# The Effect of Corporate Break-ups on Information Asymmetry: A Market Microstructure Analysis

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11 September 2006

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## Abstract

This paper investigates the information environment during and after a corporate break-up utilizing direct measures of information asymmetry developed in the market microstructure literature. The analysis is based on all corporate break-ups in the United States in the period 1995-2005. The results document that information asymmetry declines significantly as a result of a break-up. However, this reduction takes place not at the time of its announcement or its completion, but after it has been fully consummated. At the same time, not all investors are equally affected, but informed investors who generate private information by skilled analysis of public information come to play a more important role compared to traditional corporate insiders. This might explain why financial advisors promote break-ups among their corporate clients, as they are likely beneficiaries. The positive stock-market reaction to break-up announcements is significantly related to reductions in insider-related information asymmetry, indicating that the advantage of skilled information analysts does not offset the overall improvement in the information environment due to a break-up.


**Keywords:** Spin-off, Divestiture, Information asymmetry
**JEL classification:** G14, G34
**First version:** September 11, 2006
**This version:** October 26, 2008

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The authors would like to thank Narayan Naik and Grzegorz Pawlina and seminar participants at the University of Oklahoma the 2008 FMA Annual Meeting in Grapevine, Dallas for helpful comments and suggestions.

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## Abstract

This paper investigates the information environment during and after a corporate break-up utilizing direct measures of information asymmetry developed in the market microstructure literature. The analysis is based on all corporate break-ups in the United States in the period 1995-2005. The results document that information asymmetry declines significantly as a result of a break-up. However, this reduction takes place not at the time of its announcement or its completion, but after it has been fully consummated. At the same time, not all investors are equally affected, but informed investors who generate private information by skilled analysis of public information come to play a more important role compared to traditional corporate insiders. This might explain why financial advisors promote break-ups among their corporate clients, as they are likely beneficiaries. The positive stock-market reaction to break-up announcements is significantly related to reductions in insider-related information asymmetry, indicating that the advantage of skilled information analysts does not offset the overall improvement in the information environment due to a break-up.

# 1 Introduction and Motivation

There is substantial evidence of a significant stock market reaction to the announcement and implementation of corporate restructurings that break-up a firm into smaller entities.[1] There are several explanations for this stock-market reaction to break-ups.[2] The focus of this paper is on an important strand of this literature that is anchored in the hypothesis that the stock market reaction is related to improvements in the information environment. Specifically, it suggests that corporate break-ups may enhance firm value by reducing the level of information asymmetry, since value-relevant information about the different divisions of the firm become widely and transparently available when some of these divisions report individually to the financial markets. Such an information environment-based explanation is particularly important in view of the recent theoretical and empirical literature discussing the price-relevance of the exposure of investors to information asymmetry (see, e.g., Easley, Hvidkjaer, and O'Hara, 2002; Easley, Hvidkjaer, and O'Hara, 2004).

Apart from theoretical papers that show that the information environment should improve after the spin-off (e.g., see Habib et al. (1997)), there are few empirical studies that examine the information environment in the context of corporate restructurings (Gilson et al., 2001; Huson and MacKinnon, 2003; Krishnaswami and Subramaniam, 1999), analyzing stock-level residual returns or financial analysts' market participation and forecasting precision in order to assess the effect of a break-up on this group of investors. It is unclear, however, whether and if so how the

[1] See, for example, Abarbanell, Bushee, and Raedy (2003), Cusatis, Miles, and Woolridge (1993), Daley, Mehrotra, and Sivakumar (1997), and Gertner, Powers, and Scharfstein (2002).

[2] Explanations of the stock-market reaction to break-ups include the following: expected and realised improvements in efficiency (Çolak and Whited, 2007; Gertner et al., 2002; Habib, Johnsen, and Naik, 1997; Veld and Veld-Merkoulova, 2005), improvements in the quality of analysts' forecasts (Gilson, Healy, Noe, and Palepu, 2001; Krishnaswami and Subramaniam, 1999), asset re-distribution between debt holders and equity holders (Maxwell and Rao, 2003; Parrino, 1997), issues around corporate control (Chemmanur and Paeglis, 2001), expected and realized take-over premia (Cusatis et al., 1993), liquidity trading (Abarbanell et al., 2003; Brown and Brooke, 1993), and transaction costs (Vijh, 1994).

information environment faced by the public investor is affected by break-ups. The main contribution of this paper is to utilize a direct measure of information asymmetry developed in the market microstructure literature to comprehensively investigate how the information environment changes during and after a corporate break-up. Specifically, it uses intra-day transactions data of the NYSE and Nasdaq in order to analyze spin-offs, carve-outs, and other forms of corporate restructuring that break one combined firm into legally separated entities over the eleven-year period between January 1995 and December 2005. Using tick-by-tick data, the level of information asymmetry prior, during, and after the break-up is calculated and related to factors that potentially influence the information environment and break-up announcement returns.

The paper is related to the theoretical work by Habib et al. (1997) and the empirical studies by Gilson et al. (2001) and Krishnaswami and Subramaniam (1999). Habib et al. (1997) show that – assuming the existence of heterogeneously informed investors – uninformed investors value spin-offs as these improve the strength of the information in the price signal of security prices. The findings of the two empirical studies suggest that financial analysts have industry expertise and thus are able to issue more precise forecast for stocks in industries they know best. Moreover, analysts appear to have more precise and useful information after the break-up. Nevertheless, these studies do not directly measure information asymmetry faced by all investors in financial markets and, therefore, only indirectly address the question whether all investors ultimately benefit from a break-up. Furthermore, little is known about the change of information asymmetry during the break-up process as well as whether and how investors value reductions in the information environment related to corporate break-ups.

Different types of investors may face different levels of information asymmetry. Huson and MacKinnon (2003), another study this paper is related to this paper, look at the post break-up changes in residual returns, effective spreads, and price impacts of trades. Unlike most other studies, they find that information asymmetry increases after the break-up. This result, which at first seems to contradict most of the previous and our findings, can be reconciled with evidence reported in this paper that different types of informed investors are affected differently by the break-up. The best informed but likely smallest group of investors is the group of corporate insiders. These investors face little firm-specific information asymmetry, as they should have all pieces of value-relevant firm-specific information. Investors who are particularly skilled in analyzing public information in the spirit of Kim and Verrecchia (1994, 1997) can be considered second best informed. Finally, the typically largest group of investors is the uninformed public, who face information asymmetry stemming from both types of informed investors, the corporate insider and the skilled information analyst. Although Huson and MacKinnon (2003) do not make this distinction, it seems likely that their results reflect activity of the latter type of informed trader. The market microstructure perspective of this paper allows considering, for the first time, the information environment of the uninformed investor separately from the information environment of analysts and corporate insiders. Trades by informed investors that exploit private information generated from public data should lead to a co-movement between stock-level information asymmetry and variables that capture the environment of an investor (see, e.g., Bardong, Bartram, and Yadav, 2007).[3] By considering the potential sources of private information separately, this paper addresses the question whether uninformed investors benefit from a corporate break-up. It also allows examining the importance of skilled information analysts vis-à-vis uninformed investors.

[3] Empirical evidence suggests the existence of private information about the mapping of the publicly known information into returns since even in liquid and well-research markets with no insider information, such as the Treasury bond market, the price adjustment to new public information is stretched out over time (see, e.g., Boni and Leach, 2002; Fleming and Remolona, 1999). Other papers model theoretically how private information on systematic return factors affect prices (see, e.g., Admati, 1984; Hughes, Liu, and Liu, 2005).

The empirical approach of this paper allows differentiating between the predicable and unpredictable component of information asymmetry. The predicable component of information asymmetry, which can be attributed to the skilled analysis of public information, differs from the private firm-specific informational advantage, which is traditionally associated with corporate insiders, and therefore helps differentiating between these two types of informed investors.

The market microstructure perspective employed here makes it possible to analyze data on a higher frequency compared to previous studies.[4] First, using high frequency measures of information asymmetry, one can avoid attributing to the break-up the effect other events have on the information environment that happen to occur in the same month or year of the break-up, such as changes in the investor communication policy or developments in the regulatory environment. Second, high frequency data allows looking at changes in information asymmetry at precise dates over the course of the break-up process. This not only provides more detail to the analysis but is also of practical use, as the results show whether or not uninformed investors should avoid trading around the information events of the break-up process.

In this paper, alternative explanations for the stock-market reaction to break-ups that have been pursued in the literature are not directly addressed, although the results are checked for robustness to some of these alternative causes of break-ups. While several of these additional factors are surely important for explaining the stock market reaction to break-up announcements, the perspective of this paper based on the information environment may offer valuable additions to the extant literature as different explanations can be conflicting and difficult to reconcile with

[4] Huson and MacKinnon (2003) also use intra-day data in their analysis.

each other.[5] Linking information asymmetry to the different stages of the break-up process has not been undertaken before and is also one of the contributions of this paper.

Information asymmetry is estimated directly by the *ex post* adverse selection losses of liquidity suppliers to traders demanding liquidity, since these losses should arguably be zero, on average, in the absence of information asymmetry. In addition, for better comparability with existing results, the effect of break-ups on the quality of earnings forecasts and the *PIN* measure is also investigates. The results show that, consistent with Habib et al. (1997), the level of information asymmetry directly relevant to the uninformed public investor, and thus the uncertainty about asset values, is significantly lower after the break-up. Information asymmetry declines only slightly in the period between the break-up announcement and the completion of the break-up, but declines significantly after the break-up is fully consummated. Moreover, the composition of informed trades changes after the break-up. The results further suggest that informed traders who are particularly skilled in analyzing public information become more important relative to corporate insiders after the restructuring.[6]

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[5] For example, Veld and Veld-Merkoulova (2005) find a positive reaction in the stock market and the bond markets, which contradicts the asset redistribution hypothesis by Maxwell and Rao (2003) and Parrino (1997). Alternatively, Gertner et al. (2002) associate the stock market reaction to expected reductions in inefficiencies, which Çolak and Whited (2007) cannot confirm. Çolak and Whited (2007) find that spin-off activity is related to industry-level IPO activity. IPO activity itself has been found to be related to investor irrationality (Lee, Shleifer, and Thaler, 1991), implying that spin-off activity may not be entirely driven by expectations of rational investors. This is contrary to the findings of Krishnaswami and Subramaniam (1999), who show an improvement in the information environment, suggesting that investors rationally use all available information to determine firm value. Chemmanur and Paeglis (2001) and Cusatis et al. (1993) find only weak indications that investors have more information and conclude that the transfer of control is the main driver of the stock-market reaction to break-up announcements. Effects of break-up on investors' information sets are even explicitly ruled out by Abarbanell et al. (2003), Brown and Brooke (1993), and Vijh (1994), who attribute the stock market reaction to break-up announcements and the break-up consummation to preference-motivated trades and portfolio rebalancing.

[6] This can be rationalized by the improvement in the information environment. According to Harris (2003, p. 584) "insider information is material information about the value of a security that is not available to public traders". As more information is available to everyone, corporate insiders who happen to have firm-specific information lose some of their advantage. At the same time, investors who are particularly skilled in analyzing new information become more advantaged. These traders are characterized by Harris (2003, p. 177) as "informed traders that typically form their opinions from insightful analyses of publicly available information or from simple analyses of information that is not widely known".

The finding that skilled information analysts particularly benefit from break-up may explain why financial intermediaries commit more and better resources to analyzing a firm after the break-up. These institutions are likely to benefit directly from break-ups through informed trading either by these institutions themselves. In addition, as Habib et al. (1997) show, demand for the shares of the break-up firms by uninformed increases after the break-up due to the information they generate from the newly available price information. Therefore, these institutions also benefit from the additional trading by their customers. The finding that skilled information analysts benefit from and promote break-ups (Harris, 2003, p. 177) reconciles the previous finding of industry-level correlation of break-up activity with the argument of transfer of ownership as a driver of break-up activity. It is likely that industry-waves of break-up activity (Çolak and Whited, 2007) as well as in take-over activity after the break-up (Cusatis et al., 1993) reflect the improved information set of financial institutions in these transactions. Finally, the stock-market reaction to the break-up announcement appears to be significantly related to break up-related declines in information asymmetry, particularly to declines in corporate insider-related informed trading activity.

To summarize, this paper contributes to the literature in three ways. First, it uses, for the first time, a direct measure of information asymmetry developed in the market microstructure literature to provide insights into the changes of the information environment during and after corporate break-ups. It thereby specifically addresses the question whether uninformed public investors benefit from lower levels of information asymmetry after the break-up and whether skilled information analysts become more advantaged. Second, it tracks information asymmetry over the various stages of the break-up process, which may serve institutional investors, liquidity providers and retail investors to optimize the timing of their trades. Finally, it investigates the relationship between information asymmetry and stock returns, an issue that has only recently received attention in academic research (see, e.g., Easley et al., 2002; Easley and O'Hara, 2004; Hughes et al., 2005).

The remainder of this paper is structured as follows. Section 2 develops the research questions from extant literature. Section 3 describes the data. Section 4 discusses the results of the empirical analysis, and Section 5 provides a summary and the conclusion of the paper.

## 2 Research Questions

The research questions of this paper can be classified into four main groups. First, it is examined whether corporate break-up activity is associated with specific firm-level characteristics. Second, it is investigated whether and how information asymmetry changes during and after the break-up. Third, this paper intends to determine whether the composition of trades that exploit the existing information asymmetry is affected by the break-up and how the break-up announcement returns are related to the post break-up information environment.

In what follows, the following terminology is used. The *parent* is the original entity and the *sub* is the entity that is separated from the parent by means of the break-up. In addition, the break-up period is subdivided into (1) the *announcement date*, where the break-up is first publicly announced, (2) the *completion date*, where the final terms of the restructuring are made public, and (3) the *distribution date*, which is the day when the break-up is consummated.[7]

### 2.1 Main Characteristics of Break-up Firms

Research on break-ups typically finds that focus-increasing break-ups are particularly beneficial to investors (see, e.g., Habib et al., 1997; Gertner et al., 2002; Gilson et al., 2001). This implies that break-up firms may be more diversified than comparable firms, with the break-up being a

[7] At the completion date, which is typically between one and two weeks before the distribution date, the last details of the break-up are announced including the exact distribution date and distribution ratios.

mechanism to achieve a similar degree of diversification than non-break up firms. Gertner et al. (2002) and Habib et al. (1997) explain the positive stock-market reaction to break-up announcements with more efficient capital allocation, which implies that the market value of assets of break-up firms may be comparatively low due to inefficiencies. Mansi and Reeb (2002) find that the conglomerate discount is a function of leverage, implying that diversified break-up firms should have high leverage and a lower level of priced risk. According to Harris (2003, p. 315), information asymmetry is lower for conglomerates as private information about individual operations may be of little help in valuing the entire entity. According to these arguments, break-up firms should have higher leverage, a lower level of systematic and idiosyncratic risk, and a lower market value of assets than comparable non-break up firms.

