, announcements which contain material information about firms. We find that 1,969 (or 69%) of 2,840 ASX announcements are categorized as price sensitive announcements.

< Table 3.5 here >

We observe that returns reverse and gradually decrease from 3.1% to 2.1% 20 days following large price changes driven by price-sensitive announcements (Panel B). In contrast to Panel A, the magnitude of the reversal in returns is smaller and insignificant following price sensitive announcements. Similar to Panel A, returns also significantly reverse and are similar in magnitude following large no-information-based events.

We focus on stocks listed on the ASX 200 index between 1996 and 2011 with the aim of excluding smaller stocks which are subject to microstructure issues such as the bid ask bounce or non-synchronous trading (Scholes and Williams, 1977; Blume and Stambaugh, 1983). To further minimize the impact of microstructure issues driving our results, we examine subsequent patterns in returns for larger stocks using the following restrictions: i) stock price greater than $2, ii) market capitalization greater than $100 million, and iii) using midpoint prices instead of transaction prices (Park, 1995). Previous US studies use an arbitrary $5 cutoff (Pritamani and Singal, 2001; Savor, 2012). We select a lower threshold given the lower average stock price in Australia. For our sample the bottom decile by size corresponds with stocks which have a market capitalization of less than $100 million.

After controlling for various microstructure issues we observe similar findings in Panels C to F, specifically, insignificant patterns in returns (or subsequent patterns in returns which fluctuate around 0%) following large information-based price changes consistent with the semi-strong efficient markets hypothesis developed by Fama (1970). In contrast, Savor (2012) documents significant drift in returns of approximately 4% following large information-based price changes. Our results suggest a higher level of informational efficiency in the Australian market when compared to the US.[55]

[55] Prior studies find drift in returns following earnings announcements (Bernard and Thomas, 1989; 1990; Clinch et al., 2012). Our main results hold if we exclude large price changes driven by earnings announcements (see Panels U and V in Table A3.1 of the Appendix).

Following large no-information based price events we observe that returns exhibit significant reversal consistent with liquidity trading driving these particular price events. In particular, liquidity trading creates temporary price pressure that subsequently reverts back toward fundamental value (Campbell et al., 1993; Avramov et al., 2006). The magnitude of the reversal in returns varies between Panels A to F, with a more conservative estimate provided in Panel F using midpoint prices. Specifically, returns increase and reverse by up to 18.60% over the 40-day post-event horizon which is approximately 122% of the mean large price change documented in Table 3.2.[56] The magnitude of the reversal in returns in Panel F is similar to the full sample results presented by Savor (2012), however, the magnitude of reversal in Panel E is between three and five times larger for our sample than for a similar subsample documented by Savor (2012). In Section 3.5.4 we apply additional restrictions to shed light on whether investors can profit from this reversal (or overreaction) in returns.

Table 3.6 Panel A documents subsequent patterns in returns following our sample of large no-information-based price changes which coincide with or are followed by an ASX price query on day +1 (or our proxy for large price changes driven by private information).[57] Our findings show statistically insignificant patterns in returns over the entire 40-day post-event horizon consistent with the permanent imputation of private information into fundamental value (Hasbrouck 1991; 1995). Similar to our previous results, this subsample of price events is characterized by low book to market firms.

< Table 3.6 here >

In summary, after controlling for microstructure issues we observe that large price changes driven by our proxy for public information are permanent, consistent with the semi-strong efficient markets hypothesis. Large price changes are also permanent when driven by private information. In contrast, we observe that large price changes driven by liquidity trading are transient.

3.5.3. Shortcomings of our public information proxy

A potential weakness of using ASX announcements as a proxy for public information is that we ignore other sources of public information such as analyst recommendations, macroeconomics news and industry specific news. In this section we examine whether other sources of public information drive our main findings. Unless stated, all findings in this section are reported in Table A3.4 of the Appendix.

[56] The mean large price change documented in Table 3.2 is approximately 15.24% (15.42% + 16.33% + 14.93% + 14.27% / 4). Approximately 100% of the mean large price change is reversed between 10 to 20 days following the event date. We delete large price changes which occur within 20 days of each other, we acknowledge that our coefficient estimates 40 days following the event date might be confounded by subsequent large price events.

[57] The coefficient of interest in Table 3.6 is AR_0 which documents the magnitude of the drift or reversal following these large price events.

Our first approach to addressing this issue is to use analyst recommendations to examine a different source of public information not captured by ASX announcements and to compare our findings directly to Savor (2012). A large information-based price change is defined as a large price change in which at least one analyst recommendation is made in the -1 to 0 day event window around the price event.

Table 3.5 Panel I reports for a sample of larger stocks, insignificant subsequent patterns in returns (close to 0%), similar to our results using ASX announcements as a proxy for public information. We attribute the coefficient estimate of 0.078 as being due to the confounding effects of other large price changes occurring in the 21- to 40-day post event window. Further, our main results remain unaltered after excluding analyst recommendations as a source of public information not captured by ASX announcements (see Panels A and B of Table A3.4).

Our second approach to address the weakness of using ASX announcements as a sole proxy for public information excludes large price events occurring during the internet bubble (1999 to 2001) and the global subprime debt crisis (2008 to 2009). Our aim is to use two examples of macroeconomic news which may not necessarily be reflected by ASX announcements. Again our main results hold (see Panels C to F), insignificant patterns in returns following large information-based price changes for larger stocks and significant reversal following large no-information events.

As a third approach, we apply an alternative definition of large information-based price changes. This alternative definition reclassifies large no-information-based price events occurring on the same date as another firm within the same industry which also experience a large information-based price change. The aim of this reclassified subsample is that the release of ASX announcements from competing firms and/or other sources of public information might possibly drive large price changes in other firms within the same industry. Our alternative definition results in 3,551 large information-based price events which accounts for 53% of the 6,641 large price events. This proportion is larger than the 43% calculated using our original definition of a large information-based price event. We exclude these 711 reclassified large information-based price events as we cannot be certain that another source of public information not captured by ASX announcements was disclosed to the market. Our main results hold (see Panels G and H), as we observe insignificant patterns in returns following large information-based price changes for larger stocks and reversal following large no-information-based price changes.

A second weakness of using ASX announcements is that the price-sensitive flag may be a noisy indicator of the material information contained within ASX announcements, that is, the ASX may predetermine certain announcement types as containing material information about fundamental value. Table A3.5 reports the number of price-sensitive announcements among 19 different types of announcements during our sample period. We find that the ASX does not simply flag a specific type of announcement as containing price sensitive information, implying that discretion is applied to determining whether announcements contain material information. For example, in total there are

168,244 ASX announcements containing price-sensitive information regarding dividends and 26,680 announcements which did not contain price-sensitive information. For the following announcement types: Quarterly Activities Report, Quarterly Cash Flow Report, Asset Acquisition & Disposal, Stock Exchange Announcement, Dividend Announcement, Progress Report and ASX Query we observe more price-sensitive announcements than non-price-sensitive announcements consistent with these types of announcements containing material information about fundamental value.[58]

3.5.4. Can investors profit from the overreaction in returns?

In the previous sections we observed significant reversal in returns following large no-information-based price changes (or large price changes driven by liquidity trading). In this section we conduct further tests to see whether investors can profit from the overreaction in returns.

First, we divide our sample of large no-information-based price changes into the bottom and top quartiles based on the daily Amihud (2002) illiquidity measure.[59] Table 3.6 Panel B documents subsequent patterns in returns for the bottom quartile (liquid stocks). We observe significant reversal in returns of 10.9% and increasing to 23.2% during the post-event horizon. Panel C shows larger levels of reversal during the post-event horizon for the top quartile (illiquid stocks) consistent with the findings of Avramov et al. (2006). Specifically, returns reverse by approximately two to three times more than the results documented in Panel B, reaching 41.1% 20 days after the large price change.

Second, we create a subsample of large price changes for firms with low illiquidity (similar to Panel B) and use midpoint prices to provide a conservative estimate for the overreaction in returns reported following large no-information-based price changes. Again, due to confounding effects, our focus is on the subsequent patterns in returns 20 days following the event date. Panel D shows that returns reverse by up to 17.8% 20 days following the event date. Our findings suggest that approximately 100% of the average large price change (documented in Table 3.2) reverses in the subsequent 20-day period consistent with liquidity trading that creates temporary price pressure that subsequently reverse.

Third, to examine if our main findings are robust to the price impact caused by volume traded on the day of the large price change we include the Amihud (2002) illiquidity measure and the Amihud (2002) illiquidity measure multiplied by a dummy variable equal to one for large no-information-based price changes, as additional controls within our regression model expressed in Equation (3.5). Our main findings reported in Table 3.5 Panels J and K are robust to the inclusion of these additional

[58] We observe the opposite for the following announcement types: Shareholder Details, Notice of Meeting, Company Administration, Chairman's Address, Letter to Shareholders, Warrants and Prospectus consistent with these types of announcements generally containing non-material information.

[59] We calculate the average daily Amihud (2002) illiquidity measure over the 30-day period preceding the large price change. Our results hold if we use the Amihud (2002) illiquidity value calculated on the event date (day 0) only.

controls, that is, they show insignificant patterns in returns following large price changes for larger stocks and significant reversal in returns following large no-information-based price changes.

Fourth, we test the validity of trading strategies documented in past US studies by comparing the subsequent returns following large price changes calculated using closing prices adjusted for capitalization changes to our previous results that were calculated using unadjusted closing prices. Using unadjusted closing prices, Pritamani and Singal (2001) and Savor (2012) document trading strategies that result in significant annualized abnormal returns of 12-18% and 36%, respectively.

We report our findings using adjusted closing prices in Table 3.5 Panels G and H. Our main results hold: there are insignificant returns following large information-based price changes for larger stocks and significant reversals following large no-information-based price changes. The magnitude of the reversal in returns following large no-information-based price changes in Panel G (Panel H) is approximately 1.2 (1.5) times larger in magnitude than as calculated using unadjusted closing prices as documented in Panel A (Panel C) of Table 3.5.

We find that returns significantly reverse following large no-information-based price changes after controlling for microstructure effects, illiquidity and adjusted closing prices. We err on the cautious side and suggest that it would be difficult for investors to consistently profit from such predictability in returns as such patterns occur predominantly in illiquid stocks, that is, in 3,221 of 3,801 or 85% of large no-information-based price changes over the last 15 years. In addition, we suggest that care should be taken when interpreting the significant annualized abnormal returns from long-short trading strategies documented in previous US studies, as the magnitude of reversals differs using adjusted closing prices when compared to unadjusted closing prices.

3.6. Conclusion

We simultaneously examine return predictability following different drivers of large price changes, including public information, liquidity trading and private information. We show that large price changes driven by public information and private information are permanent, whereas, large price changes driven by liquidity effects are transient.

We err on the cautious side and suggest that it would be difficult for investors to consistently profit from the overreaction in returns following large price changes driven by liquidity effects. Further, our comparison of the subsequent patterns in returns using unadjusted and adjusted closing prices for capitalization changes suggests that care must be taken when interpreting significant annualized abnormal returns documented in previous US studies.

The methodology and sample period that we employ in this chapter is similar to Savor (2012). Similar US studies document significant drift in returns following large information-based price changes. In contrast we find insignificant patterns in returns (close to 0%) following large information-based price changes. This finding suggests increased informational efficiency of large price changes in Australia and raises questions over the effectiveness of disclosure rules in the US.

The investor distraction hypothesis developed by Hirshleifer et al. (2009) provides an explanation for the drift in returns documented in the US following large information-based price events. Specifically, this hypothesis predicts that the release of information from different sources will affect the reaction of investors (who are already attention constrained) to new information. Several features of the information environment in Australia help to reduce investor distraction to new information including, i) the ASX provides a central platform for the dissemination of price sensitive and non-price sensitive information, ii) ASX announcements contain a flag to identify price sensitive news and iii) firms can implement a trading halt to signal that material information will be revealed to the marketplace.[60] In contrast, in the US information can be disclosed to the public through different mechanisms including firm websites, press releases via news providers like Dow Jones Newswires, press conferences or conference calls, Form 8-K or social media. The number of different sources of information dissemination, the larger number of listed stocks and the absence of price sensitive flags are consistent with the investor distraction hypothesis, meaning it takes investors longer to determine the value of information and could explain the subsequent drift in returns observed following large US information-based price changes (Chan, 2003).

Future research could examine a sample of cross-listed stocks or matched firms to provide additional support to the notion that differences between the information environments in the US and Australia can explain differences in informational efficiency between countries.

[60] The price sensitive flag reduces the total number of ASX announcements per day from 425 to 104 price sensitive announcements (Fernandez and Michayluk, 2015).

Table 3.1. Time-series and illiquidity of large price changes

Panel A reports the number of large price changes for all ASX 200 listed stocks per year from January 1, 1996 to June 30, 2011 and Panel B reports the number of large price changes by illiquidity determined by the Amihud (2002) illiquidity measure. $Price\ events$ is the number of large price changes in excess of a 10% threshold after accounting for the Fama and French (1993) three factors and the Carhart (1997) momentum factor, $Information\ based$ is the number of large price changes accompanied by the release of at least one ASX announcement, $No\ information\ based$ is the number of large price changes not accompanied by the release of at least one ASX announcement, and $Ratio$ is the ratio of large information-based to large no-information-based price changes.

Panel A: Large price changes per year

$Year$	$Price\ Events$	$Information\ based$	$Ratio$
1996	268	73	37%
1997	320	75	31%
1998	358	93	35%
1999	456	156	52%
2000	563	216	62%
2001	573	205	56%
2002	478	216	82%
2003	440	154	54%
2004	348	160	85%
2005	347	156	82%
2006	359	197	122%
2007	330	195	144%
2008	836	400	92%
2009	635	332	110%
2010	241	157	187%
2011	89	55	162%
	6,641	2,840	

Panel B: Large price changes by illiquidity

$Illiquidity$	$Information\ based$	$No\ information\ based$	$Ratio$
0 – 0.5	1,883	1,436	131%
0.5 – 1	193	289	67%
1 – 2	214	349	62%
2 – 5	202	488	41%
5 – 10	136	371	37%
10 – 20	96	306	31%
20 – 50	53	281	19%
50 – 100	30	128	23%
100+	33	153	22%
	2,840	3,801	

Table 3.2. Descriptive statistics of large price changes

This table reports descriptive statistics for the abnormal return (AR_0) on the day of a large price change in excess of a 10% threshold after accounting for the Fama and French (1993) three factors and the Carhart (1997) momentum factor. Descriptive statistics are reported for the full sample, positive information, negative information, positive no-information and negative no-information subsamples which are determined by whether at least one ASX announcement was made in the -1 to 0 day event window around a large price change. The cumulative abnormal returns ($CAR_{1,n}$) are calculated from one day after the large price change to five, ten, twenty and forty days after the large price change (quoted as percentages).

Panel A: Full Sample (N = 6,641)					
	AR_0	$CAR_{1,5}$	$CAR_{1,10}$	$CAR_{1,20}$	$CAR_{1,40}$
Mean	5.32	-0.17	-0.23	-0.32	-0.12
Median	11.41	-0.92	-1.09	-1.42	-0.99
Panel B: Positive Information Sample (N = 1,908)					
	AR_0	$CAR_{1,5}$	$CAR_{1,10}$	$CAR_{1,20}$	$CAR_{1,40}$
Mean	15.42	-0.82	-0.44	-0.51	0.02
Median	13.22	-1.36	-1.04	-0.93	-0.21
Panel C: Negative Information Sample (N = 932)					
	AR_0	$CAR_{1,5}$	$CAR_{1,10}$	$CAR_{1,20}$	$CAR_{1,40}$
Mean	-16.33	0.59	0.19	-0.79	-1.09
Median	-13.56	0.36	0.02	-1.11	-1.27
Panel D: Positive No-Information Sample (N = 2,582)					
	AR_0	$CAR_{1,5}$	$CAR_{1,10}$	$CAR_{1,20}$	$CAR_{1,40}$
Mean	14.93	-2.26	-2.84	-2.89	-2.48
Median	13.14	-3.02	-3.59	-4.37	-4.05
Panel E: Negative No-Information Sample (N = 1,219)					
	AR_0	$CAR_{1,5}$	$CAR_{1,10}$	$CAR_{1,20}$	$CAR_{1,40}$
Mean	-14.27	4.69	5.30	5.76	5.38
Median	-12.84	3.86	4.62	4.92	4.03

Table 3.3. Abnormal behavior of trading and liquidity measures around large no-information-based price changes

This table reports the abnormal behavior of several trading and liquidity measures at an hourly level within a -2 to +2 day event window around a sample of 3,801 large no-information-based price changes. $Order\ Imbalance$ is the absolute difference between buyer initiated and seller initiated trades, $Volume$ is the total number of shares traded, $Quoted\ Spread$ is the difference between the ask price and bid price (%), $Effective\ Spread$ is the absolute difference between the transaction price and midpoint price multiplied by two (%), $Depth$ is the sum of ask depth and bid depth, $Amihud\ Illiquidity$ is the absolute value of daily returns divided by daily dollar volume multiplied by 10^6, and $Adverse\ Selection$ is calculated using the Lin et al. (1995) spread decomposition model and reported as the percentage of the bid ask spread. All spread and depth measures are time-weighted during each hourly interval and calculated using the best prices. The abnormal $Amihud\ Illiquidity$ and $Adverse\ Selection$ measures are calculated at a daily level. The abnormal behavior of each trading and liquidity measure is calculated as the difference between event and control values using each firm as its own control. The control period is a 25-day window beginning one week prior to the large price change. We calculate *t*-statistics and ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels.

Day	Hour	$Order\ Imbalance$	$Volume$	$Quoted\ Spread$	$Effective\ Spread$	$Depth$	$Amihud\ Illiquidity$	$Adverse\ Selection$
-2	10	-55,334*	-48,527	-0.01	0.41	-9,071	-1.20	-0.83
	11	-31,936**	-3,551	0.05	0.47	2,875		
	12	-5,412	-5,267	0.08	0.75**	-15,161		
	13	43,427	29,022	0.23***	0.86**	10,373		
	14	-12,808	-3,136	0.04	0.63*	-2,909		
	15	-21,571	-8,497	0.08	0.92*	5,115		
-1	10	-24,066	-17,231	0.17*	0.30	-18,042	6.53	-0.11
	11	57,099	30,461	0.05	0.77*	24,001		
	12	28,348	36,720	0.04	0.58	17,073		
	13	5,695	12,710	-0.08	0.63	16,643		
	14	40,567	22,420	0.04	0.85*	27,629		
	15	26,960	64,391***	0.14*	0.80*	29,477*		
0	10	223,484***	405,699***	0.97***	1.44**	21,700	4.58*	1.13**
	11	192,789***	329,179***	0.57***	1.23**	-762		
	12	119,711***	242,369***	0.85**	1.56**	-20,029		
	13	159,812***	206,639***	0.42***	1.43*	-55,051*		
	14	131,337***	226,303***	0.50***	1.80**	-44,929		
	15	172,951***	403,510***	0.77***	2.14***	-27,675		
1	10	166,575***	473,820***	0.49***	1.21**	-46,808*	2.30	-0.10
	11	32,192**	164,868***	0.30***	1.40**	-49,525*		
	12	40,537**	96,495***	0.22***	1.52**	-35,442		
	13	38,881***	108,604***	0.16***	1.37*	-41,000		
	14	29,127*	102,691***	0.14***	1.39**	-35,346		
	15	91,899***	151,909***	0.13**	1.46**	-39,520		
2	10	22,492	154,742***	0.32***	1.52**	-31,474	-1.70*	-1.37**
	11	24,722	73,666***	0.09	1.45**	-50,881*		
	12	32,628*	50,639***	0.04	1.49*	-50,801*		
	13	25,435	47,454***	0.03	1.65*	-41,576		
	14	44,859*	47,872**	0.20***	1.48**	-32,546		
	15	20,509	54,137***	0.17***	1.39**	-42,009		

Table 3.4. Abnormal behavior of trading and liquidity measures around large no-information based price changes accompanied by an ASX price query

This table reports the abnormal behavior of several trading and liquidity measures at an hourly level within a -2 to +2 day event window around a sample of 418 large no-information-based price changes which coincide with (are followed by) an ASX price query on day 0 (day +1). $Order\ Imbalance$ is the absolute difference between buyer initiated and seller initiated trades, $Volume$ is the total number of shares traded, $Quoted\ spread$ is the difference between the ask price and bid price (%), $Effective\ Spread$ is the absolute difference between the transaction price and midpoint price multiplied by two (%), $Depth$ is the sum of ask depth and bid depth, $Amihud\ Illiquidity$ is the absolute value of daily returns divided by daily dollar volume multiplied by 10^6, and $Adverse\ Selection$ is calculated using the Lin et al. (1995) spread decomposition model and reported as the percentage of the bid ask spread. All spread and depth measures are time-weighted during each hourly interval and calculated using the best prices. The abnormal $Amihud\ Illiquidity$ and $Adverse\ Selection$ measures are calculated at a daily level. The abnormal behavior of each trading and liquidity measure is calculated as the difference between event and control values using each firm as its own control. The control period is a 25-day window beginning one week prior to the large price change. We calculate *t*-statistics and ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels.

		$Order\ Imbalance$	$Volume$	$Quoted\ Spread$	$Effective\ Spread$	$Depth$	$Amihud\ Illiquidity$	$Adverse\ Selection$
Day	Hour							
-2	10	203,691**	448,831**	-0.09	1.13	106,241	-3.30**	0.25
	11	51,352	133,617	-0.07	1.28	86,330*		
	12	74,754	111,320*	0.07	1.24	92,802		
	13	46,550	122,885**	0.01	1.48	124,940		
	14	122,600*	166,648**	0.03	1.41	64,790		
	15	63,896	194,976**	0.03	2.43	98,797*		
-1	10	278,334***	787,797***	0.07	0.90	110,160*	-3.00**	3.09***
	11	188,211*	380,179***	0.09	1.64	109,388*		
	12	125,914**	296,821***	0.11*	1.87	98,844		
	13	280,025***	398,363***	0.07	1.79	91,184		
	14	138,799**	247,007***	0.05	1.45	43,246		
	15	133,377***	361,757***	0.06	1.55	69,644		
0	10	1,417,708***	2,309,817***	0.44***	2.72	75,985	-3.00**	1.39
	11	633,824***	1,474,263***	0.43***	2.91*	70,505		
	12	628,458**	1,360,527***	0.40***	3.39*	78,692		
	13	437,839***	940,758***	0.30***	3.28*	92,495		
	14	738,133***	1,326,277***	0.33***	3.66*	49,274		
	15	607,620***	1,463,653***	0.34***	3.64*	72,424		
1	10	863,437***	2,731,506***	0.33***	4.27*	-7,479	-3.50**	-0.28
	11	458,270***	1,116,676***	0.18***	4.12*	-20,309		
	12	189,758***	579,274***	0.04	4.01*	-2,740		
	13	123,913***	376,603***	0.03	4.06*	2,702		
	14	206,938***	618,324***	0.06	4.25*	-12,112		
	15	274,099***	857,894***	0.03	4.02*	-37,470		
2	10	593,148***	1,405,249***	0.09	3.99*	-36,346	-3.10**	-0.05
	11	265,138***	542,630***	0.10	4.25*	16,700		
	12	208,255**	510,934***	0.03	4.17	-17,372		
	13	135,090***	262,730***	0.03	4.21	-19,854		
	14	94,656**	333,620***	0.11*	4.26*	2,970		
	15	204,797***	485,163***	0.05	3.87*	22,607		

Table 3.5. Drivers of the subsequent patterns in returns: ASX announcements and analyst recommendations

This table reports coefficient estimates from the following regression:

$$CAR_{1,n} = Intercept + \beta_1(AR_0) + \beta_2(AR_0\ x\ DV) + \beta_3(SIZE) + \beta_4(BM) + \beta_5(VOL) + \beta_6(MOM) + \beta_7(AR_0 x\ VOL) + \beta_8(Amihud) + \beta_9(Amihud\ x\ DV) + \varepsilon$$

$CAR_{1,n}$ is the cumulative abnormal returns calculated from one day after the large price change over a *n* trading day horizon, where *n* is 5, 10, 20 and 40 days. AR_0 is the abnormal return on the day of a large price change in excess of a 10% threshold after accounting for the Fama and French (1993) three factors and the Carhart (1997) momentum factor, DV is a no-information dummy variable equal to one if there are zero ASX announcements made in the -1 to 0 day event window around a large price change, $SIZE$ (BM) is the market capitalization (book to market ratio) of each firm at the start of the year in which the large price change occurred expressed in logarithmic form, VOL is the total volume over the past month as a percentage of the number of shares outstanding, MOM is the return over the previous six-month period, and $Amihud$ is the Amihud (2002) illiquidity measure multiplied by 10^6 calculated on day 0. Clustered standard errors by stock and by date are applied. We calculate *t*-statistics and ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels.

