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Introduction

The separation of ownership and control is a distinctive feature of a public corporation (Berle and Means (1932)). This organizational form describes a situation where a group of individuals - managers - specialize on making decisions and another group - investors - hold the residual claims of the firm and thus bear the risk associated with the firm's uncertain cash flows. The separation of ownership and control yields several economic benefits. Shareholders do not have any active role in the firm. The continuation of the firm's operation is decoupled from the question of whether a certain individual wants to continue to hold the stock. Hence, claims are transferable. This property enables investors to diversify risk by holding many small claims in different firms. Further, investors are able to quickly respond to changes in market conditions or individual preferences and constraints by adjusting their personal portfolio accordingly. The benefits from the perspective of the investors directly translate into benefits for the firm: They can raise capital to finance investment opportunities much faster and at lower costs. Further, due to the fact that a firm can be owned by a large number of shareholders, firms can grow to a very large size. A larger firm size yields additional economic benefits due to economies of scale in production and decision making.

However, there are also costs associated with this form of organization. Asymmetric information is a key characteristic of the separation of ownership and control (see Berle and Means (1932) who were among the first to note this implication). Asymmetric information refers to the condition that managers are better informed about the true value of the firm and investment opportunities as compared to shareholders, since shareholders do not have any active role in running the firm. This causes two main problems: First, it is difficult for shareholders to monitor and control managers and thereby ensure that managers maximize shareholder value. Second, shareholders might lose money against better informed individuals when trading their claims. The first phenomenon is referred to as *agency cost* (Jensen and Meckling (1976)). These cost denote the loss in value borne by shareholders as a result of non-value maximizing behavior of managers.[1] The interests of managers may deviate from those of shareholders. Shareholders fear that the resources owned by them are not necessarily used in the most productive way. E.g., managers may invest funds in prestigious investment projects from which they derive non-monetary benefits as opposed to investing in the opportunities which maximize shareholder value. Asymmetric information makes it very difficult for shareholders to observe, evaluate and control the behavior of managers.

The second phenomenon also describes a situation where shareholders lose on their investment because they are poorly informed. Individuals with private information can profitably trade on their information advantage. These profits come at the expense of uninformed traders (e.g., Kyle (1985) or Glosten and Milgrom (1985)). The expected loss by trading against informed counterparties is referred to as *adverse selection cost*. Exploiting private information which is not available to the public is referred to as *insider trading*. There are two ways in which managers are responsible for *adverse selection cost*: First, they can trade on the private information themselves or pass along this information to family or friends. Second, they can fail in protecting this information and keep it confidential (e.g., in order to serve the interests of large shareholders who can benefit from the access to private information).

In four self-contained essays, this thesis aims at empirically exploring phenomena which emerge as a result of the asymmetric information stemming from the separation of ownership and control. Chapter 1 deals with the traditional agency conflict topic. When investors fear that managers do not act in their best interest and fail to collectively organize and control managers appropriately, is there an opportunity for professional investors to step in and reduce agency cost? In particular, are the activities of hedge funds and private equity funds in the German equity market driven by the reduction of agency costs?

The remaining three chapters deal with the second implication of asymmetric information: the phenomenon of insider trading. Both Chapter 2 and Chapter 3 investigate the trading of so called 'corporate insiders'. Corporate insiders are individuals associated with the firm and having obvious access to private information about the firm, that is, high ranking managers, board members or larger shareholders. The U.S. regulator requires them to disclose their transactions. Both chapters explore the trading behavior of corporate

[1] These cost include the direct losses due to inefficient investment but also the indirect losses due to costly monitoring.

insiders using data on transactions from the U.S. regulator, the Securities and Exchange Commission (SEC). Chapter 2 investigates whether corporate insiders exploit short-term information advantages. Chapter 3 deals with the interaction of regulation and corporate insider trading. The chapter analyzes whether corporate insiders exploit leeway in reporting their transactions.

Chapter 4 deals with a different dimension of insider trading. The analysis in this chapter focuses on illegal insider trading - the trading on material, non-public information in violation of Rule 10b-5 of the Securities and Exchange Act of 1934. Most developed countries prohibit trading on material, non-public information based on the premise that it harms other investors. Illegal trading is to be distinguished from 'legal' insider trades by corporate insiders which have to be registered with the SEC. Legal insider trades are disclosed to the public and are not necessarily based on material, non-public information. Chapter 4 investigates the extent to which the phenomenon of illegal insider trading responds to the detection and sanctioning of insider trading by the regulator.

The four chapters are summarized in the following. Chapter 1 explores whether hedge funds (HFs) and private equity funds (PEs)[2] aim at reducing agency cost.[3] Against the background of their organizational set-up and business model, both HFs and PEs are likely to have incentives to create shareholder value from agency cost reductions, which sets them apart from traditional investors. Monitoring incentives are generated by increased effective ownership that stems from performance-oriented remuneration for fund managers and, usually, high use of leverage. The present paper contributes to the existing literature in two primary respects: (i) With a particular focus on agency conflicts, this study is the first to directly compare the characteristics of HF and PE investment styles in public equity and (ii) it analyzes the interplay of HF and PE investments with the distinct features of a Continental European corporate governance system.

Based on a sample of 96 HF and 57 PE entries in German firms between 1998 and 2007, we study HF and PE investment behavior by analyzing the characteristics of target firms using binomial logistic regressions. We document empirical evidence that both HF and PE investments are driven by corporate governance improvements, but seem to address different types of agency conflicts. Whereas HFs focus on firms with no controlling share-

[2]We speak of PEs in the narrow sense, that is, later-stage investments. The wide sense of PEs includes both early-stage (i.e., venture capital) and later-stage investments.

[3]This chapter is based on joint work with Ann-Kristin Achleitner and André Betzer (Achleitner et al. (2010)).

holder, particularly no family shareholders, PEs invest in firms that exhibit the potential to align manager-shareholder interests due to low managerial ownership. Both HFs and PEs appear to address free cash flow problems differently. Aiming at increasing dividends, HFs tend to use commitment devices that can be implemented over a short horizon. In contrast, PEs are inclined to target firms that are particularly well suited for leverage increases because of low expected financial distress costs. This strategy requires a sufficiently long investment horizon. The difference in the time horizons over which corporate governance is improved can be traced to the distinct lock-up periods and compensation schemes of HFs and PEs.

Chapter 2 tests the hypothesis that corporate insiders time their trades to exploit short-term information advantages over uninformed market participants using data on 646,411 U.S. insider transactions reported to the SEC between 1986 and 2009.[4] This study is, to the best of our knowledge, the first to investigate the timing of corporate insider trading with respect to a market data based measure of time-varying information asymmetry. Knowledge about the way insiders time their trades can help to better understand their trading motives and shed light on the welfare implications of insider trading.

Several empirical studies (e.g., Seyhun (1986), Chang and Suk (1998) or Jeng et al. (2003)) document that corporate insiders are able to generate significant abnormal returns from trading. This evidence indicates that they use their advantage for profitable trading strategies. Moreover, it is likely that the information asymmetry between informed and uninformed investors and consequently the information advantage of insiders varies over time. The question then arises whether corporate insiders time their transactions in such a way that they exploit high peaks of information asymmetry.

The paper adds to the literature on corporate insider trading and presents the first study to analyze the likelihood of corporate insider trading. Its main innovation is to use a time-variant proxy for asymmetric information: idiosyncratic volatility relative to a firm's recent mean (henceforth *relivol*). This proxy allows for addressing the question of whether corporate insiders time their transactions according to variations in asymmetric information.

Consistent with our hypothesis, the empirical findings suggest that corporate insiders try to exploit short-term informational advantages. They tend to buy stocks more frequently

[4]This chapter is based on joint work with Christian Westheide (Gider and Westheide (2012)).

when *relivol* is high, i.e., at times during which it can be expected that private information is impounded into stock prices. The effect of *relivol* on the likelihood of insider trading is also economically significant. A one standard deviation increase in *relivol* increases the probability of insider trading by 2.9%. The effect of *relivol* on purchases is robust to controlling for endogeneity and cannot be explained by trading on market uncertainty or contrarian trading. We do not find robust evidence that corporate insiders time their sales. In our basic specification we find a slightly negative impact, but once we control for previous transactions, the effect becomes slightly positive (0.3%). This may be because sales are in general less likely to be driven by information, since sales are also motivated by other reasons than profit seeking, e.g., diversification or liquidation needs. Furthermore, there may be a trade-off between trading profits on the one hand and concerns about litigation and reputation risks. These risks are likely to be asymmetrically higher with respect to insider sales (see Jargolinzer and Roulstone (2009)).

Our findings also lend support to the notion that timing is profitable for insiders. We find that insiders can increase their trading profits for purchases substantially with timing. A one standard deviation increase in *relivol* increases the abnormal returns over a period of six months by 2.1%. We do not find any significant effect of timing on sales. The effect of *relivol* on profits remains robust when we control for alternative explanations, or use alternative model specifications. We also show that the effect cannot be explained by the notion that *relivol* is a priced risk factor.

Chapter 3 explores the trading behavior of corporate insiders in the pre Sarbanes-Oxley Act (SOX) era in which they enjoyed considerable flexibility to disclose their transactions.[5] The U.S. and many other countries have adopted regulations that require corporate insiders to report their trades.[6] The model of Huddart et al. (2001) provides a theoretical justification for these regulations. The authors show that information is reflected more rapidly in prices when insiders have to disclose their trades. Several empirical papers (e.g., Chang and Suk (1998), Betzer and Theissen (2009)) have shown that share price reactions occur on both the trading and reporting dates. Thus, without this reporting, the market is unable to infer the full information content of the trade, which implies that market prices are distorted in the period between the trading and reporting dates. Delayed reporting,

[5] This chapter is based on joint work with André Betzer, Daniel Metzger and Erik Theissen (Betzer et al. (2012)).

[6] Some countries (e.g., the UK) even prohibit trading by corporate insiders in certain circumstances. Similarly, many listed firms in the U.S. have adopted policies restricting trading by insiders (Bettis et al. (2000)).

then, may impede the price adjustment to information revealed by the insider trade.

In the era prior to SOX, Section 16 of the Securities Exchange Act required corporate insiders in the U.S. to report their trades by the 10th of the month following the trade. Thus, the maximum time allowed between the trade and the report was 40 days, allowing corporate insiders considerable flexibility to time their trades and reports. This flexibility could be used strategically. An insider wishing to trade a large quantity could split up the order into several smaller chunks. Splitting up a large order reduces the order's price impact and thus results in reduced execution costs (e.g., Kyle (1985), Chordia and Subrahmanyam (2004)). However, if the insider reported each individual trade immediately, the share price reaction on the reporting date would move the price against the insider, and subsequent trades would occur at less favorable prices. Consequently, the insider has an incentive to delay the reporting of a series of trades until after the last transaction. By doing so, insiders can benefit from the reduced price impacts of split-up trades while avoiding the adverse price reaction that immediate reports would trigger. The present paper analyzes incidences of strategically timed SEC filings. We identify a trade as strategic whenever it is either followed by another trade by the same insider before it is reported or executed after another trade by the same insider that has not yet been reported.

Our results can be summarized as follows: First, reporting delays were substantial in the pre-SOX period. We further find clear evidence of strategic trading. Logit models reveal that the occurrence of both late filings and strategic trades is systematically related to firm, trade, and trader characteristics. In particular, the results are consistent with the notion that insiders who are more closely monitored (and who therefore may be facing higher litigation risks) are less likely to file their trades late. Consistent with previous findings, our event study results show that share prices react to the reporting of insider trades. The cumulative abnormal returns (CARs) over 10- and 20-day windows are larger after purchases than after sales. In cross-sectional regressions we find that the magnitude of the price reaction decreases only slowly in the reporting delay (after insider sales), or not at all (after purchases). Thus, our results support the notion that market prices are distorted in the period between a trade and its report. Finally, event study CARs are larger after reports of strategic insider trades than after reports of otherwise similar nonstrategic trades. Thus, market participants apparently believe that insiders acting strategically are more likely to possess private information.

Chapter 4 investigates the consequences of the detection of illegal insider trading by the

SEC.[7] We hypothesize that detection has an impact on future insider trading: Individuals with access to material, non-public information update their subjective probabilities of getting caught when they observe a detection event in their vicinity and are less likely to exploit private information. Using a unique hand-collected dataset of 398 insider trading episodes detected by the SEC between 1995 and 2011 this paper analyzes whether the detection of insider trading by the SEC deters insider trading activities in the same stock and stocks of industry peers. Insider trading is difficult to measure because it is not directly observable. In order to measure trading ahead of price-sensitive announcements we look at abnormal runups prior to earnings announcements. This measure is likely to be monotonically linked to variations in the 'true' level of insider trading. We analyze a firm-quarter panel of 43,646 earnings announcements of detection targets, their industry peers and control firms in remote industries using a difference-in-differences approach.

The chapter contributes to the existing literature on insider trading and regulation. It is the first paper to analyze the consequences of the detection of insider trading and is, hence, complementary to the international studies which analyze the impact of regulation. Moreover, the paper contributes to the economic literature on criminality: We investigate the extent to which personal experiences and experiences in the vicinity of individuals affect their subjective probabilities of detection. Thereby, we contribute to the debate on the effect of risk perceptions of detection on criminal behavior.

We test whether runups prior to earnings announcements are lower after there has been a detection event in the firm while controlling for alternative determinants. We use a difference-in-differences approach and compare runup changes in the post detection period of detection targets, their industry peers and firms in remote industries. A detection event is the first day on which the market has learned from the detection of the case by the SEC. In a nutshell, we obtain the following results: SEC detection significantly reduces the runup prior to earnings announcements for firms with a detection event and their industry peers. More concretely, the runup over the time window of t-5 to t-1 around the earnings announcement is reduced by 0.7%. The effect on industry peers, the spillover effect, is strong and statistically indistinguishable from the effect on the detection target itself. We find weak evidence that the deterrent effect for the detection targets is slightly more pronounced for episodes which involve information leakage from within of the firm. These findings remain robust to an alternative measure of insider trading, over different

[7] This chapter is based on sole-authored work (Gider (2012)).

time windows for the runup calculation and over different subsamples. One may object that the observed effect is mechanical, because the pre detection runups for treatment firms include the runup of the insider trading episode. We rule out that the observed relationship is purely mechanical. We also discuss the limitations of the present analysis. In sum, the empirical findings lend support to the notion that detection discourages the exploitation of inside information in the vicinity of the detection target.

Chapter 1

Do Corporate Governance Motives Drive Hedge Fund and Private Equity Fund Activities?

1.1 Introduction

Hedge funds (HFs) and private equity funds (PEs),[1] which belong to the alternative investment class, have been receiving increasing media and academic attention for their public equity market activities. Anecdotal evidence suggests that they have been gaining influence over managers and interfering with corporate policy. Prominent cases include The Children's Investment Fund, which pressured Deutsche Börse to cancel its planned acquisition of the London Stock Exchange and forced the resignation of then-CEO Werner Seifert, and Kohlberg Kravis Roberts & Co. investing in RJR Nabisco, one of the all-time largest PE transactions.

Against the background of their organizational set-up and business model, both HFs and PEs are likely to have incentives to create shareholder value from agency cost reductions, which sets them apart from traditional investors. Monitoring incentives are generated by increased effective ownership that stems from performance-oriented remuneration for fund managers and, usually, high use of leverage. Previous empirical studies reveal a link between HF and PE investment decisions and the motive of agency cost reduction (for HFs, see e.g., Brav et al. (2008); Clifford (2008); Klein and Zur (2009); for PEs,

[1] We speak of PEs in the narrow sense, that is, later-stage investments. The wide sense of PEs includes both early-stage (i.e., venture capital) and later-stage investments.

see e.g., Halpern et al. (1999); Opler and Titman (1993); Renneboog et al. (2007); Weir et al. (2005)). Whether they solve the same or different agency conflicts is, however, an empirical question.

Furthermore, the regulatory debate perceives the high-profit orientation and alleged short-termism of HFs and PEs as impairing stakeholders' interests and the long-term prospects of target firms. In its 2009 Proposal for a Directive on Alternative Investment Fund Managers, the European Commission considers a new regulation of HFs and PEs that addresses these concerns. The European Commission acknowledges that a 'one size fits all approach' is not appropriate.[2] Against this background, we investigate the different investment strategies of HFs and PEs in a typical Continental European equity market. An understanding of the drivers of HF and PE investment choices is crucial to evaluating whether policy measures should address them jointly or separately.

The present paper contributes to the existing literature in two primary respects: (i) With a particular focus on agency conflicts, this study is the first to directly compare the characteristics of HF and PE investment styles in public equity and (ii) it analyzes the interplay of HF and PE investments with the distinct features of a Continental European corporate governance system. The study of the motives of HFs and PEs is particularly interesting with respect to Germany. Like many Continental European countries, Germany exhibits a corporate governance system that differs from the Anglo-Saxon model and that comprises weaker protection of minority shareholders (La Porta et al. (1999)), reduced exposure of managers to hostile takeovers (Franks and Mayer (1998); Loderer and Peyer (2002)), and a high degree of ownership concentration (Andres (2008)).[3]

The first two characteristics imply the potential for investors to pursue governance improvement strategies.[4] The third characteristic suggests that due to more concentrated ownership structures, agency conflicts can be dominated by conflicts that do not exist between shareholders and managers but, rather, between large and small shareholders. In this case, the investment may be motivated by the intention to discipline large shareholders that extract private benefits. Until the late 1990s, ownership structures in Germany were largely characterized by cross-holdings among major German firms, with banks and

[2]See European Commission, Proposal for a Directive on Alternative Investment Fund Managers, p. 5.

[3]See Drobetz et al. (2004) and Heiss and Köke (2004) for more information about the German corporate governance system.

[4]Croci (2007) is the first study to investigate the corporate governance role of active investors ('corporate raiders') in Continental Europe. The author finds a positive market reaction to the entries of these investors.

insurance companies at the centre of the shareholding network. This system - referred to as Deutschland AG - was criticized for impairing effective corporate governance control. Before the unbundling of Deutschland AG in the late 1990s, corporate control was mainly exerted by banks and other corporations via supervisory board representation, and the start of HF and PE activity in the German equity market followed shortly thereafter. This observation may not be coincidental but may be explained by HFs and PEs aiming at the profitable exploitation of the control vacuum generated by the unbundling.

Based on a sample of 96 HF and 57 PE entries in German firms between 1998 and 2007, we study HF and PE investment behaviour by analyzing the characteristics of target firms using binomial logistic regressions. Our analysis focuses on agency cost reduction as the main value driver of interest, and the analysis is restricted to the major intersection of both players, that is, investments in publicly listed firms. Furthermore, the empirical study is limited to *ex ante* target characteristics and does not include the consequences of the involvement of financial investors such as share price developments or changes in firms' financials or operations.

We document empirical evidence that both HF and PE investments are driven by corporate governance improvements but seem to address different types of agency conflicts. Whereas HFs focus on firms with no controlling shareholder, particularly family shareholders, PEs invest in firms that exhibit the potential to align manager-shareholder interests due to low managerial ownership. Both HFs and PEs appear to address free cash flow problems differently. Aiming at increasing dividends, HFs tend to use commitment devices that can be implemented over a short horizon. In contrast, PEs are inclined to target firms that are particularly well suited for leverage increases because of low expected financial distress costs. This strategy requires a sufficiently long investment horizon. The difference in the time horizons over which corporate governance is improved can be traced to the distinct lock-up periods and compensation schemes of HFs and PEs.

The remainder of the paper is organized as follows: Section 2 characterizes the distinct business models of HFs and PEs. We argue that they are expected to solve agency problems, as opposed to traditional financial investors. Section 3 develops hypotheses about the typical target characteristics of HFs and PEs. Section 4 describes the empirical design and comments on summary statistics. Subsequently, the empirical results are presented and interpreted in Section 5. Section 6 draws our conclusions.

1.2 Business model comparison

Several commonalities exist between HFs and PEs: Both are privately organized investment firms equipped with large capital resources and employ professional fund managers to maximize investment returns. They both belong to the alternative investment class, which is to be distinguished from traditional institutional investors such as asset management firms. Generally, their direct client base consists of sophisticated investors and, as a consequence, they are exempt from several regulatory obligations that usually apply to investment firms. For instance, HFs and PEs are allowed to strongly tie fund manager compensation to investment performance. Moreover, due to the reduced degree of regulation, they are allowed to make heavy use of debt financing.[5] This strategy can enhance returns and increase effective ownership. The greater degree of flexibility resulting from the incentives for fund managers and leverage can allow HFs and PEs to pursue investment strategies that are not open to traditional shareholders. Against this background, improving corporate governance may be a profitable strategy for HFs and PEs, but not for traditional funds. Empirical evidence supports this view by indicating that traditional asset managers fail in trying to benefit from agency cost reduction (e.g., Gilian and Starks (2007)).

There are substantial differences between the business models of HFs and PEs (see Table 1.1 for a summary): HFs engage in a variety of asset classes, such as equity and debt, commodities, options, futures, and foreign exchange, of which activities related to publicly listed firms represent only a few among numerous strategies;[6] in contrast, PEs focus their investment activities on equity investments. This difference is also reflected in the personnel pool from which both types recruit their investment professionals. While HFs mainly recruit employees with financial market expertise (e.g., from proprietary trading), PEs additionally recruit personnel with substantial operational expertise, for example, former management consultants and industrial top managers (Cressy et al. (2007)). These differences in the degree of equity specialisation suggest that PEs are likely to have superior abilities in understanding and evaluating a target's business and identifying potential levers to improve shareholder value.

One of the most striking differences lies in the time horizons of the two types of funds linked

[5]Often PEs use debt at the level of the target firm, whereas HFs often use leverage at the fund level.

[6]For a short overview of the different HF investment strategies, see, for example, the appendix of Gibson and Gyger (2007).

Table 1.1: General characteristics of HFs and PEs

Characteristic	HFs	PEs
Investment focus	Variety of financial instruments: e.g., public equity, fixed income, options, futures, convertible securities, commodities	Public and private equity
Expertise	Focus on financial	Both financial and industrial
Investment horizon	Average initial lock-up period of 10 months	Average period of 10 years
Performance-based compensation	High	High
Determination of performance	Periodically, based on the net asset value of the portfolio via marking to market	At liquidation, based on the final cash flow from the investment portfolio
Redemption	On a periodic basis	At liquidation
Admittance of new investors	On a periodic basis	No

This table reports characteristics of hedge funds (HFs) and private equity funds (PEs).

up to their organizational set-ups. After their initial investment in HFs, investors must wait for an average of 10 months before they can withdraw their capital and, after this lock-up period, another four months on average until they can take back their invested funds (Agarwal et al. (2009)). The performance of HFs is evaluated on a marking-to-market basis. The fees are periodically determined according to the net asset value of the fund, mostly on an annual basis. This implies a relatively short investment horizon and a preference for liquid securities such that the value can easily be determined from observing market prices.

In contrast to HFs, which in principle have an infinite life, PE funds are set up for a finite period of, on average, 10 years (Sahlman (1990)). During this time, existing investors cannot withdraw their capital and the fund is closed to new investors. This condition is likely to commit PEs to maximize fund value over a long horizon. Unlike an HF, the fund's value is not evaluated on a periodical basis but, instead, at the end of the holding period, that is, when all investments are realized. Investors cannot withdraw their capital before the fund's final liquidation. As a consequence, PEs are relatively patient investors that are able and willing to hold illiquid assets. These organizational differences are likely to be a key determinant of investment strategies with respect to public equity.

In sum, both HFs and PEs are flexible investment firms with high incentives for investment managers. These characteristics allow them to draw value from corporate governance improvements. How fundamental differences in their business models and, in particular, their investment horizons are reflected in their pursuit to reduce agency conflicts remains an empirical question.

1.3 Corporate governance related investment motives

We argue that HF and PE activities are driven by corporate governance improvements. To test this hypothesis and analyze potential differences among HF and PE investment styles, we study target characteristics that proxy for the existence of agency conflicts. We focus on two different groups of indicators for the potential to reduce agency costs: free cash flow and financial distress, as well as ownership structure. See Table 1.2 for a summary.

Table 1.2: Summary of hypotheses

Hypothesis	Variable	Expected sign
Free cash flow	Cash	+
	Debt	−
	Dividend yield	−
	Tobin's Q	−
	Research	−
Ownership structure	Management ownership	−
	Family ownership	−
	Free float	+
	Private benefits	+

This table reports the expectations regarding the empirical tests of the hypotheses. Cash denotes cash and cash equivalents scaled by sales. Debt is (short-term debt + long-term debt − cash and cash equivalents)/total assets. Dividend yield is defined as the cash dividend scaled by the market value of equity. Tobin's Q is defined as (market value of equity + book value of total liabilities)/total assets divided by the equivalent measure of the average of all firms in DAX and MDAX in the respective year. Research is set to 1 if the firm has research and development expenditures, and 0 otherwise. Management ownership denotes the stake held by members of the management board. Family ownership is defined as the stake held by family members who are neither members of the executive board nor related to them. Free float is defined as the sum of shareholdings below 5%. Private benefits is a dummy set to 1 if the largest shareholder holds more than 25% and the second largest holds less than 5% of the shares.

1.3.1 Free cash flow and financial distress

According to the free cash flow theory (Jensen (1986)), firms with excess cash positions are likely to exhibit agency problems. It is argued that cash richness creates opportunities for inefficient investment behavior. Managers can use readily available resources to pursue their own interests rather than those of their shareholders. Instead of piling up cash, managers should return excess resources to shareholders via share buybacks or dividends if high liquidity is not needed for further positive net present value investments. Agency costs stemming from free cash flow are most likely to occur in mature and stable businesses with few growth opportunities. If a mature firm needs additional liquid resources, it should address equity or debt markets that would then scrutinize the project's efficiency.

Therefore, dividends can serve as a bonding mechanism and, hence, as a substitute for other internal governance mechanisms (Da Silva et al. (2004)). A high dividend payment forces managers to generate sufficient cash flows and to pursue shareholder value maximization. This can reduce the monitoring efforts of the board of directors or shareholders and hence mitigate agency costs arising from financial slack.

Jensen (1986) argues that debt financing presents another instrument for committing managers not to waste cash on potentially inefficient investment projects. Taking on additional debt reduces financial slack since managers are bound to use cash from operations to redeem the debt. According to this view, debt financing is more binding than dividends, since the latter can be cut more easily compared to the cancellation of debt contracts. Thus, firms with unused debt capacity offer disciplinary potential. Margaritis and Psillaki (2007) present empirical support for the hypothesis that leverage can serve as a disciplinary tool to mitigate the agency costs of outside ownership and lead to an improvement in efficiency.

Following Jensen (1986), problems associated with free cash flows are more pronounced in firms that do not have attractive growth opportunities. Growing firms need liquid resources for investments, which is why they have to turn to equity and debt markets on a regular basis. Requesting new capital entails a monitoring mechanism, since investors will scrutinize the investment project prior to the supply of capital. As a consequence, large cash positions in growing firms are less likely to lead to managerial discretion. High growth opportunities are also related to information asymmetries. A mature firm with stable cash flows is less risky since a substantial part of its profit potential has already materialized. The value of a high-growth firm largely consists of the anticipation of future profits. Hence, debt financing is more easily obtainable for stable and mature firms, since they have more collateralizable assets (Opler and Titman (1993); Weir et al. (2008)).

Implementing commitment devices that reduce financial slack can have the downside of increasing expected financial distress costs, as brought forward by Opler and Titman (1993). Therefore, the potential to reduce financial slack is likely to be inversely linked to expected financial distress costs. We hypothesize that HFs and PEs can create value by resolving excess cash positions or establishing commitment devices that reduce the free cash flow available through managerial discretion. They can thereby reduce agency costs stemming from financial slack. To test this hypothesis, we analyze the firm's cash position, the actual level of debt financing as a proxy for debt potential, growth perspectives, and proxies for financial distress such as research and development (R&D) expenditures and the collateralization of assets.