Audited mandatory disclosure is more useful to investors than additional voluntarily disclosure about a firm's operations (Gigler and Hemmer, 1998). This implies that break-ups are always more effective in increasing the amount of useful information to public investors than, for instance, voluntary improvements in investor communication. As some investors appear to have a better improved information set after the break-up (Gilson et al., 2001; Krishnaswami and Subramaniam, 1999), it is likely that investors of break-up firms face a comparatively high level of information asymmetry prior the break-up. In addition, high levels of information asymmetry could be related to asset characteristics, such as a high level of diversification (Gertner et al., 2002), low analyst coverage (Bhushan, 1989a), and a high level of intangible assets (Cotter and Richardson, 2002; Kothari, Laguerre, and Leone, 2002). Therefore, break-up firms should be more diversified and have a higher level of information asymmetry, lower analyst coverage, and more intangible assets than comparable non-break up firms.

These hypotheses are tested more formally by estimating a logit regression of a control sample-matched set of break-up firms on empirical measures of these characteristics. If the empirical association of the variables with the break-up probability corresponds to what other studies have been found or what is hypothesized above, one can have confidence that the sample that is used in this study is representative of the break-up universe and comparable to previous studies. This is considered of particular importance as the sample of break-up firms, although larger than what has been used in previous break-up studies, is fairly small.

## 2.2 Information Asymmetry during the Break-up Process

The second issue this paper looks at centers around the effect of the break-up process on information asymmetry. Evidence of information leakage before the break-up announcement (Vijh, 1994) implies a higher level of information asymmetry before this date. A high level of uncertainty between the break-up announcement date and the completion date (Abarbanell et al., 2003; Vijh, 1994) should be reflected in a higher level of information asymmetry during this period. Some of the trading activity at the distribution date has been found to be uninformed (Abarbanell et al., 2003; Vijh, 1994) implying a low level of information asymmetry on that date. However, informed investors with private information about the relative value of the new post-break up entities can exploit their knowledge only over a limited period of time while public investors are about to learn this information from public sources, such as prices (Bhushan, 1989a) or return correlations (Admati and Pfleiderer, 2000), implying a higher level of information asymmetry at the distribution date.

Information-related effects should be less pronounced when investors already have the opportunity to learn price-relevant information. This is the case when the sub already has a separate stock exchange listing prior to the distribution. As there are significant differences in the information asymmetry across financial markets (Fishe and Robe (2004)), break-up related changes in information asymmetry may differ by main exchange.

As analyst forecasts become more precise after spin-offs (Krishnaswami and Subramaniam, 1999; Gilson et al., 2001), investors may then experience increases in adverse selection.[8] Therefore, whether break-ups improve the information environment of all investors or of just a sub-group of investors is an empirical issue, which may also depend on firm characteristics. As equity analysts are a source of information (Bhushan, 1989a), analyst coverage should be negatively related to potential changes in information asymmetry. As focus-increasing break-ups improve the information environment most (Desai and Jain, 1999; Gilson et al., 2001), information asymmetry should decline most for focus increasing break-ups.

To test these hypotheses, the changes in information asymmetry over the individual break-up periods are looked at relative to the control period, which we define to be some time prior to the first public announcement of the break-up. In particular, changes in information asymmetry during the various stages of the break-up process relative to changes in information asymmetry of the respective control firm over the same time-period are regressed on empirical measurements of characteristics that likely influence the level of information asymmetry and changes therein and a dummy indicating whether a firm is a break-up firm. In addition, the sample is sub-divided according to the characteristics of the break-up. This set-up is meant to test whether information asymmetry significantly changes during and after the break-up and whether the type of the break-up and characteristics of the break-up firm are related to this change.

### 2.3 Changes in the Composition of Informed Trades

This paper argues that several types of informed traders populate financial markets. From a theoretical perspective, market makers are considered uninformed as they have the obligation to ac-

[8] Subrahmanyam (1991) formalises the trade-off between trading individual securities and baskets thereof whereby trading the basket minimises adverse selection losses and is thus more attractive to uninformed traders. In this context, this implies that investors with private information about the relative value of the parent and the sub trade at public investors' expense after the break-up consummation.

commodated order flow and are thus required to trade with potentially informed traders (Glosten and Milgrom, 1985; Kyle, 1985)[9]. Informed traders can be insiders (Lakonishok and Lee, 2001) or skilled information analysts (Glosten and Harris 1988; Kim and Verrecchia, 1994, 1997), for which this paper accounts by considering information asymmetry that is due to private information and one that is due to skilled analysis of public data.

While it seems that the information set of financial analysts improves after the break-up (Krishnaswami and Subramaniam, 1999), it is not clear whether this also applies to all investors. Although financial analysts seem to use public information (Easley, O'Hara, and Paperman, 1998), there appears to be some evidence that analysts possess the ability to create private information from the analysis of public data as Gilson et al. (2001) find differences in the quality of forecasts across individual analysts. The information of analysts seems to be price-relevant (Bhushan, 1989b; Brennan, Jegadeesh, and Swaminathan, 1993) and, as the results of Brennan and Subrahmanyam (1995) imply, it appears to be exploited by informed traders if it is not made public by financial analysts themselves. Since Easley et al. (1998) find that higher analyst following is also associated with more informed trading, it could be that analysts generate private information from public information that is subsequently used by informed traders.[10] Therefore, those informed investors who exploit information generated from skilled information analysis are hypothesized to benefit from the break-up and are hence expected to increase their adverse selection profits following the break-up.

[9] This assertion also seems to be empirically validated as Sadka and Scherbina (2006) find that periods of high information uncertainty coincide with low liquidity. This implies that voluntary market makers, such as those who submit limit orders, quit the market when uncertainty is high, supposedly to avoid trading with informed traders, showing that liquidity providers are generally uninformed. An exemption is the informed value trader, who accommodates uninformed trades that drive prices away from fundamentals (see Harris (2003)).

[10] Private information is likely to be exploited by informed traders, as Grossman and Stiglitz (1980) show that private information acquisition is only done as long as the marginal benefit – the returns from informed trades – equals marginal costs – the resources committed to the creation of private information.

We then empirically examine whether the two groups of informed traders (insiders and information analysts) are equally affected by the break-up as depending on the relative importance of either group of informed investors, the overall level of information asymmetry could either decline or increase after the break-up. As stock markets generally interpret break-up announcements as positive news, investors are expected to anticipate overall reductions in information asymmetry. As the importance of insider trades is likely to decline and the trades by information analysts are likely to become more important, the announcement reaction implies that investors are more concerned with firm-specific information asymmetry to be reduced, while they hardly mind the increase in information asymmetry about systematic return components.

To empirically test these hypotheses, information asymmetry is decomposed into components that are related to the environment of a firm and its structural characteristics. The idiosyncratic, unexplained, part is considered to be a reflection of information asymmetry associated with insiders. Whether, and if so, how the thereby de-composed information asymmetry changes over the break-up process is then tested. Finally, the individual components of information asymmetry are related to the announcement returns in a regression framework to determine whether changes in information asymmetry in general, and information asymmetry associated with insider trades in particular, are associated with the announcement return.

## 3 Data and Methodology

### 3.1 Raw Data

This study looks at spin-offs and equity carve-outs during the period January 1995 to December 2005. These cases are identified by transactions that have CRSP distribution codes 3 or 5. ADRs are retained as U.S. exchanges assume an important role in the price discovery of foreign firms (Levine and Schmukler, 2006). The Financial Times on LexisNexis, EDGAR-filings, the New

York Times, Thomson Research, and the Perfect Filings database are manually checked to select only transactions that constitute a re-distribution of operations of a previously combined entity, to find information about the event dates, and to get details about the structure of the break-up. The structure of the break-up is referred to as *break-up type*. The additional requirement of sufficient data in TAQ, CRSP, and COMPUSTAT results in 166 transactions or 528 firm-event observations.[11]

Information asymmetry is captured using three alternative measures. First, yearly *PIN* values spanning the years 1993 to 2001 are downloaded from Soeren Hvidkjaer's homepage.[12] Second, one-year ahead earnings per share (hereafter EPS) forecast data are downloaded from I/B/E/S and the monthly standard deviation is calculated to create monthly values of analyst forecast dispersion. The measure of information asymmetry that most of the empirical tests rely on is based on intra-day TAQ data and is labeled $IA_1$. Its construction is described Section 3.2. To construct this measure, BBO trade and quote data is downloaded from TAQ, cleaned,[13] and signed using the Lee and Ready (1991)-algorithm.

[11] Some firms break-up into more than two entities resulting in more than twice as many firm-event observations than there are break-up events. Most of the empirical break-up studies just use the CRSP distribution codes 3762 to 3765, 5573, and 5873. This paper considers a broader sample that contains all instances with the first digit of the CRSP distribution code equal to either 3 ("exchanges and reorganisations") or 5 ("splits and stock dividends"). These fairly general pre-selection criteria allow cases that CRSP has not classified yet or cases that are break-ups but have distribution codes other than the ones typically used by empirical studies. After a first manual check to delete obvious cases of stock dividends, 2,083 individual transactions are retained that are manually checked using the sources mentioned in the main text to ascertain that each case constitutes a break-up. This search results in 270 break-up cases. As one firm has two break-ups in one month, there are 269 individual monthly observations. Requiring availability of COMPUSTAT data further reduces the sample by 87 observations to 182. Merging the sample with the TAQ database leaves 176 cases. Ten break-up observations are lost because the pre-announcement control period is earlier than January 1995 or the post-distribution control period is later than December 2005, resulting in the final sample of 166 cases.

[12] We would like to thank Soeren Hvidkjaer for making the *PIN* data available on his website:
http://www.smith.umd.edu/faculty/hvidkjaer/data.htm.

[13] Trades that are at the market open, out of sequence, with special settlement conditions, outside the market opening times or that have been corrected are excluded as are quotes that are posted at the market open, are negative, or lead to a bid-ask spread that is either negative, of above five U.S. dollars. Observations are deleted where the bid-ask spread is larger than 40 percent of the quote mid-point.

Stock prices, the number of stocks outstanding, stock returns and volume data are from CRSP. Firm size is calculated as the daily closing stock price times the number of shares outstanding. Annual total firm-risk is the yearly standard deviation of daily stock returns in excess of the risk-free rate. The one-month Treasury bill rate retrieved from the Fama-French database. Squared daily returns are used for daily values of stock-level volatility. Systematic risk is captured by the beta coefficient of a Scholes and Williams (1977)-type regression calculated by calendar year and idiosyncratic risk is the yearly average squared residual from that regression. Tick size is defined as the inverse of the closing stock price. To avoid co-linearity with volume, order-imbalance is defined as the sum of the intercept and the residual of a regression of the ratio of the daily dollar order imbalance to total dollar volume on dollar volume. Trading volume (unexpected changes in bid-ask spreads) is defined as the residual of a regression of daily dollar volume (bid-ask spread) on the market average and squared returns.

Market-level bid-ask spread, trading volume, and order-imbalance are defined as the value-weighted averages of the stock-level bid-ask spreads, trading volume, and order-imbalance. Market volatility is measured by the new methodology VIX index from the CBOE website. Outsider and insider ownership data are from the blockholders data by Dlugosz, Fahlenbrach, Gompers, and Metrick (2006) and the Option Metrics database is used to create a dummy that is one if there are options on a firm's stock and zero otherwise.

Balance sheet and income statement data are taken from COMPUSTAT and are winsorized at the top and bottom first percentile.[14] The return-on-equity, ROE, and the return-on-assets,

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[14] Operating profit is defined as the ratio of earnings before interest, taxes, and depreciation (item 13) to total sales (item 12). Leverage is calculated as the ratio of long-term debt (item 9) to the sum of long-term debt and firm size. Intangible assets are measures as total intangibles (item 33) to total assets (item 6). Tobin's Q is calculated as the sum of the book value of assets and the market value of equity less the book value of common equity (item 60) and balance sheet deferred taxes (item 74) divided by the book-value of assets (see Scharfstein, 1998). The book-to-market ratio is calculated as the sum of common equity, investment tax credits (item 208), and deferred taxes less the total value of preferred shares (items 56, 130, and 175) divided by firm size. The ratios of research and development

ROA, are calculated from COMPUSTAT data by dividing net income before extraordinary items by the average total common equity over the same fiscal year.[15]

The industry classification is based on two-digit SIC codes.[16] Diversification is measured by *unrelated entropy* defined as sum of the fraction of total sales attributed to each business segment weighted by the logarithm of the reciprocal of this ratio (see Palepu, 1985). Industry sales growth is captured by the market value-weighted average of the year-on-year percentage increase in sales within the same two-digit SIC industry. Break-ups where parent and sub are in different industries are classified as focus increasing. Analyst coverage is based on I/B/E/S data and is defined as the number of analysts making a one year-ahead earnings per share (hereafter EPS) forecast for a particular stock within the respective calendar year.

### 3.2 Direct Trade-based Measure of Information Asymmetry

To make this paper comparable to previous work, several measures of information asymmetry are constructed. First, the popular *PIN* measure is used. Second, analyst forecast dispersion and the information asymmetry measures by Krishnaswami and Subramaniam (1999) are constructed to ensure their conclusions extend to the data used in this paper.[17] In that case, results of this paper could be interpreted as extensions of and additions to Krishnaswami and Subramaniam (1999).

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(hereafter R&D) expenditure (item 46) to total sales and capital expenditures (item 128) to total sales are also calculated.

[15] Alternative measures of income, such as net income, earnings before taxes, and earnings before taxes, depreciation, and amortization, are used. Equity is alternatively captured by total stockholders' equity. The results are qualitatively similar.

[16] Alternatively, one could use four-digit SIC codes to construct the 48 Fama and French (1997)-industries, as Gertner et al. (2002) indicate that the conventional method of using the two-digit SIC code to match firms by industry is imprecise. Using this industry classification, however, would make the construction of the control sample more complicated as the more detailed Fama and French (1997) industry definition results in fewer firms per industry that satisfy the matching criteria specified in Section 4.2.

[17] These measures are *Forecast Error*, *Forecast Dispersion*, *Normalised Forecast Error*, *Announcement Reaction*, and *Residual Volatility*. The construction of these variables follows Krishnaswami and Subramaniam (1999) and Krishnaswami, Spindt, and Subramaniam (1999).