	$Intercept$	AR_0	$AR_0\ x\ DV$	$SIZE$	BM	VOL	MOM	$AR_0\ x\ VOL$	R^2 (%)
Panel A: Full Sample (N = 6,641)									
$CAR_{1,5}$	-0.015	-0.062***	-0.171***	-0.001	-0.006***	-0.001	0.001***	0.002	5.72
$CAR_{1,10}$	-0.021	-0.047**	-0.226***	-0.001	-0.008***	-0.000	0.002***	0.004	4.80
$CAR_{1,20}$	-0.036	-0.041	-0.255***	-0.002	-0.015***	-0.005	0.001	0.018	3.38
$CAR_{1,40}$	-0.056	-0.031	-0.257***	-0.003	-0.022***	-0.006	0.002	0.017	2.10
Panel B: Price Sensitive Announcements (N = 5,751)									
	$Intercept$	AR_0	$AR_0\ x\ DV$	$SIZE$	BM	VOL	MOM	$AR_0\ x\ VOL$	R^2 (%)
$CAR_{1,5}$	-0.001	-0.031	-0.207***	-0.001	-0.005***	-0.003**	0.001*	0.007*	6.31
$CAR_{1,10}$	-0.008	-0.022	-0.258***	-0.001	-0.008***	-0.002	0.002*	0.009	5.44
$CAR_{1,20}$	-0.021	-0.021	-0.284***	-0.002	-0.015***	-0.008*	0.002	0.029*	3.97
$CAR_{1,40}$	-0.027	0.002	-0.297***	-0.004	-0.021***	-0.004	0.003	0.011	2.28
Panel C: Stock Price > $2 (N = 1,070)									
	$Intercept$	AR_0	$AR_0\ x\ DV$	$SIZE$	BM	VOL	MOM	$AR_0\ x\ VOL$	R^2 (%)
$CAR_{1,5}$	-0.042	0.016	-0.229***	-0.000	-0.008**	0.005	0.006***	-0.023	6.50
$CAR_{1,10}$	-0.028	0.023	-0.235***	-0.002	-0.009**	0.008	0.009***	0.013	4.76
$CAR_{1,20}$	0.027	0.029	-0.274***	-0.005	-0.011*	0.015**	0.015***	0.047*	4.87
$CAR_{1,40}$	-0.149	0.009	-0.351***	0.002	-0.019*	-0.006	0.016**	0.049	3.86

Table 3.5. Drivers of the subsequent patterns in returns: ASX announcements and analyst recommendations (Continued)

Panel D: Price Sensitive Announcements + Stock Price > $2 (N = 897)									
	$Intercept$	AR_0	$AR_0\ x\ DV$	$SIZE$	BM	VOL	MOM	$AR_0\ x\ VOL$	R^2 (%)
$CAR_{1,5}$	-0.021	0.026	-0.246***	-0.002	-0.009**	0.002	0.008***	-0.008	7.86
$CAR_{1,10}$	0.017	0.017	-0.248***	-0.004	-0.011**	0.002	0.011***	0.049*	6.44
$CAR_{1,20}$	0.069	0.016	-0.282***	-0.007	-0.011	0.003	0.017***	0.084***	5.67
$CAR_{1,40}$	-0.055	0.032	-0.369***	-0.001	-0.014	-0.006	0.016*	0.031	3.48
Panel E: Market Capitalization > $100 million (N = 2,744)									
	$Intercept$	AR_0	$AR_0\ x\ DV$	$SIZE$	BM	VOL	MOM	$AR_0\ x\ VOL$	R^2 (%)
$CAR_{1,5}$	0.041	-0.011	-0.127***	-0.004	-0.007***	0.003	0.001**	-0.023	2.38
$CAR_{1,10}$	0.044	-0.005	-0.189***	-0.005*	-0.012***	-0.001	0.002	-0.023	2.89
$CAR_{1,20}$	0.002	0.026	-0.238***	-0.004	-0.017***	-0.005	0.003*	-0.029	2.50
$CAR_{1,40}$	-0.143	0.021	-0.235***	0.000	-0.028***	-0.018***	0.003	-0.048	2.57
Panel F: Midpoint Prices (N = 4,620)									
	$Intercept$	AR_0	$AR_0\ x\ DV$	$SIZE$	BM	VOL	MOM	$AR_0\ x\ VOL$	R^2 (%)
$CAR_{1,5}$	0.014	-0.022	-0.099***	-0.002	-0.007***	-0.001	0.000	-0.003	1.70
$CAR_{1,10}$	-0.019	-0.015	-0.141***	-0.001	-0.007***	-0.000	0.002	0.001	1.60
$CAR_{1,20}$	-0.071	-0.006	-0.162***	0.000	-0.013***	-0.005	0.001	0.012	1.44
$CAR_{1,40}$	-0.112	-0.001	-0.186***	0.002	-0.016***	-0.007	0.002	0.016	1.15
Panel G: Adjusted Closing Prices (N = 4,968)									
	$Intercept$	AR_0	$AR_0\ x\ DV$	$SIZE$	BM	VOL	MOM	$AR_0\ x\ VOL$	R^2 (%)
$CAR_{1,5}$	-0.001	-0.098***	-0.166***	-0.002*	-0.008***	-0.001	0.001	0.021*	8.02
$CAR_{1,10}$	-0.015	-0.106***	-0.207***	-0.001	-0.008***	-0.003	0.002***	0.023*	6.61
$CAR_{1,20}$	-0.051**	-0.103***	-0.252***	0.000	-0.014***	-0.012***	0.001	0.041**	5.18
$CAR_{1,40}$	-0.092**	-0.065*	-0.267***	0.001	-0.021***	-0.014***	-0.001	0.007	2.89

Table 3.5. Drivers of the subsequent patterns in returns: ASX announcements and analyst recommendations (Continued)

Panel H: Adjusted Closing Prices + Stock Price > $2 (N = 745)

	$Intercept$	AR_0	$AR_0\ x\ DV$	$SIZE$	BM	VOL	MOM	$AR_0\ x\ VOL$	R^2 (%)
$CAR_{1,5}$	-0.076	-0.022	-0.279***	0.002	-0.008*	-0.002	0.009***	0.019	8.91
$CAR_{1,10}$	-0.156**	-0.023	-0.301***	0.005*	-0.011*	-0.007*	0.015***	0.042***	8.43
$CAR_{1,20}$	-0.201***	0.003	-0.403***	0.008**	-0.011	-0.009**	0.021***	0.047***	8.05
$CAR_{1,40}$	-0.365***	0.058	-0.517***	0.015***	-0.011	-0.009*	0.019	0.015	5.48

Panel I: Analyst Recommendations + Stock Price > $2 (N = 540)

	$Intercept$	AR_0	$AR_0\ x\ DV$	$SIZE$	BM	VOL	MOM	$AR_0\ x\ VOL$	R^2 (%)
$CAR_{1,5}$	-0.043	0.023	-0.228***	-0.001	-0.011**	0.006	0.009***	-0.032	11.05
$CAR_{1,10}$	-0.083	0.024	-0.237***	-0.001	-0.016**	0.015	0.009**	0.014	8.13
$CAR_{1,20}$	0.034	-0.005	-0.267***	-0.007	-0.017*	0.024**	0.013**	0.051	6.93
$CAR_{1,40}$	-0.268	0.078	-0.456***	0.006	-0.026**	-0.025*	0.024*	-0.039	8.20

Panel J: Price Impact (N = 6,641)

	$Intercept$	AR_0	$AR_0\ x\ DV$	$SIZE$	BM	VOL	MOM	$AR_0\ x\ VOL$	$Amihud$	$Amihud\ x\ DV$	R^2 (%)
$CAR_{1,5}$	-0.014	-0.057***	-0.174***	-0.001	-0.006***	-0.001	0.001***	0.002	-0.009***	0.008***	5.91
$CAR_{1,10}$	-0.021	-0.043**	-0.228***	-0.001	-0.008***	-0.000	0.002***	0.004	-0.011***	0.008***	4.99
$CAR_{1,20}$	-0.034	-0.034	-0.261***	-0.002	-0.015***	-0.005	0.001	-0.017	-0.015***	0.014***	3.55
$CAR_{1,40}$	-0.056	-0.029	-0.256***	-0.003	-0.022***	-0.006	0.002	0.016	-0.002	-0.000	2.11

Panel K: Price Impact + Stock Price > $2 (N = 1,070)

	$Intercept$	AR_0	$AR_0\ x\ DV$	$SIZE$	BM	VOL	MOM	$AR_0\ x\ VOL$	$Amihud$	$Amihud\ x\ DV$	R^2 (%)
$CAR_{1,5}$	-0.044	0.024	-0.233***	-0.000	-0.007**	0.004	0.006***	-0.026	0.023***	0.016*	7.61
$CAR_{1,10}$	-0.029	0.033	-0.237***	-0.001	-0.009**	0.008	0.009***	0.008	-0.026***	0.016	5.68
$CAR_{1,20}$	0.024	0.041	-0.281***	-0.005	-0.011*	0.014**	0.015***	0.041	-0.034***	0.028**	5.65
$CAR_{1,40}$	-0.152	0.023	-0.359***	0.002	-0.184*	-0.007	0.016**	0.042	-0.041**	0.034*	4.45

Table 3.6. Drivers of the subsequent patterns in returns: Large no-information based price changes

This table reports coefficient estimates from the following regression:

$$CAR_{1,n} = Intercept + \beta_1(AR_0) + \beta_2(SIZE) + \beta_3(BM) + \beta_4(VOL) + \beta_5(MOM) + \varepsilon$$

$CAR_{1,n}$ is the cumulative abnormal returns calculated from one day after the large price change over a n trading day horizon, where n is 5, 10, 20 and 40 days. AR_0 is the abnormal return on the day of a large price change in excess of a 10% threshold after accounting for the Fama and French (1993) three factors and the Carhart (1997) momentum factor. The information and no-information subsamples are determined by whether at least one source of public information was made in the -1 to 0 day event window around a large price change. $SIZE$ (BM) is the market capitalization (book to market ratio) of each firm at the start of the year in which the large price change occurred expressed in logarithmic form, VOL is the total volume over the past month as a percentage of the number of shares outstanding, and MOM is the return over the previous six months. Clustered standard errors by stock and by date are applied. We calculate *t*-statistics and ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels.

Panel A: Private information (N = 150)							
	$Intercept$	AR_0	$SIZE$	BM	VOL	MOM	R^2 (%)
$CAR_{1,5}$	0.021	-0.018	-0.005	-0.021**	-0.001	0.004	3.70
$CAR_{1,10}$	-0.045	-0.058	-0.006	-0.039***	-0.011	0.012	9.74
$CAR_{1,20}$	0.024	0.046	-0.012	-0.049***	-0.054*	0.024	11.28
$CAR_{1,40}$	-0.099	0.011	-0.008	-0.056**	-0.086*	0.037	9.09
Panel B: Low Illiquidity (N = 934)							
	$Intercept$	AR_0	$SIZE$	BM	VOL	MOM	R^2 (%)
$CAR_{1,5}$	0.012	-0.109***	-0.001	-0.001	-0.003	0.006*	2.36
$CAR_{1,10}$	0.008	-0.164***	-0.003	-0.008	-0.005	0.008**	3.36
$CAR_{1,20}$	-0.036	-0.192***	-0.001	-0.011	-0.018**	0.011**	3.40
$CAR_{1,40}$	-0.284	-0.232***	0.007	-0.022**	-0.021***	0.014*	3.61
Panel C: High Illiquidity (N = 934)							
	$Intercept$	AR_0	$SIZE$	BM	VOL	MOM	R^2 (%)
$CAR_{1,5}$	-0.089	-0.335***	0.003	-0.012**	0.019	0.002	16.63
$CAR_{1,10}$	-0.023	-0.392***	-0.001	-0.014**	-0.022	0.002	14.91
$CAR_{1,20}$	-0.146	-0.463***	0.004	-0.025***	-0.013	-0.000	12.10
$CAR_{1,40}$	-0.186	-0.414***	0.009	-0.016	0.047*	0.002	5.21
Panel D: Low Illiquidity + Midpoint prices (N = 580)							
	$Intercept$	AR_0	$SIZE$	BM	VOL	MOM	R^2 (%)
$CAR_{1,5}$	0.163*	-0.039	-0.009	-0.005*	-0.004	-0.000	0.95
$CAR_{1,10}$	0.148	-0.105**	-0.009	-0.007	-0.003	-0.002	1.38
$CAR_{1,20}$	0.111	-0.178**	-0.009	-0.012	-0.018**	-0.018**	2.80
$CAR_{1,40}$	-0.056	-0.216**	-0.002	-0.015	-0.029***	0.003	3.25

Appendix – Chapter 3

Table A3.1. Drivers of the subsequent patterns in returns: Methodology robustness

This table reports coefficient estimates from the following regression:

$$CAR_{1,n} = Intercept + \beta_1(AR_0) + \beta_2(AR_0\ x\ DV) + \beta_3(SIZE) + \beta_4(BM) + \beta_5(VOL) + \beta_6(MOM) + \beta_7(AR_0 x\ VOL)\ + \varepsilon$$

$CAR_{1,n}$ is the cumulative abnormal returns calculated from one day after the large price change over a n trading day horizon, where n is 5, 10, 20 and 40 days. AR_0 is the abnormal return on the day of a large price change in excess of a 10% threshold after accounting for the Fama and French (1993) three factors and the Carhart (1997) momentum factor, DV is a no-information dummy variable equal to one if there are zero ASX announcements made in the -1 to 0 day event window around a large price change, $SIZE$ (BM) is the market capitalization (book to market ratio) of each firm at the start of the year in which the large price change occurred expressed in logarithmic form, VOL is the total volume over the past month as a percentage of the number of shares outstanding, and MOM is the return over the previous six-month period. Clustered standard errors by stock and by date are applied. We calculate *t*-statistics and ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels.

Panel A: Exclude 20 day restriction (N = 17,665)

	$Intercept$	AR_0	$AR_0\ x\ DV$	$SIZE$	BM	VOL	MOM	$AR_0\ x\ VOL$	R^2 (%)
$CAR_{1,5}$	0.021	-0.017***	-0.009	-0.002**	-0.008***	-0.153**	-0.000	-0.574*	0.62
$CAR_{1,10}$	0.143*	-0.023***	-0.007	-0.008**	-0.009**	-0.123	-0.000	-0.324	0.33
$CAR_{1,20}$	0.343**	-0.031**	-0.004	-0.019**	-0.026**	-0.286	-0.001	-0.297	0.43
$CAR_{1,40}$	0.628**	-0.015	-0.021	-0.033***	-0.037**	-0.578	-0.001	-0.568	0.66

Panel B: Exclude 20 day restriction + Stock Price > $2 (N = 1,070)

	$Intercept$	AR_0	$AR_0\ x\ DV$	$SIZE$	BM	VOL	MOM	$AR_0\ x\ VOL$	R^2 (%)
$CAR_{1,5}$	-0.127*	-0.016	-0.096**	0.004	-0.006	0.185	0.001	-1.171	2.03
$CAR_{1,10}$	-0.146	-0.015	-0.125***	0.003	-0.013**	-0.127	0.002	0.146	2.05
$CAR_{1,20}$	-0.176	-0.002	-0.143**	0.004	-0.016*	-0.614	0.003	-0.077	2.01
$CAR_{1,40}$	-0.531***	-0.043	-0.133*	0.016**	-0.026**	-2.356***	0.007	0.963	4.13

Table A3.1. Drivers of the subsequent patterns in returns: Methodology robustness (Continued)

Panel C: Bankruptcy + Count days restrictions (N = 4,040)									
	$Intercept$	AR_0	$AR_0\ x\ DV$	$SIZE$	BM	VOL	MOM	$AR_0\ x\ VOL$	R^2 (%)
$CAR_{1,5}$	0.026	-0.083***	-0.175***	-0.003***	-0.008***	-0.003	0.001	0.007	6.83
$CAR_{1,10}$	0.021	-0.082***	-0.242***	-0.003**	-0.009***	-0.007*	0.002***	0.031*	6.07
$CAR_{1,20}$	0.014	-0.081**	-0.258***	-0.004	-0.018***	-0.013***	0.000	0.052**	4.25
$CAR_{1,40}$	-0.003	-0.055	-0.269***	-0.005*	-0.024***	-0.011*	0.001	0.041	2.41
Panel D: Bankruptcy + Count days restrictions + Stock Price > $2 (N = 689)									
	$Intercept$	AR_0	$AR_0\ x\ DV$	$SIZE$	BM	VOL	MOM	$AR_0\ x\ VOL$	R^2 (%)
$CAR_{1,5}$	-0.145**	-0.001	-0.252***	0.005*	-0.009**	0.002	0.008***	-0.005	9.38
$CAR_{1,10}$	-0.189***	-0.016	-0.265***	0.006**	-0.012**	0.002	0.012**	0.056	7.84
$CAR_{1,20}$	-0.229***	-0.009	-0.313***	0.007*	-0.015**	0.005	0.018***	0.097***	7.16
$CAR_{1,40}$	-0.444***	0.005	-0.431***	0.017***	-0.019**	-0.009	0.022***	0.014	6.52
Panel E: Large Price Change 7.5% (N = 10,418)									
	$Intercept$	AR_0	$AR_0\ x\ DV$	$SIZE$	BM	VOL	MOM	$AR_0\ x\ VOL$	R^2 (%)
$CAR_{1,5}$	-0.011	-0.041***	-0.184***	-0.001	-0.005***	-0.003*	0.000	0.008	4.86
$CAR_{1,10}$	-0.016	-0.027	-0.213***	-0.001	-0.008***	-0.002	0.000	0.011	3.38
$CAR_{1,20}$	-0.034	-0.003	-0.237***	-0.001	-0.011***	-0.005*	0.001	0.024	2.13
$CAR_{1,40}$	-0.055	0.008	-0.233***	-0.002	-0.018***	-0.006**	0.001	0.024	1.30
Panel F: Large Price Change 7.5% + Stock Price > $2 (N = 2,275)									
	$Intercept$	AR_0	$AR_0\ x\ DV$	$SIZE$	BM	VOL	MOM	$AR_0\ x\ VOL$	R^2 (%)
$CAR_{1,5}$	-0.022	0.006	-0.186***	-0.001	-0.007***	0.004	0.003**	-0.002	3.52
$CAR_{1,10}$	-0.043	0.034	-0.214***	0.000	-0.007**	0.003	0.005	0.004	2.40
$CAR_{1,20}$	-0.056	0.046	-0.219***	0.000	-0.008**	0.008	0.011***	0.042	2.18
$CAR_{1,40}$	-0.137	0.035	-0.246***	0.003	-0.013**	-0.008	0.011**	0.064	1.92

Table A3.1. Drivers of the subsequent patterns in returns: Methodology robustness (Continued)

Panel G: Conventional Beta Estimation Period -244 to -6 (N = 6,458)									
	$Intercept$	AR_0	$AR_0\ x\ DV$	$SIZE$	BM	VOL	MOM	$AR_0\ x\ VOL$	R^2 (%)
$CAR_{1,5}$	-0.007	-0.056***	-0.185***	-0.001	-0.006***	-0.001	0.001	0.003	5.91
$CAR_{1,10}$	-0.013	-0.061***	-0.243***	-0.002	-0.009***	-0.005	0.001	0.019	5.49
$CAR_{1,20}$	-0.038	-0.073***	-0.256***	-0.002	-0.015***	-0.011	0.002***	0.037	3.97
$CAR_{1,40}$	-0.056	-0.092***	-0.224***	-0.003	-0.023***	-0.021***	0.002	0.063***	2.34
Panel H: Conventional Beta Estimation Period -244 to -6 + Stock Price > $2 (N = 1,053)									
	$Intercept$	AR_0	$AR_0\ x\ DV$	$SIZE$	BM	VOL	MOM	$AR_0\ x\ VOL$	R^2 (%)
$CAR_{1,5}$	-0.078	0.035	-0.229***	0.002	-0.007*	0.000	0.009***	-0.045***	6.32
$CAR_{1,10}$	-0.058	0.046	-0.245***	-0.000	-0.008*	0.003	0.009***	-0.021	3.72
$CAR_{1,20}$	-0.037	0.031	-0.203**	-0.001	-0.009	0.003	0.015***	-0.013	2.41
$CAR_{1,40}$	-0.177	-0.031	-0.231**	0.006	-0.008	-0.011	0.014*	0.036	1.97
Panel I: Market Model (N = 6,934)									
	$Intercept$	AR_0	$AR_0\ x\ DV$	$SIZE$	BM	VOL	MOM	$AR_0\ x\ VOL$	R^2 (%)
$CAR_{1,5}$	0.003	-0.045***	-0.152***	-0.001	-0.006***	-0.002	0.001	0.003	4.07
$CAR_{1,10}$	0.036	-0.035*	-0.206***	-0.003*	-0.008***	-0.001	0.001	0.004	3.44
$CAR_{1,20}$	0.067	-0.034	-0.241***	-0.005*	-0.009***	-0.004	0.001	0.023	2.66
$CAR_{1,40}$	0.092	-0.048	-0.225***	-0.007*	-0.015***	-0.011**	-0.000	0.042**	1.64
Panel J: Market Model + Stock Price > $2 (N = 1,165)									
	$Intercept$	AR_0	$AR_0\ x\ DV$	$SIZE$	BM	VOL	MOM	$AR_0\ x\ VOL$	R^2 (%)
$CAR_{1,5}$	-0.032	0.023	-0.194***	-0.001	-0.008**	0.002	0.005**	-0.025*	4.52
$CAR_{1,10}$	0.005	0.045	-0.197***	-0.003	-0.008*	0.001	0.007	-0.021	2.78
$CAR_{1,20}$	0.012	0.052	-0.174**	-0.004	-0.012**	0.004	0.006	-0.002	1.73
$CAR_{1,40}$	-0.152	-0.006	-0.212**	0.002	-0.019**	-0.007	-0.001	0.049**	2.08