1.3.2 Ownership structure

Shareholder size and identity are the main determinants of monitoring incentives (Grossman and Hart (1980); Shleifer and Vishny (1986)). The lower the shareholders' incentives to monitor, the more likely the firm will exhibit agency problems. We argue that a firm whose ownership structure fails to reduce conflicts between managers and shareholders, on the one hand, and conflicts between small and large shareholders, on the other hand, is likely to become involved with an active investor. We hypothesize that HFs and PEs aim at aligning interests between managers and shareholders and at reducing private benefits extracted by dominating shareholders.

Managerial ownership is recognized as an important mechanism for aligning the interests of owners and managers. Empirical evidence documents the success of managerial ownership in reducing agency costs (Beiner et al. (2006)). Therefore, the potential to reduce agency costs is likely to be limited in the presence of high managerial ownership. Family ownership, a phenomenon that is less prevalent in Anglo-Saxon markets, is a distinct feature of the German equity landscape. There is empirical evidence that family owners are successful in dealing with agency conflicts (Andres (2008)). This finding can be explained by families usually holding a large fraction of their wealth invested in a firm. This large and non-diversified exposure generates high monitoring incentives. Furthermore, families are generally invested over a long time horizon. Their knowledge and expertise regarding a firm's operations as well as the reputation they have built with other shareholders positively affect their ability to effectively monitor managers.[7]

Ownership concentration is another typical feature of the German equity market. Typically, ownership structure is considered to be an indicator of monitoring efficiency:

[7] There are also arguments for a negative impact of family shareholders: Families are likely to have interests that are not necessarily shared by other shareholders, such as concerns about the firm's image or reputation and debt aversion (Mishra and McConaughy (1999)).

Manager-shareholder conflicts are likely to be more prevalent in the presence of dispersed ownership. Shleifer and Vishny (1986) argue that dispersed ownership can produce a free-riding situation with respect to investments in monitoring technologies. A shareholder undertaking monitoring activities bears the entire costs, while all other shareholders free ride. In the U.S., agency problems are claimed to arise predominantly because of dispersed ownership and the resulting weak monitoring incentives. However, due to the high degree of ownership concentration, the more relevant conflict in Germany is not between managers and shareholders but, rather, between large and small shareholders (Gugler and Yurtoglu (2003)). This is because large shareholders can extract private benefits at the expense of small shareholder wealth. Private benefits are defined as the extraction of disproportionally large rents relative to the size of cash flow rights.

1.4 Empirical design and descriptive statistics

1.4.1 Methodology and dataset construction

The main goal of the empirical analysis is to develop an understanding of how target characteristics affect the odds of a firm becoming involved with HFs or PEs. The standard technique used for takeover prediction is binomial logistic regression analysis. This model tests the direction and extent to which firm characteristics affect the likelihood of a firm becoming a target. To construct the control group, a choice must be made between two sampling procedures: random sampling and matched sampling. There are good reasons for and against the use of a matched sample. Several authors argue in favour of matching because financial ratios such as leverage, operating profitability, and investment volume differ largely across industries, size categories, and growth perspectives. Against this background, matching can make the control group more comparable to the target group (Song and Walkling (1993)).

There are also compelling arguments against the use of matching (Halpern et al. (1999)). First, industry membership, size, and growth opportunities are variables of interest for our purposes. The use of matching does not allow one to determine whether these characteristics make a difference in the odds of becoming a target. Second, there are inaccuracies in the definition of an industry (Clarke (1989)), and it is therefore questionable whether industry membership is a meaningful measure. Consequently, industry matching may not necessarily result in obtaining a comparable control sample. In addition, there are two pragmatic reasons for the use of a random rather than a matched control sample: Since the German equity market is relatively small compared to the U.S. market, the number of comparable firms is also relatively small, and it would therefore be difficult to obtain a good match for some targets. Moreover, because the distribution of targets and non-targets across industries is similar in the present sample (see Table 1.3), concerns of over-representing one industry over others do not apply. There is no empirical evidence that matching significantly changes the test results (Song and Walkling (1993)). Overall, the literature has not concluded whether or not matching is superior from a methodological perspective. Due to the reasons given above, this paper employs a random control sample.

As suggested by Halpern et al. (1999), we use a temporal matching procedure to account for economy-wide influences. Temporal matching is implemented as follows: We randomly select announcement dates from the target samples to determine the dates for the collection of control sample data. As a result, the distribution of control firms over time broadly resembles that of target firms (see Table 1.4).

Table 1.3: Industry distribution

	HF		PE		Control	
Industry	No.	(%)	No.	(%)	No.	(%)
Consumer goods	6	6.3	13	22.8	9	9.4
Media	13	13.5	5	8.8	8	8.3
Industrials	27	28.1	12	21.1	18	18.8
Pharmaceuticals and healthcare	10	10.4	3	5.3	9	9.4
Telecommunication	4	4.2	3	5.3	2	2.1
Technology	8	8.3	2	3.5	8	8.3
Software	15	15.6	9	15.8	15	15.6
Utilities	0	0.0	1	1.8	3	3.1
Chemicals	5	5.2	2	3.5	3	3.1
Construction	1	1.0	1	1.8	3	3.1
Automobile	2	2.1	6	10.5	4	4.2
Basic resources	0	0.0	0	0.0	5	5.2
Retail	3	3.1	0	0.0	5	5.2
Transportation and logistics	2	2.1	0	0.0	4	4.2
N	96		57		96	

This table reports the distribution of hedge fund (HF) and private equity fund (PE) target and control firms across industries. No. denotes the absolute number of target firms in the respective industry and (%) denotes the percentage as of all HF or PE targets. The industry classification is obtained from Deutsche Börse.

The dataset underlying the present empirical analysis comprises 96 HF targets, 57 PE targets, and 96 non-targets serving as control firms. The HF and PE samples were collected from a database provided by the Bundesanstalt für Finanzdienstleistungsaufsicht (BaFin),

Table 1.4: Distribution of entries over time

	HF		PE		Control	
Year	No.	(%)	No.	(%)	No.	(%)
1998	0	0.0	1	1.8	1	1.0
1999	0	0.0	3	5.3	3	3.1
2000	0	0.0	8	14.0	5	5.2
2001	1	1.0	2	3.5	0	0.0
2002	1	1.0	3	5.3	3	3.1
2003	2	2.1	9	15.8	11	11.5
2004	6	6.3	6	10.5	10	10.4
2005	19	19.8	13	22.8	24	25.0
2006	28	29.2	9	15.8	20	20.8
2007	39	40.6	3	5.3	19	19.8
N	96		57		96	

This table reports the entry dates of hedge fund (HF) and private equity fund (PE) targets. No. denotes the absolute number of target firms in the respective year and (%) denotes the percentage as of all HF or PE. The years for which data on the control sample were collected were randomly drawn from the entry dates of HFs and PEs.

the German Federal Financial Supervisory Authority. The database comprises all reported shareholdings according to Section 21 of the German Securities Trading Act. According to this rule, an institution or person must report shareholding to BaFin and the issuer if the shares held exceeds or falls below certain threshold values of 3%, 5%, 10%, 25%, 50%, and 75%. BaFin and the issuing firm then publicize this information. The database lists the underlying share, the reporting date of the transaction, the shareholder's identity and location of incorporation, and the fraction of shares held after the transaction. The BaFin database includes the name of the investor, but no information about type, that is, whether the reporting institution is an HF, PE, mutual fund, industrial firm, individual, and so forth. Hence, further work is required to identify those PEs and HFs that acquire visible stakes in publicly listed firms. The fact that there is no legal definition for an HF or PE further complicates the identification of investments.

We proceeded as follows: The entire database was screened for reporting institutions that were neither individuals, industrial firms, banks, nor insurance companies. The existence of each remaining reporting institution was then verified by using Factiva, LexisNexis, mergermarket, Google, and investor magazines. To qualify as an HF (PE), the institution had to fulfill one of the following criteria: (i) be classified as an HF (PE) in the financial press or an investor magazine or (ii) define itself as an HF (PE) on its webpage. Several traditional asset managers, such as UBS, have set up funds whose investment strategies resemble those of HFs, for example, through the use of derivatives. It is not possible to distinguish whether the financial institution holds the equity stake as part of their HF or their traditional business, and we excluded those ambiguous cases. Furthermore, only the first entries of HFs (PEs) into a firm were included in the sample. The relevant entry dates were cross-checked with the financial press, since BaFin reports usually involve a considerable time lag.

Targets in the financial sector were excluded from both the HF and PE samples for the following reasons: (i) Financial statements are difficult to compare with the statements of industrial firms and (ii) other motivations for these investments may exist, such as strategic cooperation with the targets. A total of 96 control firms were randomly selected from CDAX firms, excluding all HF and PE targets, as well as financial firms. Firm data for the control sample were chosen from the entry years of the targets to avoid biases due to potential macro-wide influences particular to a certain year. The exact dates were randomly chosen from the target sample. To avoid potential survivorship bias, we randomly chose firms from the CDAX list of the respective year. Accounting information at the firm level refers to the figures in the fiscal year before the announcement of investor entry.

1.4.2 Summary statistics

In 1998, German publicly listed firms started to become involved with PEs (see Table 1.4). The year 2005 boasts the highest number of entries, with 13 investments. HFs assumed activity in Germany with a lag: The first HF investment detectable by the sample selection procedure described below was observed in 2001. Nearly 90% of all entries were observed between 2005 and 2007, with a peak of 40% of all HF events in 2007. This difference in distribution over time requires temporal matching, as discussed above. In the U.S., PEs existed as early as the 1980s and HF investments have been observed since the mid-1990s. Germany's time lag can be first attributed to the fact that most HFs and PEs are U.S.-based firms and they test their strategies in the domestic market before competition pushes them to expand internationally. Second, the German market became more attractive to foreign investors due to the unbundling of Deutschland AG and the concomitant reorientation of how German firms should be governed. It was argued that the complex cross-shareholdings and the mutual control of supervisory boards among German corporations impaired effective corporate governance control. Discussions in the late 1990s on the need for action resulted in the enactment of a new law allowing corporations to sell their equity stakes in other firms, tax exempt. Following the new tax rule, many key players at the center of Deutschland AG, such as Deutsche Bank AG, Allianz AG, and Münchener Rück AG, committed to sell their numerous equity stakes. The coincidence of the unbundling and the start of HF and PE activities can be interpreted as the reorientation generating the potential for investment strategies aimed at improving corporate governance.

In 2007, only three PE transactions were publicly announced, all of which occurred in the first half of the year. This could be traced to the subprime crisis, which started in mid-2007 and made it difficult to obtain debt financing at attractive terms. Table 3 shows the distribution of target and non-target firms across industries. Overall, the distribution across industries exhibits weak patterns, but no industry is clearly overrepresented. The most common HF investments are observed in the industrial, software, and media industries. The most common sectors of PE targets are consumer goods, industrials, and software. There are noticeable differences between HFs and PEs in pharmaceuticals and healthcare (preferred by HFs) and consumer goods (preferred by PEs). This difference may reflect the general preference of PEs to invest in stable businesses that exhibit a low degree of uncertainty. The distribution of financial investor targets grossly resembles the industry distribution of the firms randomly selected from CDAX.

The HF and PE targets significantly differ with respect to the size of the acquired stakes (see Table 1.5). Relative to HFs, PEs hold much more concentrated positions in the euro volume of stakes. Consistent with the statement in Section 2, HF investors almost always (95.8%) acquire minority stakes. We only observe three cases in which an HF acquired a controlling stake, that is, a stake in excess of 25%. All HF stakes remained below the threshold of 30%, which triggers a mandatory takeover offer according to Sections 29 and 35 of the German Securities Acquisition and Takeover Act. In contrast, PEs acquire controlling stakes in 91.2% of events. A total of 80.7% of the stakes are above the mandatory takeover threshold of 30%. In more than half of cases, PEs acquire more than 75% of the stakes. This finding is consistent with the initial assumptions that PE aim at full control, whereas HF intend to induce only small changes. The threshold of 75% is relevant under the assumption that PEs aim at increasing leverage, because it enables PEs to set up a control and profit transfer agreement according to Section 291 of the German Securities Act, which is likely to improve the financing terms for the transaction. Nearly half of the PE targets in our sample were delisted subsequent to PE entry. With respect to HFs, the delisted targets only account for 10% of the sample.

Table 1.5: Stake sizes

	HF	PE
In millions of euros		
Average stake size	22.6	151.2
Median stake size	7.9	44.5
Standard deviation	35.9	241.3
Fraction of shares outstanding (%)		
Average stake size	8.2	71.6
Median stake size	5.6	82.3
Standard deviation	6.1	30.7
By stake type (%)		
Minority stake	95.8	8.8
Controlling stake	4.2	91.2
Stake over 30%	0.0	80.7
Stake over 75%	0.0	54.4
Delisting	8.3	47.4

This table reports the summary statistics on the stakes acquired by hedge funds (HFs) and private equity funds (PEs). The euro volume is calculated as the maximum stake size multiplied by the market value of equity 20 trading days before the entry of the investor. The stake size (as a percentage) refers to the maximum stake that has been held over the time horizon under consideration. A minority stake is defined as a stake smaller than 25%, and a controlling stake is defined as a stake greater than 25%. If acquiring a stake greater than 30%, an investor is obliged to make a public offer to the remaining shareholders, which is why we include information on this threshold. Delisting denotes the percentage of HF and PE targets that have been delisted after the entry.

Table 1.6 summarizes the descriptive statistics of target and non-target firms and Table 1.7 shows the correlations among the variables. The univariate results suggest that HF targets differ significantly from PE targets. The ownership structure summary statistics suggest that HFs target firms with large free float. This may be due to marginal control of their small stakes being higher with increasing free float, and also their preference for holding liquid positions that can be sold quickly and at low cost. Large positions cannot be exited as easily, since this would have a considerable price impact. As opposed to evidence on the U.S. market (Klein and Zur (2009)), we do not find any support for the hypothesis that target size is particularly small compared to randomly selected CDAX firms. However, only 14% of PE targets and 19.8% of HF targets are members of HDAX. Membership in HDAX is expected to be positively related to market visibility and, accordingly, inversely related to information asymmetry.

Table 1.6: Summary statistics

	Mean			Median			Difference in mean		
	HF	PE	Control	HF	PE	Control	HF	PE	HF vs. PE
Free float (%)	58.01	43.20	47.13	56.20	42.00	48.64	10.89***	-3.93	14.82***
Family (%)	3.54	15.84	13.12	0.00	0.00	0.00	-9.58***	2.72	-12.30***
Management (%)	7.98	4.06	11.78	0.00	0.00	0.00	-3.8	-7.72***	3.92*
Private benefits (d)	33.33	57.89	52.08	0.00	100.00	100.00	-18.75***	5.81	-24.56***
Acquisition (d)	35.42	15.79	28.13	0.00	0.00	0.00	7.29	-12.34*	19.63***
Target (d)	22.92	28.07	4.17	0.00	0.00	0.00	18.75***	23.90***	-5.15
Size (MV, millions of euros)	130.73	84.09	95.27	121.24	56.00	61.01	35.46	-11.18	46.63*
Size (sales, millions of euros)	159.21	248.21	163.50	143.12	248.05	120.52	-4.29	84.71	-89.00*
Risk (%)	2.79	2.66	3.18	2.55	2.41	2.71	-0.39**	-0.52**	0.13
Prior stock performance (%)	99.89	102.20	98.66	96.97	101.33	96.29	1.23	3.54	-2.31
Tobin's Q (%)	109.47	78.90	89.40	89.32	72.90	77.42	20.06***	-10.51*	30.57***
Debt (%)	22.29	20.68	18.61	18.30	18.31	18.78	3.68	2.07	1.61
Net debt (%)	3.85	8.26	1.10	7.02	8.58	5.30	2.75	7.16	-4.41
Cash (%)	13.93	10.38	13.38	10.83	7.06	8.08	0.55	-2.99	3.55*
Dividend yield (%)	0.88	2.43	2.12	0.00	1.25	0.02	-1.24***	0.3	-1.55**
Research (d)	50.00	24.56	35.42	50.00	0.00	0.00	14.58***	-10.86	25.44***
Tax (%)	2.46	1.90	2.29	1.59	1.01	1.75	-0.39	-0.39	0.56

This table reports the summary statistics for hedge fund (HF) and private equity fund (PE) targets and control firms. Free float is defined as the sum of shareholdings below 5%. Family is defined as the stake held by family members who are neither members of the executive board nor related to them. Management denotes the stake held by members of the management board. The private benefits dummy is set to 1 if the largest shareholder holds more than 25% and the second largest holds less than 5% of the shares. Acquisition (target) refers to rumors that the firm plans an acquisition (is subject to takeover speculation). Executed acquisition refers to the firm having executed an acquisition during the two years prior to entry. Size in terms of market value refers to the value of equity, and size in terms of sales refers to the annual volume of sales. Risk denotes the standard deviation of returns over 250 trading days up to 20 days before entry. Prior stock performance is defined as the market-adjusted share price 20 trading days before entry divided by the market-adjusted average share price of the previous 250 days. Tobin's Q is defined as (market value of equity + book value of total liabilities)/total assets divided by the equivalent measure of the average of all firms in DAX and MDAX in the respective year. Net debt is (short-term debt + long-term debt – cash and cash equivalents)/total assets. Cash denotes cash and cash equivalents scaled by sales. Dividend yield is defined as the cash dividend scaled by the market value of equity. Research is set to 1 if the firm has research and development expenditures, and 0 otherwise. Tax denotes tax expenses scaled by sales. In this table (d) indicates that the variable is a dummy variable. The columns under difference in means indicate the differences of HF and PE targets to control firms, and HF to PE targets. We perform t-tests for the significance of the difference (Pearson's chi-squared tests for dummies). Here, *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels. The data are winsorized at the 3% level.

Table 1.7: Spearman correlation

	Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
1	Fam	1.00														
2	Mgmt	-0.16*	1.00													
3	Freefloat	-0.15*	-0.03	1.00												
4	PB (d)	-0.05	0.02	-0.29*	1.00											
5	Res (d)	0.08	-0.03	0.14*	0.02	1.00										
6	Risk	0.02	0.19*	0.09	0.00	-0.12*	1.00									
7	Perf	0.13*	-0.07	-0.12*	-0.05	0.03	-0.11*	1.00								
8	Size	0.00	-0.26*	-0.04	-0.01	0.06	-0.57*	0.22*	1.00							
9	Q	-0.08	0.04	0.04	-0.03	0.12*	-0.05	-0.14*	-0.16*	1.00						
10	Cash	-0.01	0.07	0.15*	-0.02	0.09	0.24*	-0.01	-0.37*	0.22*	1.00					
11	Debt	0.07	-0.12*	0.06	-0.08	-0.03	-0.07	-0.10	0.29*	-0.18*	-0.46*	1.00				
12	Dvd	0.06	-0.09	-0.14*	0.12*	0.06	-0.60*	0.15*	0.55*	-0.15*	-0.24*	0.01	1.00			
13	Tax	0.03	0.02	0.01	0.00	0.14*	-0.19*	0.24*	0.16*	0.17*	0.06	-0.19*	0.21*	1.00		
14	Acq (d)	0.11*	-0.07	0.15*	-0.05	0.17*	-0.25*	0.01	0.28*	-0.05	-0.07	0.01	0.19*	0.04	1.00	
15	Tar (d)	-0.10	-0.16*	-0.15*	0.03	-0.07	-0.18*	0.24*	0.20*	-0.01	-0.04	-0.07	0.05	0.01	-0.09	1.00

This table reports the Spearman's rank correlation coefficients of the variables. Fam is defined as the stake held by family members who are neither members of the executive board nor related to them. Mgmt denotes the stake held by members of the management board. Free float is defined as the sum of shareholdings below 5%. The variable PB is a dummy variable set to 1 if the largest shareholder holds more than 25% and the second-largest holds less than 5% of shares. Res is set to 1 if the firm has research and development expenditures, and 0 otherwise. Risk denotes the standard deviation of returns over 250 trading days, up to 20 days before the entry. Perf is defined as the market-adjusted share price 20 trading days before entry, divided by the market-adjusted average share price of the previous 250 days. Size is defined as the annual volume of sales. Q is defined as (market value of equity + book value of total liabilities)/total assets divided by the equivalent measure of the average of all firms in DAX and MDAX in the respective year. Cash denotes cash and cash equivalents scaled by sales. Debt is (short-term debt + long-term debt – cash and cash equivalents)/total assets. Here, DvD is defined as the cash dividend scaled by the market value of equity. Tax denotes tax expenses scaled by the sales. Acq (tar) refers to rumors that the firm plans an acquisition (is subject to takeover speculation), and (d) indicates that the variable is a dummy variable. * denotes significant correlation at the 10% level. The data are winsorized at the 3% level.

1.5 Empirical results

In the following, we use binomial logistic regressions to analyze the investment motives in a multivariate context. We employ several additional variables to control for alternative investment motives that are not necessarily associated with corporate governance improvements but which may yet drive investment decisions.

1.5.1 HF investment motives

Table 1.8 shows the regression results for HF investment motives. We find support for the hypothesis that HFs aim to reduce agency costs stemming from free cash flow. The dividend yield is inversely related to the odds of becoming an HF target: The negative coefficient is significant at the 5% level. These findings can be interpreted as support for the hypothesis that HFs push to raise dividends. However, the observation of a low dividend yield can be attributed to the measure's construction: HFs invest in growth firms and, since the market value of equity is in the denominator of the dividend yield measure, the measure is very small. This suggests that there may be a negative relation between dividend payout and HF targets because growth firms per se do not pay out much and prefer to reinvest the cash from operations into the expansion of their businesses. If this were the case, then the conclusion that HFs aim at pushing for dividend increases would be inappropriate. This objection cannot be upheld because, by including Q in the regression, we already control for growth perspectives. Additionally, the results remain robust with respect to the use of the retention rate, defined as 1 minus the cash dividend, divided by earnings before interest, taxes, depreciation and amortization (EBITDA), and 0 if the dividends are larger than EBITDA.

Buybacks are an alternative to return cash. The results above may be subject to the omitted variable bias: If HF targets tend to prefer buybacks over dividends, it would be inappropriate to classify HF targets as firms with low cash payouts. However, the results remain robust if we use a dummy variable for the announcement or the proceeding of share buybacks in the two years prior to HF entry. Even in terms of buybacks, HF targets distribute significantly less cash to shareholders.

We do not find any evidence for the hypothesis that HFs aim to invest in firms with the intention of making them pay out excess cash. The insignificance of cash holdings is still

Table 1.8: Binomial logistic regression: HF targets versus non-targets

Variable	(1) beta/z-stat	(2) beta/z-stat
Family	-0.04***	-0.04***
	(-2.60)	(-2.63)
Management	0.00	0.00
	(0.13)	(-0.47)
Private benefits (d)	-1.27***	
	(-2.84)	
Free float		0.02**
		(2.19)
Cash	-0.59	-0.16
	(-0.31)	(-0.09)
Net debt	1.50*	1.62*
	(1.84)	(1.76)
Tobin's Q	1.00**	1.04**
	(2.27)	(2.42)
Research (d)	9.91***	6.46***
	(2.67)	(2.80)
Dividend yield	-27.32**	-28.13**
	(-2.41)	(-2.07)
Size	-0.15	-0.13
	(-1.15)	(-1.07)
Prior stock performance	0.92	1.18
	(1.01)	(1.34)
Acquisition rumors (d)	0.82*	0.75*
	(1.85)	(1.76)
Takeover rumors (d)	2.1***	1.86***
	(3.12)	(2.89)
Tax	-3.24	-3.47
	(-0.55)	(-0.61)
Risk	-35	-37.04
	(0.97)	(-1.32)
Intercept	0.63	-0.3
	(0.32)	(-0.16)
Number of observations	192	192
Chi-squared	76.76***	68.17***
Pseudo R-squared	0.29	0.26

The table reports the results of the logistic regression analysis. The dependent variable is set to 1 for hedge fund (HF) targets, and 0 for non-targets. Family is defined as the stake held by family members who are neither members of the executive board nor related to them. Management denotes the stake held by members of the management board. The private benefits dummy is set to 1 if the largest shareholder holds more than 25% and the second-largest holds less than 5% of shares. Cash denotes cash and cash equivalents scaled by sales. Net debt is (short-term debt + long-term debt – cash and cash equivalents)/total assets. Tobin's Q is defined as (market value of equity + book value of total liabilities)/total assets divided by the equivalent measure of the average of all firms in DAX and MDAX in the respective year. Research is set to 1 if the firm has research and development expenditures, and 0 otherwise. Free float is defined as the sum of shareholdings below 5%. Dividend yield is defined as the cash dividend scaled by the market value of equity. Size is defined as the annual volume of sales. Prior stock performance is defined as the market-adjusted share price 20 trading days before entry divided by the market-adjusted average share price of the previous 250 days. Acquisition (takeover) rumors refer to rumors that the firm plans an acquisition (is subject to takeover speculation). Risk denotes the standard deviation of return over 250 trading days up to 20 days before entry. Tax denotes tax expenses scaled by total assets. (d) indicates that the variable is a dummy variable. The data are winsorized at the 3% level. Here, Chi-squared denotes the value for the likelihood chi squared, z denotes the value for the z-statistics, and *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels.

maintained when testing for several modified cash proxies, such as cash scaled by market value, the absolute size of cash, and several interaction terms with growth perspectives. Accordingly, the prominent case of The Children's Investment Fund urging Deutsche Börse to return cash to shareholders does not seem to be representative. Moreover, HF targets do not seem to be underleveraged; in fact, quite the reverse: HF targets seem to have slightly more net debt. This finding is only significant at the 10% level. Moreover, Tobin's Q significantly and positively affects the likelihood of HF entry. Tobin's Q being positively linked to the costs of financial distress suggests that HF targets do not have debt potential.

The positive and significant coefficient of the R&D measure provides further evidence of HF targets not being likely to have debt capacity under the assumption that R&D is a proxy for expected costs of financial distress. Overall, the claim that HFs invest in firms to burden them with additional debt is not supported by the empirical results. This observation is consistent with the view that HFs do not seek the target's financial turnaround. The positive influence of R&D on the odds of becoming an HF target appears puzzling. Investors with operational expertise have the ability to evaluate the efficiency of R&D projects. Due to the high technical complexity of the firm's business, R&D is acknowledged as a proxy for information asymmetry. Usually R&D projects are unique and their outcomes highly uncertain, features that make it difficult for market participants to value the firm (Aboody and Lev (2000)). Chan et al. (2001) find empirical support for the claim that the market has difficulties in sufficiently appreciating the value of R&D projects. Investors with operational expertise can invest in undervalued R&D firms and thereby make other market participants aware of the undervaluation. Furthermore, it can be argued that investors knowledgeable in R&D could cut inefficient R&D projects and thereby increase shareholder value. Against the background of HFs not being equipped with operational expertise, these investment motives are unlikely. However, there exists an alternative explanation: Free cash flow is highly sensitive to R&D expenditures. HFs can call for cuts in R&D to increase free cash flow, which can result in higher analyst valuations. This strategy is also in line with the short investment horizons of HFs. Cuts in R&D can have adverse effects on shareholder value in the long run. Further empirical investigations on the consequences of HF investment are required for a more comprehensive understanding of the role of R&D.

In general, the positive relation between financial distress proxies such as R&D and Tobin's Q can be traced to the HF preference for rather risky investments that is due to their compensation structure: Higher risk enables them to generate large returns over a short horizon. Family ownership is inversely related to the likelihood of becoming an HF target. Empirical evidence in Germany (Andres (2008)) suggests that families are able to successfully solve agency conflicts. As a consequence, the negative impact of family ownership on HF investment can be interpreted as support for the incentive alignment hypothesis.