Table 4 Panel A shows that the pre-announcement and post-distribution levels of these four measures are consistent with Krishnaswami and Subramaniam (1999). All measures are lower in the year following the distribution date as compared to the year preceding the break-up announcement date. Reductions in information asymmetry may not be as clear-cut as suggested by these financial analyst-based measures, as summary statistics show a post-distribution increase (although significant only for the paired means) of *PIN*. This implies that while the information financial analysts have and generate is more precise after the break-up, investors may not necessarily enjoy a fairer information environment in financial markets after the break-up. In addition, these measures are available at yearly or at most monthly frequency, which does not allow analyzing the information environment around precise event dates. As this paper intends to investigate the information environment on a higher frequency basis, an additional measure of information asymmetry is constructed.

Most of the analysis is based on $IA_1$, which is the spread revenue of liquidity suppliers lost to traders demanding liquidity:

$$IA_{1,t} = D_t \left( M_T - M_t \right) / M_t \,, \tag{1}$$

where $D_t$ is a trade direction indicator taking a value of +1 for a buy and –1 for a sell. $M_t$ and $M_T$ are the quote mid-points at the time of the transaction, $t$, and some time, $T$, later. The actual measure is then the daily trade-sized weighted averages of intra-day $IA_1$ values. This measure should be positive when liquidity suppliers transact with an informed trader and zero is there is no private information in trades. The daily observation frequency allows splitting the break-up period into several periods.[18] Measures similar to $IA_1$ have been previously used in the microstructure literature to capture informed trading.[19]

[18] These periods are: (1) the *pre-announcement control period* being between 100 and 20 days before the announcement, (2) the *pre-announcement period* starting 20 days right before the break-up announcement and going until but

An additional issue that needs to be taken care of is the event-study context that much of the empirical analysis of this paper is based on. In particular, the well-documented returns that accrue at the break-up announcement date and the distribution date need to be controlled for as $IA_1$ data of break-up firms would otherwise not be comparable to non-break up firms. Venkatesh and Chiang (1986) find that liquidity providers anticipate increases in information asymmetry prior to scheduled information events. As most of the break-up information dates are known in advance, one needs to control for the level of information asymmetry that liquidity providers anticipate by charging higher spreads to correctly assess how changes in information asymmetry affects the adverse selection loss of liquidity providers. The effective spread, defined as the difference between the transaction price and the concurrent quote mid-point is a measure of the *ex ante* expectation of information asymmetry by the liquidity supplier as she intends to recapture expected revenue loss by adjusting the spread accordingly (Glosten and Milgrom, 1985). $IA_1$ is therefore scaled by the average daily effective spread. Scaling the *ex post* measure of information asymmetry, $IA_1$, by the *ex ante* expectation thereof allows removing liquidity providers' expectations of the expected return associated with the break-up. This makes the $IA_1$ data of break-up firms comparable to the $IA_1$ data of the control firms and similarly makes $IA_1$ measured during non-event periods comparable to event period $IA_1$.

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excluding the day prior to the break-up announcement, (3) the three days that straddle the *break-up announcement date*, (4) the days *between the announcement and the completion date*, (5) the day before and after the *completion date*, (6) the time *between the completion and the distribution date*, (7) the days that straddle the stock *distribution date*, and (8) the *post-distribution period* being between 20 to 100 trading days after the distribution date. The lower observational frequency of *PIN* and financial analyst-based variables make these measures not useful for this particular analysis.

[19] Huang and Stoll (1996) capture this loss by the difference of the quote mid-point at the time of the transaction and the recorded transaction price a fixed time interval later. Bessembinder and Kaufman (1997) use the scaled difference of the transaction price and the quote mid-point over a fixed time interval to improve the comparability of the adverse selection loss over unequally spaced transaction times. Naik and Yadav (2003) replace transaction prices by the quote mid-point and thereby address problems related to the bid-ask bounce. According to Lease, Masulis, and Page (1991) empirical biases can be large when using transaction prices instead of the quote mid-point. This bias is particularly significant during information events, which makes the use of a robust measure particularly important in the event study context of this paper. See also Hansch, Naik, and Viswanathan (1999), Hasbrouck and Sofianos (1993), and Huson and MacKinnon (2003).

# 4 Analysis

## 4.1 Univariate Analysis

Table 2 presents some summary statistics of the data of the break-up sample (Panel A) together with the correlation matrices (Panels B and C). Break-up firms are comparatively large consistent with extant literature (see, e.g., Abarbanell et al., 2003). As break-up firms appear to have a similar book-to-market ratio as their non-break-up peers, it seems unlikely that break-ups are done by inefficient firms to increase operating efficiency. Cases with subsequent mergers have low book-to-market ratios in the announcement week. As this indicates comparatively high market values during that period this may indicate information leakage about merger activity consistent with Vijh (1994). Alternatively, these results could also be due to break-up companies being concentrated in fast growing industries as the results by Maksimovic and Phillips (2002) imply.

Foreign firms have relatively low asset values, potentially reflecting issues around investor protection relative their U.S. peers (e.g., see La Porta, Lopez-De-Silanes, Shleifer, and Vishny, 2002). Considering the comparatively large size of break-up firms, their analyst following appears to be rather low, given that analyst following tends to increase in firm size (Bhushan, 1989b). Increasing analyst coverage could therefore be another motivation for break-up activity, indicating the likely importance of investors' information set in this context.

The returns around the break-up announcement and the distribution date show that clean spin-offs earn the highest announcement return. In addition, spin-offs involving legal settlements and concentrated ownership stakes (i.e., cases with prior private placements), show fairly large negative returns at the announcement date and large positive returns at the distribution date. This likely reflects the uncertainty around pending legal cases that lead to negative announcement returns and positive returns once all uncertainty is resolved at break-up consummation. The large return for break-ups involving private placements could indicate that markets suspect large shareholders exploiting their preferential access to top management as in the model by Maug (2002). Consistent with the information asymmetry-based perspective, uninformed investors may dislike dominant investors having preferential access to information, which enables insider trades as described by Lakonishok and Lee (2001). Finally, Panel A of Table 2 shows that focus increasing break-ups have higher announcement returns than non-focus increasing ones consistent with previous studies (see, e.g., Desai and Jain, 1999). In sum, the data exhibits behavior consistent with earlier studies. In addition, not only the break-up itself but also its structure seems to be important to investors. The data therefore allow looking at cross-sectional characteristics that are hardly discussed in the extant literature and thereby improving the understanding of the effect of break-ups on the information environment. The following section continues the analysis in a multivariate setting.

### 4.2 Construction of the Control Sample

To investigate firm-level changes in information asymmetry in a multivariate setting and in the event-study framework that this study employs, a set of control firms needs to be selected, which – due to the research focus of this paper – could be matched with the break-up firms by the pre-announcement level of information asymmetry. For comparability reasons with previous studies, matching is alternatively done by firm size. For each break-up firm, one control firm is selected that is closest in the level of information asymmetry (or firm size), has the same primary market, is in the same two-digit SIC industry, and that is in the same information asymmetry and firm size decile group during the first month of the control period than the break-up firm. Every control firm is used only once. Decile groups of monthly average information asymmetry and firm size are calculated across all firms that trade in the same primary market and have sufficient data in both control periods, during the break-up periods, and in all the data sets specified in Section 3.1. Summary statistics of the control samples and the break-up firms are presented in Panel D of Table 2, showing that the control samples match the break-up sample fairly closely.

### 4.3 Main Characteristics of Break-up Firms

As suggested by the results in Section 2.1, break-up firms are likely to be riskier, are likely to be less efficient, are typically more diversified, have a lower analyst coverage, have more intangible assets, and are likely to expose their investors to a higher level of information asymmetry (see Panel D of Table 2). In addition, previous studies find that break-up firms tend to be larger (Desai and Jain, 1999), less profitable (Gertner et al., 2002), and seem to be operating in high-growth industries (Krishnaswami and Subramaniam, 1999; Maksimovic and Phillips, 2002). To control for potential interaction between these factors, a multivariate logistic regression is estimated where the occurrence of a break-up (setting dummy variable $BU_i$ equal to one) is related to a set of explanatory variables measured in the pre-announcement control period:

$$\begin{aligned}\Pr\left(BU_i\right) = {} & \beta_1 Size_i + \beta_2 BTM_i + \beta_3 Profit_i + \beta_4 UnrEntropy_i + \\ & \beta_5 IndustryGrowth_i + \beta_6 TotalRisk_i + \beta_7 Beta_i + \\ & \beta_8 IdioRisk_i + \beta_9 Leverage_i + \beta_{10} Analyst_i + \beta_{11} Intangibles_i + \varepsilon_i,\end{aligned} \tag{2}$$

where $Size_i$, $BTM_i$, $Profit_i$, and $UnrEntropy_i$ denote the firm size, the book-to-market ratio, the operating profit margin, and the diversification of firm *i*, respectively. $IndustryGrowth_i$ measures the sales growth of the industry of firm *i*. $TotalRisk_i$, $Beta_i$, $IdioRisk_i$, and $Leverage_i$ are the annual total firm risk, the systematic risk, the idiosyncratic risk, and the financial leverage of firm *i*. $Analyst_i$ is the logarithm of one plus the number of analysts following the stock of firm *i*, and *Intan-*

$gibles_i$ measures the level of intangibles assets of firm $i$. Four alternative specifications of regression (2) are estimated whereby *BTM* is replaced by Tobin's Q and *Size* is replaced by $IA_1$.[20]

Results in Panel E of Table 2 show that large, diversified firms, and firms that have a relatively low market value of assets are more likely to break-up. Controlling for these effects, one does not find that break-up firms are much different with respect to their risk attributes, which is consistent with Daley et al. (1997), or have a higher level of intangible assets. The break-up decision could therefore be related to the market value of assets and the level of diversification.

The results further suggest that break-up firms have a lower analyst coverage, which reflects the argument by Gilson et al. (2001) that break-ups may intend to increase their analyst coverage. Higher analyst coverage could also be a way to reduce the level of information asymmetry investors are exposed to as analysts help spreading price-relevant information amongst investors. In fact, break-up firms appear to have a higher level of information asymmetry as measured by analyst forecast dispersion (see Table 3). The trade-based measures *PIN* and $IA_1$ do not confirm this finding, however. This implies that the information asymmetry financial analysts face is likely to be different from the information asymmetry faced by the public investor and therefore makes this analysis an important contribution to the understanding of how break-ups affect the information environment faced by all market participants. The lower level of analyst coverage of break-up firms could be responsible for the higher level of analyst forecast dispersion of break-up firms (see Table 3). As analysts issue more precise forecasts (see Panel A of Table 4) and increase their coverage after the distribution date (see, e.g., Gilson et al., 2001), break-ups seem to be an effective way to improve the information set of financial analysts. It remains to be

[20] The explanatory variables are normalised to a mean of zero and unit variance to be able to calculate the expected change in odds of observing a break-up when increasing variable $j$ by one standard deviation by $e^{\hat{\beta}_j}$, where $\hat{\beta}$ represents the estimated regression coefficient of variable $j$. A stratified conditional logistic regression is used (see, e.g., Fleiss, Levin, and Paik, 2003) to account for the correlation structure attributable to the matched-control sample methodology employed here.

seen, whether this improvement in the information environment of financial analysts translates into a better information environment of all investor, which will be examined next.

### 4.4 Information Asymmetry during the Break-up Process

This section investigates how the different stages of the break-up process and firm characteristics interact with changes in information asymmetry. For this purpose, the difference in average information asymmetry between the control period and each break-up period of the sample firms and control firms is regressed on explanatory variables measured during the control period:[21]

$$\begin{aligned}\Delta IA_{1,i,k} = \gamma_0 + \gamma_1 Size_i + \gamma_2 Analyst_i + \gamma_3\left(Size_i \times BU_i\right) + \\ \gamma_4\left(Analyst \times BU_i\right) + \gamma_5 BU_i + \vartheta_k + \eta_{i,k},\end{aligned} \tag{3}$$

where $\Delta IA_{1,i,k}$ denotes the change in information asymmetry between the control period and the respective break-up period of firm *i* with primary exchange *k*, and the other variables are defined as above. To improve comparability across firms, all continuous data are demeaned.

The results of this regression are shown in Panel B of Table 4. The coefficients of the interaction of the break-up dummy and firm size are positive, which implies that smaller firms experience a larger decline in information asymmetry over the course of the break-up. As smaller companies tend to have a larger level of information asymmetry (Hasbrouck, 1991a,b), they have more scope to improve their information environment than larger firms. Most importantly, the level of information asymmetry, $IA_1$, is lower after the break-up, while $IA_1$ briefly spikes at the distribution date. The brief increase in information asymmetry at the distribution date shows,

[21] Extant literature shows that stock exchanges differ in the level of information asymmetry investors are generally exposed to and in terms of the way new information is processed (Fishe and Robe, 2004; Stoll, 2000). Therefore, this regression is estimated as a random intercept model to account for the potential correlation of the $IA_1$ observations within each primary market that would make OLS inappropriate (see, e.g., Davidson and MacKinnon, 1993, p. 322). Results using standard OLS and a dummy that is one if the primary exchange is the NYSE and zero otherwise are not materially different. The NYSE dummy loads negatively, which shows that information asymmetry changes more on this exchange as compared to the Nasdaq. This shows, consistent with Fishe and Robe (2004), that the NYSE is faster than Nasdaq in accounting for new price-relevant information that the break-up entities provide to investors.

consistent with the argument of Admati and Pfleiderer (2000), that uninformed investors need to complement their information set by searching for stocks with prices that are correlated with the stock price of the firm they are invested in. Until these investors have found comparable stocks to the post-break up entities, informed investors can exploit their private information, resulting in a higher level of information asymmetry at the distribution date. There is little evidence for information leakage prior to the break-up announcement, however. Analyst coverage seems to have no impact on the change in information asymmetry over time. As the skill of analysts to generate private information from public sources is fairly heterogeneous (Gilson et al., 2001), analyst following may be too noisy a measure of the information environment, which further vindicates the microstructure approach used in this paper.[22]

In sum, there seems to be little changes in the information environment during the break-up period. However, information asymmetry declines significantly after the break-up. The post break-up decline in information asymmetry is consistent with Krishnaswami and Subramaniam (1999) and shows that the positive break-up effect on the information set of skilled financial information analysts also accrues to the uninformed public investor.

### 4.5 Changes in the Composition of Informed Trades

As pointed out in Section 2, two kinds of informed investors are considered: informed traders that happen to acquire insider information and informed traders who use publicly available data to

[22] Results for sample sub-groups, e.g., by primary exchange or break-up type, are not shown for conciseness but are available from the authors on request. We find that clean spin-offs show a significant increase in information asymmetry around the announcement date, while cases where subs have a separate listing prior to the distribution date do not show such an increase. This shows that private information about subs with prior listings is already impounded into prices at the distribution date while investors in firms that do a clean spin-off do not have a possibility to learn the relative values of sub and parent from market prices prior to the distribution. We also find a smaller regression intercept of NYSE stocks as compared to Nasdaq stocks, which shows that NYSE stocks experience a larger decline in information asymmetry on average (see also footnote 21). This is likely the result of the higher level of informational efficiency on the NYSE, which leaves less room for further improvements in the information environment as compared to the Nasdaq.

create private information; as pointed out earlier, these two types of informed traders may be affected unequally by the break-up. This could be due, for instance, to the provision of more audited financial information after the break-up, improvements in analyst coverage, and better analyst forecast precision. This section therefore investigates whether the break-up makes informed traders who exploit publicly available information more important relative to corporate insiders.