Table A3.1. Drivers of the subsequent patterns in returns: Methodology robustness (Continued)

Panel K: Large information-based event on days -1 to +1 (Savor, 2012) (N = 6,487)									
	$Intercept$	AR_0	$AR_0\ x\ DV$	$SIZE$	BM	VOL	MOM	$AR_0\ x\ VOL$	R^2 (%)
$CAR_{1,5}$	-0.008	-0.068***	-0.185***	-0.001	-0.006***	-0.001	0.001**	0.002	6.08
$CAR_{1,10}$	-0.013	-0.056***	-0.236***	-0.001	-0.008***	-0.000	0.001**	0.004	4.86
$CAR_{1,20}$	-0.025	-0.048*	-0.274***	-0.002	-0.014***	-0.005	0.001	0.018	3.51
$CAR_{1,40}$	-0.042	-0.045	-0.249***	-0.004	-0.023***	-0.006	0.001	0.016	2.02

Panel L: Large information-based event on days -1 to +1 (Savor, 2012) + Stock Price > $2 (N = 1,068)									
	$Intercept$	AR_0	$AR_0\ x\ DV$	$SIZE$	BM	VOL	MOM	$AR_0\ x\ VOL$	R^2 (%)
$CAR_{1,5}$	-0.046	0.003	-0.222***	-0.000	-0.008**	0.006*	0.007***	-0.022	6.08
$CAR_{1,10}$	-0.017	0.012	-0.229***	-0.002	-0.009*	0.009	0.011***	0.015	4.26
$CAR_{1,20}$	0.021	0.013	-0.258***	-0.005	-0.011*	0.016**	0.016***	0.049	4.44
$CAR_{1,40}$	-0.174	-0.024	-0.269***	0.003	-0.019**	-0.005	0.016**	0.054	3.07

Panel M: Large information-based event after hours on day -1 and day 0 (N = 6,641)									
	$Intercept$	AR_0	$AR_0\ x\ DV$	$SIZE$	BM	VOL	MOM	$AR_0\ x\ VOL$	R^2 (%)
$CAR_{1,5}$	-0.013	-0.059***	-0.173***	-0.001	-0.006***	-0.001	0.001***	-0.002	5.77
$CAR_{1,10}$	-0.019	-0.062***	-0.197***	-0.001	-0.008***	-0.001	0.002***	0.005	4.64
$CAR_{1,20}$	-0.037	-0.041	-0.249***	-0.002	-0.015***	-0.005	0.001	0.018	3.33
$CAR_{1,40}$	-0.055	-0.036	-0.241***	-0.003	-0.022***	-0.006	0.002	0.016	2.03

Panel N: Large information-based event after hours on day -1 and day 0 + Stock Price > $2 (N = 1,070)									
	$Intercept$	AR_0	$AR_0\ x\ DV$	$SIZE$	BM	VOL	MOM	$AR_0\ x\ VOL$	R^2 (%)
$CAR_{1,5}$	-0.045	0.012	-0.218***	-0.000	-0.007*	0.004	0.006***	-0.023	6.16
$CAR_{1,10}$	-0.027	0.011	-0.197***	-0.002	-0.009*	0.008	0.009**	0.013	4.13
$CAR_{1,20}$	-0.026	0.019	-0.249***	-0.005	-0.011*	0.015**	0.015***	0.046	4.43
$CAR_{1,40}$	-0.152	-0.004	-0.312***	0.002	-0.018*	-0.006	0.016**	0.046	3.54

Table A3.1. Drivers of the subsequent patterns in returns: Methodology robustness (Continued)

Panel O: Stock Fixed Effects (N = 6,641)									
	$Intercept$	AR_0	$AR_0\ x\ DV$	$SIZE$	BM	VOL	MOM	$AR_0\ x\ VOL$	R^2 (%)
$CAR_{1,5}$	-0.002	-0.067***	-0.168***	-0.000	-0.006**	-0.001	0.000	0.002	5.32
$CAR_{1,10}$	-0.002	-0.053***	-0.219***	-0.001	-0.009***	0.001	0.001*	0.003	4.42
$CAR_{1,20}$	-0.002	-0.048*	-0.251***	-0.002	-0.017***	-0.005*	-0.000	0.017*	3.08
$CAR_{1,40}$	-0.001	-0.037	-0.246***	-0.002	-0.022***	-0.004	0.000	0.011	1.64
Panel P: Stock Fixed Effects + Stock Price > $2 (N = 1,070)									
	$Intercept$	AR_0	$AR_0\ x\ DV$	$SIZE$	BM	VOL	MOM	$AR_0\ x\ VOL$	R^2 (%)
$CAR_{1,5}$	-0.001**	0.007	-0.271***	0.003	-0.007	0.007*	0.004	-0.009	7.05
$CAR_{1,10}$	-0.011**	0.012	-0.271***	0.004	-0.008	0.012*	0.007*	0.031	4.59
$CAR_{1,20}$	-0.016**	0.021	-0.324***	0.006	-0.009	0.021***	0.013***	0.067**	4.77
$CAR_{1,40}$	-0.018*	-0.002	-0.409***	0.006	-0.017	-0.004	0.011	0.031	3.41
Panel Q: Date Fixed Effects (N = 6,641)									
	$Intercept$	AR_0	$AR_0\ x\ DV$	$SIZE$	BM	VOL	MOM	$AR_0\ x\ VOL$	R^2 (%)
$CAR_{1,5}$	-0.002	-0.048**	-0.173***	-0.001	-0.007***	0.001	0.001*	-0.004	3.06
$CAR_{1,10}$	-0.002	-0.048**	-0.229***	-0.001	-0.011***	0.000	0.002	0.003	2.96
$CAR_{1,20}$	-0.002	-0.046	-0.263***	-0.002	-0.018***	-0.005	0.000	0.016	2.26
$CAR_{1,40}$	-0.001	-0.025	-0.284***	-0.006	-0.031***	-0.004	0.002	0.001	1.64
Panel R: Date Fixed Effects + Stock Price > $2 (N = 1,070)									
	$Intercept$	AR_0	$AR_0\ x\ DV$	$SIZE$	BM	VOL	MOM	$AR_0\ x\ VOL$	R^2 (%)
$CAR_{1,5}$	-0.003	0.021	-0.173***	-0.002	-0.007	0.019***	0.001	0.028	2.99
$CAR_{1,10}$	-0.005	0.036	-0.211***	-0.002	-0.008	0.016**	0.003	0.021	2.10
$CAR_{1,20}$	-0.002	0.046	-0.272***	-0.007	-0.013*	0.028***	0.006*	0.064	2.59
$CAR_{1,40}$	-0.009	-0.014	-0.281***	-0.003	-0.021*	0.018	0.006	0.172***	2.00

Table A3.1. Drivers of the subsequent patterns in returns: Methodology robustness (Continued)

Panel S: Stock and Date Fixed Effects (N = 6,641)

	$Intercept$	AR_0	$AR_0\ x\ DV$	$SIZE$	BM	VOL	MOM	$AR_0\ x\ VOL$	R^2 (%)
$CAR_{1,5}$	-0.002	-0.055***	-0.163***	-0.000	-0.008**	0.001	0.000	-0.004	2.78
$CAR_{1,10}$	-0.002	-0.056***	-0.214***	-0.000	-0.012***	0.001	0.001	0.000	2.65
$CAR_{1,20}$	-0.002	-0.057*	-0.243***	-0.001	-0.021***	-0.004*	-0.001	0.015*	2.00
$CAR_{1,40}$	-0.001	-0.035	-0.263***	-0.004	-0.033***	-0.003	-0.001	0.003	1.25

Panel T: Stock and Date Fixed Effects + Stock Price > $2 (N = 1,070)

	$Intercept$	AR_0	$AR_0\ x\ DV$	$SIZE$	BM	VOL	MOM	$AR_0\ x\ VOL$	R^2 (%)
$CAR_{1,5}$	-0.005	0.004	-0.193***	0.001	-0.009	0.022***	-0.002	0.044*	3.54
$CAR_{1,10}$	-0.006	0.019	-0.213***	0.003	-0.009	0.018**	0.000	0.021	2.15
$CAR_{1,20}$	-0.011*	0.026	-0.279***	0.006	-0.016	0.035***	0.002	0.082*	2.89
$CAR_{1,40}$	-0.009	-0.016	-0.294***	0.001	-0.026	0.011	0.000	0.137**	1.58

Panel U: Excluding Earnings Announcements (N = 6,471)

	$Intercept$	AR_0	$AR_0\ x\ DV$	$SIZE$	BM	VOL	MOM	$AR_0\ x\ VOL$	R^2 (%)
$CAR_{1,5}$	0.009	-0.019***	-0.011	-0.003***	-0.009***	0.002	0.001	-0.007	2.03
$CAR_{1,10}$	0.078*	-0.025***	-0.021	-0.005***	-0.007	0.004*	0.001**	-0.005	0.89
$CAR_{1,20}$	0.147*	-0.034***	0.017	-0.012***	-0.019***	-0.006	0.000	0.009	0.64
$CAR_{1,40}$	0.343**	-0.014	-0.035	-0.025***	-0.031***	-0.013*	-0.000	0.016	0.59

Panel V: Excluding Earnings Announcements + Stock Price > $2 (N = 1,004)

	$Intercept$	AR_0	$AR_0\ x\ DV$	$SIZE$	BM	VOL	MOM	$AR_0\ x\ VOL$	R^2 (%)
$CAR_{1,5}$	-0.105*	0.007	-0.156***	0.003	-0.008*	0.009*	0.005**	-0.025	6.08
$CAR_{1,10}$	-0.089	0.014	-0.161**	0.001	-0.013**	0.015**	0.009**	0.023	3.98
$CAR_{1,20}$	-0.048	-0.002	-0.189**	-0.002	-0.014*	0.019**	0.013***	0.064**	3.33
$CAR_{1,40}$	-0.303**	-0.039	-0.221**	0.009	-0.022**	-0.008	0.014*	0.055	3.45

Table A3.2. Abnormal behavior of trading and liquidity measures around large no-information based price changes

This table reports the abnormal behavior of several trading and liquidity measures at an hourly level within a -2 to +2 day event window around a sample of 3,801 large no-information-based price changes. $Quoted\ Spread$ is the difference between the ask price and bid price (%), $Effective\ Spread$ is the absolute difference between the transaction price and midpoint price multiplied by two (%), $Relative\ Quoted\ Spread$ is the $Quoted\ Spread$ weighted by the midpoint price (%), $Relative\ Effective\ Spread$ is the $Effective\ Spread$ weighted by the share price (%), $Bid\ Depth$ is the number of shares available at the best bid prices, and $Ask\ Depth$ is the number of shares available at the best ask prices. All spread and depth measures are time-weighted during each hourly interval and calculated using the best prices. The abnormal behavior of each trading and liquidity measure is calculated as the difference between event and control values using each firm as its own control. The control period is a 25-day window beginning one week prior to the large price change. We calculate t-statistics and ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels.

		$Relative\ Quoted\ Spread$	$Relative\ Effective\ Spread$	$Bid\ Depth$	$Ask\ Depth$
Day	Hour				
-2	10	0.31***	-0.13	-30,443	21,364*
	11	0.45***	0.45***	-27,590	30,465**
	12	0.23***	-0.73	-35,022	19,860
	13	0.40***	0.34***	-8,456	18,829
	14	0.18***	0.31***	-21,667	18,758
	15	0.25***	0.37***	-15,696	20,812
-1	10	0.62***	2.48	-53,615***	35,561**
	11	0.59***	0.55***	-13,849	37,849***
	12	0.52***	-0.52	-22,941	40,024*
	13	0.29***	0.46***	-27,660	44,311**
	14	0.41***	0.38***	-253	27,878***
	15	0.58***	0.47***	824	28,653***
0	10	0.85***	0.51	-23,505	45,191
	11	0.97***	0.78***	-37,010**	36,249
	12	0.91***	-0.07	-24,253	4,224
	13	0.93***	0.56***	-64,458***	9,415
	14	0.90***	0.95***	-64,829***	19,899
	15	1.27***	1.11***	-42,783*	15,108
1	10	0.71***	0.32	-19,223	-27,597**
	11	0.43***	0.59***	-16,231	-33,294***
	12	0.36***	-0.50	-8,348	-27,094*
	13	0.09	0.39***	-30,867	-10,133
	14	0.28***	0.44***	-10,391	-24,966
	15	0.44***	0.51***	-15,567	-23,953
2	10	0.37***	0.21	-24,275	-7,212
	11	0.23**	0.41***	-29,789	-21,092*
	12	0.15*	-0.63	-48,735***	-2,066
	13	0.06	0.53***	-41,327*	-250
	14	0.21**	0.48***	-29,778	-2,768
	15	0.26***	0.39***	-25,489	-16,520

Table A3.3. Drivers of large no-information-based price changes

This table reports coefficient estimates from the following regression:

$$AR_0 = Intercept + \beta_1 Trade + \beta_2 Liquidity + \beta_3 Adverse\ Selection + \varepsilon$$

AR_0 is the abnormal return on the day of a large price change in excess of a 10% threshold after accounting for the Fama and French (1993) three factors and the Carhart (1997) momentum factor. $Trade$ represents the abnormal behavior of the following variables, i) $Volume$ is the number of shares traded, and ii) $Order\ Imbalance$ is the absolute difference between buyer and seller initiated trades. $Liquidity$ represents the abnormal behavior of the following variables, i) $Quoted\ Spread$ is the difference between the ask and bid prices, ii) $Effective\ Spread$ is the absolute value of the difference between the transaction price and midpoint price multiplied by two, iii) $Bid\ Depth$ is the bid depth at the best prices, iv) $Ask\ Depth$ is the ask depth at the best prices, and v) $Amihud\ Illiquidity$ is the ratio of the absolute value of daily returns to daily trading volume. $Adverse\ Selection$ represents the abnormal behavior of adverse selection costs calculated using the Lin et al. (1995) spread decomposition model. All regression variables are daily measures. All spread and depth measures are time-weighted. We multiply abnormal order imbalance, volume and total depth coefficient estimates by 10^9. The abnormal behavior of each trading and liquidity measure is calculated as the difference between event and control values using each firm as its own control. The control period is a 25-day window beginning one week prior to the large price change. Clustered standard errors by stock and by date are applied. We calculate *t*-statistics and ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels.

	$Intercept$	$Volume$	$Order\ Imbalance$	$Quoted\ Spread$	$Effective\ Spread$	$Bid\ Depth$	$Ask\ Depth$	$Amihud\ Illiquidity$	$Adverse\ Selection$	$Fstatistic$	R^2 (%)
AR_0	0.063***	1.392**		0.413		-14.112	22.745***	0.083***		5.42	3.21
AR_0	0.047***		4.161***		0.496**			-176.33***	0.129***	6.06	4.28

Table A3.4. Drivers of the subsequent patterns in returns: Alternative sources of public information

This table reports coefficient estimates from the following regression:

$$CAR_{1,n} = Intercept + \beta_1(AR_0) + \beta_2(AR_0\ x\ DV) + \beta_3(SIZE) + \beta_4(BM) + \beta_5(VOL) + \beta_6(MOM) + \beta_7(AR_0 x\ VOL) + \varepsilon$$

$CAR_{1,n}$ is the cumulative abnormal returns calculated from one day after the large price change over a n trading day horizon, where n is 5, 10, 20 and 40 days. AR_0 is the abnormal return on the day of a large price change in excess of a 10% threshold after accounting for the Fama and French (1993) three factors and the Carhart (1997) momentum factor, DV is a no-information dummy variable equal to one if there are zero ASX announcements made in the -1 to 0 day event window around a large price change, $SIZE$ (BM) is the market capitalization (book to market ratio) of each firm at the start of the year in which the large price change occurred expressed in logarithmic form, VOL is the total volume over the past month as a percentage of the number of shares outstanding, and MOM is the return over the previous six-month period. Clustered standard errors by stock and by date are applied. We calculate *t*-statistics and ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels.

Panel A: Excluding Analyst Recommendations (N = 6,229)									
	$Intercept$	AR_0	$AR_0\ x\ DV$	$SIZE$	BM	VOL	MOM	$AR_0\ x\ VOL$	R^2 (%)
$CAR_{1,5}$	-0.019	-0.079***	-0.159***	-0.000	-0.006***	-0.003**	0.001***	0.008*	6.10
$CAR_{1,10}$	-0.019	-0.062***	-0.217***	-0.001	-0.008***	-0.002	0.002**	0.009	5.00
$CAR_{1,20}$	-0.038	-0.044	-0.255***	-0.002	-0.015***	-0.009*	0.001	0.029*	3.60
$CAR_{1,40}$	-0.041	-0.028	-0.264***	-0.004	-0.022***	-0.004	0.002	0.011	2.13
Panel B: Excluding Analyst Recommendations + Stock Price > $2 (N = 856)									
	$Intercept$	AR_0	$AR_0\ x\ DV$	$SIZE$	BM	VOL	MOM	$AR_0\ x\ VOL$	R^2 (%)
$CAR_{1,5}$	-0.041	-0.007	-0.206***	-0.000	-0.007*	0.001	0.006**	-0.004	5.83
$CAR_{1,10}$	0.000	-0.004	-0.225***	-0.003	-0.009*	0.001	0.011**	0.051	5.18
$CAR_{1,20}$	0.045	0.012	-0.305***	-0.006	-0.012*	0.004	0.019***	0.106***	6.41
$CAR_{1,40}$	-0.049	-0.011	-0.378***	-0.003	-0.018*	-0.001	0.016**	0.061	4.03

Table A3.4. Drivers of the subsequent patterns in returns: Alternative sources of public information

Panel C: Excluding Sub-prime Debt Crisis (N = 5,170)									
	$Intercept$	AR_0	$AR_0\ x\ DV$	$SIZE$	BM	VOL	MOM	$AR_0\ x\ VOL$	R^2 (%)
$CAR_{1,5}$	-0.018	-0.069***	-0.183***	-0.000	-0.006***	-0.003**	0.001***	0.008*	6.89
$CAR_{1,10}$	-0.025	-0.056***	-0.235***	-0.001	-0.009***	-0.002	0.002***	0.011	5.68
$CAR_{1,20}$	-0.022	-0.038	-0.273***	-0.002	-0.014***	-0.008*	0.000	0.027*	3.84
$CAR_{1,40}$	-0.007	-0.028	-0.269***	-0.005	-0.019***	-0.003	0.002	0.008	2.08
Panel D: Excluding Sub-prime Debt Crisis + Stock Price > $2 (N = 739)									
	$Intercept$	AR_0	$AR_0\ x\ DV$	$SIZE$	BM	VOL	MOM	$AR_0\ x\ VOL$	R^2 (%)
$CAR_{1,5}$	-0.131**	0.013	-0.202***	0.003	-0.011***	0.001	0.008***	-0.017	7.76
$CAR_{1,10}$	-0.082	0.018	-0.189**	0.000	-0.012**	0.001	0.013***	0.027	6.16
$CAR_{1,20}$	-0.011	0.022	-0.185**	-0.004	-0.015**	0.008*	0.019***	0.077***	6.84
$CAR_{1,40}$	-0.069	0.025	-0.269**	-0.003	-0.021**	0.007	0.017**	0.043	4.25
Panel E: Excluding Internet Bubble (N = 5,049)									
	$Intercept$	AR_0	$AR_0\ x\ DV$	$SIZE$	BM	VOL	MOM	$AR_0\ x\ VOL$	R^2 (%)
$CAR_{1,5}$	-0.038	-0.058***	-0.163***	0.001	-0.007***	0.000	0.001**	-0.005	5.37
$CAR_{1,10}$	-0.049	-0.047**	-0.211***	0.001	-0.008***	-0.001	0.002***	0.007	4.33
$CAR_{1,20}$	-0.065	-0.038	-0.227***	-0.002	-0.015***	-0.004	0.001	0.017	2.84
$CAR_{1,40}$	-0.117	-0.055	-0.199***	0.001	-0.023***	-0.015***	0.001	0.049***	1.95
Panel F: Excluding Internet Bubble + Stock Price > $2 (N = 808)									
	$Intercept$	AR_0	$AR_0\ x\ DV$	$SIZE$	BM	VOL	MOM	$AR_0\ x\ VOL$	R^2 (%)
$CAR_{1,5}$	0.003	0.013	-0.258***	-0.002	-0.008*	0.005	0.007***	-0.014	8.05
$CAR_{1,10}$	0.018	0.024	-0.282***	-0.003	-0.009*	0.008	0.012***	0.005	6.40
$CAR_{1,20}$	0.051	0.036	-0.311***	-0.006	-0.011*	0.011*	0.013***	0.018	4.71
$CAR_{1,40}$	-0.117	-0.009	-0.325***	0.013	-0.017	-0.009	0.009	0.039	3.28

Table A3.4. Drivers of the subsequent patterns in returns: Alternative sources of public information (Continued)

Panel G: Excluding Reclassified Large Price Changes (N = 5,968)

	$Intercept$	AR_0	$AR_0\ x\ DV$	$SIZE$	BM	VOL	MOM	$AR_0\ x\ VOL$	R^2 (%)
$CAR_{1,5}$	0.009	-0.019***	-0.007***	-0.002*	-0.009***	-0.009	0.001	-1.637	1.84
$CAR_{1,10}$	0.057	-0.025***	-0.019	-0.004	-0.009***	0.236	0.001	-0.675	0.99
$CAR_{1,20}$	0.181*	-0.034***	0.047	-0.012**	-0.023***	-0.785	-0.000	0.594	0.73
$CAR_{1,40}$	0.462**	-0.014	0.009	-0.025***	-0.033***	-1.578*	-0.000	-1.331	0.56

Panel H: Excluding Reclassified Large Price Changes + Stock Price > $2 (N = 977)

	$Intercept$	AR_0	$AR_0\ x\ DV$	$SIZE$	BM	VOL	MOM	$AR_0\ x\ VOL$	R^2 (%)
$CAR_{1,5}$	-0.146**	0.012	-0.123**	0.004*	-0.008	0.851	0.007***	-2.265	4.99
$CAR_{1,10}$	-0.151	0.014	-0.108	0.003	-0.013**	1.241*	0.011***	1.869	3.48
$CAR_{1,20}$	-0.132	0.002	-0.122	0.001	-0.015**	1.758**	0.015***	6.183**	3.18
$CAR_{1,40}$	-0.448**	-0.029	-0.136	0.023	-0.026**	-0.906	0.017*	5.242	3.74

Table A3.5. ASX announcements: Price sensitive flag

This table reports the total number of announcements during our 15-year sample period between January 1, 1996 and June 30, 2011. There are 19 different $Announcement\ type(s)$, $Price\ sensitive$ are firm-specific announcements that contain material information about fundamental value as determined by the ASX, and $Non\ price\ sensitive$ are firm-specific announcements which do not contain material information about fundamental value as determined by the ASX.