To test the private benefits hypotheses, we need to empirically disentangle the degree of ownership concentration and private benefits. In general, these variables should be correlated to a certain degree, since the potential for private benefits extraction presupposes the existence of a dominant shareholder that is positively associated with ownership concentration. The size of the second largest shareholder is considered a proxy for shareholder power and the ability to prevent the largest shareholder from extracting private benefits. A more comprehensive measure should account for the difference in power between the largest and second-largest shareholders, and thus reflect an interaction between the two variables. Gugler and Yurtoglu (2003) propose the following measure: If the second-largest shareholder owns less than 5% of shares, this firm is labeled 'unchecked', meaning that no other powerful shareholder can reduce the private benefits extraction of the largest shareholder. The authors suggest that the private benefits potential is even greater if there exists a controlling shareholder (i.e., a shareholder that owns more than 25%) and the firm is unchecked. In line with this conjecture, we construct the following dummy variable: Private benefits is set equal to 1 if there is a controlling shareholder and the second-largest stake is smaller than 5%. To check for robustness, we additionally include continuous variables to test for the potential power of the largest shareholder to extract private rents: We use the ratio of the largest to the second-largest stake, as well as their difference. According to the empirical results, HFs eschew firms with potential private benefits issues: The private benefits variable has a negative coefficient, with statistical significance at the 1% level. This finding is robust with respect to the use of various alternative proxies and provides clear evidence that HFs do not aim to reduce private benefits problems. They do not build up a sufficiently large stake to control or outvote the dominating shareholder.

The involvement of a firm with mergers and acquisitions significantly affects the odds of becoming an HF target, as suggested by the positive and significant coefficients of the acquisition and target variables. Speculation in mergers and acquisitions can be profitable:

Investing in potential acquirers is attractive if HFs successfully conjecture the settlement or cancellation of the planned acquisition. Investment in potential targets can reflect the HF's belief that the takeover bid will be increased. Alternatively, this can be interpreted as the HFs being active in corporate control and investing in acquirers because they want to prevent management from a potentially inefficient acquisition, or investing in takeover targets to make reluctant managers agree to the takeover. Given the present data, it is not possible to distinguish between the merger arbitrage and the corporate control hypotheses. The *ex post* information about the success of the alleged merger is not sufficient to assess whether HFs are passive merger arbitrageurs or active corporate control agents. For example, if a target is finally being taken over, we cannot be sure whether this is due to the HF or not. Concrete information about potential HF interference is difficult to obtain from publicly available data because much of the influence happens behind the scenes. This gap could be filled by a survey approach.

Model 2 includes free float. We estimate a separate model when analyzing the role of free float to avoid multicollinearity, since free float is highly correlated with the private benefits variable (see Table 1.7). The results indicate that HFs prefer to invest in firms with large free float, which may be due to higher liquidity and higher marginal control. This finding is also in line with the assumption that HFs only assume a monitoring function if little control over the management is in place. We include prior stock performance and size as control variables. The results do not yield any evidence that HFs invest in firms that suffer from poor prior stock performance. Under the efficient market hypothesis, a poor prior stock performance indicates managerial inefficiency. Thus, in terms of prior stock performance, HFs do not seem to seek the operational turnaround of unprofitable firms. We do not find any indications of HFs investing in undervalued firms as measured by poor prior stock performance under relaxation of the efficient market assumption. Size is generally acknowledged as a proxy for information asymmetry (Frankel and Li (2004)). Small firms receive less attention in capital markets (e.g., Renneboog et al. (2007)). In particular, small firms are less interesting investment objects for traditional institutional investors because of the minimum investment sizes for these investors. As a consequence, there is little trading activity in the shares of small firms, which decreases the information content of the share price. Testing size as a proxy for information asymmetry, we cannot find any evidence that HFs target small firms. The strategy of investment in undervalued securities due to information asymmetry does not seem to be a representative investment motive of HFs.

In a nutshell, the empirical results indicate that HF investments are related to corporate governance improvements: They seem to aim at reducing agency problems associated with free cash flow by dividend increases. Furthermore, they appear to align incentives by investing in firms whose ownership structure does not generate high monitoring incentives.

1.5.2 PE investment motives

Table 1.9 shows the results that compare the characteristics of PE targets and non-targets. In contrast to other studies (e.g., Opler and Titman (1993)), we do not find that PE targets are cash rich. The cash variable and the interaction terms of cash and growth (not reported here) are insignificant. Furthermore, the empirical results do not document that PE targets are underleveraged. The coefficient of the debt variable fails to be significant. The coefficient of Tobin's Q is negative but not statistically significant, which indicates that PE targets do not have substantially low growth opportunities. However, we do find alternative support for the hypothesis that targets feature characteristics that make them attractive for an increase in leverage. As a proxy for expected financial distress costs, R&D is significantly inversely associated with the odds of PE entry. Previous studies (e.g., Lichtenberg and Siegel (1990)) document that PEs implement higher operational efficiency. The superior industry expertise of PEs may allow them to evaluate the efficiency of R&D projects. According to the empirical findings of Sorensen et al. (2011), PEs increase the efficiency of patents in non-listed companies; however, the negative sign of the R&D variable suggests that the motive for cutting R&D expenditures as part of operational engineering aimed at shareholder value maximization is unlikely. The financial distress aspect seems to dominate.

The significant and negative coefficient of risk suggests that PE targets in our sample have stable earnings, which also indicates low financial distress costs and thus makes them attractive for leverage increases. Overall, we find evidence for the potential of PE target firms to increase the use of debt financing, which potentially reduces agency costs associated with free cash flow. Compared to HFs, PEs seem to address free cash flow problems more fundamentally. Whereas dividend increases can be carried out over a short horizon, debt restructurings require a longer time horizon and also cannot be quickly reversed.

Furthermore, the results document support for the hypothesis that PEs create value from

Table 1.9: Binomial logistic regression: PE targets versus non-targets

Variable	(1) beta/z-stat	(2) beta/z-stat	(3) beta/z-stat
Family	0.00	0.00	0.00
	(0.33)	(0.33)	(-0.08)
Management	-0.03**	-0.03**	-0.03**
	(-2.28)	(-2.29)	(-2.21)
Private benefits (d)	-0.06		-0.93*
	(-0.15)		(-1.94)
Free float		0.00	
		(-0.50)	
Cash	-1.34	-1.34	-1.09
	(-0.55)	(-0.55)	(-0.40)
Net debt	0.13	0.13	0.09
	(0.14)	(0.14)	(0.08)
Tobin's Q	-1.11*	-1.12*	-1.24*
	(1.70)	(1.71)	(-1.80)
Research (d)	-7.79**	-7.76**	-8.20**
	(-2.10)	(-2.03)	(-1.98)
Dividend yield	-6.48	-6.51	-5.02
	(-1.31)	(-1.32)	(-0.91)
Size	-0.18	-0.18	-0.16
	(-1.51)	(-1.52)	(-1.24)
Prior stock performance	0.93	0.92	1.06
	(0.92)	(0.92)	(0.93)
Acquisition rumors (d)	-1.19	-1.19	-1.06*
	(1.14)	(1.23)	(-1.93)
Takeover rumors (d)	-0.02	-0.02	-0.19
	(-0.05)	(-0.05)	(-0.35)
Tax	4.96	5.38	4.96
	(1.11)	(1.09)	(1.11)
Risk	-40.99**	-34.85***	-41.30**
	(-2.10)	(-2.67)	(2.13)
Intercept	3.82*	3.80	3.28
	(1.81)	0.07	(1.38)
Number of observations	153	153	135
Chi-squared	43.12***	42.92***	40.74***
Pseudo R-squared	0.15	0.16	0.15

The table reports the results of the logistic regression analysis. The dependent variable is set to 1 for private equity fund (PE) targets, and 0 for non-targets. Family is defined as the stake held by family members who are neither members of the executive board nor related to them. Management denotes the stake held by members of the management board. The private benefits dummy is set to 1 if the largest shareholder holds more than 25% and the second-largest holds less than 5% of shares. Cash denotes cash and cash equivalents scaled by sales. Net debt is (short-term debt + long-term debt – cash and cash equivalents)/total assets. Tobin's Q is defined as (market value of equity + book value of total liabilities)/total assets divided by the equivalent measure of the average of all firms in DAX and MDAX in the respective year. Research is set to 1 if the firm has research and development expenditures, and 0 otherwise. Free float is defined as the sum of shareholdings below 5%. Dividend yield is defined as the cash dividend scaled by the market value of equity. Size is defined as the annual volume of sales. Prior stock performance is defined as the market-adjusted share price 20 trading days before entry, divided by the market-adjusted average share price of the previous 250 days. Acquisition (takeover) rumors refer to rumors that the firm plans an acquisition (is subject to takeover speculation). Risk denotes the standard deviation of return over 250 trading days up to 20 days before entry. Tax denotes tax expenses scaled by total assets. (d) indicates that the variable is a dummy variable. Model 3 refers to a subsample of PE targets and excludes observations where PEs purchase the stake from the dominating shareholder. The data are winsorized at the 3% level, Chi-squared denotes the value for the likelihood chi square, and z denotes the value for the z-statistics. Here, *, **, and *** denote statistical significance at the 10%, 5%, and 1% levels.

incentive alignment. PEs invest in firms with low prior managerial equity. Apparently, PEs aim at aligning the interests of managers and shareholders. Managerial incentives can be aligned by compensation contracts that are strongly linked to firm performance. Changes in compensation structures are difficult to implement on an ad hoc basis and are therefore consistent with the longer investment horizon of PEs. Moreover, establishing a more performance-oriented managerial compensation is likely to require substantial industry expertise, which is also more likely to be found with PEs.

In robustness checks, we control for a potential non-monotonic relation testing the square of managerial ownership. Several authors (e.g., Morck et al. (1988)) argue that larger managerial stakes lead to managerial entrenchment rather than the alignment of interests. However, the present results do not establish a significant relation between the odds of becoming a PE target and the square of managerial shareholdings. Further empirical results of Weir et al. (2005) document additional support for the undervaluation hypothesis: Targets are significantly younger and smaller and have poor prior stock performance. We do not find any support for the undervaluation hypothesis in terms of these variables. In contrast to the findings of Weir et al. (2005), who analyze UK targets, the incentive and undervaluation effects do not explain PE investment choices in Germany.

The empirical results suggest that PE entry is not driven by private benefits if we use the unchecked proxy. For the private benefits reduction strategy to be profitable, an investor has to build a 'counter-stake' to the dominating and rent-extracting shareholder. The dominating shareholder that extracts private benefits only tenders its stake to a PE if the offer price compensates the shareholder for the loss of private benefits. As a consequence, buying out shareholders that are extracting private benefits is an unprofitable strategy. Based on information from the BaFin database and financial press, we exclude all cases in which PEs purchase a stake from the dominating shareholder. Those cases make up for about one-third of the sample (18 targets). We hypothesize that, if anything, the reduction of private benefits can only be profitable in those cases. We estimate the logit regression again, using the reduced sample, which excludes cases where PEs buy from the dominating shareholder in Model 3. The results show that private benefits are unlikely to drive PE investments, because the coefficient of the private benefits proxy still fails to be significant. The explanatory power of this model specification is very limited: The chi-squared test rejects the hypothesis that all tested variables are jointly insignificant only at the 10% level.

We control for various alternative investment motives. Increasing leverage can also be attractive because of tax benefits. The coefficient is opposite to the hypothesized direction and insignificant. This finding is replicated when using tax expenses divided by the market value of equity as an alternative measure. Hence, we do not find any support for PE targets having high tax liabilities. This finding is in line with the results of Weir et al. (2005) and Weir et al. (2008), who do not find that high tax liabilities significantly increase the likelihood of PE investment in the UK. The value drivers of PE activities in Germany seem to stem from sources other than tax arbitrage. This finding is not necessarily inconsistent with the results of Achleitner et al. (2011), who find that the market reaction to PE entries is driven by tax motives: Increased use of a debt tax shield may indeed increase shareholder wealth, but the tax advantage still does not represent an original investment motive.

Size and prior stock performance fail to be significantly related to the likelihood of PE entries. Both variables are related to information asymmetries. Hence, the reduction of information asymmetries does not seem to motivate PE investments. In sum, PE strategies are characterized as follows: With stable cash flows and little R&D, PE targets are particularly well suited for increases in leverage. Moreover, they invest in firms that are likely to exhibit agency costs due to low managerial equity and, hence, a great degree of ownership control separation.

1.6 Conclusion

The present paper analyzes HF and PE target characteristics to investigate whether their investment strategies are driven by corporate governance improvements. Table 1.10 summarizes the main results. In total, the findings indicate that the investment motives of HFs and PEs are both linked to free cash flow problems and incentive alignment potential. However, they pursue distinct investment strategies, which can be explained by their particular business models.

HFs acquire minority stakes in public companies. They are likely to aim at increasing dividends and thereby mitigate free cash flow problems. Moreover, HF investments seem to be motivated by monitoring deficits, focusing on firms with a lack of controlling shareholders, in particular a lack of family ownership. In contrast, PEs often acquire controlling stakes and aim to take the target private, accompanied by an increase in leverage. PE targets

Table 1.10: Summary of results

Hypothesis	Variable	Expected sign	HF	PE
Free cash flow	Cash	+		
	Debt	−		
	Dividend yield	−	−	
	Tobin's Q	−	+	
	Research	−	+	−
Ownership structure	Management ownership	−		−
	Family ownership	−	−	
	Free float	+	+	
	Private benefits	+		

This table reports the expectations regarding the empirical tests of the hypotheses and compares them to the empirical results. Cash denotes cash and cash equivalents scaled by sales. Debt is (short-term debt + long-term debt – cash and cash equivalents)/total assets. Dividend yield is defined as the cash dividend scaled by the market value of equity. Tobin's Q is defined as (market value of equity + book value of total liabilities)/total assets divided by the equivalent measure of the average of all firms in DAX and MDAX in the respective year. Research and development is set to 1 if the firm has research and development expenditures, and 0 otherwise. Management ownership denotes the stake held by members of the management board. Family ownership is defined as the stake held by family members who are neither members of the executive board nor related to them. Free float is defined as the sum of shareholdings below 5%. Private benefits is a dummy is set to 1 if the largest shareholder holds more than 25% and the second largest holds less than 5% of the shares.

are well suited for leverage increases because they are likely to have low expected financial distress costs. They also appear to draw value from incentive alignments by targeting firms with low managerial shareholdings. Neither HFs nor PEs seem to be motivated by the reduction of private benefits.

In summary, our findings indicate that HFs implement measures that mitigate agency problems and hence create wealth in the short run; PEs mitigate agency problems and hence create wealth in the long run. These findings are consistent with the organizational set-ups of HFs and PEs, which imply joint incentives to improve corporate governance, but differences in the time horizons and depth of changes that can be implemented. The findings that HF and PE activities are driven by corporate governance improvements suggest a positive role from a welfare perspective. However, in the following respects, HFs and PEs may be detrimental to long-term welfare: HF strategies aim to create shareholder value in the short run which can come at the expense of long-run shareholder value if one assumes that markets are not efficient. Increasing leverage seems to be an important driver of the PE investment decision. The potential wealth transfer from stakeholders, particularly debtholders and employees, seems to be the most likely problem with respect to PEs. A more comprehensive assessment therefore necessitates an analysis of the long-term consequences.

Chapter 2

Idiosyncratic Volatility and the Timing of Corporate Insider Trading

2.1 Introduction

This paper tests the hypothesis that corporate insiders time their trades to exploit short-term information advantages over uninformed market participants using data on 646,411 U.S. insider transactions reported to the SEC between 1986 and 2009. This study is, to the best of our knowledge, the first to investigate the timing of corporate insider trading with respect to a market data based measure of time-varying information asymmetry. Knowledge about the way insiders time their trades can help to better understand their trading motives and shed light on the welfare implications of insider trading.

Corporate insiders, i.e., executive directors, board members or large shareholders, are likely to possess superior information about the true value of their firm compared to outside investors. They are involved in decision making processes that affect the value of the firm such as investment or merger decisions, and they receive notice about major events in advance of official public announcements. Several empirical studies (e.g., Seyhun (1986), Chang and Suk (1998) or Jeng et al. (2003)) document that corporate insiders are able to generate significant abnormal returns from trading. This evidence indicates that they use their advantage for profitable trading strategies. Moreover, it is likely that the information asymmetry between informed and uninformed investors and consequently the information advantage of insiders varies over time. The question then arises whether corporate insiders time their transactions in such a way that they exploit high peaks of information asymmetry.

The welfare implications of corporate insider trading are ambiguous. On the one hand it is argued that insider trading leads to more informative prices. The model by Kyle (1985), for instance, presents a situation in which market makers adjust prices according to the combined order flow of insiders and uninformed noise traders. On the other hand insider trading may prevent outsiders from trading in the stock because it imposes adverse selection costs (see, e.g., Bhattacharya and Spiegel (1991)). The question is whether corporate insiders trade on the foreknowledge of announcements or whether their transactions make prices more informative because their trading is based on information that would otherwise not be reflected in prices. If insiders trade on a short-term information advantage, then the positive welfare effects may be only small and the negative welfare effects are likely to dominate as the information will be incorporated into prices soon anyways. This idea is also brought forward by Hirshleifer (1971). He distinguishes two types of information: foreknowledge and discovery. While foreknowledge will be revealed to all in due time, discovery is the 'correct recognition of something that possibly already exists, through hidden from view' (p. 562) and will not be entirely revealed in due time. Hirshleifer argues that the protection of foreknowledge - the equivalent in our case would be trading on foreknowledge - does not have any social value. On this account, our analysis contributes to the evaluation of the welfare implications of corporate insider trading because it addresses the question of whether corporate insiders trade on short-term information.

The paper adds to the literature on corporate insider trading and presents the first study to analyze the likelihood of corporate insider trading. Further, its main innovation is to use a time-variant proxy for asymmetric information and link it to insider trading. This proxy allows for addressing the question of whether corporate insiders time their transactions according to variations in asymmetric information.

We use idiosyncratic volatility relative to a firm's recent mean (henceforth *relivol*) as a proxy for asymmetric information. Under the assumption that variations in our measure of information asymmetry over time are due to changes in short-term information asymmetry, we analyze whether corporate insiders exploit their temporary informational advantage. To do so, we link up the likelihood of observing an insider transaction in a given stock with *relivol*.

Our main goal is to test the hypothesis whether the prevalence of a short-term information advantage drives the trading decision of a corporate insider. If we were to design an ideal experiment, we would exogenously shock the information set of an insider and leave the information set of other market participants constant. That shock would create an information advantage of insiders over outsiders. Since such an experiment is difficult to conduct in the real world, we need a proxy to identify the points in time when there is a wedge between the knowledge of insiders and the knowledge of market participants.

The main approach that has been taken so far is to use corporate announcements as a proxy. Studies following this approach investigate whether insiders use the foreknowledge of corporate announcements that are empirically found to have a significant price impact, such as dividend announcements, corporate bankruptcy, seasoned equity offerings, stock repurchases, and takeover bids (e.g., Elliott et al. (1984), Noe (1999), Ke et al. (2003), Piotroski and Roulstone (2005)). These studies share the assumption that insiders have foreknowledge of these events or announcements, and upon announcement this private information advantage vanishes as it is turned into public information. If insiders traded on early access to corporate news, one would observe insider buying activity before good news and insider selling activity before bad news. The extant empirical literature does not arrive at a conclusive result of whether corporate insiders exploit short-term information or not.

The existing approach to use corporate announcements suffers from several shortcomings, which may serve as a potential explanation for the inconclusiveness of the results. First, this approach necessitates an ex-ante selection of corporate news types. It is difficult to produce an exhaustive list of corporate news types. There may be types of temporary information advantages of insiders not covered by the events which have been considered so far. To be able to infer the absence of timing, one would have to collect information about every announcement the firm makes or at least obtain an unbiased representative selection of all those announcements. Second, with the exception of earnings and dividend announcements for which analysts' estimates may exist, it is in general difficult to measure the surprise component of corporate announcements. It is, hence, difficult to distinguish informative announcements from uninformative ones, i.e., those which reduce the wedge between insider and outsider information and those that do not. Third, the risk of litigation and adverse publicity is likely to be higher shortly prior to such disclosure types because the prevalence of such events is easily verifiable. This is likely to prevent corporate insiders from *blatantly* exploiting this kind of information. Many firms even have self-imposed compliance guidelines which prevent insiders from trading before such events. Using *relivol* as a more direct measure of time-variant information asymmetry, we propose an alternative approach which does not suffer from these shortcomings. Idiosyncratic volatility as a measure of asymmetric information is motivated by the idea that informed traders act when significant private information exists and that trading on private information causes stock price movements to deviate from those predicted by the assumed return generating process.

To the best of our knowledge, there is only one other paper that links up corporate insider trading and idiosyncratic volatility. Ben-David and Roulstone (2009) analyze the effect of idiosyncratic volatility on the profitability of corporate transactions, i.e., insider purchases, insider sales, repurchases and seasoned equity offerings. They find that insider profits are positively linked to idiosyncratic volatility. They investigate the cause of this empirical relationship further and argue that the higher trading gains rather stem from mispricing and weak arbitrage forces than from private information. Ben-David and Roulstone recognize that the distinction between mispricing and private information is weak as private information makes it more likely to detect mispricing.

Our paper differs from the one by Ben-David and Roulstone in the following respects: First, we analyze the effect of idiosyncratic volatility on the *likelihood* of insider trading, in an attempt to learn about the motives of insider trading, whereas Ben-David and Roulstone (2009) only analyze the profitability of insider trades. Second, the concept of our measure is different from the one by Ben-David and Roulstone, which is why we capture a different effect. They use a long-term measure of idiosyncratic volatility which is calculated from 60 to 12 months before the trade, whereas we use a short-term measure of idiosyncratic volatility that is based on the period between 21 days to 1 day prior to the insider trade. Most importantly, while we look at within-firm variation, they look at a cross-section of firms. Our variable is a *relative* measure of idiosyncratic volatility, as opposed to the overall level. Thereby, Ben-David and Roulstone address an alternative research question, namely: Is insider trading more profitable with respect to firms with large overall information asymmetries? Our main focus lies on shedding light on the trading decision of an insider. In contrast to Ben-David and Roulstone, we raise the question of whether insiders exploit high peaks of asymmetric information. The insider has hardly any control over the overall level of idiosyncratic volatility. However, an insider

- up to a certain extent - has control over *when* to trade. As an auxiliary analysis, we test whether insiders that time transactions are rewarded with higher trading profits. Our analysis is therefore to be viewed as complementary to the one by Ben-David and Roulstone (2009).

A potential objection regarding to our approach is the allegation that we jointly test two hypotheses: (1) Insiders time their trades to exploit peaks of asymmetric information and (2) *relivol* is an appropriate measure for short-term variations in asymmetric information. We address these concerns using appropriate controls, or robustness checks respectively.

Consistent with our hypothesis, the empirical findings suggest that corporate insiders try to exploit short-term informational advantages. They tend to buy stocks more frequently when *relivol* is high, i.e., at times during which it can be expected that private information is impounded into stock prices. The effect of *relivol* on the likelihood of insider trading is also economically significant. A one standard deviation increase in *relivol* increases the probability of insider trading by 2.9%. The effect of *relivol* on purchases is robust to controlling for endogeneity and cannot be explained by trading on market uncertainty or contrarian trading.

We do not find robust evidence that corporate insiders time their sales. In our basic specification we find a slightly negative impact, but once we control for previous transactions, the effect becomes slightly positive (0.3%). This may be because sales are in general less likely to be driven by information, since sales are also motivated by other reasons than profit seeking, e.g., diversification or liquidation needs. Furthermore, there may be a trade-off between trading profits on the one hand and concerns about litigation and reputation risks. These risks are likely to be asymmetrically higher with respect to insider sales (see Jargolinzer and Roulstone (2009)).

Our findings also lend support to the notion that timing is profitable for insiders. We find that insiders can increase their trading profits for purchases substantially with timing. A one standard deviation increase in *relivol* increases the abnormal returns over a period of 6 months by 2.1%. We do not find any significant effect of timing on sales. The effect of *relivol* on profits remains robust when we control for alternative explanations, or use alternative model specifications. We also show that the effect cannot be explained by the notion that *relivol* is a priced risk factor.

The paper is structured as follows: The hypotheses tested in the paper are summarized in

Section 2. Section 3 introduces *relivol* as a proxy of asymmetric information. Section 4 describes the data. Section 5 presents the results of the logit regression where we analyze the effects of *relivol* on the likelihood of insider trading. Section 6 deals with the analysis of the relationship of profitability and *relivol*. Section 7 concludes.

2.2 Hypotheses

In the present study, we aim at investigating the factors that drive the trading decision of an insider. We assume that because insiders are better informed about the true value of the firm, they can also observe the asymmetry between the information of outsiders and insiders. During such periods, there is a wedge between the market price of the stock and the true value of the stock conditional on the insiders' superior information set. This is because the private information of the insider has not yet been incorporated into market prices. Relative to the *potentially* publicly available information set which includes the private information, the stock is mispriced. Exploiting such mispricing by buying stock if market prices are too low or selling stock if market prices are too high, can be profitable for the insider. We therefore hypothesize that insiders time their trades during periods of high asymmetric information, i.e.,

H1: The likelihood of insider trading is higher if the degree of asymmetric information is high.

We further claim:

H2: The effect of asymmetric information on the likelihood of insider trading is stronger for purchases than for sales.

Sales are less likely to be information-driven as compared to purchases. First, there are alternative trading motives for sales which do not apply to purchases (see, e.g., Lakonishok and Lee (2001), Friederich et al. (2002) or Fidrmuc et al. (2006)). Corporate insiders often have considerable stakes in the firm, often receive stock-based compensation and, if they are employed by the firm as an executive, they have human capital invested in the firm. Against the background of their high exposure to the firm's share price, corporate insiders are likely to sell shares for diversification purposes. Further, liquidity (e.g., when considering to buying a house) is another typical trading motive when selling shares. Second, as argued by Jargolinzer and Roulstone (2009) litigation risks are higher for sales than for purchases.

As mentioned above, we hypothesize that insiders who time their trades, i.e., they execute transactions when information asymmetry is high, generate significantly larger trading profits.

H3: Insider trading profits are higher if the trade occurs when information asymmetry is high.

2.3 Idiosyncratic volatility

2.3.1 Computation

Our measure of idiosyncratic stock returns volatility is defined as the standard deviation of residual returns unexplained by return models. We compute idiosyncratic volatility with respect to the Carhart four-factor model (Carhart (1997)). The Carhart four-factor model is the Fama-French three-factor model augmented by the momentum factor. Accordingly, the four-factor model assumes that returns are determined by sensitivities with respect to the following risk factors: market factor, size factor, market-to-book factor and momentum factor. The firms' coefficients are estimated using rolling five year windows of monthly returns. As usual in the literature, we require at least 24 return observations within the past five years.

There is a trade-off which we have to take into account when choosing the estimation window for *relivol*. We seek to measure short-term variations in asymmetric information and would like to measure the degree of asymmetric information just before an insider trade occurs, which suggests to use a very short estimation window. However, short estimation windows are subject to larger estimation errors. Our idiosyncratic volatility measure is estimated over a period of the last 21 trading days, i.e., the idiosyncratic volatility used to estimate the probability and profitability of trades on day t is based on data from days $t-21, \ldots, t-1$. While such a short window renders the estimates inexact, these errors can be expected to even out over our whole sample of insider transactions. We consider this choice an appropriate compromise.

We compute a measure of *relative* idiosyncratic volatility, i.e., the ratio of a firm's idiosyncratic volatility at a point in time to its mean idiosyncratic volatility during the prior calendar year. This serves the analysis of the effect of short-term asymmetric information as it corresponds to the abnormal idiosyncratic volatility in a firm's stock. Our main focus is not the question of whether insider trading is more likely in firms with high idiosyncratic volatility but whether insider trading is more likely when idiosyncratic volatility for a given firm peaks.

2.3.2 Interpretation

We use idiosyncratic volatility as a proxy for information asymmetry between insiders and outsiders. The measure is based on the argument that a predominance of noise trading, resulting from high information costs, induces volatility. Kelly (2007) shows that low return synchronicity reflects a poor information environment and is related to high information asymmetry. Bartram et al. (2012) find a negative relation between idiosyncratic risk and the quality of corporate disclosure. Relatedly, Jiang et al. (2009) find evidence concerning a relation between idiosyncratic volatility and selective disclosure. Furthermore, there is evidence that opaque (Hutton et al. (2009)), poorly governed firms (Khanna and Thomas (2009)) feature high levels of idiosyncratic volatility. These studies all analyze cross-sections of stocks or markets whereas we look at short-term variation in idiosyncratic volatility.