To this end, information asymmetry is decomposed into three components – the market-wide predictable component, the firm-specific predictable component, and the firm-specific unpredictable component (see Bardong et al. (2007) for a discussion and justification of this particular set-up). This decomposition allows interpreting information asymmetry as the sum of information asymmetry that is due to private information derived from the analysis of publicly available information (referred to as the predictable component in what follows) and information asymmetry that is related to insider information (referred to as the unpredictable residual component of information asymmetry).

The predictable component is hypothesized to increase after the break-up as there is more audited public information about the parent and the sub after the break-up relative to the pre-break up period. At the same time, traders using insider information should become less advantaged after the break-up as more value-relevant firm-specific information is publicly available. Therefore, the unpredictable component of information asymmetry is expected to decline while the predictable component of information asymmetry should increase after the break-up.

To investigate how beak-ups affect these two kinds of investors, $IA_1$ is regressed on explanatory variables to separate predicable from unpredictable information asymmetry.[23] The re-

[23] The following regressions are estimated with a firm-specific intercept across the entire CRSP universe of stocks that have their main listing on the NYSE or the Nasdaq:

$$IA_{1,i,k} = \delta_{i,0} + \delta_1 MBA_t + \delta_2 MVOL_t + \delta_3 MVLA_t + \delta_4 MOIB_t + \varsigma_{i,t},$$

$$IA_{2,i,k} = \phi_{i,0} + \phi_1 VLA_{i,t} + \phi_2 BA_{i,t} + \phi_3 OIB_{i,t} + \phi_4 TIC_{i,t} + \phi_5 UEDSpread_{i,t} + \phi_6 VOL_{i,t} + \upsilon_{i,k},$$

sulting unpredictable component of information asymmetry is referred to as *RAIN*; the predicable component of information asymmetry is called *EXIT*.

Insider trading should co-vary little across stocks as it typically relates to private information about firm-level idiosyncratic issues that nobody else knows as investors cannot infer this information from outside sources. *RAIN* is therefore interpreted as capturing informed trading by corporate insiders. By contrast, informed trading that co-varies with other information should be associated with informed trading that is based on exploiting public data. *EXIT* is therefore interpreted as capturing informed trading by skilled information analyst.

The resulting association of information asymmetry with the explanatory variables (see Table 5) is largely consistent across size decile and is mostly similar to what is reported in Bardong et al. (2007).[24] More importantly, Table 6 shows that the predictable component of informa-

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$$IA_{3,i,k} = \varphi_{i,0} + \varphi_1 Insider_{i,t} + \varphi_2 Outsider_{i,t} + \varphi_3 Capex_{i,t} + \varphi_4 R\,\&\,D_{i,t} + \varphi_5 BTM_{i,t} + \varphi_6 Profit_{i,t} + \varphi_7 Options_{i,t} + \varphi_8 Size_{i,t} + \xi_{i,k},$$

where $IA_{1,i,t}$ represents information asymmetry of firm *i* on day *t*. *MBA*, *MVOL*, *MVLA*, and *MOIB* are market-level bid-ask spread, U.S. dollar trading volume, volatility, and order-imbalance. These variables are meant to capture market-wide information events that are exploited by informed traders who are able to grasp the impact of economy-wide information on fundamental values faster and more effectively than the average investor. Stock-level trading characteristics are measured by the variables *VLA*, *UEDSpread*, *BA*, *VOL*, *TIC*, and *OIB*, which denote stock-level volatility, unexpected changes in bid-ask spreads, stock-level bid-ask spreads, trading volume, tick size, and order-imbalance, respectively. These variables account for informed traders that exploit their superior understanding of the trading environment (see Madrigal (1996) for a theoretical model of these investors). Firm-level structural characteristics, meant to account for the influence asset characteristics have on the information environment of a firm, are firm *Size*, the book-to-market-ratio (denoted by *BTM*), *Insider* and *Outsider* ownership, capital expenditure (denoted by *Capex*), *R&D* expenses, the operating *Profit* margin, and the availability of *Options*. To account for the size-effect, these regressions are estimated separately within size-deciles based on the daily firm size.

Taking the predictable component of market-wide variation out of $IA_1$ results in $IA_2$. $IA_3$ results if the predictable component related to stock-level trading characteristics is taken out of $IA_2$. Taking the effect of firm-specific structural characteristics out of $IA_3$ results in the unpredictable component of information asymmetry, labeled *Residual Asymmetric Information* and henceforth referred to as *RAIN*. The predicable component of information asymmetry, *Explained Informed Trading*, which is abbreviated by *EXIT*, is defined as the difference between $IA_1$ and *RAIN*.

[24] Bid-ask spreads, a rough measure of transaction costs, are negatively related with the level of information asymmetry. Trading volume, volatility, and order imbalance have a positive association, suggesting that periods of high uncertainty and asset revaluations put informed traders at an advantage. The negative coefficient of tick size, showing that information asymmetry is lower the smaller the minimum price increment implies that the price discovery process of stocks with smaller minimum tick size is more efficient. Information asymmetry is lower for larger firms and for firms with options on their common stocks, consistent with the notion that some informed investors leave the stock market and enter the options market instead. Higher ownership concentration by insiders is associated with a higher level of information asymmetry. A lower book-to-market ratio is associated with a higher level of information

tion asymmetry, *EXIT*, increases significantly after the break-up. As total information asymmetry goes down (see Table 4), this implies that skilled information analysts become more important relative to traders that exploit insider information after the break-up. Thus, the two types of informed investor are affected differently by the break-up.

Financial analysts may be among the main beneficiaries of this type of informed trading as they can sell their information to would-be informed traders or exploit their private information in the financial markets themselves. The larger resources committed by financial analysts after the break-up (Gilson et al., 2001) could therefore be motivated by the expected benefit that accrues to skilled information analysts. How public investors interpret this differential impact of break-ups on informed investors is discussed next, where the stock-market reaction to the break-up announcement is looked at.

### 4.6 Changes in Information Asymmetry and Announcement Returns

This section investigates how the stock market return reaction to break-up announcements can be explained by post-break up changes in the information environment. Easley and O'Hara (2004) show in their model that exposure to information asymmetry is a priced risk factor. The positive market reaction to the break-up could therefore be the result of investors anticipating a decline in information asymmetry. This could also explain the relatively low asset valuation of break-up firms (see Panel A of Table 2), which could therefore also be attributed to a lack of informational transparency rather than a lack of operational efficiency alone.

Cumulative abnormal break-up announcement returns of stock *i* are therefore regressed on changes in information asymmetry over the break-up period of stock *i* and some control variables using a random intercept model associated with the primary stock exchange *k* of stock *i*:

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asymmetry, which, if one interprets this ratio as a proxy for growth options, is consistent with growth firms being more active in managing investors' perception.

$$CAR_{i,k} = \lambda_0 + \lambda_1 \Delta InfoAsymmetry_{i,j,k} + \sum_m \theta_m ControlVariable_m + \omega_k + \zeta_{i,k}, \tag{4}$$

where $CAR_{i,k}$ is the cumulative abnormal break-up announcement return of break-up announcement $i$ observed on primary exchange $k$. Daily abnormal returns are the residual from a market-model estimated during the control period (following Campbell, Lo, and MacKinlay (1997)). $\Delta InfoAsymmetry_{i,j,k}$ denotes the difference between the average level in information asymmetry component $j$ ($IA_1$, *RAIN*, or *EXIT*) during the post-distribution control period and the pre-announcement control period of stock $i$ trading on primary exchange $k$. *ControlVariable* represents the set of control variables *Focus*, *Prior IPO*, *Clean Spin-off*, *Size*, *Beta*, and *Analyst*, which are measured concurrent to the break-up announcement, and *ΔROA* and *ΔROE*, which are measured over the break-up period. The dummy variable *Prior IPO* is equal to one if the sub is separately listed on a stock exchange prior to the break-up and zero otherwise. *Clean Spin-off* is a dummy variable that is equal to one if the break-up is classified as a clean, tax-free spin-off and zero otherwise and the other variables are defined as in equation (2).[25] A significantly negative loading on $\Delta InfoAsymmetry_{i,j,k}$ would indicate that the positive announcement returns are related to changes in information asymmetry component $k$.

The inclusion of the control variables *Focus*, *ΔROA*, and *ΔROE* specifically serves to verify whether our results are robust to alternative explanations of break-ups in general and to the positive stock-market reaction to break-up announcements in particular. According to the model by Habib et al. (1997), stock-holders of breakup firms benefit not only from an improvement in the information environment but also from a more efficient resource allocation. In addition, they show that this effect should be stronger for focus increasing break-ups as the improvement in the

[25] As before, all continuous data are de-meaned. Adjusting the changes in information asymmetry of the break-up firms by the change in information asymmetry of the control firms over the same time horizon leads to the same results, which have been suppressed to save space.

information environment to both, investors and managers, is most pronounced in these cases. The variable *Focus* is meant to capture whether a break-up is focus increasing as it is defined as being equal to one if the break-up is focus-increasing and zero otherwise. *ΔROA* (*ΔROE*) are meant to capture improvements in efficiency and are calculated as the difference between the return-on-assets (return-on-equity) in the fiscal year following the break-up consummation and the return-on-equity in the fiscal year of the break-up announcement. If break-ups improve the efficiency of the resource allocation of a firm and if focus increasing break-ups are more beneficial to investors we would expect the coefficient on these variables to be positive. Furthermore, for our results to be robust to these alternative explanations of break-up motivations and the stock-market reaction to break-up announcements, we should not see the significance of $\Delta InfoAsymmetry_{i,j,k}$ to be affected by the inclusion of these variables.[26]

The results in Table 7 show that break-up announcement excess returns are related to post break-up decreases in information asymmetry. In addition, the announcement returns are higher for stocks with lower analyst coverage and break-ups that are focus increasing (though not significantly so). A higher level of operational focus improves the quality of the information communicated by financial analysts to the public (Gilson et al., 2001) while a higher level of analyst coverage leads to more information to be communicated to the public. Both findings are consistent with the hypothesis that break-ups benefit investors by lowering information asymmetry.

Comparing the coefficients of the two information asymmetry components *EXIT* and *RAIN* with each other, it appears that only declines in the residual unexplained part of informa-

[26] Habib et al. (1997) also mention that managers' compensation can be better aligned with shareholders through break-ups, if company stock-based compensation is used as the managers of each of the broken-off units can be compensated with stock of each the unit she is responsible for. This is also likely to improve the performance of the post break-up entities which may also be an explanation behind the break-up announcement reaction. In the interest of space, we do not, however, control for this hypothesis as this is likely to be a second order effect that – although undoubtedly important – is likely to be weaker than improvements to the information environment or to the efficiency of the resource allocation of the firm.

tion asymmetry, *RAIN*, are significantly related to announcement returns. The significantly negative loading on *RAIN* shows that the decline in information asymmetry that is associated with insider information is beneficial to all investors. The insignificant loadings on changes in the predictable component, *EXIT*, suggest that the gain in the information-related advantage to the skilled analyst does not offset the benefits to the public investor due to the overall reduction in information asymmetry. Thus, although break-ups appear to benefit skilled information analysts, it appears that also the average investors benefit from break-ups. Both groups of investors, uninformed and skilled investors, seem to anticipate the improvement in the information environment that is associated with corporate break-ups.

While being consistent with what one would expect from extant research, our results are robust to the alternative motivations of break-ups and the stock-market reaction to break-up announcements. The coefficients of *Focus*, $\Delta ROA$, and $\Delta ROE$ are all positive and sometimes significant. This is consistent with the notion that stock markets value improvements in the information environment, next to efficiency improvements, related to the break-up as Habib at al. (1997) theoretically show. We find that the results are robust to these alternative explanations of break-ups and the stock-market reaction to their announcement.

To further verify the robustness of the results, this analysis is repeated using $IA_1$ calculated over one and two days.[27] As shown in Table 8, the results are consistent with what has been discussed so far. Break-ups are associated with a significant decline in information asymmetry as the significantly negative coefficient on the break-up dummy shows. The decline in $IA_1$ seems to

[27] In particular, the quote mid-point right before a transaction is matched with the quote mid-point in effect exactly 24 hours or 48 hours later. Information asymmetry models typically assume that private information is revealed once per trading session. Scaling $IA_1$ calculated over more than one trading session by the effective spread would therefore lump together an *ex ante* expectations of information asymmetry referring to the day of the particular trade with information revealed to informed traders only subsequently and can therefore not be anticipated by the liquidity provider. As a result scaling $IA_1$ by the effective spread is avoided if $IA_1$ is calculated over more than one day to be consistent with existing models on information asymmetry.

be the result of a decline in the unpredictable component of information asymmetry that is associated with insider trading. The part of information asymmetry that is associated with trading by skilled information analysts, referred to as *EXIT*, increases after the break-up. This evidence shows that informed trading by corporate insiders declines while informed trading by institutions that create new information from public sources increases. Consistent with the results in the previous section, investors seem to attach value to correctly anticipated future declines in *RAIN* while changes in *EXIT* are hardly relevant. Thus, the decline in the unpredictable component, which is beneficial to all investors, appears to be related to break-up announcement returns.

## 5 Summary and Conclusion

This paper utilizes direct measures of information asymmetry developed in the market microstructure literature to gain insights into changes in the information environment during and after a corporate break-up. The empirical results are consistent with extant evidence on some of the firm characteristics associated with break-up activity and show that information asymmetry plays an important role in the motivation of and the stock market reaction to break-ups.

We find that overall information asymmetry declines after the break-up. However, informed traders who derive private information from the skilled analysis of public information become relatively more important than informed traders who use insider information. Finally, the stock market reaction to break-up announcements is strongly associated with post-break up reductions in the component of information asymmetry that is associated with insider information.

The results shown in this paper strongly support the link between firm-value and information asymmetry as suggested by Easley and O'Hara (2004). Improvements in the quality and quantity of the information of financial analysts resulting from the break-up (Gilson et al., 2001; Krishnaswami and Subramaniam, 1999) are also reflected in improvements of public investor’s information set. In addition, the significant relationship between changes in information asymmetry and announcement returns shows that investors seem to correctly anticipate at the break-up announcement the post-distribution improvement in the public information set. We further find that investors have to wait until the break-up is completed to fully benefit from the reduction in information asymmetry that is associated with break-ups.