$Announcement\ type$	$Price\ sensitive$	$Non\ price\ sensitive$	$Total$
Takeover Announcement	29,793	28,871	58,664
Shareholder Details	3,832	344,741	348,573
Periodic Report	303,490	370,679	674,169
Quarterly Activities Report	73,874	2,982	76,856
Quarterly Cash Flow Report	55,020	1,705	56,725
Issued Capital	68,877	255,322	324,199
Asset Acquisition & Disposal	45,721	18,136	63,857
Notice of Meeting	3,099	122,811	125,910
Stock Exchange Announcement	44,062	15,110	59,172
Dividend Announcement	168,244	26,680	194,924
Progress Report	169,618	97,350	266,968
Company Administration	13,097	83,719	96,816
Notice of Call (Contributing Shares)	60	140	200
Other	26,515	49,049	75,564
Chairman's Address	3,464	23,855	27,319
Letter to Shareholders	2,563	28,112	30,675
ASX Query	10,580	3,268	13,848
Warrants	76	52,055	52,131
Prospectus	1,682	19,452	21,134
Total	1,023,667	1,544,037	2,567,704

Chapter 4. Disentangling the different sources of value creation from divestitures[61]

4.1. Introduction

Divestitures are reorganizations of a firm's ownership structure. A common type of divestiture is an asset sell-off – the voluntary sale of divisible assets from one business to another.[62] The literature reports mixed findings as to whether divestitures create value for acquiring and selling firm shareholders. Rosenfeld (1984) documents abnormal returns of approximately 3% for acquirers, while Sicherman and Pettway (1987) obtain similar results when they purchase related divested assets only. In contrast, Sicherman and Pettway (1992) and Datta et al. (2003) document insignificant abnormal returns. A number of US studies using various event windows report that sellers of divested assets (or divesting firms) earn abnormal returns of approximately 0% to 4% (Alexander et al., 1984; Hite and Owers, 1984; Linn and Rozeff, 1984; Rosenfeld, 1984; Jain, 1985; Klein, 1986; Hite et al., 1987; Sicherman and Pettway, 1992; John and Ofek, 1995; Datta et al., 2003; Lee and Madhavan, 2010).[63]

The use of abnormal returns to measure value creation is problematic because it confounds different sources of value creation. Bradley et al. (1983) decompose value creation from takeovers into two components. They describe each of these components of value creation as separate motivations for the acquiring firm to initiate a takeover bid. The first is the synergy hypothesis – productive gains achieved from the acquisition of the target firm, and the second is the information hypothesis – the target firm is undervalued (or mispriced) and the bid reveals new information about the target firm's stand-alone value.[64] Both of these hypotheses suggest that the selling firm will experience positive changes in shareholder wealth on the announcement date.[65] Hite et al. (1987)

[61] We thank Tom Smith for his helpful comments and access to data. In addition, we thank Jonathan Berk, Doug Foster, Bruce Grundy, Marc Lipson, Spencer Martin, Talis Putnins and Susan Thorp, participants at the Financial Management Conference 2014 (Paris), Financial Research Network Corporate Finance Meeting 2015 (Sydney) and European Financial Management Association Doctoral Student Consortium 2015 (Venice), and seminar participants at the University of Technology Sydney and University of Queensland for helpful comments.

[62] Examples of asset sell-offs include the sale of units, subsidiaries, stores, operating assets and intangibles. Other types of divestitures that we do not examine in this chapter include: i) spin-offs – creation of a distinct public company, ii) carve-outs – partial asset sale via initial public offering, and iii) leveraged buyouts – debt-financed asset sale to specific investor group.

[63] More recently, Augustin et al. (2015) report that divesting firms earn abnormal returns of 2%, however, they do not distinguish between asset sell-offs and spin-offs. Rosenfeld (1984) suggest that spin-offs are associated with larger abnormal returns than asset sell-offs. Consistent with this notion Veld and Veld-Merkoulova (2009) find that abnormal returns range between 1.32% and 5.56% across 26 spin-off event studies between 1983 and 2008.

[64] The bid made by the acquirer also reveals new information about its own stand-alone value (Bhagat et al., 2005; Barraclough et al., 2013).

[65] If the bid fails then these hypotheses have different implications. The synergy hypothesis predicts that in the absence of a subsequent bid the initial price reaction of the selling firm reverts back to its pre-announcement price. The information hypothesis predicts that the initial price reaction is permanent as the initial bid reveals new information about the stand-alone value of the seller. Both Bradley et al. (1983) and Hite et al. (1987) find evidence in support of the synergy hypothesis for takeovers and divested assets, respectively.

suggest that the synergy and information motivations are similar from the perspective of the acquirer of divested assets.[66]

On the announcement date there may be some uncertainty about the eventual completion of the divestiture, so any announcement will also include market perception about the probability of deal success. Bhagat et al. (2005) suggest that abnormal returns on the announcement date will understate the total value created to the involved parties because the market imputes some probability that the deal will fail, even deals that ultimately succeed. In addition, abnormal returns calculated over a short window around the announcement date will not capture the entire value of a successful deal, and using abnormal returns calculated up until the deal is completed will be confounded by other systematic and unsystematic factors. As a result, previous studies which rely on abnormal returns to make inferences about value creation do so with bias (Hietala et al., 2003; Barraclough et al., 2013).

The contribution of this chapter is threefold. First, we adapt a technique developed for corporate acquisitions by Barraclough et al. (2013) that overcomes a bias present in prior studies that use abnormal returns to measure value creation. In addition to stock prices, we use option prices to disentangle the different sources of value creation from divestitures into synergy gains, new information revealed about stand-alone values and the probability of deal success. Option prices provide additional information that can be used to disentangle the different sources of value creation because the option price is non-linear in the underlying stock price, and informed traders take advantage of their private information in the options market (Chakravarty et al., 2004; Patel et al., 2015). Consistent with this notion, Augustin et al. (2015) find that insiders take advantage of their private information regarding upcoming divestiture announcements in the options market as evidenced by abnormal trading in out-of-the-money and at-the-money call options and excess implied volatility.

Second, by overcoming the bias in abnormal returns we examine the extent to which divestitures create value for shareholders. In particular, we address the lack of recent evidence for acquirers of divested assets and reconcile the mixed evidence for sellers of divested assets.

Last, we examine the determinants of value creation arising from divestitures. Possible determinants include the relative size and strategic fit of the divested assets, the revelation of the transaction price and the financial condition of the selling firm (Klein, 1986; Sicherman and Pettway, 1992; John and Ofek, 1995). Our findings are important for a better understanding of the price discovery process and will be of particular interest to stakeholders including managers and shareholders.

We examine an unmatched sample of 1,287 acquisitions and 1,256 sales of divested assets between 1996 and 2012 which have a combined total deal value of more than $500 billion. Our sample consists largely of successful, cash-funded divestiture deals. We find that both acquirers and

[66] Klein (1986) also suggests a similar information hypothesis.

sellers of divested assets earn synergy gains expressed in both percentage and dollar terms following the divestiture announcement. In particular, acquirers (sellers) of divested assets achieve synergy gains of 9% (1%) or $950 ($140) million which is consistent with the acquirer purchasing positive synergies and the seller divesting negative synergies (Hite et al., 1987; Berger and Ofek, 1995).[67] For acquirers the synergy gains earned are partially offset by unfavorable new information about their stand-alone value revealed by the divestiture announcement, that is, losses of 4% or $600 million, consistent with the friendly nature of divestiture deals (Bhagat et al., 2005). In contrast, the divestiture announcement reveals favorable new information about the seller's stand-alone value which is consistent with the bid from the acquirer representing an independent and credible signal that the seller's assets are undervalued (Klein, 1986; Hite et al., 1987).

Using buy-and-hold abnormal returns we find that divestitures increase shareholder wealth by up to $62 million for acquiring shareholders and reduce selling firm shareholder wealth by as much as $492 million. The combination of synergy gains and new information revealed from the announcement shows that the total value created is $350 million for acquirers and $150 million for sellers of divested assets. Our findings show that abnormal returns understate the total value created from divestitures for shareholders.

Our multivariate regressions indicate that revelation of the transaction price in the initial announcement, relatedness of the assets and managerial quality are three key determinants of the value generated by divestitures for acquiring shareholders (Klein, 1986; Sicherman and Pettway, 1987; John and Ofek, 1995). In addition to the financial condition of the seller, we find similar determinants for the total value created from the deal for divesting firms (Myers and Majluf, 1984; Denning, 1988; Brown et al., 1994).

We also compare the total value created by acquisitions of divested assets to acquisitions of stand-alone target firms documented in Barraclough et al. (2013). We find that the acquisition of divested assets has a larger positive effect on shareholder wealth than the acquisition of stand-alone target firms. In addition, the value created for stand-alone target firms is much larger than for sellers of divested assets. Our findings are consistent with a market efficiency explanation; the seller of divested assets is committed to the sale which increases the negotiating leverage of the acquirer. Furthermore, the acquisition of stand-alone target firms is much more competitive than for divested assets (Varaiya and Ferris, 1987; Laamanen et al., 2014). Such differences in the nature of divestiture and takeover deals reduce the probability of the acquirer overpaying for the divested assets, resulting in larger (smaller) changes in shareholder wealth from the acquirer's (seller's) perspective.

There are several reasons why sellers initiate divestitures. First, the seller may benefit from the removal of underperforming assets from its business portfolio. Any benefits depend on the

[67] Few studies calculate abnormal returns expressed in dollar terms and examine the value created for both acquirers and sellers of the same divested assets; Sicherman and Pettway (1992) and Datta et al. (2003) are exceptions.

comparative advantage the acquirer has in managing the divested assets and the number of competing acquirers (Hite et al., 1987; Maksimovic and Phillips, 2001). Second, the seller may eradicate negative synergies in an attempt to reduce agency costs across different business segments and re-focus on their core activities (Berger and Ofek, 1995; Lins and Servaes, 1999). Third, the proceeds from the divestiture can be used to invest in higher yielding projects in existing or new business lines, or to manage debt (Hite et al., 1987; Lang et al., 1995). Last, asset sales may be preferable to the asymmetric information costs associated with equity carve-outs. The costs associated with carve-outs may have an adverse effect on liquidity, cost of capital and the seller's share price (Hite et al., 1987).

The literature which disentangles the different sources of value creation focuses on takeover announcements. Hietala et al. (2003) develop a system of equations to disentangle value creation in two different scenarios. The first is an unsuccessful bid from a single acquirer and the second occurs when there are two competing bids for the same target firm. The authors estimate the following sources of value creation: synergy gains, new information revealed about the stand-alone value of involved parties and whether the acquiring firm overpaid for the target firm. In their system of equations the authors use stock price information only and so the different sources of value can only be estimated for the two aforementioned scenarios.[68]

Bhagat et al. (2005) acknowledge that abnormal returns are a downward biased measure of value creation on the announcement date because there is some probability that the deal will fail, even for deals which ultimately succeed. The authors develop two alternative approaches to overcome the limitations of using the stock price reaction alone to examine value creation from takeovers. The first approach – the probability scaling method, uses ex-post data to scale upward the value created from unsuccessful takeover bids. The second approach – the intervention method, requires other material information to be released on the same day as the takeover announcement (i.e., a competing bid). This additional information is used to minimize the downward bias inherent in announcement abnormal returns.

In addition to stock prices, Bester et al. (2011), Barraclough et al. (2013) and Borochin (2014) use option prices to disentangle the different sources of value around takeover announcements. Bester et al. (2011) develop an arbitrage-free pricing formula to estimate the probability of deal success and the future target firm share price should the bid fail for 282 cash mergers. More recently, Borochin (2014) uses a Bayesian approach to evaluate the expected state-contingent stock price for 30 large takeover announcements.

The methodology employed in this chapter is similar to Barraclough et al. (2013). They use exchange-traded call option prices to develop a system of equations that is used to identify different sources of value creation from the takeover announcement. In contrast to Hietala et al. (2003), the use of both stock and option prices is advantageous and can disentangle the different sources of value for

[68] Another restriction is that the probability of the deal succeeding must equal to 0 (1) for the first (second) scenario to allow the estimation of the different sources of value.

the more general takeover scenario in which a single acquiring firm bids for the target firm. For 167 takeover bids the expected synergies total 34% of which are largely subsumed by the target firm and rationalize the large premiums paid by the acquiring firm for the target firm. In addition, the takeover announcement is found to reveal favorable new information about the target firm and unfavorable new information about the acquiring firm, regarding their stand-alone values. Of particular note, abnormal returns understate synergy gains for both parties which reconciles with the common finding that takeovers do not create value. A limitation of this model is that it requires both the acquiring firm and the target firm to have listed exchange-traded options, meaning the analysis is limited to larger, more liquid firms. In addition, these authors theoretically extend their model to allow the different sources of value creation to be determined when two acquiring firms competitively bid for the same target firm.

Section 4.2 details our data sources and sample selection criteria. Section 4.3 explains our methodology for calculating abnormal returns and for disentangling the different sources of value creation. Section 4.4 presents and discusses the different sources of value created by US divestitures and Section 4.5 concludes the chapter.

4.2. Data and sample selection

This chapter examines US divestiture announcements between January 1, 1996 and December 31, 2012. We obtain deal information for each divestiture announcement from the *Securities Data Company* (*SDC*) *Platinum US M&A database*, daily stock data from the *Center for Research in Security Prices* (*CRSP*) *daily master file*, daily option data and risk-free rate data from *OptionMetrics* and accounting data from *COMPUSTAT*.[69]

We extract 29,708 US divestiture announcements from *SDC*. As a starting point we exclude the following transactions: spinoffs, carve-outs, joint ventures, privatizations, buybacks and recapitalizations. Other sample selection constraints that we apply include: i) we exclude deals in which the acquiring firm has a toehold of greater than 50% in the target firm to focus on a sample of deals that are a surprise to the market, ii) the acquiring firm must seek to own 100% of the divested assets, iii) the consideration from the acquiring firm must be 100% cash or 100% common stock, iv) we exclude bids if the deal status is unknown, rumoured or pending, v) we exclude bids which have competing acquiring firms, vi) we exclude deals which include collar restrictions, and vii) we require the acquiring and selling firms to have a series of listed exchange-traded options. For our sample of acquirers of divested assets we match between *SDC*, *CRSP* and *OptionMetrics* using CUSIP and ticker codes. For our sample of sellers of divested assets we match between *SDC*, *CRSP* and *OptionMetrics* using the ultimate parent CUSIP and ultimate parent ticker codes. After applying the

[69] Our sample begins on January 1, 1996 as options data is unavailable prior to this date.

aforementioned criteria we have an unmatched sample of 1,287 acquirers and 1,256 sellers of divested assets.[70]

4.3. Methodology

4.3.1. Abnormal returns

We calculate buy-and-hold abnormal returns (AR) in a similar vein to Barber and Lyon (1997). For each acquirer and seller of divested assets we use Equation (4.1) to calculate AR as the excess return of the stock (R_{it}) over the *CRSP* value-weighted index (R_{mt}).

$$BHAR_{i\tau} = \prod_{t=1}^{\tau}[1 + R_{it}] - \prod_{t=1}^{\tau}[1 + R_{mt}] \tag{4.1}$$

We reconcile mixed findings in the literature by using three different pre-announcement base dates (τ) to calculate AR, beginning 60, 30 and 5 days prior to the divestiture announcement.

In addition, Moeller et al. (2004) document that studies that use abnormal returns expressed in percentage terms to make inferences about value creation may do so with error. This problem arises because mean percentage abnormal returns treat both small and large firms equally. We circumvent this problem by calculating mean dollar abnormal returns for acquirers and sellers of divested assets. For example, the dollar abnormal returns is calculated as the percentage abnormal returns multiplied by the market capitalization of the firm 60, 30 and 5 days prior to the divestiture announcement.

4.3.2. Stock and option price framework

Similar to the method employed by Barraclough et al. (2013), we disentangle the different sources of value creation for US divestitures by developing a system of stock and option price equations. We apply the same equations to both acquirers and sellers of divested assets. As a starting point, the stock price of Firm A (either an acquirer or seller of divested assets) depends on whether the divestiture ultimately succeeds or fails:

$$A_t = pA_{t+k}^S + (1 - p)A_{t+k}^F \tag{4.2}$$

where A_t is the stock price of Firm A at t, A_{t+k}^S is the stock price of Firm A if the offer succeeds at $t+k$, A_{t+k}^F is the stock price of Firm A if the offer fails at $t+k$, and p is the probability of deal success.

[70] For sellers of divested assets if we match across data sources using CUSIP and ticker codes we find only seven matches. In a typical divestiture announcement on *SDC*, the acquirer will purchase divested assets from the ultimate parent of the target firm (seller of divested assets). We find only 121 matching acquirers and sellers of divested assets. There are several reasons why we obtain only 121 matching acquirers and sellers of divested assets including the acquirer or seller: i) operates in a foreign country, ii) is a private firm and, iii) does not have at least four listed exchange-traded options on the announcement date.

Equation (4.2) is similar to $A_t = e^{-r(t+k)}E[A_{t+k}]$, except that we assume that the time between when the announcement is made (*t*) and the offer either succeeds or fails (*t*+*k*) is a short period to avoid accounting for the time value of money. The total value change of Firm A upon the successful acquisition of divested assets or sale of divested assets is simply:

$$A_{t+k}^{S} - A_{t-1}. \tag{4.3}$$

If the announced deal fails, then the total value change of Firm A can be calculated by adding and subtracting A_{t+k}^{F} to Equation (4.3):

$$(A_{t+k}^{S} - A_{t+k}^{F}) + (A_{t+k}^{F} - A_{t-1}). \tag{4.4}$$

Thus, the different sources of value for Firm A are as follows:

$$\textit{Synergy gains to Firm A} = (A_{t+k}^{S} - A_{t+k}^{F}) \tag{4.5a}$$

$$\textit{New information about Firm A} = (A_{t+k}^{F} - A_{t-1}) \tag{4.5b}$$

The intuition behind Equations (4.5a) and (4.5b) is described by both Bradley et al. (1983) and Hite et al. (1987). If the deal fails then the divestiture announcement will reveal new information about the stand-alone value of Firm A (represented by Equation (4.5b)), however, if the deal succeeds then the remainder of the total value change must be attributed to the synergy gains to Firm A (represented by Equation (4.5a)).

As documented in Barraclough et al. (2013), the isolation of the different sources of value created by the divestiture (represented in Equations (4.5a) and (4.5b)) using stock price Equation (4.2) only is problematic because at time t we only observe the stock price (A_t) and we have three unknown parameters – A_{t+k}^{S}, A_{t+k}^{F} and p. In order to estimate these unknown parameters we can use exchange-traded call option prices written on Firm A. The use of option prices to disentangle the different sources of value creation is possible because option prices are non-linear functions of the underlying stock price. Also, option prices are set by different investors with a different information set, meaning that each option provides additional information about the sources of value generated by the divestiture.

The use of call options to disentangle the different sources of value creation, rather than put options, is advantageous for several reasons. First, put options are likely to be mispriced during takeover or divestiture announcements (Barraclough et al., 2013). The increased demand for put options requires a market maker (who takes the other side of the put option contract) to delta-hedge via short selling the stock. As a result, the market maker passes on the cost of short selling the stock to investors by increasing put option prices. This problem does not arise for call options because delta-hedging a call option requires taking a long position in the stock. Second, the options in our sample are American-style and there is no standard method for estimating the value of American put options. Third, Augustin et al. (2015) document increased levels of informed trading in out-of-the-money and at-the-money call options, rather than similar put options, around divestiture announcements. Thus, call option prices will be more informative about the different sources of value creation. The value of a call option for Firm A can be formulated as follows:

$$c_t(A_t; X) = p\hat{c}_t(A^S_{t+k}, \sigma^S_{t+k}; X) + (1-p)\hat{c}_t(A^F_{t+k}, \sigma^F_{t+k}; X) \tag{4.6}$$

where: $c_t(A_t; X)$ is the call option price with exercise price X for Firm A at t, $\hat{c}_t\left(A^S_{t+k}, \sigma^S_{t+k}; X\right)$ is the call option price of Firm A for a successful deal dependent upon the future share price and volatility of Firm A at $t+k$, and $\hat{c}_t\left(A^F_{t+k}, \sigma^F_{t+k}; X\right)$ is the call option price of Firm A for a failed deal dependent upon the future share price and volatility of Firm A at $t+k$. The future call option prices ($\hat{c}_t(\dots)$) detailed in Equation (4.6) are estimated using the Black-Scholes option pricing model. Again, to avoid accounting for the time value of money we assume the time between t and $t+k$ is a short period.

Using a combination of Equations (4.2) and (4.6), that is, using one stock price equation and four call option price equations, permits the estimation of the five unknown parameters – $p, A^S_{t+k}, A^F_{t+k}, \sigma^S_{t+k}$ and σ^F_{t+k}. Following on, we use the estimated parameters to disentangle the synergy gains and new information revealed by the divestiture announcement for Firm A. We report synergy gains and new information revealed by the divestiture for both acquirers and sellers of divested assets expressed in percentage terms by dividing Equations (4.5a) and (4.5b) by three different pre-announcement base date prices (A_{t-1}), beginning 60, 30 and 5 days prior to the divestiture announcement date. In addition, to circumvent a size effect problem documented by Moeller et al. (2004), we express synergy gains and new information for both acquirers and sellers of divested assets in dollar terms. For example, the dollar synergy gains to the acquirer of divested assets is calculated by multiplying the percentage synergy gains by the market capitalization of the acquirer 60, 30 and 5 days prior to the divestiture announcement.

4.3.3. Estimation of parameters

We estimate five unknown parameters in Equation (4.7) by minimizing the sum of squared errors from the stock and call option price equations developed in the previous section (Barraclough et al., 2013). In this model we require one stock price equation ($n_S = 1$) and at least four call option price equations ($n_O \geq 4$) and construct Equation (4.7) by rewriting each equation in terms of its error term (ε_i).

$$
\begin{aligned}
Minimize \sum_{i=1}^{n_S+n_O} (w_i \varepsilon_i)^2 \\
&= 1\left[A_t - pA^S_{t+k} - (1-p)A^F_{t+k}\right]^2 \\
&+ \left\{0.5\frac{\gamma_X}{\gamma_{X^*}}\left[c_{1t}(A_t;X_1) - p\hat{c}_{1t}\left(A^S_{t+k},\sigma^S_{t+k};X_1\right) - (1-p)\hat{c}_{1t}(A^F_{t+k},\sigma^F_{t+k};X_1)\right]\right\}^2 \\
&+ \cdots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \ldots \\
&+ \left\{0.5\frac{\gamma_X}{\gamma_{X^*}}\left[c_{nt}(A_t;X_n) - p\hat{c}_{nt}\left(A^S_{t+k},\sigma^S_{t+k};X_n\right) - (1-p)\hat{c}_{nt}(A^F_{t+k},\sigma^F_{t+k};X_n)\right]\right\}^2
\end{aligned}
\tag{4.7}
$$

We apply delta weights (w_i) to each stock and option price equation. We apply a weight of 1 to the stock price equation as the delta of the underlying asset is equal to 1. For each call option price equation we apply a combination of delta and gamma weights ($0.5\frac{\gamma_X}{\gamma_{X^*}}$).[71] The intuition for applying this weighting methodology is that relative to the stock price, the gamma of at-the-money options contains the highest level of information regarding the different sources of value creation when compared to out-of-the-money and in-the-money options. As a result, our model gives a larger weight to at-the-money call options and is our attempt to account for the well-documented implied volatility smile. We calculate the gamma for each call option (γ_X) and the equivalent gamma for the at-the-money call option (γ_{X^*}), where $X^* = Se^{(r+0.5\sigma^2)T}$. We multiply $\frac{\gamma_X}{\gamma_{X^*}}$ by 0.5 because at-the-money call options have a delta of 0.5.[72] In Equation (4.7) we only use call options that are the first to expire following the date on which the divestiture is completed or withdrawn. This way our findings are not influenced by the term structure of implied volatility.