Our key assumption is that variation in idiosyncratic volatility captures variation in information asymmetry over time. We argue that private information activities are positively associated with the level of information asymmetry between informed and uninformed traders. When informed traders with the lowest information cost begin to trade against noise traders, volatility is increased. This relationship is corroborated by theoretical models (Glosten and Milgrom (1985)) and empirical evidence (French and Roll (1986)). Trading on private information is likely to take place with respect to information about an individual firm rather than general market information, which is typically publicly available. As a consequence, informed trading is expected to affect the *idiosyncratic* part of volatility which has to be distinguished from market volatility.

Further, Berrada and Hugonnier (2011) theoretically analyze the relationship between incomplete information and idiosyncratic volatility. They find that incomplete information is positively related to idiosyncratic volatility. Using analyst forecasts as a proxy, they find empirical support for their prediction. Dasgupta et al. (2010) give theoretical and empirical evidence that price informativeness decreases with idiosyncratic volatility. Arena et al. (2008) arrive at the same conclusion when considering the relation between idiosyncratic volatility and momentum profits.

Our paper follows several existing studies which use idiosyncratic volatility as a measure of asymmetric information. Dierkens (1991) analyzes the relevance of asymmetric information for the issuance of new equity. She finds that idiosyncratic volatility is high before new equity issues and drops after the equity issue is announced. Her results are consistent with the notion that managers time equity issues in order to exploit asymmetric information. Ferreira and Laux (2007) use idiosyncratic volatility as a measure of stock price informativeness which they relate to corporate governance. Krishnaswami and Subramaniam (1999) test the hypothesis that corporate spin-offs reduce asymmetric information, using idiosyncratic volatility as a measure among other proxies such as the precision or the diversion of analyst forecast errors. They find that idiosyncratic volatility is positively related to the likelihood of a spin-off and that idiosyncratic volatility drops after the spin-off.

There is also empirical evidence pointing towards an inverse relationship between idiosyncratic volatility and asymmetric information. In an international study Kim and Shi (2010) find that the adoption of IFRS by a firm is related to a greater degree of idiosyncratic volatility. However, this effect prevails in countries with poor institutional infrastructures. These opposite findings may be reconciled by the argument of Gao and Liang (2011) that 'by making private information public, disclosure reduces private information acquisition and levels the playing field'. This implies that in a situation of high opaqueness, e.g., in countries with poor institution and lax regulations, an increase in disclosure quality may increase information acquisition by enabling it in the first place and thereby increasing idiosyncratic volatility. This would explain why some studies find an opposite relation between asymmetric information and idiosyncratic volatility. In the present paper we analyze data from the U.S., a highly regulated, liquid and rather transparent market. As the studies cited above suggest, in such a market asymmetric information is likely to be positively linked to asymmetric information.

2.4 Data

2.4.1 Dataset construction

Our analysis is based on a sample of U.S. corporate insider trades from the Thomson Financial (TFN) insider trading database. The database includes trades by corporate insiders which Section 16 of the Securities Exchange Act requires them to file via Form 4. Our sample starts in 1986, as from that year on details on insider transactions begin to be reported in the TFN database, and extends up to 2009. The database includes the trading date, the reporting date, the firm, the position of the insider within the firm, the number of shares traded, the transaction price and the direction of the trade (purchase or sale). We avoid double counting due to several insiders trading on the same day, by only counting one trade per day and per firm. When there were both purchases and sales on the same day, we classify the trade as a purchase (sale), when the net amount of shares bought is positive (negative).

Daily stock returns are from CRSP. For the return models we use the monthly Fama-French factors, momentum and the riskfree rate from Kenneth French's data library. Based on the stock returns and the factors, we compute idiosyncratic volatility for each firm and day in our sample. We use annual accounting information from the firms' balance sheets and profit and loss statements as well as earnings announcement dates from COMPUSTAT. Information on the number of analysts following a firm is taken from IBES. While the other firm characteristics are used as control variables in our empirical analyses, we compute book equity in order to remove stocks with a negative one, as it is frequently done in the literature. Also, we remove financial companies, because of their usually atypical firm characteristics compared to other firms, and regulated utilities, whose informational environment is likely to be different from that of other firms.

2.4.2 Descriptive statistics

We merge the data and obtain a sample of 646,411 insider transactions, 185,613 of which are purchases and 460,798 sales. The distribution of purchases and sales over years are tabulated in Table 2.1. Our independent variables in the following analysis regarding the likelihood of insider trading, that is *relivol*, stock or market characteristics vary at a daily or quarterly frequency, where available. Firm characteristics are on an annual basis. Our sample covers 6,975 firms.

We construct two samples: a likelihood sample and a profit sample. The likelihood sample consists of daily firm observations. We define a dummy variable *purchase* (*sale*) which is set to 1 if there was a purchase (sale) by a corporate insider in the respective stock on the given day and to 0 otherwise. In total our likelihood sample consists of over 16.7 million firm days. Insider purchases occur on 0.7% of all trading days and insider sales on 2.1% of all trading days. Table 2.2 shows summary statistics of the independent variables for the firm day observations with purchases, sales, no trades and the entire firm-day sample.[1]

Our second sample, the profit sample, consists of all insider trades or purchases and the respective independent variables (stock, market, or firm characteristics) at the given date.

Table 2.1: Distribution of insider transactions over years

Year	Purchases	% of all purch.	Sales	% of all sales	Total	in % of all trades
1986	1,701	0.92%	3,887	0.84%	5,588	0.86%
1987	8,227	4.43%	10,398	2.26%	18,625	2.88%
1988	5,845	3.15%	8,667	1.88%	14,512	2.25%
1989	5,544	2.99%	10,018	2.17%	15,562	2.41%
1990	8,432	4.54%	8,805	1.91%	17,237	2.67%
1991	5,024	2.71%	15,366	3.33%	20,390	3.15%
1992	4,777	2.57%	16,068	3.49%	20,845	3.22%
1993	5,209	2.81%	16,440	3.57%	21,649	3.35%
1994	6,826	3.68%	14,081	3.06%	20,907	3.23%
1995	6,761	3.64%	18,436	4.00%	25,197	3.90%
1996	8,213	4.42%	21,003	4.56%	29,216	4.52%
1997	8,872	4.78%	21,576	4.68%	30,448	4.71%
1998	14,160	7.63%	18,402	3.99%	32,562	5.04%
1999	13,942	7.51%	18,195	3.95%	32,137	4.97%
2000	12,455	6.71%	22,548	4.89%	35,003	5.41%
2001	9,416	5.07%	24,282	5.27%	33,698	5.21%
2002	10,091	5.44%	24,382	5.29%	34,473	5.33%
2003	6,073	3.27%	29,987	6.51%	36,060	5.58%
2004	5,905	3.18%	34,335	7.45%	40,240	6.23%
2005	6,460	3.48%	30,544	6.63%	37,004	5.72%
2006	5,957	3.21%	28,834	6.26%	34,791	5.38%
2007	6,642	3.58%	27,911	6.06%	34,553	5.35%
2008	11,856	6.39%	17,750	3.85%	29,606	4.58%
2009	7,225	3.89%	18,883	4.10%	26,108	4.04%
Total	185,613	100.00%	460,798	100.00%	646,411	100.00%

This table shows the distribution of insider purchases or sales over years between 1986 and 2009. It only includes the transactions for which data in CRSP or COMPUSTAT were available.

[1] For the mean value of *relivol* for all days we expect a value close to 1. The actual mean is 1.027 and therefore slightly larger than 1. However, according to a simple t-test, this difference (0.027) fails to be statistically significant at conventional levels.

Table 2.2: Summary statistics for firm-day observations

Indicator	Variable	Mean	Median	Std. dev.	5% quantile	95% quantile
Purchases	relivol	1.165	1.038	0.542	0.532	2.313
	$bhar_+$	0.053	0	0.114	0	0.290
	$bhar_-$	-0.084	-0.036	0.110	-0.334	0.000
	volatility index	24.190	22.790	9.831	11.720	46.53
	analystfollowing	5.216	2.833	6.022	1	18.667
	bookleverage	0.322	0.302	0.260	0	0.794
	returnonequity	-0.260	0.051	1.190	-1.604	0.286
	market capitalization	1,055.703	102.620	3,618.677	6.594	4,407.974
	q	1.887	1.358	1.604	0.776	4.837
	blackout (d)	0.482	0	0.500	0	1
Sales	relivol	1.014	0.933	0.419	0.512	1.798
	$bhar_+$	0.075	0.025	0.118	0.000	0.315
	$bhar_-$	-0.035	0	0.068	-0.178	0.000
	volatility index	20.062	19.150	7.442	11	33.32
	analystfollowing	9.194	6.833	7.720	1	26.583
	bookleverage	0.250	0.204	0.242	0	0.715
	returnonequity	-0.064	0.103	0.846	-0.784	0.322
	market capitalization	2,534.584	471.363	5,593.147	18.527	16,180.050
	q	2.497	1.821	1.978	0.920	6.732
	blackout (d)	0.468	0	0.499	0	1
No trade	relivol	1.027	0.931	0.468	0.471	1.927
	$bhar_+$	0.056	0	0.110	0	0.280
	$bhar_-$	-0.057	-0.008	0.088	-0.248	0
	volatility index	21.322	20.230	8.055	11.370	36.900
	analystfollowing	5.361	2.667	6.254	1	19.500
	bookleverage	0.302	0.271	0.257	0.000	0.787
	returnonequity	-0.237	0.062	1.123	-1.627	0.287
	market capitalization	1,052.564	94.436	3508.155	3.681	4,612.091
	q	1.948	1.384	1.678	0.764	5.172
	blackout (d)	0.704	1	0.456	0	1
All	relivol	1.027	0.932	0.468	0.472	1.927
	$bhar_+$	0.057	0	0.111	0	0.281
	$bhar_-$	-0.056	-0.008	0.088	-0.248	0.000
	volatility index	21.316	20.230	8.063	11.360	36.900
	analystfollowing	5.430	2.667	6.303	1	19.667
	bookleverage	0.301	0.270	0.257	0	0.786
	returnonequity	-0.234	0.063	1.120	-1.614	0.288
	market capitalization	1,079.754	97.374	3,563.639	3.751	4,774.901
	q	1.958	1.390	1.685	0.766	5.203
	blackout (d)	0.698	1	0.459	0	1

This table shows the summary statistics of our main independent variables for the firm days with purchases, sales and no trades. *Relivol* is the stock price's idiosyncratic volatility over the past 21 trading days divided by its prior calendar year's mean. $Bhar_+$ ($bhar_-$) is the stock's BHAR over the 21 trading days prior to the insider trade for a positive (negative) value of this variable. $Volatility\,index$ is the S&P Volatility Index. *Bookleverage* is the book value of debt divided by the sum of the market value of equity and the book value of debt. $Analystfollowing$ indicates the number of analysts following the firm. $Market\,capitalization$ is market value of equity. Q denotes Tobin's q. *Returnonequity* denotes the firms' net income scaled by the book value of equity.

2.5 Relivol and the likelihood of insider trading

2.5.1 Empirical strategy

The objective of the following analysis is to link up the likelihood of observing an insider trade with relative idiosyncratic volatility. We estimate logistic regressions with firm- and year-fixed effects where the dependent variable is a binary variable that is set to 1 if there was an insider trade (purchase or sale respectively) and to 0 if there was no such trade on the respective day. We estimate the following model:

$$\ln(\frac{p_{i,t}}{1-p_{i,t}}) = constant + c_i + y_t + \beta_0 \cdot relivol_{i,t} + \beta_1 \cdot X_{i,t}, \qquad (2.5.1)$$

where $p_{i,t}$ is the probability of an insider trade in the stock of firm i on day t. c_i is a firm constant, y_t is a year constant. X stands for the vector of firm- and time-specific control variables. We include several control variables in the analysis that account for firm and time specific characteristics, which are also likely to affect the likelihood of insider trading. We thereby control for the overall level of private information activities in a firm's stock, since our goal is to capture the effect of the deviation of idiosyncratic volatility from its permanent level.

We also include the S&P Volatility Index VXO as a measure of market-wide volatility ($volatility\, index$). The measure is calculated using 30-day S&P 100 index at-the-money options.[2] Hereby, we control for the possible objection that idiosyncratic volatility simply reflects changes in the level of overall volatility. Further, we control for the buy and hold abnormal returns over the last 21 trading days to ensure that an apparent effect of idiosyncratic volatility does not merely reflect trading as a response to past abnormal returns. We separate these into positive and negative returns in order to account for possible asymmetric effects on insiders' decision making ($bhar_+$ and $bhar_-$).

Quarterly earnings announcements represent a channel through which information about firm value is communicated to investors. On this account, many U.S. firms have self-imposed insider trading restrictions in place, according to which most of them allow insider trading only in the 30 days following the quarterly earnings announcement and prohibit

[2] VIX measures the implied volatility based on the S&P 500. We choose VXO over VIX, because VIX is only available from 1990 and, hence, not available for the entire sample.

trading in the 60 days preceding the next earnings announcement which represents the so called 'blackout period' (see Bettis et al. (2000) or Roulstone (2003)). This restriction aims at preventing corporate insiders from exploiting asymmetric information that will be reduced by the following earnings announcement. When such trading restrictions are in place and enforced, insider trading is certainly more likely to occur outside blackout periods. We therefore control for blackout periods. We assume that firms have a blackout period in place that restricts insider trading such that it is allowed to trade only during the 30 days following an earnings announcement. The dummy variable *blackout* is 0 for the 30 days following the earnings announcement and 1 for the remaining days.

We include size in terms of the natural logarithm of market capitalization ($size$) and the natural logarithm of the number of analysts covering the firm plus one ($analystfollowing$) as control variables that proxy for the firms' permanent information asymmetry between insiders and outsiders. Furthermore, we include *bookleverage* defined as the book value of debt divided by the value of total assets, *returnonequity* defined as net profit divided by the book value of equity and Tobin's Q (q) proxied by the sum of the market value of equity and the book value of debt divided by the sum of the book value of equity and the book value of debt.

2.5.2 The impact of relivol on the likelihood of insider trading

Table 2.3 reports the result for our basic model specification. We find that the likelihood of an insider purchase is significantly positively related to *relivol*. The effect is economically significant: A one standard deviation increase in *relivol* increases the probability of observing an insider purchase by 2.9%. Apparently, insiders purchase stock during times where asymmetric information is relatively high. The likelihood of an insider purchase is inversely related to prior abnormal returns. Corporate insiders seem to buy after the stock has performed poorly. We confirm that purchases are less likely to occur during alleged blackout periods. Further, insiders seem to time their trades during periods of high market volatility.

The results with respect to sales do not confirm the timing hypothesis. The likelihood of observing an insider sale is significantly inversely related to *relivol*. A one standard deviation decrease in *relivol* increases the probability of observing an insider sale by 0.8%. Apparently, insiders time their sales during times of low asymmetric information.

This finding is consistent with the existing evidence that sales are less informative than purchases. First, sales are also motivated by non-information driven purposes such as liquidity needs or diversification. Corporate insiders may save on transaction costs if they trade during periods of low asymmetric information. Second, corporate insiders may choose to time their sales during periods of low asymmetric information because of litigation risks which are assumed to be higher with respect to sales. Empirically, the two alternative explanations for the inverse relationship - alternative trading motives or high litigation risk - cannot be disentangled. Further, we find that sales are more likely to occur after abnormal performance as suggested by the positive coefficient for the prior abnormal returns. Insider sales are also less likely to occur during blackout periods. Insiders are more inclined to sell their shares during periods of low market-wide volatility.

2.5.3 Controlling for endogeneity

We recognize the potential existence of an endogeneity problem. There is empirical evidence that trading occurs in clusters, i.e., insiders transact multiple times during short time horizons (see, e.g., Lebedeva et al. (2009)). If insider trading affects idiosyncratic volatility and insider trading occurs in clusters, a significant relationship between insider trading and idiosyncratic volatility may simply reflect the effects of insider trading on idiosyncratic volatility.

Hence, when we observe a positive empirical relationship between *relivol* and insider trading, timing may not be the original cause. We use two approaches in order to address this concern. First, for each stock considered we eliminate all trades from the sample that occur in the 21 trading days subsequent to a trade from our sample. This serves to demonstrate that the possible objection that our results might be driven by the contamination of *relivol* with past trades executed during the estimation period is not valid. Second, we directly control for previous trades and their impact on the relationship between *relivol* and the likelihood of a trade.

Models (1) and (2) in Table 2.4 report the results with respect to this subsample. For both purchases and sales, our previous results remain robust in this subsample. A one standard deviation increase in *relivol* increases the probability of an insider purchase by 2.7%, while a one standard deviation decrease increases the probability of an insider sale by 0.4%. The findings suggest that the relationship between *relivol* and the likelihood

Table 2.3: Relivol and the likelihood of insider trading

	(1) Purchases beta/z	(2) Sales beta/z
Relivol	0.029***	-0.007***
	(43.52)	(-10.55)
$Bhar_+$	-0.006***	0.037***
	(-7.43)	(50.91)
$Bhar_-$	-0.050***	0.048***
	(-67.51)	(47.31)
Blackout (d)	-0.209***	-0.216***
	(-109.86)	(-95.92)
Volatility index	0.054***	-0.069***
	(83.63)	(-56.79)
Analystfollowing	-0.017***	0.069***
	(-9.39)	(38.69)
Bookleverage	0.002*	-0.009***
	(1.71)	(-7.35)
Size	0.010***	0.025***
	(4.23)	(10.36)
Q	-0.012***	0.035***
	(-8.46)	(31.82)
Return on equity	-0.006***	0.013***
	(-5.86)	(10.01)
Obs	16,687,810	6,562,588
LR chi-squared	60,237.76	62314.97
Prob > chi-squared	0.00	0.00
Log-Likelihood	-721,767.58	-649,675.87

This table shows the results of the logistic regression of the dependent variable insider trading which is set to 1 if there was an insider trade on a given day, and to 0 otherwise. For Model (2) we employ random sampling with 40% of the observations, where each observation has an equal probability to be included in the regression. The regressions include year and firm fixed effects. The table reports beta coefficients and z-statistics in parentheses. *, ** and *** denote statistical significance at the 10%, 5%, and 1% level, respectively. *Relivol* is the stock price's idiosyncratic volatility over the past 21 trading days divided by its prior calendar year's mean. $Bhar_+$ ($bhar_-$) is the stock's BHAR over the 21 trading days prior to the insider trade for a positive (negative) value of this variable. $Volatility\,index$ is the S&P Volatility Index. *Bookleverage* is the book value of debt divided by the sum of the market value of equity and the book value of debt. $Analystfollowing$ indicates the natural logarithm of (number of analysts following the firm+1). *Size* is the natural logarithm of the market value of equity. Q denotes Tobin's q. *Returnonequity* denotes the firms' net income scaled by the book value of equity. All independent variables except for dummy variables are standardized such that the beta coefficient indicates the change in the dependent variable for a one standard deviation change of the independent variable.

of insider trading is not driven by a potential effect of previous insider transactions on *relivol*.

We now control for changes in relative idiosyncratic volatility which stem from the effects of previous trades on idiosyncratic volatility. To this end, we include an interaction term between a dummy for previous trades and relative idiosyncratic volatility. We also include a dummy for the occurrence of previous trades in the ivol estimation window. This aims at controlling for the fact that insider trades are often split across several days such that days with insider trading cluster. Also, insider trades may increase idiosyncratic volatility and the interaction term serves to ensure that any effects of idiosyncratic volatility on the probability of insider trading do not merely reflect the clustering of trades. We estimate the following regression:

$$\begin{aligned}\ln\left(\frac{p_{i,t}}{1-p_{i,t}}\right) = {} & constant + c_i + y_t + \beta_0 \cdot relivol_{i,t} + \beta_1 \cdot past\,purchases_{i,t} + \beta_2 \cdot past\,sales_{i,t} \\ & + \beta_3 \cdot relivol_{i,t} \cdot past\,purchases_{i,t} + \beta_4 \cdot relivol_{i,t} \cdot past\,sales_{i,t} + \beta_5 \cdot X_{i,t},\end{aligned} \tag{2.5.2}$$

where $p_{i,t}$ is the probability of an insider trade in the stock of firm i on day t. c_i is a firm constant, y_t is a year constant, *past purchases* (*past sales*) is a dummy variable set to 1 if there was an insider purchase (sale) in the estimation window of *relivol*, and to 0 otherwise. X stands for the vector of firm- and time-specific control variables. The coefficients β_3 and β_4 capture the extent to which the observed relationship between the likelihood of insider trading and relivol may be due to clustering and reverse causality.

If insider transactions cluster, we expect that the coefficient of the dummy variable *past purchases* is positive. If the endogeneity concern holds, i.e., the positive impact of *relivol* is due to the effect of clustering and previous transactions driving up *relivol* we expect the following result: The interaction term $past\,purchases * relivol$ is positive and significant, while the coefficient of *relivol* becomes insignificant.

The Models (3) and (4) in the Table 2.4 show the results. We find evidence which supports the clustering hypothesis. If there were insider purchases in the previous 21 days, it is more likely that we observe another insider purchase in the same stock. If we observe a sale before, it is less likely that we observe an insider purchase. However, we do not find any evidence that the relationship of *relivol* on the likelihood of insider trading is driven by the impact of previous purchases on *relivol*. The coefficient of the interaction term

Table 2.4: Relivol and the likelihood of insider trading

	(1)	(2)	(3)	(4)
	No overlaps		Entire sample	
	Purchases	Sales	Purchases	Sales
	beta/z	beta/z	beta/z	beta/z
Relivol	0.027***	-0.004***	0.027***	0.003**
	(26.09)	(-4.39)	(26.81)	(1.97)
Past purchases (d)			0.502***	-0.032***
			(214.95)	(-4.44)
Past sales (d)			-0.028***	0.520***
			(-13.14)	(-4.74)
Past purchases*relivol			-0.026***	-0.011***
			(-20.23)	(-12.74)
Past sales*relivol			0.004*	-0.007***
			(1.91)	(163.70)
$Bhar_+$	-0.017***	0.041***	-0.007***	0.031***
	(-12.30)	(45.21)	(-8.22)	(41.20)
$Bhar_-$	-0.060***	0.056***	-0.048***	0.036***
	(-54.54)	(44.17)	(-65.63)	(35.68)
Blackout (d)	-0.242***	-0.304***	-0.198***	-0.219***
	(-99.64)	(-154.60)	(-121.95)	(-118.67)
Volatility index	0.049***	-0.055***	0.046***	-0.047***
	(53.35)	(-40.26)	(70.67)	(-39.98)
Analystfollowing	0.006***	0.086	-0.015***	0.033***
	(2.08)	(37.19)	(-8.05)	(17.29)
Bookleverage	0.003	-0.008***	>0.001	-0.006***
	(1.52)	(-5.05)	(0.18)	(-4.28)
Size	0.015***	0.031***	0.001	0.014***
	(3.95)	(9.36)	(0.53)	(5.09)
Q	-0.013***	0.032***	-0.007***	0.023***
	(-5.88)	(19.99)	(-4.73)	(19.49)
Return on equity	-0.001	0.013***	-0.004***	0.007***
	(-0.83)	(7.41)	(-3.66)	(5.06)
Obs	15,043,225	13,733,921	16,687,810	6,562,588
LR chi-squared	27685.84	51826.36	176838.93	197255.53
Prob > chi-squared	0.00	0.00	0.00	0.00
Log-likelihood	-364,219.76	-513,218.91	-663,467.00	-582,205.59

This table shows the results of the logistic regression of the dependent variable insider trading which is set to 1 if there was an insider trade on a given day, and to 0 otherwise. In Models (1) and (2) we exclude all insider transactions which have a distance of less than 21 trading days to the previous transaction in the same stock. For Model (4) we employ random sampling with 40% of the observations, where each observation has an equal probability to be included in the regression. The regressions include year and firm fixed effects. The table reports beta coefficients and z-statistics in parentheses. *, ** and *** denote statistical significance at the 10%, 5%, and 1% level, respectively. *Relivol* is the stock price's idiosyncratic volatility over the past 21 trading days divided by its prior calendar year's mean. *Past purchases* (*past sales*) is set to 1 if there was a purchase (sale) in the 21 trading days prior to the insider transaction. $Bhar_+$ ($bhar_-$) is the stock's BHAR over the 21 trading days prior to the insider trade for a positive (negative) value of this variable. *Volatility index* is the S&P Volatility Index. *Bookleverage* is the book value of debt divided by the sum of the market value of equity and the book value of debt. *Analystfollowing* indicates the natural logarithm of (number of analysts following the firm+1). *Size* is the natural logarithm of the market value of equity. *Q* denotes Tobin's q. *Returnonequity* denotes the firms' net income scaled by the book value of equity. All independent variables except for dummy variables are standardized such that the beta coefficient indicates the change in the dependent variable for a one standard deviation change of the independent variable.

past purchases $*$ *relivol* is negative and statistically significant at the 1% level. When there were previous purchases, then the effect of *relivol* on the likelihood of an insider purchase decreases drastically: If there were purchases in the 21 trading days before, a one standard deviation increase in *relivol* increases the probability of an insider purchase by only 0.1% (summing up the coefficients of *relivol* and *past purchases* $*$ *relivol*). Clustered trades seem to be less driven by the exploitation of short-term peaks in asymmetric information. If the endogeneity concern holds, we expect that the coefficient of *relivol* is insignificant. However, the empirical results in Model (3) show that the coefficient of *relivol* is significant. In total, the results suggest that the effect of *relivol* on the likelihood of insider purchases is not driven by endogeneity.

We also confirm clustering for insider sales. If there was an insider sale before, we are more likely to observe another sale as evidenced by the negative and significant coefficient of the dummy *past sales*. The occurrence of previous purchases reduce the likelihood to observe a sale. We find weak evidence that sales which are not preceded by any other trades are timed: When there was no preceding transaction in the stock, *relivol* has a positive and significant impact on the probability of an insider sale. A one standard deviation increase in *relivol* then increases the probability by 0.3%. The economic magnitude of the effect is substantially smaller than the effect with respect to purchases. When there was a previous purchase, *relivol* is inversely linked to the likelihood of observing a sale. A one standard deviation increase decreases the probability by 0.8% (the sum of the coefficients of *relivol* and *past purchases* $*$ *relivol*). When there was a previous sale, the effect of *relivol* is also negative, but slightly less with a decrease of 0.4% in the probability. Clustered trades in the same direction or in the opposite direction are less likely to be driven by the motive to exploit short-term asymmetric information.

2.5.4 Trading aggressiveness and the impact of relivol on the likelihood of insider trading

A trader who seeks to exploit a short-term variation in asymmetric information is likely to be impatient. We measure the impatience of a trader with the dummy variable *aggressive* which is set to 1 if the transaction price of a purchase (sale) is above (below) the closing price on the trading day, or 0 otherwise. The rationale behind this variable is to capture the trader's preference for immediacy: A trader who transacts at a price which is worse than the closing price is likely to care more about trading immediately than about trading at a good price.

The volume-weighted average share price would actually present a better benchmark than the closing price, as it is more informative about the prices that have prevailed throughout the trading day. However, the availability of the volume-weighted average share price is restricted to the availability on the TAQ database which does not cover our entire sample period. By using the closing price instead of the volume-weighted average share price we follow a more conservative approach to measure impatience. The closing price is more likely to contain the share price impact of the insider trade which might have pushed up prices slightly for purchases (or downwards for sales). Accordingly, the transaction price is likely to exceed (or fall below for sales) the closing price in fewer cases as compared to the volume-weighted average. As a result, we identify less trades as impatient if we use the closing price.

Table 2.5 reports the results. There is only a slight difference between aggressive and non-aggressive trades with respect to the impact of *relivol* on the likelihood (2.6% in Model (1) versus 2.8% in Model (3)). We do not find any significant impact of *relivol* on the likelihood of an aggressive insider sale (see Model (2)). Surprisingly, we find a significant impact with respect to non-aggressive sales. However, the impact of *relivol* on the likelihood of insider sales is economically small with 0.7%. Apparently, selling shares aggressively seems to be motivated by other reasons, such as urgent liquidity needs, than timing to exploit short-term asymmetric information.

2.5.5 Discussion of alternative interpretations of relivol

The main goal of this paper is to analyze whether corporate insiders exploit advance knowledge on short-term private information. In the introduction we have mentioned that our analysis is a joint test of the hypothesis that corporate insiders exploit short-term information asymmetry and the extent to which *relivol* captures variations in short-term information asymmetries. In this subsection, we discuss alternative explanations for our findings.