Corporate break-ups benefit both the uninformed public investor – since the total level of information asymmetry is reduced – and skilled information analysts. The benefits to public investors resulting from the break-up seems to more than offset likely increases in adverse selection losses to skilled information analysts. These results are robust to alternative explanations of the break-up announcement returns.

Our findings help explain why financial institutions commit more resources to the analysis of break-up firms. Gilson et al. (2001) argue that higher analyst coverage attracts trading activity that motivates financial intermediaries to improve their analyst coverage and therefore to enhance the information environment. The findings presented here also suggest that there likely is a second route by which benefits of break-ups accrue to financial intermediaries: either they or their customers exploit more profitably the analysis public information.

Gilson et al. (2001) show that there are some information analysts that are more skilled than others and who get advantaged by the break-up. These analysts seem to turn their skills into profits by trading on the information they generate as post-break up trading activity of this type of trader increases. Therefore, it may not just be the expectation of attracting more retail trades but also the prospect of exploiting in-house analytical capabilities that makes financial institutions promote break-ups among their corporate clients. Furthermore, post break-up takeovers, which Cusatis et al. (1993) find to be fairly common, may generate additional revenue, which is a further incentive to these market participants to promote break-ups among their clients and to invest resources into research capabilities that exploit the additional information that break-ups bring to the market.

Our results imply that sophisticated institutional investors better exploit public information after the break-up. Future research could therefore investigate whether this is reflected in the trading behavior of sophisticated investors.

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# Table 1 – Variable Definitions

This table lists the names of the variables used in this paper in column *Variable Name* and the definition used to construct the respective variable in the column *Definition*.

| Variable | Definition |
|---|---|
| *Analyst* | The (logarithm of one plus) the number of analysts covering a particular firm in a given year. |
| *Announcement date* | The three days that straddle the break-up announcement. |
| *Announcement to completion* | The time period between the break-up announcement and the completion date. |
| *BA* | Stock-level bid-ask spread |
| *Beta* | Stock market beta calculated using the Scholes and Williams (1977) methodology by regressing daily stock excess returns on the market excess returns within a calendar year. |
| *BTM* | The book-to-market ratio calculated as the sum of common equity, investment tax credits, and deferred taxes less the total value of preferred shares divided by firm size. |
| $BU_i$ | A dummy variable that is equal to one if firm *i* is a break-up firm and zero otherwise. |
| *Capex* | Capital expenditures to sales |
| *CAR* | The sum of daily returns in excess of the expected return derived from a market-model estimated during the pre-announcement control period (see Campbell, Lo and MacKinlay (1997)). |
| *Clean Spin-off* | This variable is one if the break-up is classified as a tax-free spin-off and zero otherwise. |
| *Completion date* | The three days that straddle the announcement of the final details of the break-up. |
| *Completion to the distribution* | The time period between the completion date and the distribution date. |
| *Control period* | Between 100 and 20 days before the break-up announcement. |
| *Distribution date* | The date of the stock distribution. |
| *EXIT* | The difference between $IA_1$ and *RAIN*. |
| *FirmSize* | The logarithm of the market capitalisation of a firm. |
| *Focus* | This variable *is* equal to one if the break-up is focus-increasing and zero otherwise. |
| *Forecast Dispersion* | The standard deviation of one-year ahead EPS forecasts made by equity analysts in the particular month. |
| $IA_1$ | The daily trade size-weighted average of the difference between the quote mid-point right before a transaction and the quote mid-point 30 minutes later scaled by the first quote mid-point divided by the effective spread of this transaction. |
| $IA_2$ | $IA_1$ less the variation explained by market-wide commonality variables. |
| $IA_3$ | $IA_2$ less the variation explained by firm-specific trading characteristics. |
| *IdioRisk* | The yearly average of the residuals of the Scholes and Williams (1977)-regression. |
| *IndustryGrowth* | The market value-weighted average of year-on-year relative increase in total sales in the 2-digit SIC industry of each firm. |
| *Insider* | The sum of block-ownership stakes in the common stock of a firm by corporate insiders. |
| *Intangibles* | The ratio of intangible assets to total assets of a particular firm. |
| *Leverage* | The ratio of long-term debt to the sum of long-term debt and the firm size. |
| *MBA* | Market-level bid-ask spread |
| *MOIB* | Market-level order-imbalance |
| *MVLA* | Market-level volatility |
| *MVOL* | Market-level dollar trading volume |
| *OIB* | Stock-level order-imbalance |
| *Options* | This is an indicator variable being one if there are exchange-traded options on stock *i* and zero otherwise. |
| *Outsider* | The sum of block-ownership stakes in the common stock of a firm by corporate outsiders. |
| *PIN* | Yearly values are provided on Soeren Hvidkjaer's website. |
| *Post-distribution* | The period between 20 to 100 trading days after the distribution date. |
| *Pre-announcement* | Starting 20 days prior to the announcement date up to but excluding the day prior to the announcement. |
| *Prior IPO* | This variable is equal to one if the sub had a separate stock exchange listing prior to the break-up and zero otherwise. |
| *Profit* | The ratio of profits before taxes, interest payments, depreciation, and amortisation to total sales. |
| *R&D* | R&D expenses to sales |
| *RAIN* | $IA_3$ less the variation explained by firm-level structural characteristics. |
| *Returns* | Monthly stock returns |
| *ΔROA* | The level of return-on-asset measured in the fiscal year after the break-up consummation less the level of return-on-asset measured in the fiscal year of the control period. |
| *ΔROE* | The level of return-on- equity measured in the fiscal year after the break-up consummation less the level of return-on-equity measured in the fiscal year of the control period. |
| *Size* | The logarithm of market capitalisation. |
| *TIC* | Tick size |
| *Tobin's Q* | The sum of the book value of assets and the market value of equity less the book value of common equity and deferred taxes divided by the book value. |
| *TotalRisk* | The yearly average of the percentage standard deviation of daily stock returns in excess of the risk-free rate of each individual firm. |
| *UEDSpread* | Unexpected changes in bid-ask spreads |
| *UnrEntropy* | This variable is defined as the weighted sum of segment sales of each individual firm (see Palepu (1985)). |
| *VLA* | Stock-level volatility |
| *VOL* | Stock-level trading volume |

# Table 2 – Sample Summary Statistics of Break-up Sample

This table shows some summary statistics of the sample of the break-up firms around the break-up announcement and after completion (Panel A), correlation coefficients between the variables used in the empirical analysis (Panels B and C), the full sample summary statistics for the break-up firms and the control firms (Panel D) and a statistical test of the difference between sample and control firms (Panel E). In particular, Panel A shows the median values of some statistics of the break-up sample *As of the Week of the Break-up Announcement* and *As of the Week of the Stock Distribution*. The column *Break-up Type* shows a breakdown of the sample according to break-up characteristics. The columns No. *Break-ups* and *Ind. Obs.* report the number of break-ups and the number of individual firm observations across parents and subs, respectively. The variable definition is given in Table 1. The table also reports the relative firm size of the break-up companies as measured by their median *Decile* position relative to the firms in the CRSP Universe that have the same primary market as the beak-up firm. *Return*, expressed in percentages, measures the cumulative stock return in excess of the value-weighted CRSP market average during the three days straddling the break-up announcement date or the stock distribution date. The column *Relative Size* shows the firm size of the sub as percentage of its parent. Panels B and C show the correlation coefficients between the variables used in this study. The sample comprises the break-up sample and the control sample that is either *$IA_1$-matched* (Panel B) or *Size-matched* (Panel C). Frequencies are monthly, whereby the *$IA_1$*-values are monthly averages and *PIN* is available on yearly frequency only. The values displayed are means of the firm-level correlation coefficients. Panel D shows full sample summary statistics of the break-up sample and the industry and size or *$IA_1$*-matched control sample. The column *Obs* reports the number of observations in each sample. The columns *Q1*, *Q3*, *IQ Range*, and *Median* show the values of the first and the third quartile, the inter-quartile range, and the median values, respectively. The column *Wilcoxon* reports the *p*-values associated with a two-sided Wilcoxon-Mann-Whitney test of zero median difference between the break-up and the control sample. *Billion $*, *%*, and *bp* in parentheses behind the variable name indicate whether the unit of measurement is in billions of dollars, percentages, or basis points, respectively. Panel E shows the results of a stratified conditional logistic regression for matched samples of $BU_i$, a dummy variable that is equal to one if firm *i* is a break-up firm and zero otherwise, on a set of explanatory variables:

$$(1)\ \Pr(BU_i) = \beta_1 Size_i + \beta_2 BTM_i + \beta_3 Profit_i + \beta_4 UnrEntropy_i + \beta_5 IndustryGrowth_i + \beta_6 TotalRisk_i + \beta_7 Beta_i + \beta_8 IdioRisk_i + \beta_9 Leverage_i + \beta_{10} Analyst_i + \beta_{11} Intangibles_i + \varepsilon_i,$$

$$(2)\ \Pr(BU_i) = \beta_1 Size_i + \beta_2 TobinsQ_i + \beta_3 Profit_i + \beta_4 UnrEntropy_i + \beta_5 IndustryGrowth_i + \beta_6 TotalRisk_i + \beta_7 Beta_i + \beta_8 IdioRisk_i + \beta_9 Leverage_i + \beta_{10} Analyst_i + \beta_{11} Intangibles_i + \varepsilon_i,$$

$$(3)\ \Pr(BU_i) = \beta_1 BTM_i + \beta_2 Profit_i + \beta_3 UnrEntropy_i + \beta_4 IndustryGrowth_i + \beta_5 TotalRisk_i + \beta_6 Beta_i + \beta_7 IdioRisk_i + \beta_8 Leverage_i + \beta_9 Analyst_i + \beta_{10} Intangibles_i + \beta_{11} IA_{1,i} + \varepsilon_i,$$

$$(4)\ \Pr(BU_i) = \beta_1 TobinsQ_i + \beta_2 Profit_i + \beta_3 UnrEntropy_i + \beta_4 IndustryGrowth_i + \beta_5 TotalRisk_i + \beta_6 Beta_i + \beta_7 IdioRisk_i + \beta_8 Leverage_i + \beta_9 Analyst_i + \beta_{10} Intangibles_i + \beta_{11} IA_{1,i} + \varepsilon_i,$$

where subscript *i* represents firm *i*. All variables are measured in the first month that begins 100 days before the break-up announcement, whereby $IA_1$ is measured as the monthly average and *Size* as of the end of the month. All explanatory variables are standardized to a mean of zero and unit variance. *P*-values associated with the coefficients are reported in parentheses underneath the coefficients and the *R*-square (in percentages) is constructed using the log-likelihoods as generalized by Nagelkerke (1991). The column *Non-event Sample* shows whether the control firm selected from the control portfolio is *$IA_1$-matched* (information asymmetry is therefore left out of the set of explanatory variables) or whether the control firm is *Size-matched* (and size is therefore left out of the set of explanatory variables). The column *Obs.* displays the number of break-up and control firm pairs used. The asterisks *, **, and *** denote significance levels of 10%, 5% and 1%, respectively.

*(continued)*

# Table 2 – Sample Summary Statistics of Break-up Sample (continued)

## Panel A – General Characteristics of Break-up Sample

| | | | As of Week of the Break-up Announcement | | | | | | | As of the Week of the Stock Distribution | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | No. | Ind. | | Firm | | Decile | | | | | Firm | | Decile | | | | Relative |
| Brea-up Type | Break- | Obs. | BTM | Size | Analyst | BTM | Size | Analyst | Return | BTM | Size | Analyst | BTM | Size | Analyst | Return | Size |
| Previous IPO (carve-out) | 27 | 94 | 0.4 | 23.6 | 11.5 | 4.0 | 8.0 | 8.0 | 1.6 | 0.5 | 8.6 | 8.0 | 5.0 | 7.0 | 7.0 | 0.5 | 27.0 |
| Previous private placement | 6 | 22 | 0.3 | 27.1 | 13.0 | 3.0 | 9.0 | 7.0 | -2.5 | 0.5 | 3.6 | 3.0 | 4.0 | 7.5 | 3.5 | 3.0 | 21.3 |
| Break-up part of legal settlement | 4 | 11 | 0.4 | 16.3 | 17.0 | 3.0 | 6.5 | 6.5 | -1.5 | 0.6 | 8.7 | 12.0 | 7.5 | 7.0 | 7.0 | 2.5 | 31.2 |
| Clean spin-off | 126 | 385 | 0.4 | 24.1 | 11.0 | 5.0 | 9.0 | 7.0 | 2.8 | 0.5 | 8.3 | 8.0 | 5.0 | 8.0 | 6.0 | 0.8 | 25.5 |
| Break-up part of merger | 3 | 16 | 0.8 | 0.6 | 3.0 | 8.0 | 6.0 | 5.0 | 0.5 | 0.4 | 1.5 | 3.5 | 6.5 | 6.0 | 4.0 | 1.3 | 69.1 |
| Foreign firm | 19 | 47 | 1.2 | 17.8 | 7.5 | 9.0 | 9.0 | 6.0 | -0.2 | 1.5 | 6.0 | 6.0 | 9.0 | 7.5 | 5.0 | 0.3 | 20.9 |
| U.S. firm | 147 | 481 | 0.4 | 23.0 | 11.5 | 4.0 | 9.0 | 7.0 | 2.2 | 0.5 | 8.5 | 8.0 | 5.0 | 8.0 | 7.0 | 1.2 | 27.0 |
| NYSE is primary stock market | 119 | 347 | 0.4 | 33.1 | 13.0 | 4.0 | 9.0 | 7.0 | 2.2 | 0.5 | 16.5 | 12.0 | 5.0 | 8.0 | 7.0 | 1.1 | 20.7 |
| Nasdaq is primary stock market | 47 | 181 | 0.6 | 2.2 | 5.0 | 5.0 | 8.0 | 7.0 | 1.8 | 0.5 | 1.2 | 3.0 | 6.0 | 7.0 | 4.5 | 0.7 | 53.3 |
| Break-up is not focus increasing | 76 | 233 | 0.4 | 21.6 | 11.0 | 4.0 | 9.0 | 7.0 | 1.3 | 0.5 | 7.0 | 7.5 | 5.0 | 7.0 | 6.5 | 1.2 | 30.9 |
| Break-up is focus increasing | 90 | 295 | 0.4 | 26.2 | 12.0 | 4.0 | 9.0 | 7.0 | 2.8 | 0.5 | 8.5 | 9.0 | 5.0 | 8.0 | 6.0 | 0.8 | 24.8 |
| Restructuring after the break-up | 2 | 14 | 0.4 | 37.4 | 5.0 | 4.5 | 8.0 | 3.0 | 7.7 | 0.6 | 5.8 | 3.0 | 7.0 | 6.0 | 3.0 | 6.1 | 81.5 |
| Merger after the break-up | 14 | 53 | 0.4 | 18.3 | 8.0 | 3.0 | 10.0 | 7.0 | 1.3 | 0.5 | 4.6 | 4.0 | 4.0 | 8.0 | 3.0 | 0.4 | 43.3 |
| No M&A or Restructuring after break-up | 150 | 461 | 0.4 | 23.3 | 11.5 | 4.0 | 9.0 | 7.0 | 2.2 | 0.5 | 8.7 | 8.5 | 5.0 | 8.0 | 7.0 | 0.8 | 24.8 |
| Total sample | 166 | 528 | 0.4 | 22.5 | 11.0 | 4.0 | 9.0 | 7.0 | 2.1 | 0.5 | 8.3 | 8.0 | 5.0 | 8.0 | 6.0 | 0.9 | 26.8 |