We use pre-announcement prices and return volatility as starting values to estimate future stock prices and volatility, midpoint stock and call option prices as inputs into the model and we adjust stock prices for cash dividends which occur prior to the maturity of the call option.[73]

4.4. Results

4.4.1. Descriptive statistics

Table 4.1 Panel A reports descriptive statistics for our unmatched sample of US acquirers and sellers of divested assets between 1996 and 2012. Similar to prior divestiture studies, for both parties we observe that more than 98% of the deals ultimately succeed and are funded using cash (Datta et

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[71] For robustness we apply vega weights and obtain similar results.

[72] Note, r is the continuously compounded risk-free rate, σ is the annualized standard deviation of returns and T is the time to maturity.

[73] Due to differences between cumulative adjustment factors in the *CRSP* and *Optionmetrics* databases, we exclude deals in which stock dividends or stock splits occurred prior to the maturity of the call option.

al., 2003). In addition, none of the deals are classified as hostile and we exclude deals in which the acquirer has a toehold prior to the announcement date. Using a two-digit SIC code, approximately 35% of the deals are between acquirers and sellers operating in the same industry, or 20% using a four-digit SIC code. On average, the deal value is $195 million for acquirers and $214 million for sellers of divested assets, and it takes approximately 45 days for the deal to conclude.

<Table 4.1 here>

Panel B compares descriptive statistics for our sample of divestitures to other US divestitures reported in the *SDC* database that do not meet our sample selection criteria. Our sample includes 32% of the total acquirers and 43% of the total sellers of divested assets reported by *SDC*. The percentage of successful and cash-funded deals is similar in the two samples, however, firm characteristics suggest that our sample includes larger acquirers and sellers of divested assets. We report that our sample of acquirers and sellers are approximately four times larger by market capitalization, have larger daily dollar volumes (three times larger in magnitude) and smaller annualized stock return volatility. Similar to Barraclough et al. (2013), our sample contains larger firms because we require the acquirer and seller of divested assets to have exchange-traded options. For example, to have listed options on the Chicago Board Options Exchange a stock must have more than seven million shares on issue, more than 2,000 shareholders, and trading volume that exceeds 2.4 million shares in the previous year (Mayhew and Mihov, 2004).

<Table 4.2 here>

Table 4.2 reports the mean number of options series, open interest, trading volume and implied volatility for call options during the pre-announcement period and on the announcement date. For acquirers and sellers we find that the number of option series, open interest and trading volume increases on the announcement date in response to increased demand for new call options when new information is released into the marketplace. The number of option series and open interest increases by approximately 3% and 4% for the acquiring and selling firms, respectively. In comparison to acquirers, we observe for sellers a much larger increase in trading volume on the announcement date (3.1% versus 12.7%), which is consistent with sellers being twice as large (as measured by market capitalization) and with such deals attracting more investor attention. The pervasive level of informed trading prior to the divestiture announcement, in particular in at-the-money call options, could explain why we do not observe larger changes in call option trading activity on the announcement date (Augustin et al., 2015). The increases in the number of option series, open interest and trading volume on the announcement date suggest that options contain an additional piece of information that can be

used to solve the identification problem outlined in Section 4.3.2, allowing for the estimation of the different sources of value arising from divestitures.

In contrast, Barraclough et al. (2013) document that the number of option series, open interest and trading volume increase by 28.5% (25%), 90.6% (168.4%) and 212.3% (1619.8%) for acquiring (target) firms, respectively, during takeover announcements. The much larger increase in option activity in takeovers compared to divestitures can be explained by the fact that takeovers are the purchase of an entire target firm and attract more widespread attention.

4.4.2. Minimum sum of squared errors

Table 4.3 presents descriptive statistics for the minimum sum of squared errors estimation procedure that we perform using Equation (4.7). Our sample mainly consists of successful cash-funded divestitures and so our analysis focuses on these particular deals. For each announcement we estimate five unknown parameters – $p, A_{t+k}^{S}, A_{t+k}^{F}, \sigma_{t+k}^{S}$ and σ_{t+k}^{F}, that require at least four exchange-traded options listed on the acquirer or seller of divested assets (in addition to the stock price series). For our sample of acquirers and sellers of divested assets there are approximately nine and ten exchange-traded options available on the divestiture announcement date ($Noptions$), respectively, indicating that our estimation model is over-identified. On average, the minimum sum of squared errors ($MinSSE$) is very close to 0 which adds support to estimates obtained from our model.

<Table 4.3 here>

The minimum sum of squared errors model that we employ also estimates the ex-ante probability that the divestiture will succeed (P). For both acquirers and sellers we find that the market can distinguish between deals which ultimately succeed and deals which fail. The mean probabilities of success for completed deals, for acquirers and sellers respectively, are 0.66 and 0.71. These are larger than the corresponding probabilities of 0.46 and 0.59 for withdrawn deals. In addition, for acquirers and sellers the median probability of success for completed deals is 0.74 and 0.83 respectively, compared to 0.39 and 0.62 for withdrawn deals. We report that most divestitures eventually succeed, our median estimates for the probability of success for such deals are reasonable and provide additional support to the estimates of value creation obtained from the minimum sum of squared errors model. We also observe that the probability of success for withdrawn deals is larger for sellers than for an unmatched sample of acquirers. This finding is consistent with the notion that the seller initiates the deal with the intention of successfully divesting assets from its portfolio.

4.4.3. Sources of value creation expressed in percentage terms

The output of our minimum sum of squared errors model allows for the estimation of the different sources of value created from divestitures. Table 4.4 reports buy-and-hold abnormal returns (AR), synergy gains ($Synergy$) and new information revealed about stand-alone values ($News$) for our sample of acquirers and sellers of divested assets expressed in percentage terms. Again, our analysis focuses on successful cash-funded divestitures. Similar to prior studies, we find that both acquirers and sellers of divested assets earn significantly positive buy-and-hold abnormal returns. For the full sample both parties earn abnormal returns of a similar magnitude, acquirers earn abnormal returns between 0.42% and 1.96%, and sellers earn between 0.89% and 1.43%.

The difficulty with using abnormal returns to make inferences about value creation is that it confounds several different sources of value, including synergy gains, new information revealed about the stand-alone value of the involved parties and the probability of deal success (Bradley et al., 1983; Hite et al., 1987). In addition, announcement date abnormal returns understate the value created from the deal as the market imputes some probability that the deal will fail, even for deals that eventually succeed (Hietala et al., 2003; Bhagat et al., 2005; Barraclough et al., 2013).

We find that, irrespective of the base price used, the acquirer of successful, cash-funded divested assets obtains significant synergy gains of approximately 9.15% from the deal. Using a base price of t-30, synergy gains to the acquirer are more than twelve times larger than respective abnormal returns. For similar transactions, sellers achieve smaller, but significant synergy gains of approximately 1.03%, similar in magnitude to buy-and-hold abnormal returns. Our results are consistent with the acquirer purchasing positive synergies or assets in which they have a comparative advantage in managing, and the seller divesting negative synergies in order to re-focus on core operations, consistent with the findings of Hite et al. (1987) and Berger and Ofek (1995). Although of a different magnitude, our findings show that both acquirers and sellers of divested assets achieve synergy gains for deals that are withdrawn or funded using common stock.

<Table 4.4 here>

In addition to identifying the synergy gains from the deal, our methodology is also able to disentangle new information revealed by the divestiture announcement about the stand-alone value of both parties. For the acquirer of divested assets the announcement reveals unfavorable new information of approximately -4.60%, using a base price of t-30 or t-5. Given that divestitures are friendly transactions; our findings are consistent with Bhagat et al. (2005) who suggest that in comparison to hostile bids, the market will revise downwards the acquirer's stand-alone value for friendly deals because such deals indicate poorer cash-flow prospects and a weaker alignment of principal and agent interests. Using a base price of t-5 we observe that the unfavorable new information revealed by the announcement is similar in magnitude to the synergy gains resulting from 19 stock-funded deals.

New information revealed about the stand-alone value of the seller is sensitive to the pre-announcement base price. We observe that the announcement reveals favorable new information causing a 1.10% market price reaction using a base price of *t-60* for successful cash-funded deals. In contrast, using base prices of *t-30* and *t-5* we observe insignificant new information revealed about the seller's stand-alone value.

In contrast to much of the takeover literature, a large number of divestitures are confirmed or effective on the announcement date. We report findings for 408 (879) deals that are confirmed (unconfirmed) on the announcement date for acquirers of divested assets and 425 (831) deals that are confirmed (unconfirmed) on the announcement date for sellers of divested assets. For deals which are confirmed on the announcement date, we observe that synergy gains are offset by unfavorable new information revealed about the stand-alone value for both acquirers and sellers of divested assets. Thus, deals confirmed on the announcement date do not add value to shareholders. These findings are similar using different pre-announcement base prices.

The different sources of value creation are similar in sign but larger in magnitude for unconfirmed deals when compared to our full sample results. Although acquirers earn larger synergy gains of 12.4%, this is offset by more unfavorable new information revealed about its stand-alone value (-6.0%). One key difference to our full sample results is that the announcement reveals significant and favorable new information about the seller of divested assets (2.08% using a base price of *t-60*), which is consistent with the acquirer's bid representing an independent and credible signal that the seller's assets are undervalued (Klein, 1986; Hite et al., 1987). An explanation for the larger reaction to unconfirmed (non-signed) deals is that such deals are associated with higher levels of information asymmetry (Krishnaswami and Subramaniam, 1999). For example, we could expect larger changes in the seller's shareholder value for unconfirmed deals due to the arrival of competing bids or subsequent revisions in offer price (Hite et al., 1987; Jindra and Walkling, 2004). Alternatively, if the seller is financially constrained, then this may increase the negotiating leverage of the acquirer and result in larger value creation from unconfirmed deals (Sicherman and Pettway, 1992). We note that our sample of unconfirmed deals for acquirers contains i) 90% of deals in which the relative size of the divested assets is greater than 10% of the selling firm, ii) 69% of total deals in which the acquirer and seller have the same two-digit SIC code, iii) 68% of deals in which the acquirer and seller both operate in the US, and iv) 91% of deals in which the seller is actively seeking an acquirer on the announcement date. A combination of these features may result in larger synergies and reveal favorable or less unfavorable new information about the acquirer's stand-alone value. We examine the determinants of value creation within a panel regression framework in Section 4.4.6.

The combination of synergy gains and new information regarding stand-alone value suggests the total value created for successful cash-funded divestitures is approximately 5% (= 9% - 4%) for acquirers and 2% (= 1% + 1%) for sellers of divested assets which is consistent with both parties viewing the divestiture as a positive net present value decision (Rosenfeld, 1984). Using a base price of *t-30*, the total value created from successful cash-funded divestitures is more than six times larger in magnitude than when calculated using buy-and-hold abnormal returns for acquirers, and at least a third as large for sellers of divested assets. Our findings show that prior studies which draw conclusions using abnormal returns understate the total value created from divestitures.

4.4.4. Sources of value creation expressed in dollar terms

In this section we estimate the different sources of value creation expressed in dollar terms to ensure our results in Table 4.4 are not driven by a size effect documented by Moeller et al. (2004). Table 4.5 reports mean dollar abnormal returns ranging between \$31 million and \$62 million for our full sample of acquirers. Prior studies document similar changes in shareholder wealth ranging between -\$8 million and \$24 million (Sicherman and Pettway, 1992; Datta et al., 2003). Using pre-announcement base prices of *t-60* and *t-30*, we document a size effect, that is, a difference in sign between abnormal returns calculated in percentage and dollar terms for sellers of divested assets. In dollar terms, sellers of divested assets earn negative abnormal returns of up to -\$427 million from successful cash-funded deals.[74]

<Table 4.5 here>

Our full sample findings show that both acquirers and sellers of divested assets achieve significant synergy gains of approximately \$950 and \$140 million, respectively, across different base prices. Similar findings are observed for successful and cash funded deals. In addition, the divestiture announcement reveals unfavorable new information about the stand-alone value of the acquirer of divested assets totalling approximately \$600 million. We observe mixed findings for sellers of divested assets. As the base price approaches *t=0*, the announcement reveals less unfavorable new information about the stand-alone value of the seller for cash-funded deals.

Similar to our findings in Table 4.4, the value created from deals that are confirmed or effective on the announcement date are marginal when compared to unconfirmed deals.[75] Unconfirmed deals result in larger synergy gains and larger unfavorable new information revealed about the acquirer's stand-alone value (\$1,320 million versus \$830 million). Again, a key difference when compared to our full sample findings is that the announcement reveals favorable new information about the seller ranging between \$47 million and \$179 million.

[74] Sicherman and Pettway (1992) and Datta et al. (2003) report dollar abnormal returns ranging between \$13 and \$62 million for sellers of divested assets.
[75] Using base prices of *t-60* and *t-30* suggests that divestitures are value-destroying for sellers if the deal is confirmed on the announcement date.

Our findings expressed in dollar terms are largely similar to those expressed in percentage terms in Table 4.4, meaning our results are not subject to the size effect documented by Moeller et al. (2004). Using a base price of *t-30*, we find that the total value created from divestitures is \$370 million (= \$985 million - \$615 million) for acquirers of divested assets, which is more than eight times larger than estimated using buy-and-hold abnormal returns. The divestiture increases shareholder wealth of sellers by \$122 million (= \$75 million + \$47 million) for deals unconfirmed on the announcement date. Similar buy-and-hold abnormal returns suggest that divestitures are value-destroying (-\$92 million). In contrast to using abnormal returns as a measure of value creation, our methodology and findings suggest that divestitures actually create value for acquiring and selling firm shareholders.

4.4.5. The determinants of abnormal returns

We examine the determinants of buy-and-hold abnormal returns – the standard measure for value creation used in the finance literature. The purposes of this section are to show that abnormal returns are amalgamations of the total value created from divestitures as calculated using our option price methodology, and to show that abnormal returns on the announcement date will understate the value created to involved parties because the market imputes some probability that the deal will fail (Bhagat et al., 2005). The dependent variable is announcement date buy-and-hold abnormal returns (AR) and the independent variables include: the total value created from the divestiture (TVC) which is calculated as the summation of the synergy gains ($Synergy$) and new information revealed about the stand-alone value of involved parties ($News$), and the probability of deal success (P). In addition, to control for omitted variable bias we apply both industry and year fixed effects. We run a series of regressions in which AR and TVC are expressed in percentage and dollar terms and calculated using pre-announcement base prices of *t-60*, *t-30* and *t-5*.

<Table 4.6 here>

Table 4.6 Panel A reports results for acquirers and Panel B reports results for sellers of divested assets. In all twelve specifications, we observe a significantly positive relationship between AR and TVC. Such findings indicate that AR is a function of TVC and suggest that our estimates of the different sources of value creation obtained from our option price methodology are in the same ballpark as the conventional method for estimating changes in shareholder wealth.

In addition, Panel A documents a significantly positive relation between P and AR in all six specifications. Note that the probability of deal success has an inverse relation with the probability of deal failure ($1 - P$), that is, there is a negative relation between the probability that the deal fails and AR. Consistent with this notion, our findings suggest that abnormal returns on the announcement date are depressed as the market imputes some probability that the deal will fail. Panel B reports similar findings when AR are expressed in dollar terms only.

4.4.6. The determinants of the value created by divestitures

To better understand what drives value creation around divestitures we examine several competing hypotheses in a multivariate regression framework, including i) relative size of assets, ii) revelation of transaction price, iii) confirmed deal at the time of the initial announcement, iv) relatedness of assets, v) over-diversified seller, vi) financial condition of the seller, vii) cross-border deals, viii) managerial quality, and ix) private versus public deals. We attempt to examine a more complete set of determinants of the value created by divestitures, rather than specific determinants examined in prior studies. We report results using buy-and-hold abnormal returns (AR), but focus on total value creation (TVC) calculated as the summation of synergy gains ($Synergy$) and new information revealed about the stand-alone value of involved parties ($News$), as it provides a cleaner measure of changes in shareholder wealth.

Klein (1986) examines several determinants of abnormal returns for voluntary asset sell-offs including: i) relative size, ii) revelation of transaction price, and iii) signed (or confirmed) agreements at the time of the initial announcement. First, the relative size of asset sales can be associated with larger abnormal returns, as such deals have a larger material effect on shareholder wealth. Klein finds abnormal returns of 0.54%, 2.53% and 8.09% when the relative size of the deal is less than 10%, between 10% and 50%, and greater than 50% of market value, respectively.[76] John and Ofek (1995) and Lang et al. (1995) document similar findings. We expect to observe a monotonic relation between the value created from divestitures and the relative size of the deal.

Second, Klein (1986) suggests that the revelation of the transaction price will provide information about the net present value of the divestiture.[77] For the seller of divested assets, abnormal returns of 2.47% are observed for announcements that specify the transaction price versus 0.02% when the transaction price is omitted in the initial announcement. Similarly, Sicherman and Pettway (1992) suggest that failure to disclose the transaction price will be a negative signal to the acquirer as to the quality of the divested assets. They find abnormal returns of 0.82% (1.48%) for acquirers

[76] Augustin et al. (2015) find consistent findings for their sample of divestitures that includes both asset sell-offs and spin-offs. A number of studies that examine spin-offs find increased value creation for larger deals (Hite and Owers, 1983; Miles and Rosenfeld, 1983; Krishnaswami and Subramaniam, 1999; Veld and Veld-Merkoulova, 2004).

[77] Similarly, Lee and Madhavan (2010) note that the transaction price is not always revealed in the announcement and suggest that the transaction price can be used as a signal as to the subsequent performance of the divestiture. Myers and Majluf (1984) suggest that the revelation of the transaction price reduces information asymmetry about the value of the divested assets between managers and shareholders.

(sellers) of divested assets when the transaction price is revealed in the announcement and close to 0% for both parties when the price is not revealed.[78]

Last, Klein (1986) examines whether the revelation of the transaction price is a proxy for the probability of deal success. She suggests an increased probability of deal success for a signed (or confirmed) agreement between the involved parties on the announcement date. The abnormal returns for signed agreements that report the transaction price is 1.62%, a fraction of the abnormal returns of 6.79% for non-signed agreements that report the transaction price. Within a multivariate framework, both relative size and transaction price are found to significantly explain abnormal returns, even after controlling for signed agreements, which suggests that the transaction price is not a proxy for the probability of deal success.

The strategic fit or relatedness of divested assets is an important determinant of the value created from the deal. Sicherman and Pettway (1987) show that the acquirer of divested assets benefits from purchasing related assets which can be managed more efficiently when compared to the purchase of unrelated assets, that is, 3.23% versus -0.75%, respectively.[79] The seller of divested assets benefits from selling off unrelated assets or negative synergies, as such firms can refocus on their core business activities (Rosenfeld, 1984; Hite et al., 1987; Datta et al., 2003). For example, John and Ofek (1995) report that abnormal returns are 2.4% higher for sellers that divest unrelated assets when compared to related assets. To capture the strategic fit of divested assets, past studies have examined whether the acquirers and sellers of divested assets share similar industry SIC codes (Sicherman and Pettway, 1987; John and Ofek, 1995; Augustin et al., 2015).

The "negative synergy" (Berger and Ofek, 1995; Lins and Servaes, 1999) and "empire-building" (Jensen and Meckling, 1976) theories both suggest that over-diversified firms underperform when compared to firms which focus on core operations. Such underperformance arises due to agency costs and inefficient use of resources. Subsequently, Haynes et al. (2003) and Ahn and Walker (2007) show that over-diversified firms are more likely to divest assets in an attempt to focus on core operations. We also examine the impact asset sales made by over-diversified firms have on shareholder wealth.

A number of studies suggest that the lower bargaining power of financially constrained sellers will force such firms to sell at a discount, resulting in marginal changes in shareholder wealth (Shleifer and Vishny, 1992; Pulvino, 1998; Brau et al., 2003; Lee and Madhavan, 2010). Alternatively, the sale of divested assets by financially constrained firms increases slack and reduces the probability of default, which increases firm value (Myers and Majluf, 1984; Denning, 1988; Brown et al., 1994). In support of this notion, Sicherman and Pettway (1992) document that financially constrained sellers earn larger dollar abnormal returns of $11 million versus $1 million for

[78] In dollar terms, the acquirer (seller) earns abnormal returns of $31 ($15) million when the transaction price is revealed and -$11 ($11) million if the transaction price is not revealed.

[79] A similar rationale is that the acquirer can extract larger rents from the divested assets than the seller (Alexander et al., 1984; Hite et al., 1987; John and Ofek. 1995; Vijh, 1999; Laamanen et al., 2014). Datta et al. (2003) find that if the acquirer purchases related (unrelated) assets they earn $6 (-$62) million.

sellers with a strong financial position. Further, a matching sample of acquiring firms earns abnormal returns of \$1 million by purchasing divested assets from a financially strong seller when compared to \$37 million from a financially constrained seller.

A deal between acquirers and sellers operating in different countries is another important determinant of value creation. For the selling firm, the divestiture of assets operating in foreign countries will incrementally reduce monitoring costs when compared to the sale of domestic assets, and will have a positive effect on shareholder wealth (Augustin et al., 2015). In addition, foreign acquirers are likely to pay a larger premium to set up operations in other markets (Borisova et al., 2010). This will result in positive effects on shareholder wealth if the seller is divesting domestic assets, or if it is divesting assets operating in a different country to the foreign acquirer.

Datta et al. (2003) examine the relation between managerial quality and abnormal returns resulting from the divestiture decision. The takeover literature finds that the value created for both parties individually and combined is larger when a bidder with strong manager quality purchases a target with poor manager quality, where Tobin's Q is used as a proxy for manager quality (Lang et al., 1989; Servaes, 1991). Datta et al. (2003) find increased value creation for acquirers of similar divestiture transactions. In addition, they find that abnormal returns for sellers is a function of manager quality consistent with better quality managers having the ability to effectively use the funds raised from the divestiture to increase shareholder wealth.

A factor that has received much less attention in the literature is the acquisition of privately-held divested assets. In comparison to acquisitions of publicly-held assets, privately-held assets will be sold at a discount as a result of a less competitive and liquid market, and because of the increased levels of information asymmetry associated with privately-held assets (Silber, 1991; Koeplin et al., 2000; Capron and Shen, 2007; Ragozzino and Reuer, 2007). Consistent with this notion, Laamanen et al. (2014) find that the announcement abnormal returns from acquisitions of privately-held stand-alone assets (0.02%) is greater than those from publicly-held stand-alone assets (-2.40%) in the US software industry. In addition, these authors find larger abnormal returns associated with acquisitions of divested assets (0.80%) consistent with the market for divested assets being less competitive and liquid than the market for privately- and publicly-held stand-alone acquisitions.