One may object that *relivol* does not capture variations in short-term asymmetric information, but instead it proxies for the general level of asymmetric information. First, we control for characteristics of the general information environment of the firm such as size, analyst following, or Tobin's Q. Furthermore, we include firm-fixed effects in our

Table 2.5: Trading aggressiveness and the likelihood of insider trading

	(1)	(2)	(3)	(4)
	Aggressive		Non-aggressive	
	Purchases	Sales	Purchases	Sales
	beta/z	beta/z	beta/z	beta/z
Relivol	0.028***	0.002	0.026***	0.006***
	(19.84)	(1.26)	(18.56)	(3.13)
Past purchases (d)	0.495***	-0.028***	0.507***	-0.040***
	(176.53)	(-8.06)	(112.80)	(-10.95)
Past sales (d)	-0.029***	0.497***	-0.027***	0.519***
	(-9.64)	(86.98)	(-9.44)	(84.77)
Past purchases*relivol	-0.026***	-0.012***	-0.025***	-0.012***
	(-14.81)	(-3.27)	(-14.55)	(-3.39)
Past sales*relivol	0.001	-0.010***	0.006***	-0.006***
	(0.41)	(-4.86)	(2.15)	(-3.00)
$Bhar_+$	-0.008***	0.031***	-0.006***	0.029***
	(-6.99)	(29.25)	(-4.79)	(26.90)
$Bhar_-$	-0.048***	0.040***	-0.047***	0.031***
	(-47.17)	(27.51)	(-45.12)	(21.70)
Blackout (d)	-0.201***	-0.213***	-0.193***	-0.212***
	(-92.24)	(-70.47)	(-75.60)	(-67.89)
Volatility index	0.052***	-0.065***	0.040***	-0.026***
	(59.15)	(-36.28)	(42.13)	(-17.04)
Analystfollowing	-0.009***	0.037***	-0.021***	0.031***
	(-3.40)	(14.08)	(-8.19)	(11.22)
Bookleverage	0.002	-0.008***	-0.002	-0.007***
	(1.01)	(-4.10)	(-0.97)	(-3.43)
Size	0.002	0.003	0.003	0.022***
	(0.42)	(0.69)	(0.75)	(5.72)
Q	-0.005***	0.023***	-0.010***	0.023***
	(-2.31)	(14.41)	(-4.93)	(13.56)
Return on equity	-0.006***	0.014***	-0.001	0.002
	(-4.46)	(6.86)	(-0.63)	(1.25)
Obs	16,010,483	6,014,232	15,676,692	6,030,575
LR chi-squared	86749.02	99046.21	92759.94	93623.28
Prob > chi-squared	0.00	0.00	0.00	0.00
Log-likelihood	-370,116.73	-328,207.15	-371,040.26	-305,302.15

This table shows the results of the logistic regression of the dependent variable insider trading which is set to 1 if there was an insider trade on a given day, and to 0 otherwise. In Models (1) and (2) we exclude all non-aggressive insider trades, while in Models (3) and (4) we excludes all aggressive trades. For Models (2) and (4), we employ random sampling with 40% of the observations, where each observation has an equal probability to be included in the regression. The regressions include year and firm fixed effects. The table reports beta coefficients and z-statistics in parentheses. *, ** and *** denote statistical significance at the 10%, 5%, and 1% level, respectively. *Relivol* is the stock price's idiosyncratic volatility over the past 21 trading days divided by its prior calendar year's mean. *Past purchases* (*past sales*) is set to 1 if there was a purchase (sale) in the 21 trading days prior to the insider transaction. $Bhar_+$ ($bhar_-$) is the stock's BHAR over the 21 trading days prior to the insider trade for a positive (negative) value of this variable. *Volatility index* is the S&P Volatility Index. *Bookleverage* is the book value of debt divided by the sum of the market value of equity and the book value of debt. *Analystfollowing* indicates the natural logarithm of (number of analysts following the firm+1). *Size* is the natural logarithm of the market value of equity. Q denotes Tobin's q. *Returnonequity* denotes the firms' net income scaled by the book value of equity. All independent variables except for dummy variables are standardized such that the beta coefficient indicates the change in the dependent variable for a one standard deviation change of the independent variable.

regressions. In addition, we focus on deviations of idiosyncratic volatility from an average level. As a consequence, it is not the *level* of asymmetric information which is captured by *relivol* but the *deviation* from the average level. If these deviations were random, we would not expect to find any significant impact.

A further objection could be that insiders trade on market-wide uncertainty. We observe a significant relationship between the likelihood of insider trading and *relivol* because *relivol* is correlated with market-wide uncertainty. We control for market-wide uncertainty using the S&P volatility index as a measure. The effect of *relivol* is still significant. This observation suggests that our main result is not driven by correlation of *relivol* with market-wide uncertainty.

Previous research (e.g., Piotroski and Roulstone (2005)) documents evidence that insiders pursue contrarian trading strategies in order to exploit short-term misvaluations. By controlling for previous abnormal returns (using $bhar_+$ and $bhar_-$) we show that our main result is not driven by contrarian trading.

One might still cast doubt on the appropriateness of our measure. One may further object that our measure does not capture variations in private information, but variation in liquidity. First, this assumption is not corroborated by neither the existing theoretical nor empirical literature on idiosyncratic volatility. Second, the objection is inconsistent with the documented difference with respect to purchases and sales. If *relivol* measures liquidity, we would expect that the coefficient is positive and significant for sales, since in particular sales are less information-driven. Third, the empirical evidence in the following section shows that timing increases trading profits. This finding also provides support for the notion that *relivol* indeed captures short-term information advantages and not liquidity.

2.6 Relivol and the profitability of insider trading

2.6.1 Empirical strategy

In the following, we test whether insiders have an incentive to time their trades. We hypothesize that insiders increase their profits by trading during times of high information asymmetry. We expect that long-term profits of insiders are higher if they trade during periods of high relative idiosyncratic volatility.

In order to obtain a proxy for the profits accruing to the insider, we construct buy and hold abnormal returns (BHAR) subsequent to the insider transaction over periods of 1, 3, 6 and 12 months. The 6-month period is the most important as it is motivated by the short-swing rule according to Section 16(b) of the Securities Exchange Act of 1934. The rule intends to prevent corporate insiders from making short-term profits at the expense of outside shareholders. It mandates that profits made within less than six months have to be returned to the firm (see Jeng et al. (2003)). The period for the abnormal return calculation starts on the day after the insider trading day. We calculate the abnormal return with respect to the Carhart four-factor model, i.e., by adjusting for market risk, size risk, book-to-market risk and momentum risk. We then regress the abnormal return on our proxy for timing (*relivol*) and several control variables that are expected to affect the size of the abnormal return. We estimate the following regression:

$$BHAR_{i,t} = constant + c_i + y_t + \beta_0 \cdot relivol_{i,t} + \beta_1 \cdot X_{i,t}, \tag{2.6.1}$$

where $BHAR_{i,t}$ is the abnormal return of the firm's stock subsequent to the insider trade i on day t. c_i is a firm constant, y_t is a year constant. X stands for the vector of firm- and time-specific control variables. As control variables we use firm size, book leverage, Tobin's Q and return on equity. We include year and firm-fixed effects in the regression. Further, we cluster standard errors at the firm level.

2.6.2 The impact of relivol on profits

Table 2.6 reports the results of the regressions for the 6 month abnormal returns for purchases and sales. Model (1) is the basic specification and Model (2) adds a measure for market volatility and firm characteristics as independent variables. If the trade occurs during a period of relatively high idiosyncratic volatility, the abnormal return is greater. The effect is statistically significant at the 1% level and also economically significant: For purchases we find an effect between 1.7% (Model (1)) and 2.1% (Model (2)) when controlling for firm characteristics for a one standard deviation increase in *relivol*. The S&P volatility index is positively associated with trading profits. A one standard deviation increase in the volatility index increases trading profits by 1.7%. The fact that the effect of *relivol* remains robust to the inclusion of a measure for market wide uncertainty again supports our hypothesis that *relivol* captures the exploitation of firm-specific asymmetric information. In sum, the results for purchases are consistent with our hypothesis that trading during periods of high asymmetric information increases trading profits.

Table 2.6: The impact of relivol on profits

Dep. var.: 6m BHAR	(1) Purchases beta/t	(2) Purchases beta/t	(3) Sales beta/t	(4) Sales beta/t
Relivol	0.017***	0.021***	-0.003	-0.003
	(3.28)	(3.36)	(-0.56)	(-0.63)
Volatility index		0.017***		-0.002
		(3.99)		(-0.72)
Bookleverage		0.020		-0.007
		(0.91)		(-0.96)
Analystfollowing		-0.061***		-0.058***
		(-4.49)		(-5.51)
Size		-0.220***		-0.228***
		(-4.94)		(-16.62)
Q		0.010		-0.005
		(0.59)		(-1.32)
Returnonequity		0.005		-0.000
		(1.37)		(-0.34)
Obs	195126	185613	477489	460798
Adj. R-squared	0.473	0.482	0.645	0.659

This table shows the results of the regressions of 6 months post-insider trading buy and hold abnormal returns (6m BHAR) with respect to the Carhart four-factor model. The regressions include year and firm fixed effects. Standard errors are clustered at the firm level. The table reports beta coefficients and t-statistics in parentheses. *, ** and *** denote statistical significance at the 10%, 5%, and 1% level, respectively. *Relivol* is the stock price's idiosyncratic volatility over the past 21 trading days divided by its prior calendar year's mean. *Volatility index* is the S&P Volatility Index. *Bookleverage* is the book value of debt divided by the sum of the market value of equity and the book value of debt. *Analystfollowing* indicates the natural logarithm of (number of analysts following the firm+1). *Size* is the natural logarithm of the market value of equity. q denotes Tobin's q. *Returnonequity* denotes the firms' net income scaled by the book value of equity. All independent variables except for dummy variables are standardized such that the beta coefficient indicates the change in the dependent variable for a one standard deviation change of the independent variable.

Model (3) and (4) present the regression results for sales. For sales, we expect opposite signs for the coefficients as trading profits carry opposite signs of the abnormal returns. The coefficient of *relivol* is negative but fails to be statistically significant. Insiders who sell shares do not increase their trading profits by trading during times of high asymmetric information. This is consistent with the existing evidence in the literature that sales are less information-driven as they are also motivated by diversification and liquidity needs.

2.6.3 Trading aggressiveness and profits

Next, we analyze how the aggressiveness of a trader is related to trading profits and the influence of *relivol* on trading profits. Table 2.7 reports our results. We find that *aggressive* has a statistically and economically significant effect. The abnormal returns subsequent to aggressive trades exceed those of patient traders by 1.2% for purchases and by 0.6% for sales. Trade aggressiveness seems to be a strong predictor of subsequent abnormal returns. In Models (3) and (4) we also include the interaction term $aggressive * relivol$ to analyze whether aggressive traders are able to increase their profits more by timing. The coefficient of the interaction term is positive and significant for purchases. While non-aggressive traders increase their profits by 1.7% for a one standard deviation of *relivol*, aggressive traders are able to increase their profits slightly, by 2.1% (sum of the coefficients of *relivol* and $aggressive * relivol$). This difference is statistically significant at the 5% level. The interaction term is insignificant for sales.

In several cases, transaction prices are not reported in the Insider Filings. In those cases, Thomson Reuters sets the transaction price equal to the closing price. As a consequence, we do not have information about the impatience in this subsample. In a robustness check, we exclude the cases in which transaction prices are equal to the closing prices. The results are reported in Models (5) and (6). For purchases we have to exclude 11.7% of the cases, for sales we have to exclude 7.4%. The results are robust in this subsample.

2.6.4 Discussion and robustness

Relivol as a priced risk factor

One might object that the observed relationship between *relivol* and profits is due to a pricing effect. The significance of *relivol* in explaining abnormal returns could be the attributed to the possibility that *relivol* is a priced risk factor which is not taken into account by our expected return model, the Carhart model.

We argue that this is not the case for two reasons. First, if *relivol* was a priced risk factor, we would expect that the sign of the coefficient for purchases and sales is the same. However, we find that *relivol* is positively related to the abnormal returns after purchases, while there is no significant relationship of *relivol* and the abnormal returns after sales. These findings are inconsistent with the hypothesis that *relivol* is a priced risk factor. If

Table 2.7: Trading aggressiveness and the impact of relivol on profits

	(1)	(2)	(3)	(4)	(5)	(6)
	All		All		Excl. tprice=closing price	
	Purchases	Sales	Purchases	Sales	Purchases	Sales
Dep. var.: 6m BHAR	beta/t	beta/t	beta/t	beta/t	beta/t	beta/t
Relivol	0.021***	-0.003	0.017***	-0.005	0.017***	-0.006
	(3.36)	(-0.58)	(3.04)	(-0.88)	(3.01)	(-0.87)
Aggressive (d)	0.012***	-0.006***	0.011***	-0.006***	0.012***	-0.005***
	(6.63)	(-5.83)	(6.35)	(-5.67)	(6.00)	(-4.57)
Aggressive*relivol			0.005**	0.004	0.005*	0.004
			(2.00)	(1.12)	(1.73)	(1.03)
Volatility index	0.017***	-0.003	0.017***	-0.003	0.019***	-0.003
	(3.89)	(-0.84)	(3.88)	(-0.85)	(4.17)	(-0.80)
Bookleverage	0.020	-0.007	0.020	-0.007	0.022	-0.009
	(0.92)	(-0.98)	(0.92)	(-0.98)	(0.98)	(-1.27)
Analystfollowing	-0.062***	-0.057***	-0.062***	-0.057***	-0.061***	-0.059***
	(-4.55)	(-5.47)	(-4.56)	(-5.47)	(-4.30)	(-5.67)
Size	-0.219***	-0.228***	-0.219***	-0.228***	-0.220***	-0.218***
	(-4.91)	(-16.67)	(-4.91)	(-16.66)	(-4.58)	(-15.96)
Q	0.011	-0.005	0.011	-0.005	0.012	-0.006
	(0.62)	(-1.27)	(0.62)	(-1.28)	(0.69)	(-1.41)
Returnonequity	0.006	-0.000	0.006	-0.000	0.006	-0.000
	(1.55)	(-0.33)	(1.55)	(-0.32)	(1.34)	(-0.23)
Obs	184835	460199	184835	460199	163226	426165
Adj. R-squared	0.484	0.660	0.484	0.660	0.465	0.673

This table shows the results of the regressions of 6 months post-insider trading buy and hold abnormal returns (6m BHAR) with respect to the Carhart four-factor model. The regressions include year and firm fixed effects. Standard errors are clustered at the firm level. The table reports beta coefficients and t-statistics in parentheses. *, ** and *** denote statistical significance at the 10%, 5%, and 1% level, respectively. *Relivol* is the stock price's idiosyncratic volatility over the past 21 trading days divided by its prior calendar year's mean. *Volatility index* is the S&P Volatility Index. *Aggressive* is a dummy variable which is set to 1 for purchases (sales) if the transaction price is greater (smaller) than the closing price, and to 0 otherwise. *Bookleverage* is the book value of debt divided by the sum of the market value of equity and the book value of debt. *Analystfollowing* indicates the natural logarithm of (number of analysts following the firm+1). *Size* is the natural logarithm of the market value of equity. *Q* denotes Tobin's q. *Returnonequity* denotes the firms' net income scaled by the book value of equity. All independent variables except for dummy variables are standardized such that the beta coefficient indicates the change in the dependent variable for a one standard deviation change of the independent variable.

relivol were unrelated to timing with respect to information asymmetry and affects profits for other reasons than timing by corporate insiders, we would not expect that there is a difference between purchases and sales.

Second, if there is any relation between future stock returns and idiosyncratic risk measured using the previous month's daily returns, the existing literature suggests that this effect is negative. This implies that any significant results showing that abnormal returns subsequent to insider buying increase with the previous 21 trading days' idiosyncratic volatility could only be understated because of possible asset pricing effects.

Several authors find that the past month's idiosyncratic volatility is a negative predictor of future abnormal returns (Ang et al. (2006), Ang et al. (2009), Fink et al. (2011), Malagon et al. (2011), Peterson and Smedema (2011)). Huang et al. (2010) show that this predictability disappears once one corrects for the previous month's stock returns. Han and Lesmond (2011) provide evidence that the pricing becomes insignificant if the mid quotes instead of final trade prices are used for the computation of daily returns.

Contrarian strategies

The existing literature has documented that corporate insiders seem to pursue contrarian strategies, i.e., they buy after periods of poor performance and sell after periods of good performance (e.g., Piotroski and Roulstone (2005)). We control for contrarian strategies by including a variable that measures recent returns. Our goal is to test whether the timing effect can be explained by the exploitation of misvaluations.

We construct the measure as follows: Based on the Carhart model, we compute deviations between actual and expected returns for the period of 21 days prior to the trade. We then split negative and positive recent returns, i.e., we build separate variables for positive recent returns and one for negative recent returns. Table 2.8 reports the results from these regressions. We find that insider trading profits are inversely related to the prior performance. For purchases, insider trading profits are greater when there were negative abnormal returns and lower when there was a positive abnormal returns. For sales, we find the reverse result which is also consistent with contrarian trading. For purchases, the effect of *relivol* on returns is still large (1.6% for a one standard deviation increase) and statistically significant at the 1% level. The timing effect can apparently not be solely explained by trading on contrarian motives. For sales, we confirm the insignificance of *relivol* for trading profits.

Table 2.8: Contrarian trading strategies

Dep. var.: 6m BHAR	(1) Purchases beta/t	(2) Sales beta/t
Relivol	0.016**	0.006
	(2.48)	(1.26)
$Bhar_+$	-0.010**	-0.028***
	(-1.98)	(-3.03)
$Bhar_-$	-0.026***	-0.018**
	(-5.47)	(-2.35)
Aggressive (d)	0.012***	-0.006***
	(6.57)	(-5.72)
Volatility index	0.017***	-0.005
	(3.84)	(-1.60)
Bookleverage	0.020	-0.008
	(0.89)	(-1.02)
Analystfollowing	-0.065***	-0.058***
	(-4.66)	(-5.52)
Size	-0.226***	-0.235***
	(-5.20)	(-16.79)
Q	0.011	-0.005
	(0.60)	(-1.28)
Returnonequity	0.006	-0.000
	(1.58)	(-0.32)
Obs	184835	460199
Adj. R-squared	0.485	0.661

This table shows the results of the regressions of 6 months post-insider trading buy and hold abnormal returns (6m BHAR) with respect to the Carhart four-factor model. The regressions include year and firm fixed effects. Standard errors are clustered at the firm level. The table reports beta coefficients and t-statistics in parentheses. *, ** and *** denote statistical significance at the 10%, 5%, and 1% level, respectively. *Relivol* is the stock price's idiosyncratic volatility over the past 21 trading days divided by its prior calendar year's mean. $Volatility\,index$ is the S&P Volatility Index. *Aggressive* is a dummy variable which is set to 1 for purchases (sales) if the transaction price is greater (smaller) than the closing price, and to 0 otherwise. $Bhar_+$ ($bhar_-$) is the stock's BHAR over the 21 trading days prior to the insider trade for a positive (negative) value of this variable. *Bookleverage* is the book value of debt divided by the sum of the market value of equity and the book value of debt. $Analystfollowing$ indicates the natural logarithm of (number of analysts following the firm+1). *Size* is the natural logarithm of the market value of equity. Q denotes Tobin's q. *Returnonequity* denotes the firms' net income scaled by the book value of equity. All independent variables except for dummy variables and prior return measures are standardized such that the beta coefficient indicates the change in the dependent variable for a one standard deviation change of the independent variable.

Large versus small variations in relivol

It may be the case that our results are mainly driven by firms with large variations in asymmetric information between insiders and outsiders and only managers in those firms actually time their trades. We put this hypothesis to the data by testing whether there is a difference in the effects for firms with a large variation in *relivol* as opposed to a medium or low variation. We sort the firms into terciles according to their standard deviation of *relivol*. The dummy variable *highsd* (*lowsd*) is set to 1 if the firm lies within the top (bottom) tercile.

The variables *highsd* and *lowsd* are collinear to the firm-fixed effects. Hence, we cannot estimate a model which includes the dummy variables *highsd* or *lowsd* and firm-fixed effects. When we run the model without fixed effects (results available upon request), the R-squared drops below 1%. This suggests that the model is not informative. Instead, we run the regression on separate subsamples for firms with high, low, or medium variation in *relivol*.

The results in Table 2.9 show that for purchases the effect of *relivol* on profits is strongest for the tercile of firms with a high variation in *relivol* (2.6% in Model (1)). The profitability effect of 1.5% is smaller with respect to firms with a medium variation in *relivol*. For firms with the most stable level of *relivol*, the sample of firms with a low variation the coefficient of *relivol* is of similar magnitude though insignificant at conventional levels. These results document a cross-sectional difference with respect to the profitability of timing. The effect of timing on profits apparently is most pronounced for firms with substantial variations in the degree of asymmetric information between insiders and outsiders.

With respect to sales, the impact of *relivol* on profits remains insignificant for all subsamples. We repeat the analysis sorting the firms into quintiles instead of terciles in terms of the standard deviation of *relivol* as a further robustness check. The results are comparable to the ones above.

Alternative trading horizons

We test whether the effect of *relivol* on profits remains robust to the use of alternative assumed holding periods. Specifically we look at returns for 1 month, 3 months, and 12 months. Table 2.10 reports the results. For purchases, the coefficient of *relivol* is statistically significant at the 1% level for all horizons: 1.3% for the 1 month window, 2.4% for the 3 months window and 2.4% for the 12 months window for a one standard deviation of *relivol*. The relatively strong effect for the shorter window of 1 month together with the fact that the abnormal return does not increase much for longer horizons suggest that the information advantage was indeed of a rather short-term nature. For sales, we do not find any significant effect of *relivol* on returns for any event window.

Table 2.9: High versus low variation in relivol

	(1)	(2)	(3)	(4)	(5)	(6)
	High variation		Medium variation		Low variation	
	Purchases	Sales	Purchases	Sales	Purchases	Sales
Dep. var.: 6m BHAR	beta/t	beta/t	beta/t	beta/t	beta/t	beta/t
Relivol	0.026***	-0.006	0.015**	0.007	0.013	-0.003
	(2.74)	(-0.82)	(2.10)	(0.94)	(1.47)	(-0.38)
Aggressive (d)	0.012***	-0.006***	0.012***	-0.004	0.014***	-0.013***
	(5.21)	(-3.54)	(3.53)	(-1.54)	(3.06)	(-5.45)
Volatility index	0.016**	0.006	0.018***	-0.012	0.028**	-0.019**
	(2.31)	(1.35)	(2.70)	(-1.29)	(2.53)	(-2.11)
Bookleverage	0.042	0.002	0.003	-0.025	-0.014	-0.022
	(0.99)	(0.15)	(0.27)	(-1.50)	(-0.59)	(-1.25)
Analystfollowing	-0.068***	-0.041***	-0.046**	-0.071***	-0.152***	-0.114***
	(-4.03)	(-2.85)	(-1.97)	(-2.62)	(-3.95)	(-4.15)
Size	-0.183***	-0.152***	-0.213***	-0.339***	-0.384***	-0.440***
	(-2.77)	(-7.79)	(-7.21)	(-10.03)	(-5.74)	(-11.80)
Q	-0.014	-0.005	0.042	-0.029*	0.022	0.023
	(-0.80)	(-1.07)	(0.97)	(-1.85)	(0.80)	(1.21)
Returnonequity	0.007	0.001	0.002	-0.022***	0.011	-0.007
	(0.97)	(1.51)	(0.39)	(-3.11)	(0.90)	(-0.63)
Obs	76861	130929	63473	156875	44501	172395
Adj. R-squared	0.430	0.749	0.662	0.288	0.343	0.325

This table shows the results of the regressions of 6 months post-insider trading buy and hold abnormal returns (6m BHAR) with respect to the Carhart four-factor model. The regressions include year and firm fixed effects. Standard errors are clustered at the firm level. The table reports beta coefficients and t-statistics in parentheses. *, ** and *** denote statistical significance at the 10%, 5%, and 1% level, respectively. *Relivol* is the stock price's idiosyncratic volatility over the past 21 trading days divided by its prior calendar year's mean. *Highsd* (*lowsd*) is a dummy variable which is set to 1 if the firm is in the bottom (top) tercile in terms of the standard deviation of relivol. *Volatility index* is the S&P Volatility Index. *Aggressive* is a dummy variable which is set to 1 for purchases (sales) if the transaction price is greater (smaller) than the closing price, and to 0 otherwise. *Bookleverage* is the book value of debt divided by the sum of the market value of equity and the book value of debt. *Analystfollowing* indicates the natural logarithm of (number of analysts following the firm+1). *Size* is the natural logarithm of the market value of equity. *Q* denotes Tobin's q. *Returnonequity* denotes the firms' net income scaled by the book value of equity. All independent variables except for dummy variables are standardized such that the beta coefficient indicates the change in the dependent variable for a one standard deviation change of the independent variable.

Table 2.10: Alternative trading horizons

	(1)	(2)	(3)	(4)	(5)	(6)
	1m BHAR		3m BHAR		12m BHAR	
	Purchases	Sales	Purchases	Sales	Purchases	Sales
Relivol	0.013***	-0.000	0.024***	-0.004	0.024***	-0.015
	(5.55)	(-0.16)	(4.36)	(-1.18)	(5.41)	(-1.15)
Aggressive (d)	0.012***	-0.003***	0.012***	-0.004***	0.010***	-0.002**
	(9.12)	(-6.85)	(6.94)	(-5.59)	(4.48)	(-2.33)
Volatility index	-0.009***	-0.003**	0.003	-0.005*	0.017***	0.004
	(-2.85)	(-1.96)	(0.60)	(-1.78)	(4.36)	(0.98)
Bookleverage	0.009	-0.003	0.011	-0.007	0.011	0.005
	(1.40)	(-1.35)	(0.65)	(-1.50)	(0.66)	(0.60)
Analystfollowing	-0.010	-0.010***	-0.033***	-0.023***	-0.121***	-0.037***
	(-1.49)	(-2.84)	(-3.09)	(-2.86)	(-6.06)	(-3.49)
Size	-0.072***	-0.052***	-0.163***	-0.144***	-0.261***	-0.057**
	(-5.89)	(-11.61)	(-4.91)	(-16.04)	(-10.04)	(-2.05)
Q	0.005	-0.002	-0.001	-0.003	0.004	-0.002
	(0.73)	(-1.61)	(-0.10)	(-1.32)	(0.22)	(-0.87)
Returnonequity	0.001	-0.000	0.006*	-0.000	0.012*	-0.000
	(0.58)	(-0.59)	(1.93)	(-0.30)	(1.96)	(-0.55)
Obs	184835	460199	184835	460199	184832	460199
Adj. R-squared	0.832	0.894	0.600	0.738	0.504	0.178

Standardized beta coefficients; t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

This table shows the results of the regressions of 1, 3, and 12 months post-insider trading buy and hold abnormal returns (BHAR) with respect to the Carhart four-factor model. The regressions include year and firm fixed effects. Standard errors are clustered at the firm level. The table reports beta coefficients and t-statistics in parentheses. *, ** and *** denote statistical significance at the 10%, 5%, and 1% level, respectively. *Relivol* is the stock price's idiosyncratic volatility over the past 21 trading days divided by its prior calendar year's mean. $Volatility\,index$ is the S&P Volatility Index. *Aggressive* is a dummy variable which is set to 1 for purchases (sales) if the transaction price is greater (smaller) than the closing price, and to 0 otherwise. *Bookleverage* is the book value of debt divided by the sum of the market value of equity and the book value of debt. $Analystfollowing$ indicates the natural logarithm of (number of analysts following the firm+1). *Size* is the natural logarithm of the market value of equity. Q denotes Tobin's q. All independent variables except for dummy variables are standardized such that the beta coefficient indicates the change in the dependent variable for a one standard deviation change of the independent variable.