*(continued)*

# Table 2 – Sample Summary Statistics of Break-up Sample (continued)

## Panel B – Break-up Firms and $IA_1$-matched Control Firms

| | Size | Tobin's Q | BTM | Profit | Unrelated Entropy | Industry Growth | Total Risk | Beta | Idiosyncratic Risk | Leverage | Analyst | Intangibles | Returns | Forecast Dispersion | PIN |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Tobin's Q | 0.61 | | | | | | | | | | | | | | |
| BTM | -0.52 | -0.76 | | | | | | | | | | | | | |
| Profit | 0.26 | 0.16 | -0.16 | | | | | | | | | | | | |
| Unrelated entropy | -0.05 | -0.06 | 0.05 | -0.03 | | | | | | | | | | | |
| Industry growth | 0.10 | 0.14 | -0.13 | 0.09 | 0.01 | | | | | | | | | | |
| Total risk | -0.07 | -0.02 | 0.05 | -0.02 | 0.22 | 0.10 | | | | | | | | | |
| Beta | 0.10 | 0.06 | -0.05 | -0.05 | -0.13 | -0.07 | 0.05 | | | | | | | | |
| Idiosyncratic risk | -0.09 | -0.02 | 0.06 | -0.02 | 0.19 | 0.13 | 0.95 | -0.06 | | | | | | | |
| Leverage | -0.34 | -0.38 | 0.28 | -0.20 | 0.02 | -0.13 | 0.07 | 0.04 | 0.06 | | | | | | |
| Analyst | 0.22 | 0.00 | -0.01 | 0.15 | -0.08 | -0.03 | -0.06 | 0.11 | -0.06 | -0.05 | | | | | |
| Intangibles | 0.05 | -0.15 | 0.12 | 0.03 | -0.02 | -0.12 | -0.01 | 0.07 | -0.02 | 0.18 | 0.07 | | | | |
| Returns | 0.12 | 0.16 | -0.18 | -0.03 | -0.01 | 0.00 | -0.03 | -0.01 | -0.03 | 0.04 | -0.04 | -0.01 | | | |
| Forecast dispersion | 0.01 | -0.08 | 0.09 | 0.00 | -0.01 | 0.00 | 0.04 | 0.04 | 0.03 | 0.00 | 0.13 | 0.04 | -0.05 | | |
| PIN | -0.20 | 0.04 | -0.04 | -0.05 | -0.03 | 0.04 | -0.20 | 0.00 | -0.17 | -0.02 | -0.10 | -0.14 | 0.03 | -0.07 | |
| $IA_1$ | 0.16 | 0.08 | -0.10 | 0.01 | -0.02 | -0.06 | -0.02 | 0.14 | -0.05 | -0.05 | 0.06 | 0.07 | 0.08 | 0.04 | -0.07 |

*(continued)*

# Table 2 – Sample Summary Statistics of Break-up Sample (continued)

## Panel C – Break-up Firms and Size-matched Control Firms

| | Size | Tobin's Q | BTM | Profit | Unrelated Entropy | Industry Growth | Total Risk | Beta | Idiosyncratic Risk | Leverage | Analyst | Intangibles | Returns | Forecast Dispersion | PIN |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Tobin's Q | 0.60 | | | | | | | | | | | | | | |
| BTM | -0.52 | -0.76 | | | | | | | | | | | | | |
| Profit | 0.23 | 0.14 | -0.13 | | | | | | | | | | | | |
| Unrelated entropy | -0.02 | -0.04 | 0.06 | -0.01 | | | | | | | | | | | |
| Industry growth | 0.13 | 0.15 | -0.12 | 0.08 | -0.02 | | | | | | | | | | |
| Total risk | -0.07 | -0.01 | 0.06 | -0.04 | 0.25 | 0.08 | | | | | | | | | |
| Beta | 0.12 | 0.09 | -0.07 | 0.00 | -0.11 | -0.08 | 0.06 | | | | | | | | |
| Idiosyncratic risk | -0.10 | -0.03 | 0.07 | -0.05 | 0.22 | 0.11 | 0.95 | -0.05 | | | | | | | |
| Leverage | -0.33 | -0.38 | 0.27 | -0.20 | 0.00 | -0.11 | 0.04 | 0.01 | 0.05 | | | | | | |
| Analyst | 0.21 | -0.01 | 0.00 | 0.15 | -0.03 | -0.03 | -0.04 | 0.09 | -0.05 | -0.04 | | | | | |
| Intangibles | 0.04 | -0.14 | 0.11 | 0.05 | 0.01 | -0.11 | 0.00 | 0.07 | -0.01 | 0.16 | 0.05 | | | | |
| Returns | 0.12 | 0.15 | -0.17 | -0.03 | -0.01 | 0.00 | -0.04 | -0.01 | -0.03 | 0.05 | -0.04 | -0.02 | | | |
| Forecast dispersion | 0.03 | -0.06 | 0.07 | 0.01 | 0.00 | -0.01 | 0.03 | 0.05 | 0.02 | -0.02 | 0.13 | 0.05 | -0.04 | | |
| PIN | -0.14 | 0.06 | -0.06 | -0.06 | -0.08 | 0.01 | -0.21 | 0.04 | -0.19 | -0.05 | -0.09 | -0.12 | 0.04 | -0.04 | |
| $IA_1$ | 0.19 | 0.10 | -0.11 | 0.02 | -0.03 | -0.06 | -0.02 | 0.11 | -0.05 | -0.06 | 0.06 | 0.06 | 0.08 | 0.02 | -0.05 |

*(continued)*

# Table 2 – Sample Summary Statistics of Break-up Sample (continued)

## Panel D – Full Sample Statistics of Break-up Firms and Control Sample

| | Break-up firms | | | | | Individual control firms – $IA_1$-matched | | | | | | Individual control firms – Size-matched | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Variable | Obs | Q1 | Median | Q3 | IQ Range | Obs | Q1 | Median | Q3 | IQ Range | Wilcoxon | Obs | Q1 | Median | Q3 | IQ Range | Wilcoxon |
| Size (billion $) | 166 | 0.3 | 2.2 | 7.7 | 7.4 | 166 | 0.3 | 1.8 | 6.2 | 5.9 | 0.55 | 166 | 0.3 | 2.0 | 6.2 | 5.9 | 0.70 |
| Tobin's Q | 166 | 1.1 | 1.5 | 2.2 | 1.2 | 166 | 1.2 | 1.7 | 2.8 | 1.6 | 0.06 | 166 | 1.2 | 1.7 | 3.1 | 1.9 | 0.03 |
| Book-to-market | 166 | 0.2 | 0.4 | 0.8 | 0.6 | 166 | 0.2 | 0.3 | 0.5 | 0.4 | 0.01 | 166 | 0.2 | 0.3 | 0.5 | 0.4 | 0.02 |
| Profit (%) | 166 | 8.0 | 17.0 | 23.2 | 15.2 | 166 | 7.4 | 15.2 | 23.0 | 15.6 | 0.87 | 166 | 9.0 | 16.2 | 26.1 | 17.1 | 0.52 |
| Unrelated entropy (%) | 166 | 0.0 | 26.7 | 66.6 | 66.6 | 166 | 0.0 | 0.0 | 26.2 | 26.2 | 0.00 | 166 | 0.0 | 0.0 | 36.2 | 36.2 | 0.00 |
| Industry growth (%) | 166 | 8.4 | 18.9 | 28.1 | 19.7 | 166 | 8.1 | 15.8 | 24.0 | 15.9 | 0.10 | 166 | 8.0 | 15.4 | 24.0 | 16.0 | 0.04 |
| Total risk (%) | 166 | 1.8 | 2.5 | 3.6 | 1.8 | 166 | 1.8 | 2.6 | 3.7 | 1.9 | 0.42 | 166 | 1.9 | 2.7 | 3.7 | 1.8 | 0.27 |
| Beta | 166 | 0.4 | 0.8 | 1.1 | 0.7 | 166 | 0.4 | 0.8 | 1.3 | 1.0 | 0.78 | 166 | 0.4 | 0.8 | 1.3 | 0.9 | 0.98 |
| Idiosyncratic risk (bp) | 166 | 2.7 | 5.0 | 10.0 | 7.3 | 166 | 2.5 | 5.9 | 12.9 | 10.4 | 0.44 | 166 | 3.1 | 6.4 | 11.4 | 8.4 | 0.30 |
| Leverage (%) | 166 | 1.6 | 14.4 | 27.8 | 26.2 | 166 | 0.7 | 9.2 | 27.6 | 26.9 | 0.36 | 166 | 1.0 | 10.0 | 27.6 | 26.6 | 0.30 |
| Analyst | 166 | 7.0 | 21.0 | 53.0 | 46.0 | 166 | 10.0 | 32.0 | 65.0 | 55.0 | 0.07 | 166 | 10.0 | 32.0 | 68.0 | 58.0 | 0.09 |
| Intangibles (%) | 166 | 0.0 | 4.8 | 13.9 | 13.9 | 166 | 0.0 | 1.8 | 16.0 | 16.0 | 0.35 | 166 | 0.0 | 2.6 | 14.3 | 14.3 | 0.28 |
| $IA_1$ (%) | 166 | 26.9 | 42.5 | 54.2 | 27.3 | 166 | 26.7 | 43.5 | 52.6 | 25.9 | 0.87 | 166 | 24.6 | 44.0 | 52.0 | 27.4 | 0.85 |

## Panel E – Differences between Break-up Firms and Comparable Non-break up Firms

| Non-event Sample | Speci-fication | Size | Book-to-Market | Tobin's Q | Profit | Unrelated Entropy | Industry Growth | Total Risk | Beta | Idiosyncratic Risk | Leverage | Analyst | Intangibles | $IA_1$ | R-Square | Obs. |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| $IA_1$-matched | (1) | 1.05** | 6.9*** | | 1.10 | 0.49*** | 0.67*** | 0.31 | 0.11 | -0.75 | 0.03 | -0.58*** | -0.01 | | 40.4 | 166 |
| | | (0.04) | (0.01) | | (0.38) | (0.00) | (0.01) | (0.58) | (0.58) | (0.16) | (0.88) | (0.01) | (0.91) | | | |
| | (2) | 0.94* | | 0.02 | 0.87 | 0.42*** | 0.61*** | 0.11 | 0.05 | -0.53 | 0.24 | -0.43** | -0.01 | | 29.4 | 166 |
| | | (0.06) | | (0.88) | (0.44) | (0.00) | (0.01) | (0.86) | (0.80) | (0.46) | (0.10) | (0.03) | (0.91) | | | |
| Size-matched | (3) | | 1.73 | | 0.05 | 0.44*** | 0.63*** | -0.12 | 0.15 | -0.26 | -0.06 | -0.35* | 0.09 | 0.64 | 28.7 | 166 |
| | | | (0.14) | | (0.77) | (0.00) | (0.01) | (0.81) | (0.48) | (0.61) | (0.70) | (0.09) | (0.50) | (0.47) | | |
| | (4) | | | 0.06 | 0.09 | 0.46*** | 0.64*** | -0.29 | 0.12 | -0.15 | 0.10 | -0.28 | 0.02 | 0.97 | 24.9 | 166 |
| | | | | (0.66) | (0.56) | (0.00) | (0.01) | (0.59) | (0.56) | (0.80) | (0.49) | (0.17) | (0.88) | (0.27) | | |

## Table 3 – Break-up Characteristics with Alternative Measures of Information Asymmetry

The table below shows the results of a stratified conditional logistic regression for matched samples of $BU_i$, a dummy variable that is equal to one if firm *i* is a break-up firm and zero otherwise, on a set of explanatory variables:

$$(1)\ \Pr\left(BU_i\right)=\beta_1 Size_i+\beta_2 BTM_i+\beta_3 Profit_i+\beta_4 UnrEntropy_i+\beta_5 IndustryGrowth_i+\beta_6 TotalRisk_i+\beta_7 Beta_i+\beta_8 IdioRisk_i+\beta_9 Leverage_i+\beta_{10} Analyst_i+\beta_{11} Intangibles_i+\varepsilon_i,$$

$$(2)\ \Pr\left(BU_i\right)=\beta_1 Size_i+\beta_2 TobinsQ_i+\beta_3 Profit_i+\beta_4 UnrEntropy_i+\beta_5 IndustryGrowth_i+\beta_6 TotalRisk_i+\beta_7 Beta_i+\beta_8 IdioRisk_i+\beta_9 Leverage_i+\beta_{10} Analyst_i+\beta_{11} Intangibles_i+\varepsilon_i,$$

$$(3)\ \Pr\left(BU_i\right)=\beta_1 BTM_i+\beta_2 Profit_i+\beta_3 UnrEntropy_i+\beta_4 IndustryGrowth_i+\beta_5 TotalRisk_i+\beta_6 Beta_i+\beta_7 IdioRisk_i+\beta_8 Leverage_i+\beta_9 Analyst_i+\beta_{10} Intangibles_i+\beta_{11} IA_{1,i}+\varepsilon_i,$$

$$(4)\ \Pr\left(BU_i\right)=\beta_1 TobinsQ_i+\beta_2 Profit_i+\beta_3 UnrEntropy_i+\beta_4 IndustryGrowth_i+\beta_5 TotalRisk_i+\beta_6 Beta_i+\beta_7 IdioRisk_i+\beta_8 Leverage_i+\beta_9 Analyst_i+\beta_{10} Intangibles_i+\beta_{11} IA_{1,i}+\varepsilon_i,$$

where subscript *i* represents firm *i* and the variables are as defined in Table 1. *IA* denotes information asymmetry captured by either *PIN* (Panel A) taken from Soeren Hvidkjaer's website or *Analyst Forecast Dispersion* (Panel B), which is measured as the standard deviation of one-year ahead EPS forecasts made by equity analysts. The industry classification is based on two-digit SIC codes. All variables are measured in the first month that begins 100 days before the break-up announcement, whereby *Firm-Size* is measured as of the end of the month. All explanatory variables are standardised to a mean of zero and unit variance. P-values associated with the coefficients are reported in parentheses underneath the coefficients and the R-square (in percentages) is constructed using the log-likelihoods as generalised by Nagelkerke (1991). The column *Non-event Sample* shows whether the control firm selected from the control portfolio is *IA-matched* (information asymmetry is therefore left out of the set of explanatory variables) or whether the control firm is *Size-matched* (and size is therefore left out of the set of explanatory variables). The column *Obs.* displays the number of break-up and control firm pairs used. The asterisks ***, **, * appended to the coefficients indicate statistical significance levels of 1%, 5%, and 10, respectively.