We examine the determinants of value creation arising from the divestiture using a panel regression framework:

$$\begin{aligned} VC_{it} = \alpha + \beta_1 RelSize_{it} + \beta_2 PriceDV_{it} + \beta_3 UnconfirmDV_{it} + \beta_4 FitDV_{it} + \beta_5 Leverage_{it} \\ + \beta_6 DomesticDV_{it} + \beta_7 TobinQ_{it} + \beta_8 PublicDV_{it} + \sum\nolimits_j \gamma_j \, Controls_{j,it} + \varepsilon_{it} \end{aligned} \tag{4.8}$$

where VC_{it} is value creation on the announcement date measured by i) buy-and-hold abnormal returns (AR_{it}), synergy gains ($Synergy_{it}$), iii) new information revealed about stand-alone value ($News_{it}$), and iv) total value creation (TVC_{it}) calculated as the summation of $Synergy_{it}$ and $News_{it}$. We measure the determinants of value using the following variables: $Relsize_{it}$ is the value of the deal scaled by average market capitalization during the 60-day pre-announcement period, $PriceDV_{it}$ is a dummy variable equal to one if the transaction price was revealed in the initial divestiture announcement, $UnconfirmDV_{it}$ is a dummy variable equal to one if the divestiture was not signed (not effective) by the acquirer and seller on the initial announcement date, $FitDV_{it}$ is a dummy variable equal to one if the acquirer and ultimate parent of the seller share the same four-digit SIC code, $CoreDV_{it}$ is a dummy variable equal to one if the divested assets and ultimate parent of the seller share the same four-digit SIC code, $Diverse_{it}$ is the number of four-digit SIC codes associated with the seller of divested assets, $Leverage_{it}$ is book value of debt scaled by market value of assets, $Coverage_{it}$ is earnings before interest and tax scaled by interest expense, $DomesticDV_{it}$ is a dummy variable equal to one if the acquirer and ultimate parent of the seller are based in the US, $TobinQ_{it}$ is market value of assets scaled by book value of assets, and $PublicDV_{it}$ is a dummy variable equal to one if the divested assets were publicly-held. In addition, we include several deal and firm control variables: $Withdrawn_{it}$ is a dummy variable equal to one if the status of the deal is withdrawn, $Days_{it}$ is number of days until the deal is completed or withdrawn, $SeekingDV_{it}$ is a dummy variable equal to one if the seller was seeking an acquirer on the initial announcement date, $CashDV_{it}$ is a dummy variable equal to one if the acquirer used cash only to purchase the divested assets, $OptionVolDV_{it}$ is a dummy variable equal to one if trading volume in options was greater than zero on the announcement date, $OveridDV_{it}$ is a dummy variable equal to one if there are more than four exchange-traded options used in our minimum sum of squared errors model, and FCF_{it} is operating income before depreciation, tax and capital expenditure scaled by book value of assets. We apply clustered standard errors by industry and by year, industry fixed effects and we winsorize our regression variables at the 5th and 95th percentiles.

<Table 4.7 here>

Table 4.7 reports our regression results. We run several specifications in which the dependent variable is expressed in percentage and dollar terms and is calculated using different pre-announcement base prices (*t-60*, *t-30* and *t-5*). Panels A and B report findings for acquirers and Panels C and D report findings for sellers of divested assets. We focus our analysis on value creation which is estimated using a base price of *t-30* and expressed in dollar (*$*) terms to mitigate the size effect inherent in value creation expressed in percentage (*%*) terms.

The relative size of the divested assets from the acquirer's perspective has a positive and similar relationship with both $\%AR$ and $\%TVC$, however, only significant using a base price of *t-5*. A 1% increase in the relative size of the assets is associated with a 7% increase in shareholder wealth measured using both $\%AR$ and $\%TVC$. Similarly, $\$News$ has a significantly positive relationship with the relative size of divested assets consistent with larger divested assets having a material effect upon shareholder wealth. However, $\$Synergy$ losses offset $\$News$, resulting in decreases in total shareholder wealth. Such decreases could be attributed to the larger net spend on larger divested assets.

For sellers, we find that the relative size of the divested assets has a positive relation with AR and TVC expressed in both percentage and dollar terms. A 1% increase in relative size is associated with a \$7.61 million increase in shareholder wealth. Although statistically insignificant, such value creation is driven by $\$News$ and is consistent with the size of the divested assets having a material effect on shareholder wealth (Klein, 1986; John and Ofek, 1995; Lang et al., 1995).

We report that the revelation of the transaction price in the initial announcement ($PriceDV_{it}$) is a significant determinant of $\$TVC$ for both acquirers and sellers. The coefficient estimates indicate that the revelation of the transaction price is associated with a \$140.5 million and \$430.4 million increase in shareholder wealth for acquirers and sellers, respectively. Our findings are consistent with the transaction price being a signal of the quality of the divested assets (Klein, 1986; Sicherman and Pettway, 1992). In addition, $\$TVC$ for the seller is driven by $\$News$ which is consistent with the transaction price and bid from the acquirer providing a credible piece of new information regarding it's the stand-alone value (Bradley et al, 1983).

The $FitDV_{it}$ is used to capture the relatedness of the divested assets to the acquirer. We document a positive relation between $FitDV_{it}$ and $\$AR$ and $\$TVC$, where $\$TVC$ is driven by $\$News$ (\$141.7 million). Our results are consistent with acquirers being able to extract larger rents from related divested assets when compared to unrelated assets, resulting in positive effects on shareholder wealth (Alexander et al., 1984; Sicherman and Pettway, 1987; Vijh, 1999)

We measure the relatedness of divested assets for sellers in two ways, i) the sale of core assets ($CoreDV_{it}$) and ii) the sale of assets by over-diversified firms ($DiverseDV_{it}$). Consistent with the literature we find that the sale of core assets, rather than non-core assets, reduces shareholder wealth ($\$TVC$) by approximately \$194.3 million (Hite et al., 1987; John and Ofek, 1995; Datta et al., 2003). We also report evidence which suggests that the divestment of assets by over-diversified firms results in significant synergy gains of \$20.6 million consistent with the "negative synergy" hypothesis (Berger and Ofek, 1995; Lins and Servaes, 1999). Our analysis of the relationship between value creation and $CoreDV_{it}$ and $FitDV_{it}$ suggests that firms use divestitures to remove inefficient assets and re-focus on core operations (Haynes et al., 2003; Ahn and Walker, 2007).

There are two clear hypotheses for explaining the relationship between value created from divestitures and the financial condition of the seller. Similar to the results of Sicherman and Pettway (1992), we also find that financially constrained sellers of divested assets (coefficient estimate of the $Coverage_{it}$ variable = -27.8) are associated with increases in shareholder wealth ($\$TVC$). The sale of divested assets raises cash that can be used to reduce the probability of default and increase firm value (Myers and Majluf, 1984; Denning, 1988; Brown et al., 1994). We obtain similar results using $Leverage_{it}$ to capture the financial condition of the seller.

We observe opposing effects of cross-border deals upon the acquirer's shareholder value. We find that purchasing foreign assets is associated with larger $\$Synergy$ of \$253.6 million when compared to purchasing domestic assets, however, domestic assets are associated with favorable $\$News$ of \$298.7 million. Using a base price of *t-5*, we find a significantly negative relation between $DomesticDV_{it}$ and $\$TVC$. Given the entire pool of available domestic and foreign assets, acquirers benefit more from the purchase of idiosyncratic foreign assets.

Similar to Datta et al. (2003) we proxy for managerial quality using $TobinQ_{it}$. We document a significantly positive relation between $TobinQ_{it}$ and $\$TVC$. A 1% increase in $TobinQ_{it}$ is associated with a \$794,000 and \$4.57 million increase in shareholder wealth for acquirers and sellers of divested assets, respectively. For acquirers our results suggest that better quality managers are able to identify value-adding assets, and for sellers our results are consistent with better quality managers having the ability to effectively use the proceeds raised from divestitures to increase shareholder value. We leave it to future research to examine a matched sample of firms to jointly test the value created from divestitures involving high-Q acquirers and low-Q sellers. We also document an insignificant difference between the value created from divestures of privately-held and publicly-held assets ($PublicDV_{it}$).

For both parties of the divestiture we observe a positive relationship between the $UnconfirmDV_{it}$ and $\$TVC$. The increase in shareholder value is attributed to significant $\$Synergy$ (\$265.8 million) for acquirers and to significant $\$News$ for sellers (\$561.4 million).[80] We also observe that deals which ultimately succeed ($WithdrawnDV_{it}$), deals which take longer to conclude ($Days_{it}$) and deals in which the seller is seeking an acquirer on the announcement date ($SeekingDV_{it}$), are associated with positive effects on $\$TVC$ for both firms.[81] In particular, the relationship of these variables with $\$TVC$ suggests that such deals are associated with higher levels of information asymmetry (Krishnaswami and Subramaniam, 1999). For the acquirer this is consistent with the purchase of assets at a more favorable price, perhaps from financially constrained sellers (Shleifer and Vishny, 1992; Pulvino, 1998). For the seller this is consistent with competing acquirers and revisions in offer price, resulting in a more favorable sale price (Hite et al., 1987; Jindra and Walking, 2004).

We also include $OptionVolDV_{it}$ and $OveridDV_{it}$ as additional explanatory variables. We find that deals in which option trading volume was greater than zero on the announcement date are

[80] We also find that the $PriceDV_{it}$ continues to be a significant determinant of $\$TVC$ (after including the $UnconfirmDV_{it}$), which suggests that the transaction price is not a proxy for future deal success, consistent with Klein (1986).

[81] The exception is the relationship between $Days_{it}$ and $\$TVC$ for sellers of divested assets.

associated with a significantly larger market reaction ($\$TVC$) of \$238.4 million and \$106.2 million for acquirers and sellers of divested assets (using a base price of *t-5*), respectively. Similarly, we observe that deals in which our minimum sum of squared errors model is over-identified (i.e., stocks which have more listed options) create more value for acquiring (selling) shareholders of approximately \$285.6 (\$77.2) million. These findings are consistent with informed traders utilizing their private information in the options market and taking advantage of the leverage inherent in options contracts to maximise their investment returns (Chakravarty et al., 2004; Patel et al., 2015).

The bias associated with AR as a measure of value creation is also evident from our regression models. In contrast to using $\$Synergy$, $\$News$ and $\$TVC$ as dependent variables, we observe that the determinants of $\$AR$ are generally insignificant in both the acquirer and seller regressions. Prior studies which use abnormal returns to make inferences about synergy gains, new information revealed about stand-alone value, or total value creation from acquisitions, are convoluted because abnormal returns combine all these sources of value into one number.

4.4.7. Heckman (1979) two-stage sample selection test

In this section we examine whether our findings are driven by a sample selection bias. This bias arises because we require both the acquirer and seller of divested assets to have at least four exchange-traded options in our minimum sum of squared errors model. By definition, larger and more heavily traded firms have exchange-traded options. We apply Heckman's (1979) two-stage methodology to test for sample selection bias.

Mayhew and Mihov (2004) and Barraclough et al. (2013) find that stocks that have listed options are larger and more liquid when compared to stocks without listed options. Specifically, such stocks have a larger market capitalization, are more actively traded and have larger return volatility.[82] The first stage probit regression estimates the probability that the acquiring and selling firms have listed options on the announcement date. The dependent variable is a dummy variable which is equal to one if the divestiture announcement is included in our sample. Independent variables include the following firm characteristics: i) $Capitalization$ is the average market capitalization of the firm during the 60 days prior to the announcement reported in billions, ii) $Volume$ is the average trading volume during the 60 days prior to the announcement date reported in billions, and iii) $Volatility$ is the annualized stock return volatility. We use these three firm characteristics as instruments to identify the sample selection bias. These firm characteristics are likely to be correlated with, and will directly affect the different sources of value creation through the independent variables used in our second stage regression models. We believe this makes these firm characteristics valid instruments as they satisfy the exclusion restriction. Table 4.8 Panel A reports that our sample of acquirers and sellers of

[82] Barraclough et al. (2013) find lower return volatility associated with their sample of target firms when compared to other target firms reported in the *SDC* database.

divested assets are associated with larger market capitalization and trading volume, and lower return volatility when compared to other acquirers and sellers reported in the *SDC* database.

We run several second stage regression specifications. Again, we measure the value created from divestitures using i) buy-and-hold abnormal returns (AR_{it}) and ii) total value creation (TVC_{it}) calculated as the summation of $Synergy_{it}$ and $News_{it}$. The coefficient of interest is the $Inverse\ Mills$ ratio which is obtained from the first stage regression. We also include several determinants of value creation as additional independent variables including: $Relsize_{it}$, $PriceDV_{it}$, $UnconfirmDV_{it}$, $FitDV_{it}$, $Leverage_{it}$, $DomesticDV_{it}$ and $PrivateDV_{i}$. In addition, we include several firm and deal characteristics as control variables including: $CompletedDV_{it}$, $Days_{it}$, $SeekingDV_{it}$, $CashDV_{it}$ and FCF_{it}.

<Table 4.8 here>

The Inverse Mills ratio is significantly positive in two cases for acquirers (Panel B) – $TVC60_{it}$ and $TVC5_{it}$, and in zero cases for sellers (Panel D) when value creation is expressed in percentage terms. Again, we focus our analysis on value creation expressed in dollar terms to mitigate a size effect. We observe in Panel C that the Inverse Mills ratio is significantly negative in five of six cases, indicating that acquirers of divested assets with listed options are associated with lower changes in shareholder wealth as measured using AR and TVC. Panel E reports one case in which the Inverse Mills ratio is significantly negative for sellers of divested assets. Similar to Barraclough et al. (2013) our sample contains sample selection bias. Given that the bias understates, rather than overstates, the large changes in shareholder wealth for acquirers and sellers of divested assets, we still conclude that divestitures are value-creating decisions for both firms.

4.4.8. Comparison to Barraclough et al. (2013)

In this section we compare value creation from the acquisition of divested assets as reported in Tables 4.4 and 4.5 of this chapter to the acquisition of stand-alone target firms documented in Barraclough et al. (2013). Table 4.9 presents the different sources of value creation in both percentage and dollar terms reported by Barraclough et al. (2013) for a sample of 167 takeover announcements between 1996 and 2012. Due to the large number of successful cash-funded divestitures, we focus our comparison on such deals. In addition, we focus on unconfirmed deals on the announcement date as the takeovers examined in Barraclough et al. (2013) are not confirmed on the announcement date.

We find that the total value created to acquirers of successful divested assets is approximately 6% (= 12% - 6%) or \$450 million (= \$1300 million - \$850 million) across different base prices. For similar samples, Barraclough et al. (2013) document that the total value created for acquirers of stand-alone target firms ranges from -1.3% (= 2.9% - 4.2% using a base price of *t-5*) to 3.4%, or -\$133 (=

$2,206 million – $2,339 million using a base price of *t-5*) to $920 million depending on which base date price is used. Using both percentage and dollar terms (the exception using a base price of *t-60*), our findings show that acquisitions of divested assets create more shareholder value than acquisitions of stand-alone target firms.

<Table 4.9 here>

In contrast, the value created for the stand-alone target firm is significantly larger in both percentage and dollar terms when compared to the value created for the seller of divested assets. In percentage and dollar terms, the deal results in the stand-alone target firm achieving value in excess of 35% (= 39.9% + 5.2% using a base price of *t-60*) or $400 million (= $359 million + $57 million using a base price of *t-60*), whereas as the seller of divested assets earns 2.1% (= 0.60% + 1.50%) or $150 million (= $75 million + $75 million).

Our findings are consistent with a market efficiency explanation: the seller of divested assets is committed to the sale which increases the negotiating leverage of the acquirer. Furthermore, the acquisition of stand-alone target firms is much more competitive than for divested assets (Varaiya and Ferris, 1987; Laamanen et al., 2014). Such differences in the nature of divestiture and takeover deals reduce the probability of the acquirer overpaying for the divested assets, resulting in larger (smaller) changes in shareholder wealth from the acquirer's (seller's) perspective. We note that the sample of firms examined in this chapter and in Barraclough et al. (2013) differ in both the number of observations and firm size. The discussion in this section provides a simple comparison between the value created by acquisitions of divested assets and stand-alone target firms.

4.5. Conclusion

We disentangle the different sources of value for US divestiture announcements. The literature commonly uses abnormal returns to measure value creation, however, abnormal returns are downward biased on the announcement date and confound the synergy gains, new information revealed about the stand-alone values of involved parties and the probability of deal success.

For an unmatched sample of 1,287 acquirers and 1,256 sellers of divested assets, we find that acquirers and sellers both earn positive synergy gains consistent with the acquirer purchasing positive synergies and the seller divesting negative synergies. However, such synergy gains are partially offset by unfavorable new information that is revealed from the divestiture announcement about the stand-alone value of the acquirer consistent with the friendly nature of divestiture deals. For the seller, the announcement reveals favorable new information about its stand-alone value consistent with the bid made by the acquirer representing a credible and independent signal that the seller's assets are undervalued. In contrast to the literature, we find that divestitures create value for both acquirers and sellers of divested assets and our results will be of interest to both managers and shareholders. Our results almost entirely reflect successful deals in which cash is used as a form of consideration and are consistent in both percentage and dollar terms.

We find that the key determinants of value creation arising from the divestiture decision include the revelation of the transaction price in the initial announcement, relatedness of divested assets to the acquirer, sale of non-core assets and the financial condition of the seller, and managerial quality.

The value created from divestitures when compared to takeovers is consistent with a market efficiency explanation; the seller of divested assets is committed to the sale which increases the negotiating leverage of the acquirer. In addition, the acquisition of stand-alone target firms is much more competitive than for divested assets. These differences in the nature of divestiture and takeover transactions reduce the probability of the acquirer overpaying for the divested assets, resulting in larger (smaller) changes in shareholder wealth from the acquirer's (seller's) perspective.

We leave it to future research to incorporate the information contained in put option prices to refine estimates of the different sources of value created from corporate acquisitions. Informed traders will utilize put options for poor acquisitions of stand-alone target firms and divested assets.

Table 4.1. Descriptive statistics of US divestiture announcements

This table reports descriptive statistics for our sample of US divestitures between January 1, 1996 and December 31, 2012. $Deals$ is the number of deals in our sample, $Successful$ ($Unsuccessful$) is the number of successful (unsuccessful) deals, $Industry$ is the number of deals in which the acquirer and ultimate parent of the seller have the same two-digit SIC code, $Hostile$ is the number of hostile deals, $Toehold$ is the number of deals in which the acquirer had a toehold prior to the announcement date, $Value$ is the value of the deal reported in millions, $Days$ is the number of days until the deal was completed or withdrawn, $Cash$ ($Stock$) is the number of deals funded using 100% cash (stock), $Capitalization$ ($Volume$) is the average market capitalization of the firm (dollar volume) during the 60 days prior to the announcement date reported in millions, and $Volatility$ is the annualized stock return volatility. Panel A reports descriptive statistics for our unmatched sample of 1,287 acquirers (ACQ) and 1,256 sellers ($SELL$) of divested assets. Panel B reports descriptive statistics for both our sample and other US divestitures reported in the *SDC* database.

Panel A	$Full\ sample$		$Cash$		$Stock$	
	N	$\%\ of\ total$	N	$\%\ of\ total$	N	$\%\ of\ total$
$Deals_{ACQ}$	1,287		1,268		19	
$Deals_{SELL}$	1,256		1,238		18	
$Successful_{ACQ}$	1,271	98.8%	1,252	98.7%	19	100%
$Successful_{SELL}$	1,241	98.8%	1,223	98.8%	18	100%
$Industry_{ACQ}$	467	36.3%	461	36.4%	6	26.3%
$Industry_{SELL}$	440	35.0%	431	34.8%	9	50.0%
$Hostile_{ACQ}$	0	0.0%	0	0.0%	0	0.0%
$Hostile_{SELL}$	0	0.0%	0	0.0%	0	0.0%
$Toehold_{ACQ}$	0	0%	0	0%	0	0%
$Toehold_{SELL}$	0	0%	0	0%	0	0%
$Value_{ACQ}$	195		196		141	
$Value_{SELL}$	214		212		320	
$Days_{ACQ}$	42		42		44	
$Days_{SELL}$	45		44		80	

Panel B	$Full\ sample$		SDC	
	N	$\%\ of\ total$	N	$\%\ of\ total$
$Deals_{ACQ}$	1,287		2,721	
$Deals_{SELL}$	1,256		1,650	
$Cash_{ACQ}$	1,268	98.5%	2,621	96.3%
$Cash_{SELL}$	1,238	98.6%	1,623	98.4%
$Stock_{ACQ}$	19	1.5%	100	3.7%
$Stock_{SELL}$	18	1.4%	27	1.6%
$Successful_{ACQ}$	1,271	98.8%	2,682	98.6%
$Successful_{SELL}$	1,241	98.8%	1,623	98.4%
$Unsuccessful_{ACQ}$	16	1.2%	39	1.4%
$Unsuccessful_{SELL}$	15	1.2%	27	1.6%
$Capitalization_{ACQ}$	16,155.5		4,600.8	
$Capitalization_{SELL}$	33,923.2		8,163.2	
$Volume_{ACQ}$	94.8		33.8	
$Volume_{SELL}$	159.7		55.7	
$Volatility_{ACQ}$	39.2%		42.1%	
$Volatility_{SELL}$	39.5%		50.3%	

Table 4.2. Exchange-traded call options

This table reports descriptive statistics for American-style exchange-traded call options listed on our sample of US acquirers and sellers of divested assets between January 1, 1996 and December 31, 2012. $Series$ is the number of option series, $Open\ Interest$ is the number of option contracts which have not been delivered, $Volume$ is daily trading volume, and $Implied\ Volatility$ is the implied volatility using the Black-Scholes model. We report daily averages across the 60 days prior to the announcement date ($Pre\ announcement$) and on the announcement date ($Announcement$). Our sample consists of 1,287 acquirers (ACQ) and 1,256 sellers ($SELL$) of divested assets.

	$Pre\ announcement$	$Announcement$	
	$Mean$	$Mean$	$\%\ change$
$Series_{ACQ}$	41.8	42.9	2.6%
$Series_{SELL}$	50.2	51.2	2.0%
$Open\ Interest_{ACQ}$	52,093.3	53,920.6	3.5%
$Open\ Interest_{SELL}$	127,035.9	132,187.2	4.1%
$Volume_{ACQ}$	2,278.9	2,349.7	3.1%
$Volume_{SELL}$	5,449.0	6,140.5	12.7%
$Implied\ Volatility_{ACQ}$	43.6%	43.5%	-0.2%
$Implied\ Volatility_{SELL}$	41.5%	41.6%	0.2%

Table 4.3. Minimum sum of squared errors

This table reports descriptive statistics from our minimum sum of squared errors estimation of the different sources of value for our sample of US divestitures between January 1, 1996 and December 31, 2012. N is the number of divestiture announcements in our sample, $Noptions$ is the average number of American exchange-traded options used in the minimum sum of squared errors model, $MinSSE$ is the average minimum sum of squared errors, and P is the probability of deal success on the announcement date. We subsample our findings based on whether the method of payment was cash or common stock and whether the divestiture was completed or withdrawn. Asterisks represent estimates significantly different from zero at the 1%***, 5%** and 10%* confidence levels.