2.7 Conclusion

We find empirical evidence that corporate insiders time their purchases during times of high asymmetric information between insiders and outsiders. We offer a novel approach which is different from the established approach in the literature. The existing approach focuses on specific corporate events. Instead, we use a market-based measure of short-term variations in information asymmetry, the variation of idiosyncratic volatility over time (*relivol*). Based on a sample of U.S. insider transactions registered to the SEC between 1986 and 2009, we find that insider purchases are significantly more likely on a given day when recent idiosyncratic volatility is relatively high. With a probability increase of 2.9%, the impact is also economically meaningful. However, we do not find any robust evidence that this effect prevails for insiders sales. This observed difference between purchases and sales is consistent with the notion of alternative trading motives such as diversification or liquidity needs as well as with asymmetrically higher litigation risk for sales.

Our findings also lend support to the notion that timing is profitable for insiders. We find that insiders can increase their trading profits for purchases substantially with timing. A one standard deviation increase in *relivol* raises profits by 2.1%. We do not find any significant effect of timing on sales. The effect of *relivol* on profits remains robust when we control for alternative explanations, or use alternative model specifications. We also show that the effect cannot be explained by the notion that *relivol* is a priced risk factor.

These results appear somewhat sobering given the regulatory attempts to avoid trading on the foreknowledge of information. Insiders seem to profitably exploit short-term variations in asymmetric information. These profits come at the detriment to uninformed market participants. Forcing corporate insiders to randomize their trades could present a possible regulatory strategy to reduce the insiders' leeway to time their trades. Under such a rule, they can choose the quantity they want to trade, but not the exact point in time, e.g., the trade could be randomly executed during a period of several weeks. This strategy could preserve the signaling effect of insider trading for a longer horizon, while limiting the extent of unfair trading on short-term information advantages.

Chapter 3

Strategic Trading and Trade Reporting by Corporate Insiders

3.1 Introduction

Corporate insiders arguably know more about the prospects of their firms than other market participants. This hypothesis is supported by a host of papers documenting that insider trades, and purchases in particular, convey information to the market (e.g., Seyhun (1986) and Chang and Suk (1998) for the U.S.; Fidrmuc et al. (2006) and Friederich et al. (2002) for the UK). The U.S. and many other countries have adopted regulations that require corporate insiders to report their trades.[1] The model of Huddart et al. (2001) provides a theoretical justification for these regulations. The authors show that information is reflected more rapidly in prices when insiders have to disclose their trades. Several empirical papers (e.g., Chang and Suk (1998), Betzer and Theissen (2009)) have shown that share price reactions occur on both the trading and reporting dates. Thus, without this reporting, the market is unable to infer the full information content of the trade, which implies that market prices are distorted in the period between the trading and reporting dates. Delayed reporting, then, may impede the price adjustment to information revealed by the insider trade.

In the era prior to the Sarbanes-Oxley Act (SOX), Section 16 of the Securities Exchange Act required corporate insiders in the U.S. to report their trades by the 10th of the

[1] Some countries (e.g., the UK) even prohibit trading by corporate insiders in certain circumstances. Similarly, many listed firms in the U.S. have adopted policies restricting trading by insiders (Bettis et al. (2000)).

month following the trade. Thus, the maximum time allowed between the trade and the report was 40 days, allowing corporate insiders considerable flexibility to time their trades and reports. This flexibility could be used strategically. An insider wishing to trade a large quantity could split up the order into several smaller chunks. Splitting up a large order reduces the order's price impact and thus results in reduced execution costs (e.g., Kyle (1985), Chordia and Subrahmanyam (2004)). However, if the insider reported each individual trade immediately, the share price reaction on the reporting date would move the price against the insider, and subsequent trades would occur at less favorable prices. Consequently, the insider has an incentive to delay the reporting of a series of trades until after the last transaction. By doing so, insiders can benefit from the reduced price impacts of split-up trades while avoiding the adverse price reaction that immediate reports would trigger. The present paper analyzes incidences of strategically timed U.S. Securities and Exchange Commission (SEC) filings. We identify a trade as strategic whenever it is either followed by another trade by the same insider before it is reported or executed after another trade by the same insider that has not yet been reported.

Note that the incentive to strategically time trades and reports does not depend on the assumption that the insider trades on private information. The only assumption necessary for our argument is that other market participants believe that insiders possess private information with a positive probability. The stylized fact that prices react to the publication of insider trades supports this assumption.

This paper asks four related questions. First, how long are reporting delays during the pre-SOX era? Second, do insiders strategically use their flexibility in choosing the timing and reporting of their trades, and, if so, is this strategic behavior systematically related to the characteristics of the insider or the firm? Third, what are the implications of delayed reporting on the informativeness of prices? Fourth, how does the market react to the strategic timing of trades and reports?

The first question is important because, as argued above, delayed reporting can impede the adjustment of prices to the information revealed by the insider trades. The relevance of the second question derives from the observation that strategic timing benefits the insider at the expense of other market participants. If each trade were reported immediately, the second and subsequent trades of a series of insider trades would be executed at prices less favorable to the insider but more favorable to the insider's counterparties. The answer to the third question allows us to assess the relevance of the issues addressed in this paper.

The fourth question is important because its answer enables us to draw inferences on the trading motives of insiders engaging in strategic timing. On reporting dates, market participants learn whether the strategic delay of reports has occurred. If market participants believe that insiders possessing private information are more likely to time their trades and reports, one should observe a larger price reaction than that for an otherwise similar but nonstrategic trade.

Our results can be summarized as follows. First, reporting delays were substantial in the pre-SOX period. The mean reporting delay was 35 days and the median was 24 days, with 13.2% of all trades in our sample reported later than on the 10th of the month following the trade. The very large number of violations of the trade reporting requirement implies that the requirement was apparently not well-enforced. We further find clear evidence of strategic trading. Only 32.1% of the trades in our sample were nonstrategic trades (i.e., these trades were reported before the same insider traded again, and they were not preceded by a trade by the same insider that had not yet been reported).

Logit models reveal that the occurrence of both late filings and strategic trades is systematically related to firm, trade, and trader characteristics. In particular, the results are consistent with the notion that insiders who are more closely monitored (and who therefore may be facing higher litigation risks) are less likely to file their trades late.

Consistent with previous findings, our event study results show that share prices react to the reporting of insider trades. The cumulative abnormal returns (CARs) over 10- and 20-day windows are larger after purchases than after sales. In cross-sectional regressions we find that the magnitude of the price reaction decreases only slowly in the reporting delay (after insider sales), or not at all (after purchases). Thus, our results support the notion that market prices are distorted in the period between a trade and its report. Finally, event study CARs are larger after reports of strategic insider trades than after reports of otherwise similar nonstrategic trades. Thus, market participants apparently believe that insiders acting strategically are more likely to possess private information.

Our results clearly support the more stringent trade reporting requirements established by SOX. They also suggest that countries that currently allow longer reporting delays should consider revising and/or enforcing their regulations. Recent evidence reported in Fidrmuc et al. (2009) suggests that some countries do not yet mandate and enforce timely trade reporting. Using recent samples (ending May 2007), the authors find median reporting delays of five days for Italy, seven days for Belgium, and 14 days for France.

Our paper is related to recent papers by Cheng et al. (2007), Betzer and Theissen (2010), Brochet (2010), Carter et al. (2003), and Lebedeva et al. (2009). Cheng et al. (2007) exploit the feature that corporate insiders in the U.S. could, in certain circumstances, delay the reporting of non-open market trades until the end of the fiscal year of the firm (SEC Form 5 trades). The authors find that insider sales by top executives in Standard & Poor's 500 firms disclosed in such a delayed manner predict negative future returns and lower operating profitability relative to analyst forecasts. Insider purchases, on the other hand, are hardly predictive of future returns. Cheng et al. (2007) conclude that 'managers in large firms may have used late-disclosure Form 5 sales for information-based trading' (p. 1861). Betzer and Theissen (2010) use data from Germany to show that substantial reporting delays are common, that the delays are systematically related to firm characteristics, and that abnormal returns after the reporting dates of insider trades are independent of reporting delays. The latter finding implies that prices are distorted in the period between the trading and reporting dates. Carter et al. (2003) analyze a sample of insider buy transactions between 1991 and 1994 and find evidence of substantial reporting delays. They further report that CARs in the period between the trading and the reporting date are positively related to the length of the reporting delay. Brochet (2010) focuses on differences in the information content of insider trades before and after SOX. The author regresses event study CARs on a set of explanatory variables, including the reporting delay, and finds that price reactions after purchases are weaker when trades are reported with longer lags, but that the reverse is true for insider sales. Lebedeva et al. (2009) find strong evidence that corporate insiders in the U.S. break up larger trades into series of smaller trades. The authors refer to this as stealth trading. They also find that liquidity-based explanations for this behavior have more explanatory power than information-based explanations.

Our paper differs from these papers in that it is the first to systematically document strategic trade reporting and to analyze the determinants and implications of this phenomenon. It further differs from Cheng et al. (2007) in that we do not analyze the relatively small sample of non-open market trades eligible for late reporting but, rather, the much larger sample of all insider trades that were required to be filed on SEC Form 4.[2] Betzer and

[2]The number of Form 5 sales (purchases) for S&P 500 stocks during 1998-2001 amounts to 438 (419). The corresponding figures for Form 4 trades are 10,166 and 7,217, respectively (Cheng et al. (2007), Table 1D).

Theissen (2010) analyze reporting delays in Germany, but have a much smaller sample (1,977 observations as compared to 314,696 in the present paper), and, more importantly, the regulatory regime in Germany is distinctly different from that in the U.S. Brochet (2010) includes a reporting delay variable in his analysis but interprets it as a control variable measuring information leakage between trading and reporting dates. This leakage is also the focus of the study of Carter et al. (2003). Lebedeva et al. (2009) focus on the motives for stealth trading, but do not analyze late filings or how reporting delays affect CARs on the reporting dates.

The remainder of the paper is organized as follows. Section 2 describes the data set and presents descriptive statistics. Section 3 presents evidence on delayed trade reporting. Section 4 determines whether incidences of strategic trading and trade reporting took place and also analyzes whether so-called strategic trades are systematically different from nonstrategic trades. Section 5 uses event study methodology to compare market responses to strategic and nonstrategic trades. Robustness tests for the analysis of the market responses are presented in Section 6. Section 7 concludes.

3.2 Data

Our analysis requires data on insider trades, firm characteristics, and stock prices. The data selection process follows that of Lakonishok and Lee (2001) and Marin and Olivier (2008) and merges data from four different sources, namely, the TFN Insider Filing Data Files, the Center for Research in Security Prices (CRSP) database, the COMPUSTAT database, and the IBES database. The initial sample consists of insider trades reported on SEC Form 4 in companies listed on the New York Stock Exchange, the American Stock Exchange, or the NASDAQ during 1992-2001. It covers the last 10 calendar years before the implementation of SOX, which marked a change in regime, since it requires insiders to report a trade within two working days.

We begin sample construction with the TFN database. We include all open market or private purchases (transaction code P) and all open market or private sales (transaction code S) of non-derivative securities whose records were not amended (amendment indicator 'blank') between January 1, 1992 and December 31, 2001. Of these transactions, we retain only those filings whose data can be verified by TFN with a high level of confidence (cleanse indicators R and H). The TFN Insider Filing Data Files contain the following information:

- Company name and CUSIP
- Transaction date and reporting date (SEC receipt date)
- Transaction code (purchase or sale), number of shares exchanged in the transaction, and transaction price
- Insider's position within the firm, which we classify into four groups:
  - CEO (also possibly the chairman of the board)
  - Chairman (only if not also the CEO)
  - Executive directors, excluding the CEO
  - Other non-executive officers, affiliates, beneficial owners, or other persons required to report their trades

We exclude all filings that have no entry for transaction price, number of shares, reporting date to the SEC, position of insider, or sector fields, leaving 741,653 records remaining. We also exclude insider transactions whenever the reported transaction price was not within a 20% interval around the CRSP closing price on the insider trading day. We further exclude trades when the number of shares traded exceeded 20% of total shares outstanding. We do not attempt to single out Rule 10b5-1 trades, because very few of these pre-planned trades took place during the pre-SOX era. Brochet (2010), using a sample covering the period 1997-2002, reports that Rule 10b5-1 trades accounted for only 0.55% of the trades in his sample.

We complement the data on insider transactions with supplementary data from various sources. We obtain financial data from COMPUSTAT. All data items are taken from firm financial statements at the end of the fiscal year preceding the reporting of the insider trades. We measure book leverage (the variable Leverage) as the ratio of long-term debt (data item 9) plus debt in current liabilities (item 34) to long-term debt plus debt in current liabilities plus stockholder equity (item 216). Firm size (Size) is defined as the natural logarithm of the market value of equity. Tobin's Q (Q) is calculated as the ratio of the market value of assets to the book value of total assets (item 6). Following Malmendier and Tate (2007), we define the market value of assets as total assets plus market equity (item 25 times item 199) minus book equity. We calculate book equity as the sum of stockholder equity and balance-sheet deferred taxes and investment tax credits (item 35), where available, minus the preferred stock liquidating value (item 10) and minus post-retirement assets (item 336), where available.[3]

Further, we obtain data on analyst forecasts and announcement dates of quarterly or annual earnings reports from the IBES and COMPUSTAT. We define variable Numest as the total number of analysts covering a company in the last available yearly earnings forecast before the transaction date of the insider trade. We further obtain the dates of all quarterly earnings announcements. For an observation to be included in our analysis, all the necessary data items in the CRSP, COMPUSTAT, and IBES databases must be available. This requirement reduces the sample to 314,696 observations.

In our empirical analysis, we use the following additional variables. The variable delay is the difference in days between the reporting and transaction dates. We calculate the variable TradeVolume as the number of shares exchanged in a transaction times the transaction price, divided by the market value of equity. We define NumInsider as the total number of insiders who traded shares in the same company on the same day.

Our analysis uses two different data sets: a 'transaction sample' and an 'event study sample'. For the transaction sample, we aggregate all transactions by the same insider that are a) executed on the same day, and b) jointly reported on the same day. We present an aggregated transaction as one trade with the net amount traded. The (net) transaction volume is positive (negative) if the sum of all the individual trades by this particular insider on the same trading day is positive (negative).[4] Following these calculations, we classify each aggregated transaction as a purchase or a sale. Our final transaction sample consists of 98,933 purchases and 215,763 sales (314,696 observations in total). These observations relate to 6,808 different firms and 25,836 distinct firm years. Note that in the transaction sample, two trades by different insiders are treated as two distinct observations, even if they are executed and/or reported on the same day.

The announcement date in our event study analysis is the day on which an insider trade

[3]When stockholder equity was not available as data item 216, we calculated stockholder equity alternatively as common equity (item 60) plus the preferred stock par value (item 130) or total assets minus total liabilities (item 181). If the preferred stock liquidating value was not available as data item 10, we calculated the preferred stock liquidating value alternatively as redemption value (item 56) or par value (item 130). Return on equity (the variable RoE) is net income (item 172) divided by book equity.

[4]Arguably, a report that includes both purchases and sales made by the same insider provides a weaker signal than a report that reports only unidirectional trades. However, only 0.51% of the reports in our sample contain both purchases and sales. This low number is likely to be due to the 'short swing rule', which requires insiders to return to the firm all profits from roundtrip trades completed within six months.

was filed with the SEC. Therefore, we aggregate all insider trades in the shares of a given firm that were reported on the same day, irrespective of whether the trades were reported by the same insider or by different insiders. We refer to this sample as our event study sample. Again, aggregated transactions are treated as one trade, and the net trade direction and net volume are as defined above. In our regression analysis we control for the aggregate trade volume and the number of insiders that traded on a given day. The final data set for the event study consists of 34,648 purchases and 65,319 sales (99,967 trades in total).

Table 3.1 presents descriptive statistics for the firms in our sample. Average firm size, as measured by the market value of equity, is USD 4,544.39 million. Firm size distribution is heavily skewed. The average Tobin's Q of sample firms is 3.52, average return on equity is 8.90%, and mean book leverage is 31.43%. Mean trade size, expressed as a percentage of the market value of equity, is 0.121%. In 62.10% of cases, only one insider traded on a given day. In the remaining cases, more than one insider traded on the same day. The average number of insiders trading on a given day is 2.04, with a maximum of 32. The average insider trade was executed 57 calendar days before the firm reported its next annual or quarterly earnings report.

Table 3.1: Descriptive statistics

Variables	Mean	St. dev.	Min	Median	Max
Market value of equity (USD millions)	4,544.39	21,599.05	0.83	463.78	508,329.50
Tobin's Q	3.52	6.18	0.21	1.81	105.09
RoE	0.09	0.27	-0.80	0.10	9.89
Leverage	0.31	0.58	0.00	0.25	69.18
TradeVolume	0.00	0.01	0.00	0.00	0.58
NumInsider	2.04	2.12	0.00	1.00	32.00
Days to next report	57.00	23.37	0.00	62.00	91.00
Numest	7.57	7.43	1.00	5.00	51.00
Delay (days)	35.00	95.15	0.00	24.00	3,815.00

This table reports summary statistics for the transaction sample. Tobin's Q is calculated as the ratio of the market value of assets to the book value of total assets. The variable RoE is net income divided by book equity. We measure leverage as the ratio of long-term debt plus debt in current liabilities to long-term debt plus debt in current liabilities plus stockholder equity. We define the variable Numest as the total number of analysts covering a company in the month preceding the reporting date of an insider trade. We calculate the variable TradeVolume as the ratio of the number of shares exchanged in a transaction times the transaction price to the market equity of the company whose stocks were bought or sold in the insider trade. We define NumInsider as the total number of insiders who traded their shares in the same company on the same day. Days to next report denotes the number of days from a transaction to the next quarterly earnings announcement. Delay indicates the lag in days between the trading and reporting of a transaction.

Figure 3.1 shows the distribution of trading dates. Although it appears to follow a weak

Figure 3.1: Distribution of trading dates by day of the month

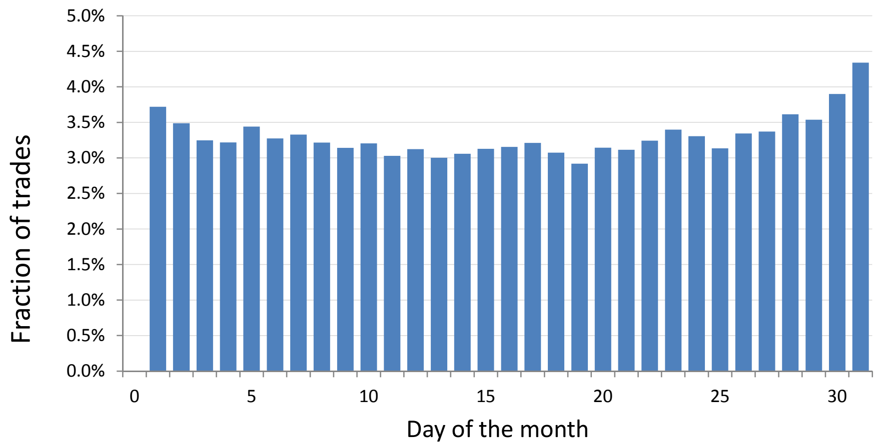
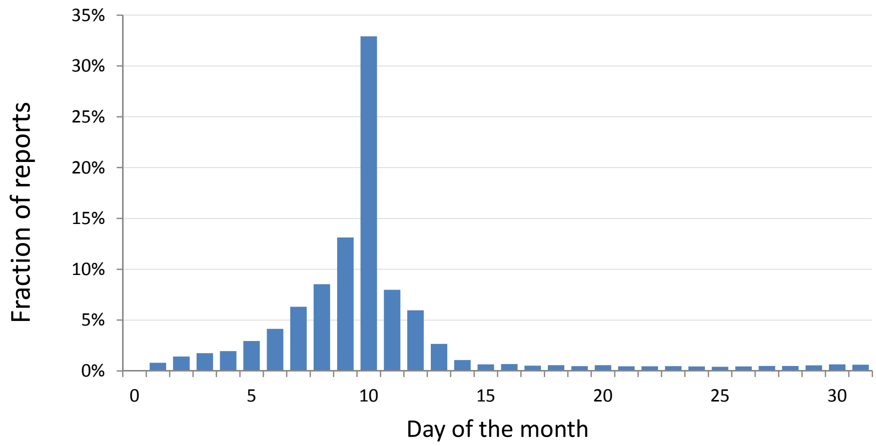


Figure 3.2: Distribution of reporting dates by day of the month



U-shaped pattern, the general impression from Figure 3.1 is that trades are more or less evenly distributed over the month. The distribution of reporting dates shown in Figure 3.2 is dramatically different. The daily frequency start low (only 0.81% of trades are reported on the first day of the month), then increases strongly until the 10th of the month; almost 32% of all trades are reported on this day alone. When we weight the trades by their volume, this number increases further to 42.7%. After the 10th, the frequency declines sharply. In the second half of the month, there is no single day on which more than 0.75% of trades are reported.

There are two not mutually exclusive (and observationally equivalent) explanations for the strong pattern we document. First, many corporate insiders may routinely report all trades made during the previous month on the 10th. This practice may delay the adjustment of prices to the information revealed by the insider trades, and it may be to the disadvantage of other traders (although not intentionally). Whenever share prices react to the reporting of an insider trade, reporting delays imply distorted prices in the period between the trading and filing dates. If an insider executes several trades on different days but reports them jointly, the later trades are executed at prices that are more favorable than they would have been in the case in which each trade had been reported immediately. This practice is beneficial for the insider but obviously to the disadvantage of the counterparties to the insider's trades. Second, some insiders may *intentionally* delay the reporting of their trades to avoid the price impact triggered by the report. By considering only the trading and filing dates, the two cases mentioned cannot be distinguished from each other. However, the share price reaction on the filing date can be expected to reflect the market's beliefs about the insiders' motives. Therefore, analyzing the price reaction will allow us to draw inferences about these motives and the economic significance of strategic trade reporting.

3.3 Reporting delays

This section presents evidence concerning the magnitude of reporting delays and the determinants of late filings. The frequency distributions of trading and reporting dates shown in Figure 3.1 and Figure 3.2 demonstrate that trades are approximately evenly distributed over the month, whereas reports cluster around the 10th. If insider trades were indeed equally distributed over the days of the month and if each trade were reported on the 10th of the month after the trade (i.e., on the last permissible day), we would expect an average reporting delay of approximately 25 days. Table 3.2 shows the actual reporting delays. The median delay (24 days for purchases and sales) corresponds roughly to the benchmark value derived above. The mean delay is much longer, at 35.0 days.[5] Purchases are reported with longer delays than sales (40.4 days, compared to 32.5 days, respectively). This difference may be indicative of strategic delaying, because previous papers (e.g., Seyhun (1986) and Brochet (2010) for the U.S., and Fidrmuc et al. (2006) for the UK) document that insider purchases are more informative, as evidenced by larger abnormal returns. This finding, in turn, implies that insiders who purchase shares are more likely to possess private information and therefore have greater incentives to conceal their trading activity.

[5]This figure is greater than that given in Table 1 of Brochet (2010). The author uses a shorter sample period (starting in 1997) and confines his analysis to trades initiated by the CEO, CFO, COO, board chairs, and presidents.

Table 3.2: Distribution of delays

	All	Purchases	Sales
Observations	314696	98933	215763
Mean	35	40.42	32.51
St. dev.	95.15	114.54	84.66
0.25 quantile	15	14	16
Median	24	24	24
0.75 quantile	33	34	33
Percentage of late filings	13.21%	17.48%	11.25%

This table reports summary statistics for the distribution of reporting delays.

The discrepancy between the mean and median reporting delays implies that the distribution of reporting delays is heavily skewed. The magnitude of the average delay further implies that a significant fraction of trades, particularly the purchases, are reported too late (i.e., later than the 10th of the month following the trade). In fact, Table 3 reveals that 13.2% of the trades in our sample were reported too late.[6] We use the term *late filings* for these cases. Late filings are more common for purchases than for sales (17.5%, compared to 11.3%, respectively).

The high percentage of late filings is stunning and implies that in the pre-SOX era, reporting requirements were not enforced.[7] This observation is surprising because violations of the reporting requirement are easily detectable: SEC filings include trading and reporting dates, together with a unique person identification number that allows for easy identification of the insider.

The percentage of late filings is too large to be explained by accidental omission. Apparently, a substantial fraction of insiders exists who do not care about the reporting requirements or who deliberately (and possibly strategically) file their reports late. To shed light on this issue, we estimate a logit model in which the dependent variable is zero if a trade was reported on time (i.e., by the 10th of the month following the trade), and 1 if the trade was reported late. The independent variables include firm and trade characteristics. We use the number of analysts following as a proxy for investor attention.[8]

[6] These figures take into account the fact that when the 10th of a month is a Saturday or a Sunday, the trade needs only be reported on the 12th or the 11th of that month, respectively.

[7] The Securities Enforcement Remedies and Penny Stock Reform Act of 1990 allows penalties against delinquent filings, and we are aware of several cases in which the SEC filed a complaint in District Court.

[8] To avoid multicollinearity, we do not include firm size (the correlation between firm size and number of analysts following is 0.79 in the transaction sample). We obtain very similar results, however, when we replace the number of analysts by firm size.

Trade characteristics include trade volume relative to firm market capitalization and the number of different insiders trading on the same day. We include three further control variables: namely, Tobin's Q as a proxy for valuation of the firm, return on equity as a measure of operating profitability, and book leverage. We do not have a clear prediction regarding the sign and significance of the coefficients.

Many firms restrict insider trading by defining a blackout period during which trading is prohibited. Typically, the blackout period is in effect just prior to an earnings announcement. A common arrangement is to allow trading only within a short period after an earnings announcement (Bettis et al. (2000), Roulstone (2003)). We include the dummy variable 'pre-announcement' in our model, which is set to 1 if a trade was not executed within a 30-calendar-day window after an earnings announcement, and zero otherwise.[9]

We further define three dummy variables that describe the insider's position in the firm. The first dummy is set to 1 when the CEO is among the traders trading on a given day, and 0 otherwise.[10] The second dummy identifies trades by the chairman of the board (unless the chairman is simultaneously the CEO), and the third dummy identifies trades by other executive directors of the firm. Trades by outside directors, beneficial owners, and others thus constitute the base group.

We estimate a pooled model that includes both purchases and sales and two separate models including only purchases and sales, respectively. The pooled model includes a dummy variable that captures differences in the probability of late reporting between purchases and sales. All models include sector dummies (where we adopt the classification used in the TFN insider filings) and year dummies. Standard errors are clustered at the firm level. Table 3.3 reports marginal effects (the change in probability of late filing for a unit change in the explanatory variable, evaluated at the mean values of the explanatory

[9]Two comments are in place. First, Bettis et al. (2000) survey 663 firms and report that the most common restriction is to allow insiders to trade only within a short window (e.g., days 3 to 12) after an earnings announcement. Roulstone (2003) analyzes a large sample of insider trades. From the observed trading pattern, he deduces whether a firm has a restriction in place. Specifically, he assumes that a firm has a restriction in place when more than 75% of the insider trades occur in the 20 trading days (approximately one month) after earnings announcements are made. Since our sample is closer to Roulstone's than to the sample of firms surveyed by Bettis et al. (2000), we adopt a one-month period. Second, data on earnings announcement dates are missing in some cases. We address this by excluding all observations where the time between the insider trade and the date of the publication of the next quarterly earnings announcement is more than 91 days. We obtain similar results when we include all observations. In the latter case, we misclassify insider trades that were executed within a 30-day window after the publication date of an earnings announcement not included in our data set.

[10]As a robustness check, we re-estimated the logit model including only trades made by the CEO. The results are similar to those presented below. The main difference is that for the CEO-only sample, we do not find that purchases are more likely to be filed late than sales.

variables) and the respective z-statistics.

The probability of late filings is generally higher for purchases than for sales. This result is consistent with the earlier finding that average reporting delays are longer for purchases than for sales. Trades by insiders in firms followed by more analysts are less likely to be filed late. This finding is intuitive, given that these firms tend to be larger and are under closer scrutiny by analysts and investors in general. We further find that sales by insiders in more highly leveraged firms are more likely to be reported late. No such relation is found for insider purchases.