### Panel A – Information Asymmetry Measured by PIN

| Non-event Sample | Specification | Size | BTM | Tobin's Q | Profit | Unrelated Entropy | Industry Growth | Total Risk | Beta | Idiosyncratic Risk | Leverage | Analyst | Intangibles | IA | R-Square | Obs. |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| IA-matched | (1) | 1.72** | 0.28 | | 0.24 | 0.46** | 0.57* | 1.43 | 0.17 | -1.07 | -0.22 | -0.53* | 0.27 | | 35.5 | 105 |
| | | (0.04) | (0.30) | | (0.64) | (0.03) | (0.07) | (0.14) | (0.56) | (0.29) | (0.36) | (0.05) | (0.15) | | | |
| | (2) | 1.89** | | -0.02 | 0.26 | 0.49** | 0.56* | 1.26 | 0.15 | -0.87 | -0.11 | -0.52** | 0.25 | | 34.4 | 105 |
| | | (0.02) | | (0.94) | (0.66) | (0.02) | (0.07) | (0.16) | (0.58) | (0.35) | (0.62) | (0.05) | (0.22) | | | |
| Size-matched | (3) | | 0.40 | | 1.38 | 0.59*** | 0.45 | 1.36 | 0.51 | -1.10 | -0.48* | -0.26 | 0.24 | 0.45 | 35.4 | 105 |
| | | | (0.12) | | (0.21) | (0.00) | (0.11) | (0.13) | (0.11) | (0.19) | (0.06) | (0.27) | (0.22) | (0.66) | | |
| | (4) | | | 0.21 | 1.42 | 0.66*** | 0.40 | 1.21 | 0.38 | -0.85 | -0.24 | -0.23 | 0.19 | 0.43 | 33.7 | 105 |
| | | | | (0.36) | (0.20) | (0.00) | (0.13) | (0.17) | (0.20) | (0.30) | (0.26) | (0.31) | (0.32) | (0.67) | | |

*(continued)*

# Table 3 – Break-up Characteristics with Alternative Measures of Information Asymmetry (continued)

## Panel B – Information Asymmetry Measured by Analyst Forecast Dispersion

| Non-event Sample | Speci-fication | Size | BTM | Tobin's Q | Profit | Unrelated Entropy | Industry Growth | Total Risk | Beta | Idiosyncratic Risk | Leverage | Analyst | Intangibles | IA | R-Square | Obs. |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| IA-matched | (1) | 1.04 | -0.12 | | 0.69 | 0.55*** | 0.46** | 1.33* | -0.49** | -0.97 | -0.05 | -0.31 | 0.25 | | 32.0 | 150 |
| | | (0.17) | (0.47) | | (0.50) | (0.00) | (0.03) | (0.06) | (0.03) | (0.12) | (0.78) | (0.17) | (0.11) | | | |
| | (2) | 1.06 | | -0.23 | 0.45 | 0.42*** | 0.42** | 2.14*** | -0.4* | -1.75** | -0.12 | -0.44* | 0.17 | | 30.0 | 150 |
| | | (0.27) | | (0.30) | (0.57) | (0.01) | (0.04) | (0.01) | (0.10) | (0.01) | (0.49) | (0.06) | (0.28) | | | |
| Size-matched | (3) | | 0.00 | | 0.72 | 0.49*** | 0.43** | 2.15*** | -0.47* | -1.7** | -0.10 | -0.36 | 0.24 | 0.58* | 31.6 | 150 |
| | | | (0.98) | | (0.57) | (0.00) | (0.03) | (0.01) | (0.06) | (0.02) | (0.59) | (0.12) | (0.14) | (0.07) | | |
| | (4) | | | -0.17 | 0.66 | 0.48*** | 0.43** | 2.21*** | -0.47* | -1.76** | -0.13 | -0.4* | 0.23 | 0.58* | 32.1 | 150 |
| | | | | (0.43) | (0.59) | (0.00) | (0.03) | (0.01) | (0.06) | (0.01) | (0.45) | (0.09) | (0.15) | (0.07) | | |

# Table 4 – Break-ups and Changes in Information Asymmetry

This table shows the change in information asymmetry as a result of the break-up. Panel A shows the *Mean* and *Median* values of the *Pre-announcement Level* and the *Change in Level Post-distribution* of *PIN* and the information asymmetry measures proposed by Krishnaswami and Subramaniam (1999) of the parents of *All cases* of break-ups that are used in the sample or of cases that involve *Clean spin-offs* (all values in percentages). Pre-announcement (post-distribution) *Forecast Error* is calculated as the absolute difference between the realized earnings per share number and the mean forecast in the last month of the fiscal year prior to the announcement (after the distribution date) scaled by the stock price at the beginning of the month. *Forecast Dispersion* is the standard deviation of all forecasts in the last month of the fiscal year prior to the announcement (after the distribution date). The *Normalized Forecast Error* is the *Forecast Error* scaled by the standard deviation of the de-trended quarterly earnings over the past five fiscal years prior to the announcement (the following two years after the distribution). *Announcement Reaction* is the standard deviation of the three-day cumulative abnormal returns around quarterly earnings announcements during the five fiscal years prior to the announcement (the following two years after the distribution). *Residual Volatility* is the standard deviation of the residual of a market model fitted to daily returns in the year preceding the break-up announcement (following the distribution). Values of *PIN* are as of the year prior to the break-up announcement (following the distribution) and are taken from Soeren Hvidkjaer's website. The significance levels associated with the mean (median) change in information asymmetry between pre-announcement and post-distribution levels are calculated as a two-sided paired two-sample t-test (Wilcoxon-Mann-Whitney test) of zero mean (median) difference. Panel B shows the results of regressing changes in information asymmetry over the break-up period on set of explanatory variables across break-up and control firms:

$$\Delta IA_{1,i,k} = \gamma_0 + \gamma_1 Size_i + \gamma_2 Analyst_i + \gamma_3 \left(Size_i \times BU_i\right) + \gamma_4 \left(Analyst \times BU_i\right) + \gamma_5 BU_i + \vartheta_k + \eta_{i,k},$$

where $\Delta IA_{1,i,k}$ denotes the difference in average information asymmetry during the pre-announcement control period and the respective break-up period of firm *i*, which has its stock traded on primary exchange *k*. For conciseness, only results calculated across the entire sample are shown. The other explanatory variables and the break-up periods are defined in Table 1. The continuous explanatory variables are demeaned by the cross-sectional mean calculated across the two time-periods and the control and break-up firms. Control firms are matched on $IA_1$. The first column reports the break-up. The estimation uses a random intercept model associated with the primary exchange of stock *i*. The asterisks ***, **, * next to the coefficients (in percentages) denote significant levels of 1%, 5%, and 10%, respectively.

## Panel A – Change of Alternative Measures of Information Asymmetry

| | | Pre-announcement Level | | | | | | Change in Level Post-distribution | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Sample | Statistic | Forecast Error | Forecast Dispersion | Normalised Forecast Error | Announcement Reaction | Residual Volatility | PIN | Forecast Error | Forecast Dispersion | Normalised Forecast Error | Announcement Reaction | Residual Volatility | PIN |
| Clean spin-offs | Mean | 0.72 | 8.51 | 0.05 | 5.27 | 2.29 | 14.18 | -1.01 | 0.70 | -0.02 | -0.72* | -0.45*** | 2.02*** |
| | Median | 0.12 | 3.00 | 0.01 | 4.35 | 1.97 | 12.77 | -0.03 | 0.00 | 0.00 | -0.94** | -0.56*** | 0.97 |
| All cases | Mean | 1.14 | 8.33 | 0.06 | 5.29 | 2.49 | 14.13 | -1.36* | -0.02 | -0.28 | -1.67*** | -0.4*** | 2.03*** |
| | Median | 0.14 | 3.00 | 0.00 | 4.75 | 2.23 | 12.59 | -0.07 | 0.00 | 0.00 | -0.66*** | -0.29** | 0.67 |

*(continued)*

# Table 4 – Break-ups and Changes in Information Asymmetry (continued)

## Panel B – Change of Information Asymmetry over Break-up Period

| Control Sample | Change in $IA_1$ relative to the Control Period | Intercept | Size | Analyst | Size * BU | Analyst * BU | BU | $R^2$ |
|---|---|---|---|---|---|---|---|---|
| *$IA_1$* -matched | Pre-announcement | 2.1 | -0.8 | 0.3 | 3.1 | -0.5 | -4.0 | 8.0 |
| | Announcement date | -2.1 | -1.4 | 2.4 | 4.8 | -3.3 | 4.0 | 25.7 |
| | Announcement to completion | 0.8 | 0.3 | -0.9 | 1.5 | 1.6 | -2.1 | 33.1 |
| | Completion date | -0.9 | -2.1 | 1.8 | 3.5 | -1.4 | -0.3 | 94.7 |
| | Completion to distribution | 0.7 | -0.3 | 1.1 | 4.4 ** | -1.4 | -0.1 | 97.1 |
| | Distribution date | -3.1 | 0.8 | -1.0 | 1.8 | 0.9 | 6.3 | 10.3 |
| | Post-distribution | 0.5 | -0.3 | 0.0 | 3.3 * | -0.5 | -4.9 * | 7.1 |
| Size-matched | Pre-announcement | 1.6 | 0.9 | 0.1 | 1.9 | -1.0 | -3.0 | 17.2 |
| | Announcement date | 1.6 | 0.9 | 0.1 | 1.9 | -1.0 | -3.0 | 17.2 |
| | Announcement to completion | 0.6 | 0.2 | -0.1 | 2.0 | 0.4 | -1.7 | 43.5 |
| | Completion date | 0.1 | -1.0 | -1.4 | 3.8 | 0.2 | -1.1 | 75.6 |
| | Completion to distribution | -0.7 | -0.2 | 1.0 | 4.7 ** | -1.8 | 1.4 | 59.6 |
| | Distribution date | -4.2 | -0.3 | -0.2 | 3.7 | -1.2 | 7.2 ** | 4.4 |
| | Post-distribution | 0.0 | -0.9 | 0.4 | 4.5 ** | -1.7 | -4.3 * | 9.5 |

# Table 5 – Decomposition of Information Asymmetry

The table below shows the results of regressing information asymmetry, $IA_1$, on a set of explanatory variables estimated by firm size-decile:

$$IA_{1,i,k} = \delta_{i,0} + \delta_1 MBA_t + \delta_2 MVOL_t + \delta_3 MVLA_t + \delta_4 MOIB_t + \varsigma_{i,t},$$

$$IA_{2,i,k} = \phi_{i,0} + \phi_1 VLA_{i,t} + \phi_2 BA_{i,t} + \phi_3 OIB_{i,t} + \phi_4 TIC_{i,t} + \phi_5 UEDSpread_{i,t} + \phi_6 VOL_{i,t} + \upsilon_{i,k},$$

$$IA_{3,i,k} = \varphi_{i,0} + \varphi_1 Insider_{i,t} + \varphi_2 Outsider_{i,t} + \varphi_3 Capex_{i,t} + \varphi_4 R\,\&\,D_{i,t} + \varphi_5 BTM_{i,t} + \varphi_6 Profit_{i,t} + \varphi_7 Options_{i,t} + \varphi_8 Size_{i,t} + \xi_{i,k},$$

where subscripts $i$ and $t$ denote the individual firm on day $t$. The variables are defined in Table 1. All continuous explanatory variables are de-meaned across the cross-section (third regression), across the stock-level time-series (second regression), or simply across time (first regression). The estimated regression coefficients (in basis points) are shown in the first column of each size decile and the associated $p$-value in parentheses to the right. The R-square statistics are in percentages.