		Full sample			*Cash*			*Stock*	
	All	*Completed*	*Withdrawn*	*All*	*Completed*	*Withdrawn*	*All*	*Completed*	*Withdrawn*
N_{ACQ}	1,287	1,271	16	1,268	1,252	16	19	19	0
N_{SELL}	1,256	1,241	15	1,238	1,223	15	18	18	0
$Noptions_{ACQ}$	8.52	8.50	10.44	8.53	8.50	10.44	8.18	8.18	-
$Noptions_{SELL}$	9.69	9.72	7.47	9.70	9.73	7.67	8.50	8.50	-
$MinSSE_{ACQ}$	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-
$MinSSE_{SELL}$	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-
P_{ACQ}	0.66***	0.66***	0.46***	0.66***	0.66***	0.46***	0.67***	0.67***	-
P_{SELL}	0.70***	0.71***	0.59***	0.71***	0.71***	0.54***	0.61***	0.61***	-

Table 4.4. Percentage abnormal returns, synergy and new information revealed about stand-alone value

This table reports mean abnormal returns, synergy gains and new information revealed by the divestiture for the acquirer of divested assets (ACQ) and the seller of divested assets ($SELL$) expressed in percentage terms. AR is abnormal returns calculated as the difference between buy-and-hold abnormal returns for each stock and the $CRSP$ value-weighted index, $Synergy$ is calculated as the difference between the stock prices should the divestiture succeed and fail scaled by the pre-announcement base price, and $News$ is calculated as the difference between the stock price should the divestiture fail and pre-announcement base price scaled by the pre-announcement base price. Panel A reports findings using a pre-announcement base price occurring 60 days prior to the divestiture announcement date. Panel B (C) reports findings using a pre-announcement base price occurring 30 (5) days prior to the divestiture announcement date. Our sample consists of 1,287 acquirers and 1,256 sellers of divested assets between January 1, 1996 and December 31, 2012. For each panel we report subsamples based on whether the method of payment was cash or common stock, whether the divestiture was completed or withdrawn and whether the divestiture was confirmed (effective) or unconfirmed between the acquirer and seller on the announcement date. We report findings for 408 (879) deals which are confirmed (unconfirmed) on the announcement date for acquirers of divested assets and 425 (831) deals which are confirmed (unconfirmed) on the announcement date for sellers of divested assets. Asterisks represent estimates significantly different from zero at the 1%***, 5%** and 10%* confidence levels.

		Full sample			*Cash*			*Stock*		*Confirm*	*Unconfirm*
	All	*Completed*	*Withdrawn*	*All*	*Completed*	*Withdrawn*	*All*	*Completed*	*Withdrawn*	*All*	*All*
Panel A: Base price: *t-60*											
AR_{ACQ}	1.96%***	1.87%***	8.69%	1.92%***	1.84%***	0.87%*	4.45%	4.45%	-	2.04%**	1.80%***
AR_{SELL}	1.32%**	1.38%**	-3.03%	1.34%**	1.39%**	-2.68%	-0.19%	-0.19%	-	-0.01%	1.99%
$Synergy_{ACQ}$	9.20%***	9.13%***	14.69%***	9.16%***	9.16%***	14.69%***	7.15%***	7.15%***	-	2.25%***	12.44%***
$News_{ACQ}$	-3.64%***	-3.64%***	-3.69%	-3.65%***	-3.65%***	-3.69%	-2.83%	-2.83%	-	-1.05%	-5.05%***
$Synergy_{SELL}$	1.03%***	1.04%***	0.58%*	1.03%***	1.03%***	0.63%*	1.25%***	1.25%***	-	1.73%***	0.67%***
$News_{SELL}$	1.01%**	1.07%**	-3.28%	1.07%**	1.10%**	-1.85%	-3.20%	-3.20%	-	-1.09%	2.08%***
Panel B: Base price: *t-30*											
AR_{ACQ}	0.77%***	0.73%**	0.46%	0.78%***	0.73%***	4.65%	0.08%	0.08%	-	0.86%	0.64%*
AR_{SELL}	0.89%*	0.88%*	1.97%	0.88%*	0.87%*	1.57%	1.45%	1.45%	-	-0.35%	1.53%
$Synergy_{ACQ}$	9.13%***	9.08%***	12.93%***	9.15%***	9.12%***	12.93%***	7.68%***	7.68%***	-	2.24%***	12.34%***
$News_{ACQ}$	-4.67%***	-4.64%***	-8.84%*	-4.69%***	-4.64%***	-8.84%*	-5.23%	-5.23%	-	-1.75%***	-6.17%***
$Synergy_{SELL}$	1.02%***	1.03%***	0.58%*	1.02%***	1.02%***	0.62%*	1.26%***	1.26%***	-	1.71%***	0.66%***
$News_{SELL}$	0.23%	0.21%	1.81%	0.23%	0.21%	1.82%	0.64%	0.64%	-	-2.20%***	1.48%***
Panel C: Base price: *t-5*											
AR_{ACQ}	0.42%***	0.43%***	0.04%	0.46%***	0.46%***	0.04%	-2.16%*	-2.16%*	-	0.36%	0.45%***
AR_{SELL}	1.43%**	1.44%**	0.74%	1.43%**	1.45%**	0.43%	1.43%	1.43%	-	-0.36%	2.35%
$Synergy_{ACQ}$	9.16%***	9.11%***	12.34%***	9.18%***	9.14%***	12.34%***	7.31%***	7.31%***	-	2.32%***	12.35%***
$News_{ACQ}$	-4.60%***	-4.57%***	-6.93%***	-4.58%***	-4.55%***	-6.93%***	-6.31%***	-6.31%***	-	-1.89%***	-6.17%***
$Synergy_{SELL}$	1.05%***	1.06%***	0.56%*	1.05%***	1.06%***	0.59%*	1.29%***	1.29%***	-	1.83%***	0.65%***
$News_{SELL}$	-0.02%	-0.02%	0.15%	-0.02%	-0.02%	0.23%	-0.09%	-0.09%	-	-1.65%***	0.81%***

Table 4.5. Dollar abnormal returns, synergy and new information revealed about stand-alone value

This table reports mean abnormal returns, synergy gains and new information revealed by the divestiture for the acquirer of divested assets (ACQ) and the seller of divested assets ($SELL$) expressed in dollar terms. AR is abnormal returns calculated as the difference between buy-and-hold abnormal returns for each stock and the $CRSP$ value-weighted index, $Synergy$ is calculated as the difference between the stock prices should the divestiture succeed and fail scaled by the pre-announcement base price, and $News$ is calculated as the difference between the stock price should the divestiture fail and pre-announcement base price scaled by the pre-announcement base price. We express AR, $Synergy$ and $News$ in dollar terms by multiplying by the market capitalization of the firm on the pre-announcement base date. Panel A reports findings using a pre-announcement base price occurring 60 days prior to the divestiture announcement date. Panel B (C) reports findings using a pre-announcement base price occurring 30 (5) days prior to the divestiture announcement date. Our sample consists of 1,287 acquirers and 1,256 sellers of divested assets between January 1, 1996 and December 31, 2012. For each panel we report subsamples based on whether the method of payment was cash or common stock, whether the divestiture was completed or withdrawn and whether the divestiture was confirmed (signed) or unconfirmed between the acquirer and seller on the announcement date. We report findings for 408 (879) deals which are confirmed (unconfirmed) on the announcement date for acquirers of divested assets and 425 (831) deals which are confirmed (unconfirmed) on the announcement date for sellers of divested assets. Asterisks represent estimates significantly different from zero at the 1%***, 5%** and 10%* confidence levels.

		$Full\ sample$			$Cash$			$Stock$		$Confirm$	$Unconfirm$
	All	$Completed$	$Withdrawn$	All	$Completed$	$Withdrawn$	All	$Completed$	$Withdrawn$	All	All
Panel A: Base price: *t-60*											
AR_{ACQ}	60	62*	-107	55	57	-107	452*	452*	-	64	47
AR_{SELL}	-422***	-421***	-155	-427***	-424***	-631	-149	-149	-	-600	-332
$Synergy_{ACQ}$	946***	948***	798***	950***	952***	798***	703*	703*	-	143***	1320***
$News_{ACQ}$	-605***	-588***	-1236*	-594***	-586***	-1236*	-712	-712	-	-117*	-832***
$Synergy_{SELL}$	143***	144***	64	142***	143***	72	214	214	-	273***	76***
$News_{SELL}$	-177*	-73	-483	-159	-155	-498	-1418	-1418	-	-874***	179
Panel B: Base price: *t-30*											
AR_{ACQ}	47	45*	142	46*	44	142	121	121	-	110**	15
AR_{SELL}	-144**	-155**	647	-151**	-161**	692	316	316	-	-246	-92
$Synergy_{ACQ}$	982***	985***	803***	984***	985***	803***	930*	930*	-	145***	1372***
$News_{ACQ}$	-625***	-615***	-1287**	-628***	-620***	-1287**	-283	-283	-	-104**	-868***
$Synergy_{SELL}$	140***	141***	63	139***	140***	71	210	210	-	267***	75***
$News_{SELL}$	-145**	-141**	-451	-139**	-133	-536	-599	-599	-	-520***	47
Panel C: Base price: *t-5*											
AR_{ACQ}	31***	33***	-64	33***	34***	-64	-76	-76	-	62***	18
AR_{SELL}	25	21	231	26	23	245	-74	-74	-	-22	48
$Synergy_{ACQ}$	961***	962***	826***	962***	964***	826***	888*	888*	-	146***	1339***
$News_{ACQ}$	-520***	-518***	-710***	-521***	-519***	-710***	-449	-449	-	-92***	-719***
$Synergy_{SELL}$	143***	145***	63	142***	143***	71	210	210	-	276***	76***
$News_{SELL}$	-22	-25	-180	-20	-22	207	-179	-179	-	-197***	67***

Table 4.6. Determinants of abnormal returns

This table reports coefficient estimates from the following regression:

$$AR_{it} = \alpha + \beta_1 TVC_{it} + \beta_2 P_{it} + \varepsilon_{it}$$

AR_{it} is buy-and-hold abnormal returns, $Synergy_{it}$ is synergy gains, $News_{it}$ is new information revealed about the stand-alone value of involved firms, TVC_{it} is total value created from the divestiture and calculated as the sum of $Synergy_{it}$ and $News_{it}$, and P_{it} is the probability of success estimated from the minimum sum of squared errors model. Panel A reports findings for 1,287 acquirers of divested assets and Panel B reports findings for 1,256 sellers of divested assets between January 1, 1996 and December 31, 2012 in percentage (%) and dollar ($) terms, and using a base price of 60, 30 and 5 days prior to the announcement date. Standard errors are clustered by industry and by year, and we apply industry and year fixed effects. We calculate *t*-statistics and ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels.

Panel A: Acquirer						
	$AR60\%_{it}$	$AR30\%_{it}$	$AR5\%_{it}$	$AR60\$_{it}$	$AR30\$_{it}$	$AR5\$_{it}$
$Intercept$	-0.083***	-0.064	-0.041***	-210.7***	-285.2***	-131.7***
TVC_{it}	0.605***	0.548***	0.359***	0.4***	0.3***	0.1***
P_{it}	0.063***	0.049***	0.034***	235.9***	265.8***	113.1***
R^2 (%)	56.14	51.64	30.50	34.29	28.15	7.38
Panel B: Seller						
	$AR60\%_{it}$	$AR30\%_{it}$	$AR5\%_{it}$	$AR60\$_{it}$	$AR30\$_{it}$	$AR5\$_{it}$
$Intercept$	-0.057	-0.025***	0.017	-222.5***	-707.2***	45.7
TVC_{it}	0.964***	1.101***	1.702***	0.7***	0.6***	0.5***
P_{it}	0.012	0.011	0.002	599.6**	300.1**	71.5
R^2 (%)	55.84	55.52	13.10	48.91	48.06	32.05

Table 4.7. Determinants of the value created from US divestitures

This table reports coefficient estimates from the following regression:

$$VC_{it} = \alpha + \beta_1 RelSize_{it} + \beta_2 PriceDV_{it} + \beta_3 UnconfirmDV_{it} + \beta_4 FitDV_{it} + \beta_5 Leverage_{it} + \beta_6 DomesticDV_{it} + \beta_7 TobinQ_{it} + \beta_8 PublicDV_{it} + \sum_j \gamma_j \, Controls_{j,it} + \varepsilon_{it}$$

VC_{it} is value created from divestitures using i) AR_{it} is buy-and-hold abnormal returns, ii) $Synergy_{it}$ is synergy gains, iii) $News_{it}$ is new information revealed about the stand-alone value of involved firms, and iv) TVC_{it} is total value created from the divestiture and calculated as the sum of $Synergy_{it}$ and $News_{it}$. $Relsize_{it}$ is the value of the deal scaled by average market capitalization during the 60-day pre-announcement period, $PriceDV_{it}$ is a dummy variable equal to one if the transaction price was revealed in the initial divestiture announcement, $UnconfirmDV_{it}$ is a dummy variable equal to one if the divestiture was not signed (not effective) by the acquirer and seller on the initial announcement date, $FitDV_{it}$ is a dummy variable equal to one if the acquirer and ultimate parent of the seller share the same four-digit SIC code, $CoreDV_{it}$ is a dummy variable equal to one if the divested assets and ultimate parent of the seller share the same four-digit SIC code, $Diverse_{it}$ is the number of four-digit SIC codes associated with the seller of divested assets, $Leverage_{it}$ is book value of debt scaled by market value of assets, $Coverage_{it}$ is earnings before interest and tax scaled by interest expense, $DomesticDV_{it}$ is a dummy variable equal to one if the acquirer and ultimate parent of the seller are based in the US, $TobinQ_{it}$ is market value of assets scaled by book value of assets, and $PublicDV_i$ is a dummy variable equal to one if the divested assets were publicly held. $Controls_{j,it}$ include the following deal and firm characteristics: $WithdrawnDV_{it}$ is a dummy variable equal to one if the status of the deal is withdrawn, $Days_{it}$ is number of days until the deal is completed or withdrawn, $SeekingDV_{it}$ is a dummy variable equal to one if the seller was seeking an acquirer on the initial announcement date, $CashDV_{it}$ is a dummy variable equal to one if the acquirer used cash only to purchase divested assets, $OptionVolDV_{it}$ is a dummy variable equal to one if trading volume in options was greater than zero on the announcement date, $OveridDV_{it}$ is a dummy variable equal to one if there are more than four exchange-traded options used in our minimum sum of squared errors model, and FCF_{it} is operating income before depreciation, tax and capital expenditure scaled by book value of assets. Panels A and B report findings for 1,287 acquirers of divested assets and Panels C and D report findings for 1,256 sellers of divested assets between January 1, 1996 and December 31, 2012, in percentage (%) and dollar ($) terms, and using a base price of 60, 30 and 5 days prior to the announcement date. Standard errors are clustered by industry and by year, and we apply industry fixed effects. We calculate *t*-statistics and ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels.

Panel A: Acquirer (%)

	$AR60_{it}$	$Synergy60_{it}$	$News60_{it}$	$TVC60_{it}$	$AR30_{it}$	$Synergy30_{it}$	$News30_{it}$	$TVC30_{it}$	$AR5_{it}$	$Synergy5_{it}$	$News5_{it}$	$TVC5_{it}$
$Intercept$	-0.069	-0.016	-0.039	-0.054**	-0.022	-0.007	-0.013	-0.019	-0.026**	-0.008	-0.023	-0.031
$RelSize_{it}$	0.031	-0.035	0.071	0.035	0.004	-0.038	0.041	0.003	0.067***	-0.037	0.109***	0.072*
$PriceDV_{it}$	0.009	0.009**	0.003	0.013	0.014**	0.012***	0.017**	0.029***	0.002	0.008	-0.004	0.004**
$UnconfirmDV_{it}$	-0.008	0.032***	0.000	0.032*	0.003	0.033***	0.005	0.038***	-0.005	0.031***	-0.011***	0.019***
$FitDV_{it}$	-0.003	-0.004	0.006	0.002	0.004	-0.004	0.006	0.003	0.01	-0.003	0.009	0.006
$Leverage_{it}$	-0.029	0.046***	-0.121***	-0.075*	-0.036	0.041**	-0.094***	-0.053	-0.026**	0.048***	-0.036**	0.011
$DomesticDV_{it}$	0.013*	-0.000	0.021*	0.021	0.004	-0.001	0.014*	0.012*	-0.005*	-0.004	0.001	-0.003
$TobinQ_{it}$	0.022***	0.002	0.005	0.006	0.004	0.001	-0.001	0.000	0.002	0.001	0.001	0.002
$PublicDV_{it}$	-0.001	-0.001	-0.006	-0.007	0.002	-0.001	0.002	0.001	0.005***	-0.001	0.005*	0.004
$WithdrawnDV_{it}$	0.092**	0.003	0.042	0.045	0.056***	-0.015	-0.006	-0.021	0.003	-0.022	-0.003	-0.025
$Days_{it}$	0.000	0.001***	-0.001***	0.000	-0.000	0.001***	-0.001***	0.000	0.000	0.001***	-0.001***	0.001***
$SeekingDV_{it}$	-0.003	-0.015***	0.027**	0.012	0.005	-0.012***	0.041***	0.029**	0.003	-0.016***	0.016***	0.000
$CashDV_{it}$	-0.017	0.016	-0.007	0.009	0.005	0.009	0.003	0.013	0.027***	0.014	0.023***	0.037**
$OptionVolDV_{it}$	0.013	0.012*	0.012	0.024*	0.008	0.009	0.003	0.013	0.005	0.009	-0.002	0.007
$OveridDV_{it}$	-	0.023***	-0.028***	-0.006	-	0.022***	-0.026***	-0.004	-	0.023***	-0.021***	0.002
FCF_{it}	-0.075	0.004	0.002	0.005	-0.005	0.011	0.026	0.036	0.022	0.014	0.002	0.016
R^2 (%)	3.49	30.46	5.20	4.16	1.60	30.10	8.58	5.89	3.36	31.26	13.96	20.80

Table 4.7. Determinants of the value created from US divestitures (Continued)

Panel B: Acquirer ($)	$AR60_{it}$	$Synergy60_{it}$	$News60_{it}$	$TVC60_{it}$	$AR30_{it}$	$Synergy30_{it}$	$News30_{it}$	$TVC30_{it}$	$AR5_{it}$	$Synergy5_{it}$	$News5_{it}$	$TVC5_{it}$
$Intercept$	-61.8	-903.8**	307.7	-596.1	-41.6	-824.9**	635.5	-189.4	-133.9	-739.6**	438.8	-300.7
$RelSize_{it}$	-128.4	-6376.6***	3886.1***	-2490.6**	8.7	-6708.1***	4032.1***	-2676.1**	264.9	-6448.2***	3780.7***	-2667.5**
$PriceDV_{it}$	122.8*	235.9***	-120.4	115.5	30.1	260.8***	-120.3**	140.5***	24.4	219.5***	-117.5	102.0
$UnconfirmDV_{it}$	-122.1	239.6**	-187.4	52.2	-46.2	265.8**	-67.3	198.4	-49.1	260.4**	-148.4**	111.9
$FitDV_{it}$	-58.3*	-42.9	110.7*	67.7**	67.3***	-39.5	141.7***	102.2	13.3	-50.1	35.2	-14.8
$Leverage_{it}$	-300.1	283.9	-933.7**	-649.8	-303.0**	233.3	-884.1**	-650.8*	112.6	308.9	-143.8	165.1
$DomesticDV_{it}$	68.2	-266.2***	180.9***	-85.3	13.3	-253.6***	298.7***	45.1	-53.6***	-262.3***	101.2	-161.1***
$TobinQ_{it}$	138.7***	94.9	-36.8	58.1**	55.2	112.1	-32.7	79.4***	26.2	105.6	-8.3	97.3
$PublicDV_{it}$	-13.8	30.5	18.4	48.8	37.9	43.1	67.4	110.5	46.5	41.4	28.2	69.7
$WithdrawnDV_{it}$	-143.2	-1082.8***	-143.9	-1226.7	149.1	-1159.7***	-161.0	-1320.7*	-64.3	-1077.7***	278.8	-798.9***
$Days_{it}$	1.4	18.2***	-11.4***	6.74***	-0.9	18.8***	-13.6***	5.1***	-0.4	18.2***	-9.9***	8.2***
$SeekingDV_{it}$	236.3*	442.7**	317.1	759.7***	117.1	461.2**	303.2	764.5***	23.4	436.6**	-103.4	333.2***
$CashDV_{it}$	-248.2	60.6	264.8	325.4	-41.4	-138.3	-203.2	-341.6	119.7	-104.3	57.3	-47.1
$OptionVolDV_{it}$	130.1***	548.3***	-185.4*	362.8***	134.3***	553.9***	-254.2***	299.7***	42.4	536.8***	-298.4***	238.4***
$OveridDV_{it}$	-	529.8***	-356.1***	173.8	-	555.6***	-269.9**	285.6***	-	546.3***	-326.5***	219.8***
FCF_{it}	-491.4	126.7	-252.5	-125.8	-271.3	99.7	-244.1	-144.4	-15.6	85.9	-260.9	-175.0
R^2 (%)	2.62	32.20	9.08	6.60	2.06	30.98	15.48	10.02	3.00	32.34	22.29	24.89

Table 4.7. Determinants of the value created from US divestitures (Continued)