Considering trade-specific variables, we find that trades executed during the period prior to earnings announcements are significantly more likely to be reported late. There are two not mutually exclusive explanations for this finding. First, insiders are more likely to possess relevant private information prior to an earnings announcement and therefore have an incentive to strategically delay the reporting of their trades. Second, as noted above, many firms have adopted policies that allow insider trades only in a window open for a specified period after the quarterly earnings announcement (Bettis et al. (2000)). Insiders in these firms are more likely to trade shortly after an earnings announcement and, at the same time, are more likely to be scrutinized and may therefore tend to file their reports on time.

The other two trade-specific variables, trade size and the number of insiders trading on a given day, do not yield significant results. With respect to the position of the insider within the firm, we find that CEOs, chairmen of the board, and executive directors are significantly less likely to file late than other corporate insiders (such as, e.g., non-executive directors and beneficial owners). This finding is again consistent with the notion that insiders who are under closer scrutiny are more reluctant to file their reports late.

In summary, our results are consistent with the notion that the occurrence of late filings is not random. In particular, it appears that insiders who are more closely monitored (and who therefore may be facing higher litigation risk) are less likely to file their trades late.

Table 3.3: Determinants of late filing

Independent variables	All dy/dx / z-stat	Purchases dy/dx / z-stat	Sales dy/dx / z-stat
Purchase (d)	0.031**		
	(5.44)		
Tobin's Q	0.000	0.001	0.000
	(0.12)	(0.94)	(-0.13)
RoE	0.000	0.000	0.000
	(-0.53)	(-1.31)	(-0.12)
Leverage	0.007	0.003	0.010**
	(1.15)	(0.85)	(2.85)
Numest	-0.005**	-0.006**	-0.004**
	(-11.17)	(-6.77)	(-9.69)
TradeVolume	-0.115	0.517	-0.175
	(-0.56)	(0.84)	(-0.92)
NumInsider	0.000	0.001	-0.001
	(0.09)	(0.41)	(-0.35)
Pre-ann. (d)	0.027**	0.035**	0.022**
	(8.62)	(5.31)	(6.81)
CEO (d)	-0.049**	-0.074**	-0.037**
	(-12.23)	(-8.41)	(-8.90)
Chairman (d)	-0.040**	-0.059**	-0.033**
	(-6.15)	(-4.60)	(-4.55)
Executive (d)	-0.048**	-0.057**	-0.042**
	(-11.6)	(-6.18)	(-10.27)
Predicted prob.	0.121	0.164	0.104
Year dummies	Included	Included	Included
Industry dummies	Included	Included	Included
Observations	314,696	98,933	215,763
McFadden R-squared	0.039	0.035	

This table reports the results of a logit regression of the dichotomized variable filed late on the explanatory variables listed in the first column. A trade is classified as having been filed late when it was reported later than the 10th of the month following the trade. If the 10th of the month falls on a weekend, the trade is classified as having been filed late when it was reported later than the following Monday. Purchase is a dummy variable that takes the value 1 if the (net) transaction volume of the respective insider trade is positive, and zero otherwise. Tobin's Q is calculated as the ratio of the market value of assets to the book value of total assets. RoE is net income divided by book equity. We measure leverage as the ratio of long-term debt plus debt in current liabilities to long-term debt plus debt in current liabilities plus stockholder equity. We define Numest as the total number of analysts covering a company in the month preceding the reporting date of the insider trade. We calculate TradeVolume as the number of shares exchanged in the transaction times the transaction price, divided by the market equity of the company whose stocks were bought or sold in the insider trade. We define NumInsider as the total number of insiders who traded their shares in the same company on the same day. Pre-ann. is a dummy variable that takes the value 1 if the trade occurs during the 60-day period preceding the next earnings announcement. We classified all insiders into four groups (four variables): CEO if the trader was the CEO, chairman if the trader was the chairman but not the CEO, executive if the trader was an executive director but not the CEO, and reference group other, which includes all other insiders. Standard errors are clustered at the firm level. dy/dx denotes change in probability for a unit change in the explanatory variable evaluated at the average value of the explanatory variable. With respect to dummy variables, dy/dx is for discrete change of dummy variable from 0 to 1. (d) denotes a dummy variable. Here, * and ** denote statistical significance at the 5% and 1% levels, respectively.

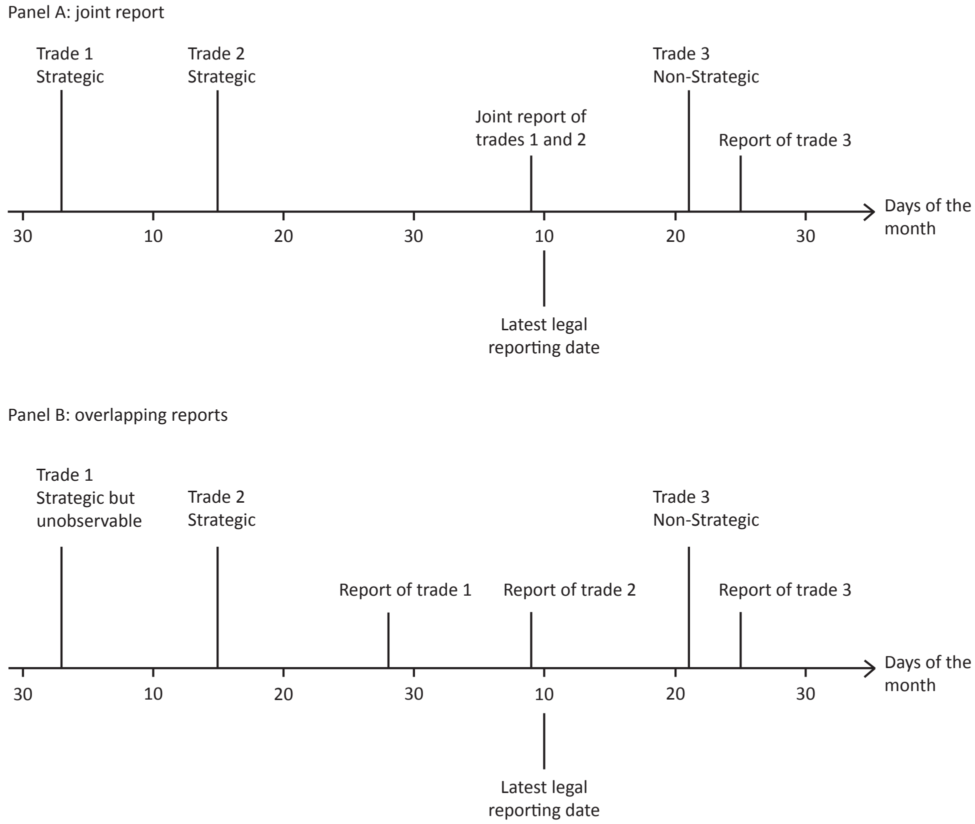
3.4 Incidences of strategic trading and strategic trade reporting

Thus far, we have documented that considerable reporting delays exist and that the reporting requirement is violated in more than 13% of cases. Delayed reporting per se may delay the adjustment of prices, but it does not necessarily benefit the insider. An insider who wants only to execute a single trade has no incentive (beyond convenience) to delay the filing. This incentive is different, however, when the insider intends to trade more than once. In this case, delaying the reporting of earlier trades avoids the price reaction the report would trigger. Thus, later trades are executed at prices that are more favorable than those that would have prevailed had each trade been reported immediately. Note that this is true irrespective of whether the insider trades on private information. It is sufficient that other market participants believe the insider to be informed with positive probability.

In this section, we search for evidence of strategic trade reporting. We classify a trade as nonstrategic if it is a) not preceded by another trade that has not been reported until the trading date, and b) is not followed by another trade before it is reported.[11] All other trades are classified as strategic because they are part of a series of trades in which some trades were executed while other trades were not yet reported. Figure 3.3 demonstrates two cases. Trades 1 and 2 in panel A of Figure 3.3 are executed on different days but reported jointly. According to the definition above, both trades are classified as strategic. Because they are reported jointly, market participants may infer that the trades are strategic. Panel B of Figure 3.3 shows a different situation, in which trades 1 and 2 are executed on different days, as well as reported on different days. Because trade 1 is reported after trade 2 is executed, both trades are strategic according to our definition. However, on the date on which trade 1 is reported, market participants cannot infer that trade 1 is strategic. Upon trade 2 being reported, however, it becomes apparent that both trades are strategic. When we analyze the market response to strategic trades in the next section, we adjust our definition of strategic trades accordingly. A trade is considered strategic only when market participants can infer that it was a strategic trade. Consequently, trade 1 in Panel B of Figure 3.3 is classified as nonstrategic when we analyze the abnormal returns after

[11] We use an alternative definition as a robustness check. We consider only trades in the same direction (i.e., only purchases or only sales) and consider a series to be terminated when no further trades took place for at least 40 days (the maximum admissible reporting delay). This definition, which is similar to that used in Lebedeva et al. (2009) to identify stealth trading, yields the same conclusions.

Figure 3.3: Definition of strategic trading



This figure illustrates our definition of strategic trade reporting. Panel A illustrates the more common case in which two trades (labeled trade 1 and 2) are executed and then reported jointly. Trade 3 is non-strategic because a) there is no unreported trade by the same insider on the trading day and b) trade 3 is reported before the insider makes another trade. Panel B illustrates the case of overlapping reports. Trades 1 and 2 are strategic because trade 1 has not yet been reported on the day on which trade 2 is executed. However, the trades are not reported jointly. Therefore, on the reporting day of trade 1, market participants cannot infer that trade 1 is strategic.

the filing of insider trades in Section 6. In the current section, however, we stick with our original definition because here we take the point of view of the insider.

We acknowledge that our classification is conservative. The group of strategic trades does not contain only trades that were deliberately reported late. As noted previously, it is likely that some corporate insiders routinely report their trades on the 10th of the following month. If an insider adhering to this reporting practice trades several times in a month, our classification scheme will treat these trades as strategic.[12] There are two reasons why we stick to our classification. First, we cannot distinguish *why* we observe a specific

[12]Our results are also conservative in a second sense. We classify a trade as strategic only when the same insider trades several times before reporting the trade. Besides such cases, there are a large number of cases in which insiders trade while the SEC filing of another insider is still pending. This sequence also puts the counterparties to the later insider trades at a disadvantage, because they would have traded at more favorable prices had the insider who traded first reported the trade immediately.

pattern of trades and reports. Second, even if an insider does not intentionally delay the reporting of the earlier trades of a series, the delayed report still puts the counterparties to the later trades at a disadvantage, since they would have traded at more favorable prices had the insider reported all trades immediately.

The results of a descriptive analysis are reported in Table 3.4. Only 32.1% of the trades in our sample are categorized as nonstrategic.[13] This percentage is larger for purchases than for sales (38.0% versus 29.4%, respectively). This finding is surprising at first, since purchases are known to have larger price impacts (which should increase the incentive to strategically delay the reporting of a trade). Further, we documented earlier that average reporting delays are larger for purchases. A potential explanation for the result is the difference in trade size. Table 3.4 reveals that insider sales are, on average, much larger than insider purchases. The large sizes of sell orders provide an incentive to split up trades and report individual trades only after all the trades of a sequence have been executed.

A total of 67.9% of trades in our sample are classified as strategic. Each strategic trade is part of a sequence of trades. The end of a sequence is reached when there are no more unreported trades. Table 3.4 reveals that 15.0% of trades are classified as the first trade of a sequence, while 52.9% are classified as second or subsequent trades of a sequence. These numbers imply that a sequence, on average, consists of 4.5 trades. This number is higher for purchases than for sales (4.9, compared to 4.4, respectively).

Table 3.4 documents that strategic trade reporting is widely practiced. We therefore now analyze whether strategic trades are systematically different from nonstrategic trades. To this end, we estimate logit models in which the dependent variable indicates whether a trade is classified as strategic or nonstrategic. The independent variables are the trade, firm, and trader characteristics introduced in the previous section. We add a dummy variable that identifies trades that were filed late.[14] We estimate a pooled model as well as separate models for purchases and sales. Standard errors are clustered at the firm level.

The results (marginal effects and z-statistics) are reported in Table 3.5. Purchases are less likely than sales to be classified as strategic, which is consistent with the descriptive

[13] As one might expect, the percentage of non-strategic trades is lower in the subsample of trades that are filed late. Only 22% of these trades are classified as non-strategic.

[14] We obtain similar results when we replace the 'late reporting' dummy by the reporting delay measured in days. We prefer the specification that includes the dummy because it is more robust in the presence of outliers (i.e., trades reported with extremely long delays). As an additional robustness check, we re-estimated the logit models after excluding all late filings from the data set. The results are similar to those presented in the text.

Table 3.4: Descriptive statistics of strategic trades

	All		Purchases		Sales	
Observations	314,696		140,734		215,763	
	Fraction	Mean volume	Fraction	Mean volume	Fraction	Mean volume
Nonstrategic	0.321	1,291,563	0.380	197,628	0.294	1,938,516
Strategic	0.679	1,015,069	0.620	284,504	0.706	1,309,553
First of series	0.150	1,389,175	0.126	213,350	0.161	1,811,510
Serial trades	0.529	909,106	0.494	302,631	0.545	1,161,429

This table presents descriptive statistics for the transactions in our sample sorted by classifying trades into non-strategic and strategic categories. A trade is classified as strategic when it is followed by at least one additional trade by the same insider before it is reported, or if it follows a trade by the same insider that has not yet been reported, and nonstrategic otherwise. The strategic category is split into first of series and serial trades. A trade is classified as first of series if the trade is the first trade in a series of trades in which at least one trade is followed by at least one additional trade by the same insider before it is reported. A trade is classified as a serial trade if it follows a trade by the same insider that has not yet been reported. Fraction is the number of trades in the respective category divided by the number of all transactions, all purchases, or all sales, respectively. Mean volume denotes the average USD volume of the trade, that is, the number of shares bought or sold multiplied by the transaction price.

results presented above, and may be related to the fact that insider purchases on average are much smaller than insider sales. The likelihood of observing strategic trades is lower in firms followed by more analysts. This finding is intuitive because insiders in these firms are more closely monitored. We further find the likelihood for strategic trades to be increased in firms with lower returns on equity. Insider sales in firms with higher Q and in less leveraged firms are more likely to be classified as strategic, whereas no such relation is found for insider purchases.

Turning to the trade-specific variables next, we find that larger trades are less likely to be classified as strategic trades. This finding is consistent with the conjecture that strategic trades are the result of large orders that have been split up into smaller chunks. We also find that trades that are filed late are more likely to be classified as strategic. The dummy variable identifying trades executed in the period prior to publication of an earnings announcement is positive and significant for insider purchases, but insignificant for sales. Interestingly, the chairman of the board is more likely to engage in strategic trading, whereas executive directors (excluding the CEO) are less likely to engage in strategic trading than members of the base group (non-executive directors, beneficial owners, and others). The results for the CEO are somewhat less clear, with an (insignificant) negative coefficient for purchases and a (significant) positive coefficient for sales.[15]

[15]We re-estimated the logit models including *only* trades made by the CEO. The conclusions are similar to those described in the text. The main differences are that a) the probability that a CEO reports a

Table 3.5: Determinants of strategic trades

Independent variables	All dy/dx / z-stat	Purchases dy/dx / z-stat	Sales dy/dx / z-stat
Purchase (d)	-0.138**		
	(-17.68)		
Tobin's Q	0.007**	-0.002	0.007**
	(7.37)	(-0.70)	(7.39)
RoE	-0.001**	-0.001	-0.001**
	(-2.68)	(-1.69)	(-2.86)
Leverage	0.002	0.026	-0.006*
	(0.80)	(1.11)	(-1.73)
Numest	-0.008**	-0.013**	-0.006**
	(-14.50)	(-12.06)	(-11.95)
TradeVolume	-4.512**	-1.304	-4.598**
	(-8.91)	(-1.33)	(-8.92)
NumInsider	0.003	0.003	0.002
	(1.05)	(0.53)	(0.58)
Pre-ann. (d)	0.008*	0.026**	-0.001
	(2.21)	(3.92)	(-0.21)
Late (d)	0.106**	0.140**	0.084**
	(18.7)	(13.9)	(15.3)
CEO (d)	0.018*	-0.019	0.039**
	(2.19)	(-1.34)	(4.18)
Chairman (d)	0.078**	0.042*	0.089**
	(5.81)	(1.67)	(5.80)
Executive (d)	-0.185**	-0.246**	-0.156**
	(-27.76)	(-22.53)	(-19.94)
Predicted Prob.	0.698	0.632	0.727
Year dummies	Included	Included	Included
Industry dummies	Included	Included	Included
Observations	314,696	98,933	215,763
McFadden R-squared	0.081	0.085	0.080

This table reports the results of a logit regression of the dichotomized variable strategic on the explanatory variables listed in the first column. A trade is classified as strategic when it is followed by at least one additional trade by the same insider before it is reported, or if it follows a trade by the same insider that has not yet been reported, and nonstrategic otherwise. Purchase is a dummy variable that takes the value 1 if the transaction is a purchase, and zero if the transaction is a sale. Tobin's Q is calculated as the ratio of the market value of assets to the book value of total assets. RoE is net income divided by book equity. We measure leverage as the ratio of long-term debt plus debt in current liabilities to long-term debt plus debt in current liabilities plus stockholder equity. We define Numest as the total number of analysts covering a company in the month preceding the reporting date of the insider trade. TradeVolume is the number of shares exchanged in the transaction times the transaction price, divided by the market equity of the company whose stocks were bought or sold in the insider trade. We define NumInsider as the total number of insiders who traded their shares in the same company on the same day. Pre-ann. is a dummy variable that takes the value 1 if the trade occurs within 60 days prior to the next quarterly earnings announcement. Late is a dummy that takes the value 1 if the trade is reported later than the 10th of the month following the trade. If the 10th of the month falls on a weekend, the trade is classified as illegal if it was reported later than the following Monday. We classified all insiders into four groups (four variables): CEO if the trader was the CEO, chairman if the trader was the chairman but not the CEO, executive if the trader was an executive director but not the CEO, and the reference group other, which includes all other insider groups. Standard errors are clustered at the firm level. dy/dx denotes the change in probability for a unit change in the explanatory variable evaluated at the average value of the explanatory variable. With respect to dummy variables, dy/dx is for a discrete change of dummy variable from 0 to 1. (d) denotes a dummy variable. Here, * and ** denote statistical significance at the 5% and 1% levels, respectively.

Our results lend support to the hypothesis that insiders strategically time their trades and make strategic use of pre-SOX reporting rules. The next section addresses whether market reactions to the reporting of insider trades take this into account.

3.5 Market response to strategic trades

This section analyzes share price reactions after the reporting of insider trades using standard event study methodology. This analysis serves a dual purpose. First, we want to test our conjecture that delayed reporting impedes the adjustment of prices to the information contained in the insider trades. To this end, we analyze whether reporting day CARs decrease with the length of the reporting delay and, if so, how quickly. The potential finding that CARs decrease quickly with the length of the delay would provide evidence that the market is able to learn the information contained in the insider trade from other sources and thus does not have to rely on the report. If, on the other hand, we find that the CAR decreases slowly, or not at all, with the length of the delay, this finding could be interpreted as evidence that market prices are indeed distorted in the period between the trading and reporting dates. Second, we wish to analyze whether the CARs are larger after the reporting of strategic trades. The result will allow us to draw conclusions about the market's belief about insider trading motives. If the market reaction after strategic trades is stronger than after otherwise similar nonstrategic trades, this would constitute evidence that the market attributes higher information content to these trades.

As noted above, we use standard event study methodology. The event date is defined to be the day on which an insider trade is filed with the SEC. The analysis is based on the event study sample introduced in Section 1. This sample is obtained by aggregating all insider trades in shares of the same firm that were reported on the same day. We must aggregate reports filed by different insiders because otherwise we would double-count observations. We estimate the market model over a 255-day estimation window ending 46 days[16] prior to the announcement date. We use the CRSP value-weighted index as our market proxy,

strategic trade decreases in the number of insiders reporting trades on the same day, and b) the dummy variable identifying trades executed in the period prior to the publication of an earnings announcement is insignificant.

[16] We choose a longer delay between the end of the estimation window and the event window because we do not want the estimation window to be contaminated by the execution of the insider trade. Note that 46 days is slightly more than the maximum admissible delay for reporting in the pre-SOX era.

and t-statistics are based on the standardized cross-sectional test proposed by Boehmer et al. (1991).

The event study results are reported in Table 3.6. We report CARs over four event windows, namely, (0; 1), (0; 2), (0; 10), and (0; 20), and we report separate results for insider purchases and insider sales. Consistent with previous research, we find that CARs over a short event window are small. The CARs over the two-day window (0; 1) amount to 0.29% for purchases and -0.21% for sales. The CARs increase significantly when the lengths of the event window are increased. The CARs over the event window (0; 10) are 1.99% for purchases and -0.87% for sales; the corresponding values for the 21-day event window (0; 20) are 2.97% and -2.05%, respectively. These results confirm previous findings that the share price reaction is stronger after insider purchases than after insider sales.

Table 3.6: Event study result

	Purchases					Sales				
	No.	(0; 1)	(0; 2)	(0; 10)	(0; 20)	No.	(0; 1)	(0; 2)	(0; 10)	(0; 20)
All	34,648	0.29**	0.59**	1.99**	2.97**	65,319	-0.21**	-0.29**	-0.87**	-2.05**
Strategic	13,782	0.36**	0.76**	2.54**	3.75**	34,735	-0.25**	-0.38**	-1.05**	-2.55**
Nonstrategic	20,866	0.25**	0.49**	1.64**	2.45**	30,584	-0.17**	-0.21**	-0.66**	-1.49**
Difference		0.11*	0.27**	0.90**	1.30**		-0.07	-0.17**	-0.39**	-1.06**
Pre-ann.	20,643	0.34**	0.64**	2.16**	3.18**	37,849	-0.19**	-0.24**	-0.91**	-1.99**
Non pre-ann.	14,005	0.22**	0.52**	1.76**	2.66**	27,470	-0.23**	-0.35**	-0.81**	-2.14**
Difference		0.12*	0.12*	0.40**	0.52**		0.04	0.11*	-0.10	0.14
Timed	6,472	0.26**	0.40**	1.28**	1.87**	8,793	0.05	0.03	-0.50**	-1.21**
Non-timed	28,176	0.30**	0.64**	2.16**	3.22**	56,526	-0.24**	-0.33**	-0.92**	-2.19**
Difference		-0.05	-0.23**	-0.88**	-1.34**		0.30**	0.36**	0.43**	0.98**
Filed late	8,105	0.31**	0.52**	1.65**	2.69**	14,897	-0.22**	-0.30**	-0.79**	-2.04**
Filed in time	25,430	0.27**	0.58**	2.06**	3.02**	47,816	-0.21**	-0.29**	-0.88**	-2.06**
Difference		0.04	-0.06	-0.41**	-0.32*		-0.01	-0.01	0.09	0.02
Delay 0 to 5	1,160	0.92**	1.32**	3.81**	4.52**	780	0.38**	0.35**	-0.01	-1.07**
Delay 6 to 10	3,602	0.31**	0.83**	2.31**	3.35**	4,216	-0.26**	-0.36**	-0.65**	-1.71**
Delay 11 to 5	5,402	0.21**	0.51**	2.07**	2.93**	9,068	-0.13**	-0.19**	-0.86**	-2.01**
Delay 16 to 20	4,833	0.40**	0.69**	2.02**	3.35**	9,760	-0.11**	-0.20**	-0.91**	-2.11**
Delay 21 to 25	5,082	0.39**	0.72**	2.23**	3.36**	11,356	-0.22**	-0.30**	-0.81**	-2.04**
Delay 26 to 30	4,781	0.28**	0.54**	1.57**	2.47**	11,135	-0.31**	-0.46**	-1.05**	-2.32**
Delay 31 to 35	3,943	0.08	0.38**	1.95**	3.12**	8,448	-0.24**	-0.36**	-0.99**	-2.29**
Delay 36 to 40	3,788	-0.03	0.22**	1.67**	2.52**	4,570	-0.32**	-0.44**	-0.80**	-2.45**
Delay 41 to 45	669	0.33**	0.75**	1.15**	1.99**	1,068	-0.23**	-0.15**	-0.69**	-1.52**
Delay greater 45	3,202	0.38**	0.55**	1.49**	2.40**	4,918	-0.15**	-0.16**	-0.71**	-1.61**

This table shows the CARs over various event windows and various subsamples. Here, * and ** denote statistical significance at the 5% and 1% levels, respectively. The significance levels for the CARs are based on the standardized cross-sectional test of Boehmer et al. (1991), and those for the differences are based on a t-test for equality of means.

We next compare the CARs after strategic and nonstrategic trades. As noted previously, we categorize a trade as strategic only when, on the filing date, market participants can infer that the trade was strategic. The results provide clear evidence that market participants attribute higher information content to strategic trades. The share price reaction after these trades is stronger than that after nonstrategic trades, irrespective of whether we consider purchases or sales or the length of the event window. Consider the CAR over the 20-day window (0; 20) as an example: It is 3.75% after strategic purchases but only 2.45% after nonstrategic purchases. The corresponding figures for strategic and nonstrategic sales are -2.55% and -1.49%, respectively. The difference between the price reactions after both strategic and nonstrategic trades is (based on a t-test for equality of means) statistically significant in all cases.

Table 3.6 also reports the results of further cross-tabulations. As already noted, many firms restrict insider trading by defining a blackout period during which trading is prohibited. Typically, the blackout period is the period just prior to an earnings announcement (often two months; see Bettis et al. (2000) and Roulstone (2003)). Such a restriction is based on the assumption that the informational asymmetry between corporate insiders and other market participants is larger prior to earnings announcements. If this assumption is true, we should observe larger CARs after trades that non-restricted insiders execute prior to earnings announcements. To test this hypothesis, we define the dummy variable 'pre-announcement' as set to 1 if at least one of the trades reported on a given day was executed within a 60-day window prior to an earnings announcement. We find that purchases made during the pre-announcement period result in significantly larger share price reactions. This finding is consistent with the notion that earnings announcements reduce informational asymmetries. For insider sales, there are no significant differences between trades executed during the pre-announcement period and other trades.

We next consider the timing of trades relative to earnings announcement dates. We look at trades that were executed in the period before an earnings announcement but reported after the announcement. To this end, we define the dummy variable timed, which is set to 1 if all trades reported on a given day were executed before and reported after the earnings announcement date. We find that timed trades convey significantly less information to the market. Considering again the (0; 20) event window as an example, we find a CAR of 3.22% for non-timed purchases and a CAR of only 1.87% for timed purchases. The corresponding figures for sales are 2.19% and 1.21%, respectively. These results are consistent with the notion that earnings announcements reduce the informational asymmetry between insiders and the market.

Next we compare trades that were reported on time with trades that were filed late. We define a dummy variable late filing that is set to 1 if all of the trades reported on a given day were filed late. The results are inconsistent. Over longer event windows (10 or 20 days), trades reported on time trigger stronger share price reactions (3.02% versus 2.69% for purchases and 2.06% versus -2.04% for sales). The difference is significant only for insider purchases, however.

Trades that are filed late are, by definition, reported with longer delays. Thus, finding that insider purchases that are filed late trigger smaller share price reactions is consistent with the notion that the market learns some of the information contained in the report from other sources. To shed more light on this important issue, we next sort the insider trades in our sample into 10 groups with respect to their weighted average reporting delays (delay 0 to 5 days, 5 to 10 days, and so on, with trades in the 10th group having a weighted average delay of more than 45 days). We find that the CARs are significantly different from zero irrespective of the trading delay. They tend to slightly decrease with the length of the delay for purchases, but not for sales.[17] These results imply that prices are distorted in the period between the execution and filing of an insider trade.

The results in Table 3.6 suggest that timed trades, that is, trades executed before but reported after an earnings announcement, and trades executed within a 30-day window after an earnings announcement trigger smaller share price reactions. The results also suggest that CAR decreases with the length of the reporting delay for insider purchases but not for sales. However, up to now, we did not control for other firm and trade characteristics. Including such controls is important because we have shown previously that trades that are filed late are systematically different from trades that are filed on time. Similarly, we have shown that strategic trades are different from nonstrategic trades. In addition, reporting strategic trades typically involves reporting several trades on the same day,[18] and therefore the total reported volume is larger. It may be the larger volume rather than the strategic nature of the trade per se that causes the larger CARs.