| | | Size Decile | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Regression | Variable | 1 (Low) | 2 | 3 | 4 | 5 | 6 | 7 | 8 | 9 | 10 (High) |
| Market-wide | Intercept | 39.9 (0.06) | 43.4 (0.00) | 61.9 (0.00) | 64.1 (0.00) | 53.6 (0.00) | 118.8 (0.00) | 62.4 (0.00) | 54.4 (0.00) | 68.2 (0.00) | -53.2 (1.00) |
| | MBA | -30.1 (0.00) | -39.5 (0.00) | -43.0 (0.00) | -40.0 (0.00) | -38.1 (0.00) | -29.8 (0.00) | -28.1 (0.00) | -29.9 (0.00) | -19.9 (0.00) | -10.0 (0.00) |
| | MVOL | 0.1 (0.00) | 0.2 (0.00) | 0.2 (0.00) | 0.3 (0.00) | 0.3 (0.00) | 0.3 (0.00) | 0.3 (0.00) | 0.3 (0.00) | 0.3 (0.00) | 0.3 (0.00) |
| | MVLA | 0.1 (0.00) | 0.0 (0.49) | 0.0 (0.10) | 0.1 (0.00) | 0.2 (0.00) | 0.1 (0.00) | 0.1 (0.00) | 0.0 (0.00) | 0.0 (0.06) | 0.0 (0.10) |
| | MOIB | 0.9 (0.07) | 1.9 (0.00) | 3.8 (0.00) | 3.8 (0.00) | 5.1 (0.00) | 5.3 (0.00) | 5.8 (0.00) | 7.3 (0.00) | 9.2 (0.00) | 11.5 (0.00) |
| | $R^2$ | 5.5 | 4.7 | 4.1 | 4.0 | 3.9 | 4.1 | 4.1 | 3.9 | 3.6 | 3.9 |
| Stock-level trading | Intercept | 32.6 (0.12) | 47.9 (0.00) | 65.9 (0.00) | 64.0 (0.00) | 53.6 (0.00) | 115.4 (0.00) | 62.0 (0.00) | 52.0 (0.00) | 63.8 (0.00) | -34.3 (1.00) |
| | VLA | 0.8 (0.00) | 3.9 (0.00) | 0.3 (0.00) | 4.8 (0.00) | 3.9 (0.00) | 7.2 (0.00) | 7.9 (0.00) | 11.8 (0.00) | 16.3 (0.00) | 29.3 (0.00) |
| | UEDSpread | -27.2 (0.00) | 128.3 (0.00) | 47.5 (0.03) | 235.8 (0.00) | 168.7 (0.00) | 25.6 (0.55) | -279.7 (0.00) | -80.0 (0.18) | -550.7 (0.00) | -283.1 (0.01) |
| | BA | -0.6 (0.00) | -3.9 (0.00) | -5.1 (0.00) | -8.1 (0.00) | -8.8 (0.00) | -7.2 (0.00) | -7.9 (0.00) | -10.9 (0.00) | -14.0 (0.00) | -12.6 (0.00) |
| | VOL | 2.9 (0.00) | 3.4 (0.00) | 3.8 (0.00) | 4.1 (0.00) | 4.4 (0.00) | 4.9 (0.00) | 5.6 (0.00) | 7.0 (0.00) | 8.2 (0.00) | 11.5 (0.00) |
| | TIC | -1.2 (0.00) | -32.3 (0.00) | -41.1 (0.00) | -56.6 (0.00) | -71.3 (0.00) | -90.6 (0.00) | -121.7 (0.00) | -77.3 (0.00) | -50.3 (0.00) | -139.6 (0.00) |
| | OIB | 0.7 (0.00) | 0.2 (0.00) | 0.6 (0.00) | 0.1 (0.00) | 0.1 (0.00) | 0.7 (0.00) | 1.0 (0.00) | 0.7 (0.00) | 0.0 (0.01) | 3.5 (0.00) |
| | $R^2$ | 6.5 | 5.5 | 4.5 | 4.5 | 4.2 | 4.5 | 4.7 | 4.6 | 4.5 | 5.5 |
| Firm-specific structural | Intercept | 24.8 (0.23) | 46.9 (0.00) | 65.2 (0.00) | 60.6 (0.00) | 50.9 (0.00) | 110.5 (0.00) | 63.3 (0.00) | 54.2 (0.00) | 64.7 (0.00) | -76.8 (1.00) |
| | Size | -0.8 (0.00) | -0.4 (0.00) | -0.3 (0.00) | 0.3 (0.00) | 0.3 (0.00) | 0.3 (0.00) | 0.4 (0.00) | 0.9 (0.00) | 0.4 (0.00) | 0.0 (0.00) |
| | BTM | -1.0 (0.00) | -0.6 (0.01) | -0.3 (0.22) | 1.2 (0.00) | 0.5 (0.18) | 1.8 (0.00) | 2.1 (0.00) | 2.0 (0.00) | 3.6 (0.00) | 6.1 (0.00) |
| | Insider | 12.4 (0.00) | 1.6 (0.61) | 9.5 (0.00) | 8.0 (0.00) | 1.7 (0.48) | 6.3 (0.01) | 7.6 (0.00) | 4.9 (0.08) | 5.9 (0.02) | 9.2 (0.00) |
| | Capex | 1.3 (0.10) | 0.7 (0.49) | 1.6 (0.06) | 0.5 (0.61) | 3.1 (0.01) | -1.1 (0.36) | 1.1 (0.39) | -6.1 (0.00) | 5.2 (0.00) | -6.5 (0.00) |
| | Outsider | 10.4 (0.00) | 7.2 (0.00) | 11.7 (0.00) | 7.1 (0.00) | 4.0 (0.00) | 3.2 (0.01) | 3.9 (0.00) | 5.8 (0.00) | 10.7 (0.00) | 5.1 (0.00) |
| | R&D | -5.4 (0.54) | -25.3 (0.01) | -31.6 (0.01) | 2.7 (0.78) | -6.3 (0.57) | -0.4 (0.96) | -10.9 (0.16) | -46.9 (0.00) | -32.6 (0.00) | -39.9 (0.00) |
| | Profit | 1.2 (0.18) | -1.8 (0.12) | -1.5 (0.26) | -1.6 (0.22) | -6.0 (0.00) | -8.9 (0.00) | -9.5 (0.00) | -8.2 (0.00) | -7.2 (0.00) | -2.1 (0.13) |
| | Options | -0.5 (0.00) | -0.3 (0.01) | -0.7 (0.00) | 0.6 (0.00) | 0.8 (0.00) | 1.2 (0.00) | -0.9 (0.00) | -0.7 (0.00) | -2.5 (0.00) | 1.3 (0.00) |
| | $R^2$ | 5.4 | 5.1 | 4.7 | 4.5 | 4.5 | 4.3 | 4.6 | 3.9 | 3.6 | 4.0 |

## Table 6 – Change of Components of Information Asymmetry over Break-up Process

The table below shows the *Change in Components of Information Asymmetry* of the break-up firms after the break-up. The changes are calculated as the *Mean* (*Median*) difference of the stock-level mean (median) of $IA_2$, $IA_3$, *EXIT*, or *RAIN* during the post-distribution control period less the mean (median) of the same information asymmetry component of the same stock during the control-period. $\Delta RAIN - \Delta IA_1$ shows the differences in changes in *RAIN* and $IA_1$ over the break-up period and the *p*-value associated with a two-sided paired two-sample t-test (Wilcoxon-Mann-Whitney test) of zero mean (median) difference between the post-distribution period and the control period.

| Change in Components of Information Asymmetry | Mean Change | Mean *p*-value | Median Change | Median *p*-value |
|---|---|---|---|---|
| $IA_2$ | -239.4 | (0.056) | -218.9 | (0.064) |
| $IA_3$ | -169.1 | (0.147) | -290.7 | (0.167) |
| EXIT | 88.9 | (0.009) | 105.1 | (0.142) |
| RAIN | -193.7 | (0.103) | -257.7 | (0.096) |
| $\Delta$RAIN - $\Delta IA_1$ | -86.0 | (0.019) | -143.6 | (0.213) |

# Table 7 – Change in Information Asymmetry and the Price Reaction to Break-ups

The table below shows the results of regressing the stock market return reaction to the break-up announcement on post-distribution changes of the different components of information asymmetry and some control variables using a random intercept model associated with the primary exchange $k$ of each stock:

$$CAR_{i,k} = \lambda_0 + \lambda_1 \Delta InfoAsymmetry_{i,j,k} + \sum_m \theta_m ControlVariable_m + \omega_k + \zeta_{i,k},$$

where $CAR_{i,k}$ is the cumulative abnormal break-up announcement return of break-up announcement $i$ on primary exchange $k$. $\Delta InfoAsymmetry_{i,j,k}$ denotes the difference between the average level of information asymmetry component $j$ during the post-distribution period and the average level during the pre-announcement control period of firm $i$ traded on primary exchange $k$. *ControlVariable* represents the set of control variables *Focus*, *Prior IPO*, *Clean Spin-off*, *Size*, *Beta*, and *Analyst* measured concurrent to the break-up announcement. The variables *ΔROA* and *ΔROE* are change in return on asset and return on equity, respectively. The variables are defined in Table 1. The information asymmetry components are $IA_1$, *RAIN*, or *EXIT*. The variable definition is given in Table 1. The continuous explanatory variables are de-meaned by the cross-sectional mean across the two time-periods. In the table below, the column *Variable* shows the name of the explanatory variable and the columns *Specification (1)* to *(18)* lists the alternative specifications of the above regression. The $p$-values associated with a two-sided $t$-test that the regression coefficient is equal to zero are reported underneath the respective coefficients in parentheses. The asterisks ***, **, * next to the coefficients (in percentages) denote statistical significant levels of 1%, 5%, and 10%, respectively.

| Variable | Specification | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) | (13) | (14) | (15) | (16) | (17) | (18) |
| $\Delta IA_1$ | -14.45 ** | | | -14.58 ** | | | -14.43 ** | | | -14.58 ** | | | -10.75 * | | | -10.47 * | | |
| ΔRAIN | | -15.31 ** | | | -15.66 ** | | | -15.50 ** | | | -15.80 ** | | | -12.24 * | | | -12.19 * | |
| ΔEXIT | | | 18.15 | | | 21.35 | | | 21.24 | | | 23.04 | | | 3.11 | | | 5.00 |
| ΔROA | | | | | | | | | | | | | 10.83 | 11.08 | 12.94 | | | |
| ΔROE | | | | | | | | | | | | | | | | 7.97 | 8.24 | 8.87 * |
| Focus | | | | | | | | | | 0.92 | 1.04 | 0.95 | 0.74 | 0.80 | 1.16 | 0.81 | 0.86 | 1.21 |
| Prior IPO | | | | | | | 2.86 | 2.76 | 3.74 | 3.38 | 3.34 | 4.28 | 3.27 | 3.34 | 4.25 | 3.67 | 3.74 | 4.71 |
| Clean spin-off | | | | 1.99 | 2.10 | 2.07 | 4.73 | 4.74 | 5.65 | 5.10 | 5.16 | 6.06 | 4.90 | 5.10 | 5.83 | 5.31 | 5.49 | 6.33 |
| Size | 0.02 | 0.07 | 0.23 | -0.03 | 0.03 | 0.20 | -0.02 | 0.03 | 0.21 | -0.01 | 0.04 | 0.23 | -0.18 | -0.14 | -0.09 | -0.21 | -0.18 | -0.10 |
| Beta | 2.68 * | 2.59 | 2.29 | 2.68 * | 2.59 | 2.27 | 2.70 * | 2.62 | 2.31 | 2.94 * | 2.89 * | 2.54 | 2.58 | 2.49 | 2.81 | 2.45 | 2.34 | 2.69 |
| Analyst | -0.98 | -1.07 | -1.39 * | -0.84 | -0.92 | -1.27 | -0.83 | -0.91 | -1.26 | -0.88 | -0.97 | -1.32 | -0.99 | -1.07 | -1.23 | -1.00 | -1.08 | -1.27 |
| Intercept | 4.02 *** | 3.84 *** | 3.98 *** | 2.51 *** | 2.23 *** | 2.37 *** | -0.24 *** | -0.41 *** | -1.22 *** | -1.14 *** | -1.43 *** | -2.19 *** | -0.48 *** | -0.63 *** | -1.51 *** | -0.80 *** | -0.93 *** | -1.87 *** |
| $R^2$ | 17.7 | 17.0 | 19.6 | 22.1 | 21.3 | 23.8 | 25.0 | 24.2 | 26.5 | 30.1 | 29.2 | 31.4 | 46.3 | 45.9 | 47.1 | 46.4 | 45.8 | 47.0 |

## Table 8 – Information Environment over Long Horizons

This table shows the results of repeating the three main test of this paper with *$IA_1$* calculated over the *Horizon* of *1 day* and *2 days*. *$IA_1$* is defined as the daily trade size-weighted average of the difference between the quote mid-point right before a transaction and the quote mid-point *1 day* or *2 days* later scaled by the first quote mid-point. Components of *$IA_1$* are calculated according to regressions (4) to (6), estimated by firm size-deciles based on the daily market capitalisation. All continuous explanatory variables are de-meaned either across the cross-section (for firm-specific structural characteristics), across the stock-level time-series (for stock-level trading characteristics), or simply across time (for variables capturing market-wide commonality). The remaining variables are defined in Table 1. The name of each *Test* is displayed in the first column. *Change in post-distribution $IA_1$ relative to the control period* refers to estimating equation (3) using the difference in the average level of information asymmetry between the pre-announcement control period and the post-distribution period on the left hand side. The control samples are once *$IA_1$-matched* and once *Size-matched*. The column *Coeff* shows the estimated regression coefficient (in basis points) and the associated *p-value* to its right estimated using a random intercept model associated with the main exchange of the respective stock. The *Mean change in components of information asymmetry* shows the mean change (multiplied by 100) of *$IA_2$*, *$IA_3$*, *EXIT*, *RAIN*, and the difference between the change in *RAIN* and *$IA_1$*, *$\Delta RAIN - \Delta IA_1$*, between the control and the post-distribution period in the column *Coeff*. The *p*-value to the right of the coefficients refers to a two-sided t-test of the value in the column *Coeff* being equal to zero. The *Change in information asymmetry and the price reaction to break-ups* shows the results of estimating equation (7) using a random intercept model associated with the main exchange of the respective stock. The cumulative abnormal break-up announcement excess returns are regressed on the difference between average post-distribution *$IA_1$*, *RAIN* or *EXIT* and average control period *$IA_1$*, *RAIN* or *EXIT*. Additional explanatory variables are *Size*, *Beta*, and *Analyst*, which are suppressed in the table below. The pre-announcement control period is between 100 and 20 days before the announcement date and the post-distribution period goes from day 20 after the distribution date up to 100 days after the stock distribution.

| | | Horizon | | | |
|---|---|---|---|---|---|
| | | 1 day | | 2 days | |
| Test | Variable | Coeff | *p*-value | Coeff | *p*-value |
| Change in post-distribution $IA_1$ | Intercept | 9.2 | (0.91) | 228.3 | (0.51) |
| relative to the control period | Size | 0.5 | (0.90) | -8.5 | (0.45) |
| ($IA_1$-matched control sample) | Analyst | -4.6 | (0.34) | -3.7 | (0.75) |
| | Size * BU | 7.8 | (0.11) | 15.2 | (0.19) |
| | Analyst * BU | -3.9 | (0.55) | -7.5 | (0.55) |
| | BU | -162.0 | (0.07) | -332.5 | (0.16) |
| | $R^2$ | 20.8 | | 48.4 | |
| Change in post-distribution $IA_1$ | Intercept | 29.2 | (0.72) | 681.5 | (0.27) |
| relative to the control period | Size | -1.5 | (0.66) | -28.1 | (0.06) |
| (Size-matched control sample) | Analyst | 0.9 | (0.83) | -6.6 | (0.72) |
| | Size * BU | 9.4 | (0.04) | 43.4 | (0.01) |
| | Analyst * BU | -8.9 | (0.14) | -6.4 | (0.74) |
| | BU | -176.8 | (0.04) | -975.2 | (0.00) |
| | $R^2$ | 20.9 | | 48.4 | |
| Mean change in components of | $IA_2$ | -0.1 | (0.01) | -0.2 | (0.04) |
| information asymmetry | $IA_3$ | -0.1 | (0.01) | -0.2 | (0.02) |
| | EXIT | 0.7 | (0.00) | 0.7 | (0.00) |
| | RAIN | -0.6 | (0.00) | -0.6 | (0.00) |
| | $\Delta RAIN - \Delta IA_1$ | -0.6 | (0.00) | -0.6 | (0.00) |
| Change in information asymmetry and | $\Delta IA_1$ | -4.4 | (0.03) | -1.0 | (0.07) |
| the price reaction to break-ups | $R^2$ | 13.4 | | 12.6 | |
| | $\Delta RAIN$ | -0.3 | (0.07) | -1.2 | (0.02) |
| | $R^2$ | 17.1 | | 13.0 | |
| | $\Delta EXIT$ | 0.6 | (0.54) | 1.4 | (0.12) |
| | $R^2$ | 16.8 | | 12.3 | |