Panel C: Seller (%)	$AR60_{it}$	$Synergy60_{it}$	$News60_{it}$	$TVC60_{it}$	$AR30_{it}$	$Synergy30_{it}$	$News30_{it}$	$TVC30_{it}$	$AR5_{it}$	$Synergy5_{it}$	$News5_{it}$	$TVC5_{it}$
$Intercept$	-0.081	0.007	-0.069	-0.062	-0.161***	0.008	-0.146***	-0.139***	-0.009	0.007	-0.036**	-0.029
$RelSize_{it}$	0.383***	0.001	0.203*	0.203	0.511***	0.000	0.242***	0.242***	0.382	0.001	0.079***	0.081***
$PriceDV_{it}$	0.018	0.001	0.029***	0.029***	0.007	0.001	0.011	0.012	-0.016	0.001	-0.002	-0.001
$UnconfirmDV_{it}$	0.019	-0.009***	0.024	0.015	0.011	-0.009***	0.029***	0.019*	0.019	-0.011***	0.021***	0.011**
$CoreDV_{it}$	-0.008	0.000	-0.009	-0.008	-0.015**	0.001	-0.007	-0.007	0.009	0.001	-0.001	-0.001
$Diverse_{it}$	-0.005***	-0.000**	-0.002	-0.002*	-0.004**	-0.000**	-0.002	-0.003*	-0.002	-0.000	0.000	-0.000
$Coverage_{it}$	-0.001	-0.000	-0.001	-0.001	-0.002***	-0.000	-0.001***	-0.001***	-0.001	-0.000	-0.000	-0.000
$DomesticDV_{it}$	0.006	0.002	0.001	0.002	0.011	0.001	0.004	0.005	-0.003	0.001	0.000	0.002
$TobinQ_{it}$	0.041**	-0.000	0.035***	0.035***	0.027***	-0.000	-0.026***	0.026***	-0.005	-0.001	0.000	-0.000
$PublicDV_{it}$	0.008	0.000	0.005	0.005	0.002	0.000	0.003	0.004	-0.006	0.001	-0.002	-0.001
$WithdrawnDV_{it}$	-0.027	-0.000	-0.038	-0.039	0.025	-0.000	0.016	0.015	-0.013	-0.000	-0.005	-0.005
$Days_{it}$	-0.000	-0.000	0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	-0.000	0.000	-0.000
$SeekingDV_{it}$	0.028***	-0.000	0.024***	0.024***	0.026*	-0.000	0.024***	0.023***	-0.011	-0.000	-0.006	-0.006*
$CashDV_{it}$	0.051*	-0.005	0.079***	0.075***	0.029	-0.005	0.031*	0.026	-0.005	-0.005	0.007	0.001
$OptionVolDV_{it}$	0.023	0.002	0.009	0.011	0.029*	0.001	0.018**	0.019**	0.034	0.002	0.007***	0.009***
$OveridDV_{it}$	-	-0.001	0.009	0.008	-	-0.001	0.015*	0.014*	-	-0.001	0.008	0.007
FCF_{it}	-0.057	0.003	-0.017	-0.014	0.136	0.004	0.077*	0.081*	-0.159	0.000	-0.000	-0.000
R^2 (%)	3.85	7.81	4.26	3.95	5.93	7.83	6.92	6.17	2.35	8.69	9.77	4.60

Table 4.7. Determinants of the value created from US divestitures (Continued)

Panel D: Seller ($)												
	$AR60_{it}$	$Synergy60_{it}$	$News60_{it}$	$TVC60_{it}$	$AR30_{it}$	$Synergy30_{it}$	$News30_{it}$	$TVC30_{it}$	$AR5_{it}$	$Synergy5_{it}$	$News5_{it}$	$TVC5_{it}$
$Intercept$	275.3	-252.1*	-1702.2	-1954.2	-247.3	-244.8*	-1194.4*	-1439.2**	-194.5	-260.8*	-232.9	-493.8
$RelSize_{it}$	2281.9*	-427.2**	105.9	-321.4	1495.2	-404.1***	1165.6	761.4	177.5	-418.1***	325.8	-92.3
$PriceDV_{it}$	375.7	-17.9	789.0***	771.0***	117.1	-13.5	443.9***	430.4***	42.9	-15.9	23.4	7.5
$UnconfirmDV_{it}$	563.9*	-185.6***	984.4***	798.8**	123.1	-180.5***	561.4**	380.9	52.4	-187.7***	228.5***	40.7
$CoreDV_{it}$	-129.9	-18.3	-544.9	-563.2*	14.1	-15.8	-178.4	-194.3*	-85.3	-17.7	-50.6*	-68.3***
$Diverse_{it}$	-103.9***	22.5***	-80.0*	-57.6	-45.7**	20.6***	-62.5*	-41.8	3.5	22.8***	-9.8	12.9
$Coverage_{it}$	-28.5	0.9	-26.7	-25.7***	-22.9**	0.8	-28.6***	-27.8***	0.2	0.9	-1.8	-0.8
$DomesticDV_{it}$	497.9***	11.3	-12.1	-0.8	124.7	11.2	9.4	20.6	-8.0	11.8	-12.9	-1.2
$TobinQ_{it}$	494.4*	-8.6	779.5***	770.9***	250.5	-6.3	464.2***	457.9***	-27.0	-6.1	14.8	8.7
$PublicDV_{it}$	-306.3	24.7	-67.2	-42.5	-156.1	20.5	-134.5	-114.1	-3.0	20.6	-16.3	4.3
$WithdrawnDV_{it}$	49.2	-19.9	-351.8	-371.8	841.0*	-16.3	-406.4**	-422.8***	201.2	-19.2	156.2	127.1
$Days_{it}$	-4.9***	-0.1	1.1	1.0	-1.7	-0.1	-0.5	-0.6	0.3	-0.1	0.1	0.0
$SeekingDV_{it}$	643.3**	-17.1	576.3*	559.2*	417.3*	-15.1	532.6*	517.4*	-54.3	-18.1	-10.8	-28.9
$CashDV_{it}$	-127.4	-84.9	2079.6	1994.7*	-197.7	-83.6	973.1**	889.6**	125.8	-81.9	217.3	135.4
$OptionVolDV_{it}$	-234.3	105.6***	-258.3	-152.7	84.7	100.6***	-29.1	71.5	70.2	106.6***	-0.5	106.2***
$OveridDV_{it}$	-	13.6	-39.5	-25.9	-	23.8	53.4	77.2	-	12.3	67.2	79.4
FCF_{it}	3375.1	-224.1	2060.9	1836.9	-3925.9**	-149.9	3500.4***	3350.6**	54.4	-237.5	175.3	-62.3
R^2 (%)	3.26	12.28	5.33	4.76	2.75	11.80	5.41	4.48	1.20	12.62	3.15	1.58

Table 4.8. Heckman (1979) two-stage sample selection test

This table reports findings from conducting a Heckman (1979) sample selection test. Panel A reports findings from a first-stage probit regression where the dependent variable is a dummy variable equal to one if the divestiture announcement is included in our sample. Independent variables include the following firm characteristics: $Capitalization$ ($Volume$) is the average market capitalization of the firm (trading volume) during the 60 days prior to the announcement date reported in millions, and $Volatility$ is the annualized stock return volatility. Panel B reports findings from second-stage regressions where the dependent variable is the value created from divestitures using i) AR_{it} is buy-and-hold abnormal returns, ii) $Synergy_{it}$ is synergy gains, iii) $News_{it}$ is new information revealed about the stand-alone value of involved firms, and iv) TVC_{it} is total value created from the divestiture and calculated as the sum of $Synergy_{it}$ and $News_{it}$. Independent variables include: $Relsize_{it}$ is the value of the deal scaled by average market capitalization during the 60-day pre-announcement period, $PriceDV_{it}$ is a dummy variable equal to one if the transaction price was revealed in the initial divestiture announcement, $UnconfirmDV_{it}$ is a dummy variable equal to one if the divestiture was not signed (not effective) by the acquirer and seller on the initial announcement date, $FitDV_{it}$ is a dummy variable equal to one if the acquirer and seller share the same four-digit SIC code, $Leverage_{it}$ is book value of debt scaled by market value of assets, $DomesticDV_{it}$ is a dummy variable equal to one if the acquirer and ultimate parent of the seller are based in the US, $TobinQ_{it}$ is market value of assets scaled by book value of assets, and $PublicDV_{i}$ is a dummy variable equal to one if the divested assets were publicly-held. $Controls_{j,it}$ include the following deal and firm characteristics: $WithdrawnDV_{it}$ is a dummy variable equal to one if the status of the deal is withdrawn, $Days_{it}$ is number of days until the deal is completed or withdrawn, $SeekingDV_{it}$ is a dummy variable equal to one if the seller was seeking an acquirer on the initial announcement date, $CashDV_{it}$ is a dummy variable equal to one if the acquirer used cash only to purchase divested assets, FCF_{it} is operating income before depreciation, tax and capital expenditure scaled by book value of assets, and $Inverse\ Mills$ is the Inverse Mills ratio obtained from the first stage regression. Panels A and B report findings for 1,287 acquirers of divested assets and Panels C and D report findings for 1,256 sellers of divested assets between January 1, 1996 and December 31, 2012, in percentage (%) and dollar ($) terms, and using a base price of 60, 30 and 5 days prior to the announcement date. Standard errors are heteroscedastic-consistent. We calculate *t*-statistics and ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels.

Panel A: First-stage regression		
	ACQ_{it}	$SELL_{it}$
N	4,008	2,906
$Intercept$	-0.463	-0.193***
$Capitalization_{it}$	0.007***	0.009***
$Volume_{it}$	12.151*	8.386***
$Volatility_{it}$	-0.201***	-0.322***
$Log\ likelihood$	-2,441	-1,856

Panel B: Second-stage regression – Acquirer (%)						
	$AR60_{it}$	$TVC60_{it}$	$AR30_{it}$	$TVC30_{it}$	$AR5_{it}$	$TVC5_{it}$
$Intercept$	-0.039	-0.088	0.017	-0.007	-0.033	-0.045
$RelSize_{it}$	-0.004	-0.012	-0.017	-0.012	0.008	0.021
$PriceDV_{it}$	0.004	0.011	0.013	0.026**	0.004	0.006
$UnconfirmDV_{it}$	0.007	0.063***	0.006	0.058***	0.005	0.042***
$FitDV_{it}$	-0.011	-0.001	-0.000	0.012	0.003	0.011*
$Leverage_{it}$	-0.005	-0.035	-0.042	-0.055	-0.022	0.012
$DomesticDV_{it}$	0.017*	0.019	0.011	0.018*	-0.004	-0.006
$TobinQ_{it}$	0.016***	0.009***	0.004***	0.005**	0.002***	0.003***
$PublicDV_{it}$	0.004	0.003	0.007	0.007	0.006*	0.007
$WithdrawnDV_{it}$	0.012**	0.114*	0.074**	0.003	0.011	-0.032
$Days_{it}$	-0.000	0.000	-0.000	-0.000	-0.000*	0.000***
$SeekingDV_{it}$	0.001	0.023	0.000	0.035**	0.004	0.006
$CashDV_{it}$	-0.024	0.003	-0.034	-0.055	0.021	0.007
FCF_{it}	0.021	0.032	0.004	-0.017	-0.016	-0.008
$Inverse\ Mills$	0.029	0.054*	0.001	0.025	0.008	0.025**
R^2 (%)	5.61	4.22	2.84	5.45	2.72	17.77

Table 4.8. Heckman (1979) two-stage sample selection test (Continued)

Panel C: Second-stage regression – Acquirer ($)						
	$AR60_{it}$	$TVC60_{it}$	$AR30_{it}$	$TVC30_{it}$	$AR5_{it}$	$TVC5_{it}$
$Intercept$	1152.8*	1913.1**	1056.8**	3793.3***	202.0	3096.2***
$RelSize_{it}$	267.5**	-198.8	268.4**	-95.5	95.2*	-404.5**
$PriceDV_{it}$	88.9	56.7	21.7	65.6	20.1	49.3
$UnconfirmDV_{it}$	-18.2	466.2***	-108.9	463.5***	7.8	352.8***
$FitDV_{it}$	-117.9	25.8	12.2	104.9	17.1	-47.9
$Leverage_{it}$	-331.4	-425.3	-595.5**	-1080.7**	-136.3	-69.8
$DomesticDV_{it}$	120.1	-107.4	82.1	157.4	-33.4	-122.4*
$TobinQ_{it}$	75.0***	49.9	22.4	20.6	13.3**	45.2**
$PublicDV_{it}$	-69.2	-6.3	9.9	41.5	37.4	18.5
$WithdrawnDV_{it}$	134.9	-1029.8	518.9*	-1263.9	12.8	-714.3***
$Days_{it}$	-0.4	-0.7	-0.7	-0.9	-0.9***	2.9***
$SeekingDV_{it}$	250.7*	883.2***	-35.3	729.2***	3.2	265.5**
$CashDV_{it}$	-268.6	555.3	-17.7	-859.2	54.0	-543.2
FCF_{it}	-369.9	-151.1	-193.3	-133.3	-71.2	-8.92
$Inverse\ Mills$	-953.1**	-2311.4***	-867.0**	-2777.3***	-202.0	-2354.1***
R^2 (%)	4.73	8.96	4.84	15.79	4.02	36.03
Panel D: Second-stage regression – Seller (%)						
	$AR60_{it}$	$TVC60_{it}$	$AR30_{it}$	$TVC30_{it}$	$AR5_{it}$	$TVC5_{it}$
$Intercept$	-0.043	-0.027	-0.003	0.007	0.129	0.008
$RelSize_{it}$	0.171**	0.089*	0.257***	0.119***	0.186	0.048***
$PriceDV_{it}$	0.009	0.006	0.001	0.002	-0.001	0.000
$UnconfirmDV_{it}$	0.014	0.013	0.003	0.016*	0.025	0.012***
$FitDV_{it}$	-0.018	-0.023	-0.007	-0.005	-0.023	0.002
$Leverage_{it}$	-0.096	-0.131***	-0.026	-0.052*	0.208	0.003
$DomesticDV_{it}$	0.004	0.005	-0.000	0.001	-0.007	0.002
$TobinQ_{it}$	0.011	0.005	-0.007	0.004	0.009	-0.001
$PublicDV_{it}$	0.015	0.015	-0.001	0.004	-0.000	-0.001
$WithdrawnDV_{it}$	-0.034	-0.058	-0.009	0.007	-0.022	0.002
$Days_{it}$	0.000	0.000	-0.000	-0.000	-0.000	0.000
$SeekingDV_{it}$	-0.006	0.003	0.018	0.014	-0.004	-0.005
$CashDV_{it}$	0.026	0.051	-0.001	0.001	-0.015	-0.011
FCF_{it}	-0.098	-0.047	-0.119	-0.015	0.092	0.009
$Inverse\ Mills$	0.002	-0.014	-0.004	-0.013	0.114	0.002
R^2 (%)	2.97	3.59	5.58	3.64	4.15	5.26
Panel E: Second-stage regression – Seller ($)						
	$AR60_{it}$	$TVC60_{it}$	$AR30_{it}$	$TVC30_{it}$	$AR5_{it}$	$TVC5_{it}$
$Intercept$	-839.3	-1953.1	473.3	-562.9	38.2	590.2**
$RelSize_{it}$	448.7	59.4	705.9**	362.0	96.1	133.8
$PriceDV_{it}$	124.7	555.3*	68.5	337.4*	77.5	-7.8
$UnconfirmDV_{it}$	385.9	853.0***	60.0	447.2**	93.9	82.3
$FitDV_{it}$	-230.1	-525.8*	-140.1	-315.4*	-64.8	-5.8
$Leverage_{it}$	-844.7	-1505.3	289.4	-132.4	-16.3	46.9
$DomesticDV_{it}$	494.8	-10.5	89.7	-16.9	7.1	-1.9
$TobinQ_{it}$	93.9	236.8	126.8	214.3*	-27.7	4.4
$PublicDV_{it}$	-34.7	140.8	-114.1	-83.7	-3.0	11.8
$WithdrawnDV_{it}$	-357.8	-571.8	828.1	-752.7	292.6	179.2
$Days_{it}$	-1.8	1.3	-0.5	-0.5	-0.0	-0.1
$SeekingDV_{it}$	225.7	128.4	215.9	247.2	-46.9	-43.7
$CashDV_{it}$	-449.7	1752.6	-782.9	182.0	-16.0	-151.2
FCF_{it}	-67.1	-440.9	690.7	280.2	-94.9	-63.5
$Inverse\ Mills$	424.4	-991.4	-239.8	-431.7	-74.9	-453.6**
R^2 (%)	1.02	4.71	1.37	3.25	0.85	2.48

Table 4.9. Barraclough et al. (2013) percentage/dollar abnormal returns, synergy and new information revealed about stand-alone value

This table reports the abnormal returns, synergy gains and new information revealed by the takeover for the acquiring firm (ACQ) and the target firm (TGT) expressed in percentage and dollar terms as reported in Barraclough et al. (2013). AR is abnormal returns calculated as the difference between buy-and-hold abnormal returns for each stock and the *CRSP* value-weighted index, $Synergy$ is calculated as the difference between the stock prices should the takeover succeed and fail scaled by the pre-announcement base price, and $News$ is calculated as the difference between the stock price should the takeover fail and the pre-announcement base price scaled by the pre-announcement base price. We express AR, $Synergy$ and $News$ in dollar terms by multiplying by the market capitalization of the firm on the pre-announcement base date. Panel A reports findings using a pre-announcement base price occurring 60 days prior to the takeover announcement date. Panel B (C) reports findings using a pre-announcement base price occurring 30 (5) days prior to the takeover announcement date. Barraclough et al. (2013) examine a sample 167 takeover announcements between January 1, 1996 and December 31, 2008. We report findings for deals funded with cash only. Asterisks represent estimates significantly different from zero at the 1%***, 5%** and 10%* confidence levels.

	Cash (%)			**Cash ($)**		
	All	$Completed$	$Withdrawn$	All	$Completed$	$Withdrawn$
Panel A: Base price: *t-60*						
AR_{ACQ}	2.5%	1.4%	20.6%	738	772	152
AR_{TGT}	35.4%***	35.0%***	41.4%	344***	352***	209
$Synergy_{ACQ}$	6.0%***	5.3%***	18.1%	2029***	2206***	-981
$News_{ACQ}$	-1.9%	-1.9%	-3.0%	-1241***	-1286***	-475
$Synergy_{TGT}$	40.4%***	39.9%***	48.2%	353***	359***	252
$News_{TGT}$	5.0%*	5.2%***	0.5%	55***	57***	14
Panel B: Base price: *t-30*						
AR_{ACQ}	-1.0%	-1.2%	2.8%	357	337	698***
AR_{TGT}	38.0%***	37.6%***	46.3%	359***	357***	389
$Synergy_{ACQ}$	4.1%	3.7%	10.4%	2029***	2206***	-981
$News_{ACQ}$	-4.5%***	-4.4%***	-5.7%	-1786***	-1894***	61
$Synergy_{TGT}$	39.0%***	38.7%***	44.6%	353***	359***	252
$News_{TGT}$	7.5%*	7.2%*	13.7%	70***	63***	195
Panel C: Base price: *t-5*						
AR_{ACQ}	-0.2%	-0.1%	-0.6%	-100	-66	-668
AR_{TGT}	31.3%***	31.1%***	34.4%***	288***	285***	325
$Synergy_{ACQ}$	3.3%	2.9%	10.1%	2029***	2206***	-981
$News_{ACQ}$	-4.6%***	-4.2%***	-12.6%	-2281***	-2339***	-1293
$Synergy_{TGT}$	35.8%***	35.8%***	35.5%	353***	359***	252
$News_{TGT}$	0.8%	0.7%	2.3%	-2	-9	127

Chapter 5. Conclusion

Empirically, price discovery has been examined in three broad contexts: where price discovery occurs, how it occurs, and the informational efficiency of prices. This dissertation makes several contributions to the price discovery literature in three separate essays.

In Chapter 2, we use a new metric, the information leadership share, which unlike conventional measures captures which price series is the first to reflect new information, and we utilize illegal insider trades as prosecuted by the SEC to examine price discovery in the US stock and options markets. In Chapter 3, we utilize the unique information environment in Australia, including a central information dissemination platform (a primary source of data), price sensitive flags and ASX price queries to examine how price discovery occurs and the information efficiency of prices. Our methodology overcomes identification issues between large price changes and public information inherent in prior studies. In Chapter 4, we use both stock and option prices to disentangle the different sources of value creation from US divestitures, including synergy gains, new information regarding the stand-alone value of involved parties and the probability of deal success. This methodology overcomes issues with using abnormal returns as a measure of value creation, as abnormal returns convolute the different sources of value creation and understate the total value created by acquisitions on the announcement date.

5.1. Where does price discovery occur?

We show that price discovery occurs in both US stock and options markets. Using the information leadership share metric we find that approximately one-third of price discovery occurs in the options market relative to the stock market. Our findings suggest that the share of price discovery occurring in the options market is two and six times larger than documented in Chakravarty et al. (2004) and Muravyev et al. (2013) respectively, and suggests that the options market is an important source of price discovery and venue for informed trading, consistent with early theoretical predictions (Black, 1975; Easley et al., 1998). In addition, we provide supporting evidence from the analysis of illegal insider trades made in stock and options markets. We find that insiders trade in the options market in one-third of cases, one-third of the total number of trades are made in the options market and up to half of the amount invested is in the options market relative to the stock market.

Our findings increase our understanding of the characteristics of insider trading strategies which can help to make more efficient use of regulatory resources to prevent, monitor and detect insider trading, and to reduce the negative effects on financial markets including reduced investor confidence and participation in markets that have an adverse effect on liquidity. In addition, knowledge that a meaningful amount of informed trading takes place in options markets is informative to option and stock market makers in managing bid ask spreads and adverse selection risks.

5.2. How does price discovery occur?

Price discovery occurs due to the incorporation of public and private information into prices. We capture public information using ASX announcements and US corporate announcements, in particular divestiture announcements. We use the information leadership share metric, illegal insider trades made in stock and options markets as prosecuted by the SEC, adverse selection costs estimated using the Lin et al. (1995) decomposition model, and ASX price queries as proxies for private information. In contrast to prior studies, for example, Chakravarty et al. (2004), our findings suggest that leverage rather than liquidity draws informed traders to trade in the options market.

Using price discovery resulting from US divestiture announcements, our analysis provides additional support to the notion that abnormal returns understate the total value created by corporate acquisitions. In contrast to the literature, we find divestitures create value for both acquirers and sellers of divested assets. These findings will be of interest to various stakeholders in particular managers and shareholders.

In addition, we show that liquidity trading can cause prices to change, and that such changes in price are transient, consistent with liquidity trading being motivated for non-informational reasons including cash needs, portfolio rebalancing and hedging.

5.3. Informational efficiency of prices

We examine return predictability following different drivers of large price changes in the Australian stock market. In contrast to similar US studies (Pritamani and Singal, 2001; Chan, 2003; Savor, 2012) which document investor under-reaction, we find that large price changes driven by public information are permanent, consistent with the semi-strong efficient markets hypothesis of Fama (1970). Our findings have implications for continuous disclosure rules in the US, where information can be revealed through a number of different channels including Form 8-K, Dow Jones Newswires or firm websites. We attribute differences in findings to the unique information environment in Australia which helps to reduce investor distraction and under-reaction to new information.

We note that the information leadership share metric focuses on where price discovery occurs and is a proxy for informed trading (or how price discovery occurs). More conventional metrics of price discovery, including the Hasbrouck (1995) information share and the Gonzalo and Granger (1995) component share metrics are found to partly capture how efficient each price series is (or the relative avoidance of noise).

5.4. Other avenues for future research

Insider trading represents large social costs, for example, last year the SEC spent more than $500 million in combatting insider trading (SEC, 2013). In contrast to microstructure theory, Collin-Dufresne and Fos (2015) find that conventional measures of information asymmetry, including price impact, bid ask spreads and midquote price changes in response to order flow, do not capture informed trading. A clear direction for future research is increasing our understanding of insider trading characteristics in order to develop a set of metrics which can better detect insider trading in stock and options markets.

Other worthwhile avenues for future research are to re-examine the share and determinants of price discovery taking place between different markets using the information leadership share metric, for example, between the stock and futures market or the stock and emissions trading market. As our access to data improves, further studies can examine price discovery taking place in dark markets or over-the-counter markets. We calculate the information leadership share metric on a stock-day basis; another extension could be to examine price discovery at an intraday or hourly level. This may increase regulators' detection of insider trading.

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