We therefore estimate cross-sectional regressions that control for the total reported volume and other potentially relevant variables. The dependent variable is CAR. We report results for CARs measured over the event window (0; 20). Using the shorter event window (0; 10) yields results that are qualitatively similar.

[17] Brochet (2010) reports a similar result.

[18] The typical case is illustrated in Panel A of Figure 3.3. Several trades are executed on different days but reported jointly. The case illustrated in Panel B of Figure 3.3, where strategic trades are reported individually, is much less common.

The independent variables include measures of firm characteristics (Tobin's Q, return on equity, book leverage, and number of analysts following) and trade characteristics (trading volume relative to the firm's market capitalization and aggregated over all trades that were reported jointly, number of different insiders trading on the same day, and weighted average reporting delay). We further include dummy variables identifying strategic trades, trades executed in the period prior to an earnings announcement, and timed trades (i.e., those executed in the period prior to an earnings announcement and reported after the announcement, but prior to the next earnings announcement). We also include the interaction between the timed dummy and the strategic dummy. Three additional dummy variables control for the position of the insider in the firm (CEO, chairman of the board, other executive directors[19]). Finally, we include year and industry dummies.

We estimate separate models for purchases and sales. Note that we expect different signs for the coefficients in the two regressions, because the CARs after purchases are predominantly positive while those after sales are predominantly negative. We include firm fixed effects. Standard errors are clustered at the reporting day level. The results are shown in Table 3.7. The CARs after insider purchases are smaller for firms with higher values of Tobin's Q and for firms with more analysts following. The other firm characteristics are insignificant. Share price reaction after a purchase does not depend on transaction volume. It is larger when more than one insider reports trades on the same day. Consistent with our earlier results, we find that purchases executed during the period prior to an earnings announcement trigger significantly larger price reactions. Timed purchases - those that are executed before but reported after an earnings announcement - trigger significantly smaller share price reactions than other purchases. These results are consistent with the notion that earnings announcements convey information to the market and reduce informational asymmetries. Purchases by the CEO, the chairman of the board, and other executive directors result in higher CARs than purchases by members of the base group (non-executive directors, affiliates, beneficial owners, and others). This result in general and the relative sizes of the coefficients in particular are consistent with the informational hierarchy hypothesis, which posits that trades by insiders with more privileged access to information convey more information to the market.

The most important results are those with respect to the strategic trading dummy and

[19]If several insiders report their trades on the same day, we choose the highest insider position; that is, we set the dummy to 1 if at least one of the insiders is the CEO, the chairman of the board, or an executive director, and 0 otherwise.

Table 3.7: Determinants of CARs (0; 20)

Independent variables	Purchases Coef.	Sales Coef.
Tobin's Q	-1.266**	-0.635**
	(-6.79)	(-7.05)
RoE	0.020	-0.016
	(0.45)	(-0.56)
Leverage	0.417	-0.031
	(1.62)	(-0.17)
Numest	-0.311**	-0.299**
	(-4.20)	(-5.49)
TradeVolume	-7.634	-11.083
	(-0.63)	(-1.47)
NumInsider	0.356**	-0.387**
	(3.59)	(-4.18)
Pre-ann. (d)	0.913**	0.233
	(3.62)	(1.04)
Timing (d)	-0.964*	0.522
	(-2.39)	(1.42)
Strategic (d)	0.905**	-0.615**
	(3.05)	(-3.35)
Timing*strategic	-0.186	0.039
	(-0.38)	(0.09)
Delay	-0.002	0.003*
	(-1.55)	(2.09)
CEO (d)	2.316**	-0.835*
	(6.77)	(-2.40)
Chairman (d)	1.957**	-0.672
	(2.96)	(-1.73)
Executive (d)	1.040**	-0.615**
	(3.72)	(-2.84)
Constant	2.566	-1.523
	(0.96)	(-0.55)
Year dummies	Included	Included
Industry dummies	Included	Included
Observations	34,648	65,319
Adjusted R-squared	0.111	0.080

This table reports the results of a regression with firm fixed effects of the reporting day CARs (0; 20) on the explanatory variables listed in the first column. If several transactions in the same stock were reported on the same day, the transactions count as a single observation. A report is classified as a purchase if the net transaction volume reported is positive. Tobin's Q is calculated as the ratio of the market value of assets to the book value of total assets. RoE is net income divided by book equity. Leverage is the ratio of long-term debt plus debt in current liabilities to long-term debt plus debt in current liabilities plus stockholder equity. We define Numest as the total number of analysts covering the company in the month preceding the reporting date of the insider trade. We calculate TradeVolume as the number of shares exchanged in the transaction times the transaction price, divided by the market equity of the company whose stocks were bought or sold in the insider trade. If several trades were reported on the same day, we sum the total volume of these trades. We define NumInsider as the total number of insiders who reported their trades in the same company on the same day. Pre-ann. is a dummy variable that takes the value 1 if the trade (or at least one trade, if several trades are reported on the same day) occurs during the 60-day period preceding the next earnings announcement; timing is a dummy variable that takes the value 1 if the trade is executed within 60 days prior to the next earnings announcement and is reported after the announcement (but before the following announcement); and strategic is set to 1 when a) the trade is followed by at least one additional trade by the same insider before it is reported or if it follows a not-yet-reported trade by the same insider, and when b) the market can infer on the reporting date that the trade was strategic (see Figure 3.3 for an illustration). All other trades are classified as nonstrategic. Timing*strategic is an interaction term of the variables timing and strategic. Delay is the trading-volume-weighted average delay of all insider trades of a firm reported on the same day. We classified all insiders into four groups (four variables): CEO if the trader is the CEO, chairman if the trader is the chairman but not the CEO, executive if the trader is an executive director but not the CEO, and the reference group other, which includes all other insider groups. If there were several trades in the same stock on the same day, the highest insider position is selected according to rank, i.e., CEO, chairman, executive, and other. Standard errors are clustered at the reporting day level. (d) denotes a dummy variable. Here, * and ** denote statistical significance at the 5% and 1% levels, respectively.

the reporting delay. Strategic purchases trigger a significantly larger share price reaction, even after controlling for other relevant variables. Note that, on the reporting day (our event day), market participants observe whether a report contains strategic trades. Our results thus imply that market participants believe that strategic purchases are more likely to be motivated by private information than otherwise similar nonstrategic trades. Note that since we control for aggregate trading volume and the number of insiders reporting their trades on the same day, the effect of the strategic variable does not merely stem from more trades reported jointly. The additional abnormal return is 0.9%, which is also economically significant. The coefficient on the reporting delay is insignificant, indicating that CARs do not decrease when a trade is reported with a longer delay. Thus, once we control for trade and firm characteristics, the negative relation reported in Table 3.6 disappears. This result supports our conjecture that delayed reporting causes delays in the adjustment of prices.

The results for insider sales differ from those for purchases in several respects. Trades by insiders in more highly valued firms (larger Q) trigger stronger (more negative) price reactions, as do trades by insiders in firms followed by more analysts. Price reactions after insider sales filings are stronger when more than one insider reports a trade on the same day. Trading volume, on the other hand, does not have a systematic impact. Trades by CEOs and other executive directors cause stronger price reactions. The insignificant coefficients on the pre-announcement and timing dummies indicate that the timing of the trade itself and of the report relative to earnings announcements do not significantly affect the abnormal returns.

The coefficient for the reporting delay is significantly positive, though small in magnitude. Thus, CARs following insider sales tend to decrease when a trade is reported with a longer delay. The decrease is very slow, however. The coefficient of 0.003 implies that increasing the reporting delay by one day decreases the reporting day CAR by 0.003%. It would thus take a reporting delay of 683 days until the average reporting day CAR of -2.05% is reduced to zero. Therefore, the conclusion that delayed reporting impedes the adjustment of prices is still valid.

Strategic sales apparently convey more information to the market than nonstrategic trades, as is evidenced by the significantly negative coefficient on the strategic trade dummy. We note, though, that the absolute magnitude of the coefficient is smaller than that of the corresponding coefficient in the regression for insider purchases. This result, combined with our findings that CARs after insider sales are generally smaller and that the timing of the trade and of the report does not affect the magnitude of the price reaction, is consistent with the view that insider sales are generally less likely to be motivated by private information than insider purchases.

3.6 Robustness

3.6.1 Routine reporting

As noted earlier, many insiders appear to routinely file their reports on the 10th of the month following their trades. Consequently, a large fraction of insiders report their trades on the same date (see Figure 3.2 for evidence). The stronger market response to strategic trading we identified could simply be the result of many insiders reporting trades on the same day. In the baseline regression above we have addressed this issue by controlling for the aggregate trading volume and for the number of insiders who report their trade on the same day.

It is conceivable that routine reports are less informative than reports filed on other days. Therefore, we re-estimate the regression with two additional dummy variables. The first identifies reports filed on the 10th of a month, the second interacts this dummy with the dummy identifying strategic trades. For purchases we find that, indeed, reports filed on the 10th of a month trigger smaller CARs. However, the coefficient on the interaction term is positive and significant. Thus, the result that strategic trades trigger larger abnormal returns also holds for those reports filed on the 10th of a month. When we run the same regression for sales, none of the additional coefficient estimates is significant.

3.6.2 Weak rules vs. weak enforcement

In this paper we have addressed two distinct phenomena. First, the lax reporting requirements in the pre-SOX era which allowed insiders to time their reports strategically without violating the rules, and second, the apparent lack of enforcement which is likely to be responsible for the long reporting delays and the substantial fraction of late filings. The question thus arises whether our results are driven by those cases in which the rules were violated (i.e., the late filings as defined previously).

To address this issue, we re-estimate both regressions (those for purchases and sales) including only trades that were reported within the legal boundaries. The coefficient of the variable delay in the sales regression is insignificant. All other results are unchanged. Additionally, we re-estimate the regressions with all observations but include a dummy that identifies late filings. Again, our conclusions remain unchanged. Thus, our main findings are not simply driven by the lax enforcement in the pre-SOX era.

As a final robustness check, we include a dummy variable that identifies trades made during the first five days of a month and reported between the 9th and the 13th of the following month. The timing of execution and reporting of these trades is such that the reporting delay is maximized within the legal boundaries. The results are again similar to those reported in section 5. We thus conclude that our results are not driven by a small sub-sample of cases in which insiders maximized the reporting delay within the legal boundaries.

3.6.3 Other robustness checks

One potential problem with our variable delay lies in the fact that there are obvious outliers in the sample. This is evidenced by a maximum reporting delay in excess of 10 years. We address this issue by estimating three alternative versions of the model. We use a) a delay variable that is winsorized at 42 (the maximum delay allowed in the pre-SOX era), b) the log of 1 plus the delay, and c) a dummy variable that identifies trades that were filed late. All three specifications reduce the impact of outliers on the results. They all yield results similar to those reported earlier. We thus conclude that our results are not driven by outliers.

To avoid multicollinearity, we do not include firm size in our baseline regression (the correlation between firm size and number of analysts following is 0.80 in our event study sample). When we replace the number of analysts with firm size we obtain very similar results. We also estimate versions of our models that include additional firm characteristics (a measure of asset tangibility as defined in Almeida and Campello 2007 and the standard deviations of returns in the 60 days prior to the event date). Tangibility turned out to be insignificant, return volatility was positive and significant for purchases but not for sales.

In those cases in which several different insiders traded shares of the same firm it may make a difference whether all insiders traded in the same direction or whether some of them traded in the opposite direction. Therefore, we re-estimate our model including a continuous variable measuring aggregate trade direction. It is defined as (number of buys – number of sells) / (number of buys + number of sells). The coefficient on this variable has the expected sign and is significant. The other results are similar to those presented in Table 8.

3.7 Conclusion

In the pre-SOX era, corporate insiders in the U.S. were required to report their trades by the 10th of the month following the trade. Thus, the maximum time allowed between the trade and the report was 40 days, giving corporate insiders considerable flexibility to time their trades and reports. This flexibility may be used strategically. An insider wishing to trade a large quantity may split up an order into several smaller chunks. Splitting up a large order reduces its price impact and thus results in reduced execution costs. By delaying the reporting of the trades of a series until after the last transaction, an insider can avoid the price impact caused by the reports.

This paper asks four related questions. First, how long are the reporting delays in the pre-SOX era? Second, do insiders strategically use their flexibility in choosing the timing of their trades and reports? If so, is strategic behavior systematically related to the characteristics of the insider or the firm? Third, what are the implications of delayed reporting on the informativeness of prices? Fourth, how does the market react to the strategic timing of trades and reports?

Our results demonstrate that substantial reporting delays exist. The mean reporting delay was 35 days. More than 13% of the trades in our sample were filed late (i.e., later than on the 10th of the month following the trade). The very large number of violations of the trade reporting requirement implies that the requirement was not enforced in the pre-SOX era. Corporate insiders apparently used their discretion to time their reports. More than two-thirds of the trades in our sample are part of a sequence of trades in which some trades were executed while earlier trades were not yet reported. Strategic trade reporting benefits the insider but is disadvantageous to the counterparties to the insider's trades. If each trade were reported immediately, the second and subsequent trades of a series of insider trades would be executed at prices less favorable to the insider but more favorable to the counterparties.

We find that both the occurrence of late filings and the occurrence of strategic trades are systematically related to the characteristics of the firm, the trade, and the trader. In particular, our results are consistent with the notion that insiders who are more closely monitored (and who therefore may be facing higher litigation risk) are less likely to file their trades late. The probability of observing a strategic trade is larger in firms followed by fewer analysts as well as for larger trades.

Our event study results reveal that share prices react to the reporting of insider trades. In cross-sectional regressions, we find that the magnitude of the price reaction does not decrease with the reporting delay after purchases, and decreases very slowly after sales. Thus, our results support the notion that market prices are distorted in the period between the trade and the report. Consequently, delayed reporting of insider trades impedes the adjustment of prices. Finally, event study CARs are larger after reports of strategic insider trades compared to the aftermath of otherwise similar nonstrategic trades for both purchases and sales. Thus, market participants apparently believe that insiders acting strategically are more likely to possess private information.

Our results support the more stringent trade reporting requirements established by SOX. They also suggest that strict enforcement of existing regulations is beneficial. Further, our results lead to the conclusion that countries that currently allow for long reporting delays (or do not require corporate insiders to report trades in the shares of their firm) should consider tightening their regulations.

Chapter 4

Do SEC Detections Deter Insider Trading? Evidence from Earnings Announcements

4.1 Introduction

What are the consequences of the detection of illegal insider trading by the Securities and Exchange Commission (SEC)? We hypothesize that detection has an impact on future insider trading: Individuals with access to material, non-public information update their subjective probabilities of getting caught when they observe a detection event in their vicinity and are less likely to exploit private information. Using a unique hand-collected dataset of 398 insider trading episodes detected by the SEC between 1995 and 2011 this paper analyzes whether the detection of insider trading by the SEC deters insider trading activities in the same stock and stocks of industry peers. Insider trading is difficult to measure because it is not directly observable. In order to measure trading ahead of price-sensitive announcements we look at abnormal runups prior to earnings announcements. This measure is likely to be monotonically linked to variations in the 'true' level of insider trading. We analyze a firm-quarter panel of 43,646 earnings announcements of detection targets, their industry peers and control firms in remote industries using difference-in-differences approach.

The analysis focuses on illegal insider trading, i.e., the trading on material, non-public information in violation of Rule 10b-5 of the Securities and Exchange Act of 1934. Illegal trading is to be distinguished from 'legal' insider trades by corporate insiders which have to be registered with the SEC. Legal insider trades are disclosed to the public and are not necessarily based on material, non-public information. Most developed countries prohibit trading on material, non-public information based on the premise that it harms other investors.[1] Uninformed market participants lose when trading against market participants with superior information because the uninformed buy at prices which are too high and sell at prices which are too low. This idea is, e.g., analyzed in the model by Glosten and Milgrom (1985). In their model, a specialist, the provider of liquidity, anticipates these cost, so called adverse selection cost, caused by the presence of informed traders. The specialist increases the bid-ask spread accordingly to offset these losses, i.e., he sells at higher prices and buys at lower ones. Uninformed market participants in turn ask for compensation of these costs which results in higher required returns.[2] Bhattacharya and Daouk (2002) show that the introduction of insider trading rules reduces the cost of equity and thus provide additional support for the notion that insider trading is costly for uninformed market participants and ultimately to shareholders.

The phenomenon of insider trading has attracted considerable public attention recently, in particular in connection with the largest insider trading episode in the U.S.: the professional insider trading ring around Raj Rajaratnam, the founder of hedge fund Galleon Group. Rajaratnam and his accomplices generated about USD 60 million in profits by trading in advance of the public announcement of price-sensitive information. The prevalence of insider trading is actually readily identifiable when there were suspicious trading activities prior to important announcements. However, from a practical law-making perspective, insider trading is very difficult to detect and prosecute. It is difficult to identify the individuals which have caused the suspicious price movements because of the great number of traders in the market and market anonymity. Individuals who want to trade on material, non-public information are also likely to cover up their trading, by, e.g., trading through accounts of remote friends or relatives. Further, even if it is possible to identify the traders, it is difficult to prove that a defendant has known the private information and has also been aware that it is non-public. As a result, there are only very few cases of insider trading publicly detected and brought to justice. Recently, U.S. prosecutors have announced to fight insider trading more aggressively, by employing techniques previously

[1] There is an academic debate of whether insider trading is beneficial or detrimental to welfare. See, e.g., Bainbridge (2001) for a discussion of the arguments. Welfare implications of insider trading are not addressed in the current paper.

[2] See Amihud and Mendelson (1986) for a theoretical model of this link and Brennan and Subrahmanyam (1996) for empirical evidence. Easley et al. (2002) find evidence that more trading on private information as indicated by the probability of informed trading is associated with higher returns.

uncommon in the control of white collar crime, such as search warrants or wiretaps.[3].

Despite of the substantial public interest in fighting insider trading, little is known of its systematic determinants. There is empirical evidence on the impact of legislation: E.g., the empirical studies by Bris (2005) or Ackerman et al. (2008) investigate how insider trading activity varies with the enactment and first enforcement of insider trading rules at the country level. The existing evidence at the country level suggests that insider trading laws and their enforcement have an impact on the magnitude of insider trading. But how does the insider trading activity vary within a given legal context? Little is known so far about the effects detection has on subsequent insider trading activity. In particular, it is unclear whether SEC actions have spillover effects and thereby lead to reduced insider trading in neighboring firms. Our paper aims at filling this gap.

The present paper contributes to the existing literature on insider trading and regulation. It is the first paper to analyze the consequences of the detection of insider trading and is, hence, complementary to the international studies which analyze the impact of regulation at the country level. Moreover, the paper contributes to the economic literature on criminality: We investigate the extent to which personal experiences and experiences in the vicinity of individuals affect their subjective probabilities of detection. Thereby, we contribute to the debate on the effect of risk perceptions about detection on criminal behavior.

Earnings announcements offer an attractive case to study trading ahead of price-sensitive announcements: There are less individuals involved as compared to M&A transactions and the informed individuals are typically more closely related to the firm which allows for a more representative measurement of the general level of insider trading in a given stock. Moreover, quarterly earnings announcements are regular and frequent. This allows for a comparison of the insider trading activity before and after the detection event. Further, earnings announcements are available for a large sample of firms. As a consequence, the sample is not likely to suffer from a selection bias which could be induced by looking at announcement events which are endogenously chosen such as M&A announcements.[4] Lastly, the magnitude of the surprise component can be quantified.

[3]See, e.g., the speech by U.S. Attorney Preet Bharara to the New York City Bar Association on October 20, 2010

[4]See, e.g., Hasbrouck (1985), Palepu (1986) or Ambrose and Megginson (1992) for evidence which suggests that the likelihood to be acquired is endogenous or, e.g., Harford (1999) or Paliwal (2008) for evidence that the likelihood to acquire is endogenous.

We test whether runups prior to earnings announcements are lower after there has been a detection event in the firm while controlling for alternative determinants. We use a difference-in-differences approach and compare runup changes in the post detection period of detection targets, their industry peers and firms in remote industries. A detection event is the first day on which the market has learned from the detection of the case by the SEC. In a nutshell, we obtain the following results: SEC detection significantly reduces the runup prior to earnings announcements for firms with a detection event and their industry peers. More concretely, the runup over the time window of t-5 to t-1 around the earnings announcement is reduced by 0.7%. The effect on industry peers, the spillover effect, is strong and statistically indistinguishable from the effect on the detection target itself. We find weak evidence that the deterrent effect for the detection targets is slightly more pronounced for episodes which involve information leakage from within of the firm. These findings remain robust to an alternative measure of insider trading, over different time windows for the runup calculation and over different subsamples. One may object that the observed effect is mechanical, because the pre detection runups for treatment firms include the runup of the insider trading episode. We rule out that the observed relationship is purely mechanical. We also discuss the limitations of the present analysis. In sum, the empirical findings lend support to the notion that detection discourages the exploitation of inside information in the vicinity of the detection target.

The paper is structured as follows: Section 2 introduces the main hypothesis and relates the paper to the existing literature on the economics of crime and insider trading. Section 3 describes the construction of the dataset and report summary statistics. Section 4 explains the empirical approach. Section 5 presents the empirical findings, robustness checks are reported in Section 6 and potential caveats and limitations are discussed in Section 7. Section 8 concludes.

4.2 Hypothesis and related literature

Our paper is related to several strands of literature: First, it is related to the literature on the economics of crime which deals with the determinants of the subjective probability of detection. Second, our paper is related to the existing work on the effects of insider trading legislation. Third, it is related to the empirical literature which seeks to construct measures which capture illegal insider trading activities. The present section summarizes the related literature and sets out how the present paper relates to the existing work.

4.2.1 Probability of detection and economics of crime

The objective of the paper is to test the following hypothesis: The detection of insider trading in a given stock reduces illegal insider trading activities. Existing work on the economics of crime provide a theoretical underpinning for this hypothesis. The core of the argument consists of three parts: First, the propensity of an individual to commit a crime depends on the probability of detection. Second, when the probability of detection is not common knowledge, the individual forms beliefs about it based on past experience. Third, individuals use information from their vicinity when forming and updating expectations about the probability of detection.

The idea of crime as the outcome of rational choice is mainly shaped by Becker (1968). According to this cost-benefit view of crime, a rational individual chooses between criminal and non-criminal behavior by trading off expected benefits against expected costs. The costs are determined by the severity and the likelihood of punishment. Increases in the probability of detection and punishment lead to higher expected costs and, hence, to a lower propensity to commit crime. The hypothesis that variations in the likelihood of detection and punishment lead to changes in the observed crime rate has also been empirically tested. E.g., Bar-Ilan and Sacerdote (2001) analyze traffic data from a series of experiments. The authors investigate an exogenous variation in the likelihood of getting caught. The introduction of a camera enforcement program to monitor driving through red light provides for an exogenous increase in the likelihood of getting caught. Analyzing the consequences of this increase in the probability of detection, the authors find that individuals are substantially less likely to cross red lights.

In the model by Becker (1968) the probability and severity of punishment is common knowledge. However, the real world often exhibits great uncertainty with respect to the true frequencies of crime and detection. This observation applies to insider trading in particular. Detection and enforcement events of insider trading are infrequent. In addition, information about the true crime rate are also very opaque, because they are not directly observable. Further, the SEC investigates secretly, so not much is known about the sources and methods of investigation. Hence, apart from the notion that the likelihood of detection is probably small, not much is known about its determinants. Rather than the actual 'true' probability of detection, individual behavior is more likely to respond to the *perceived* probability of detection. Several existing papers study how these perceptions shape the propensity to commit crime. E.g., Ben-Sahar (1997) argues that individuals are imperfectly informed about detection efforts and the true rate of detection. Enforcement events contribute to learning, because they help individuals to form more precise expectations about the detection rate. Lochner (2007) provides empirical evidence based on longitudinal survey data with information about reported perceptions about the probability of arrest. His results show that personal experiences with enforcement actions shape individual perceptions about the likelihood of detection and sanction.

Information is costly and difficult to obtain. As a result, individuals use information from their close environment rather than 'global' information. When forming and updating subjective probabilities of detection, individuals are likely to use personal experiences or experiences by their vicinity.[5]

Sah (1991) theoretically analyzes the evolution of the probability of detection over time as it is shaped by past experiences. His model explains differences across groups which otherwise face identical economic fundamentals. As argued by Sah, individuals use information from their personal experiences and the experiences of their vicinity to form and update their subjective probabilities of detection. Rincke and Traxler (2011) analyze data on the compliance of Austrian households with paying TV license fees. They find that enforcement actions increase the propensity of neighboring households to comply and pay the fees. Thereby, the empirical evidence in their paper supports the vicinity effect of detection and enforcement actions.

In addition to updating beliefs about the probability of detection, learning about social stigma might present an alternative channel over which individuals are affected by detection and enforcement actions in their neighborhood. Social stigma refers to the reluctance to interact socially and economically with convicted criminals. Thereby, being convicted of a criminal act involves costs which go beyond legal penalties such as monetary fines or imprisonment. The idea is introduced and theoretically analyzed by Rasmusen (1996). By observing how convicted individuals are stigmatized, individuals learn about the costs involved with criminal actions such as illegal insider trading which makes them less likely to trade on private information.

[5] The 'neighborhood effect' is analyzed in various alternative economic and social contexts, e.g., by Aneshensel and Sucoff (1996), Clampet-Lundquist and Massey (2008), Grinblatt et al. (2008), or Kuhn et al. (2011).

We hypothesize that the detection of illegal insider trading affects the perceptions of individuals in the vicinity of the defendant, namely other individuals who are associated with the firm. Further, we hypothesize that a detection event also impacts insider trading activities at neighboring firms, i.e., industry peers. When trading off expected costs and benefits of exploiting private information for profitable trading, individuals with access to private information take their updated subjective detection probability into account and are less likely to trade.

4.2.2 Legislation and insider trading

Based on an international sample of 103 countries, Bhattacharya and Daouk (2002) analyze the impact of regulation and enforcement of insider trading laws on the cost of equity. Their test is actually a test of two joint hypotheses: First, insider trading regulation reduces insider trading activity. Second, more insider trading activity leads to higher cost of equity. According to the authors, insider trading is costly to uninformed investors because they lose against informed traders. As a result, investors require compensation for these anticipated losses and ask for a higher rate of return which should be ultimately reflected in greater cost of equity. The cost of equity do not change significantly after the introduction of the prohibition of insider trading. However, they decrease after the first prosecution of insider trading. This suggests that insider trading activity is sensitive with respect to enforcement.[6] Bris (2005) also analyzes a country cross section. However, he takes an alternative approach by more directly investigating the impact of regulation on insider trading activity. His sample consists of 4,541 acquisitions from 52 countries between 1990 and 1999. He uses abnormal returns and volumes in the days prior to takeover announcements as a measure of suspicious trading. His study documents that insider trading enforcement increases both the incidence and the profitability of insider trading. Bris further finds that tougher laws reduce the incidence of illegal trading activity.

Similar to the study by Bris (2005), Ackerman et al. (2008) study the run ups prior to the announcements of ca. 19,000 acquisitions in 48 countries from 1990 to 2003. They find that the enactment of insider trading laws significantly reduces the extent to which the

[6] In a more recent paper Bhattacharya and Daouk (2009) show that the introduction of a law can lead to higher cost of equity if the law is not enforced. According to the authors, the underlying mechanism is the following: If there are some individuals who follow the law when is merely enacted and not enforced, the individuals who are not following the law will violate the law with even greater intensity. However, this result only applies to environments with a low general level of enforcement, i.e., emerging markets and not to developed and highly regulated markets such as the U.S.

information about the pending acquisition is released prior the announcement. However, in contrast to Bris (2005) they find that the effect of the initial enforcement is small and statistically insignificant.

4.2.3 Measuring insider trading

How does 'true' insider trading affect returns and volume? Meulbroek (1992) addresses this question by looking at illegal insider trading data from the SEC. Her sample consists of 183 insider trading episodes where individuals were charged with insider trading by the SEC between 1980 and 1989. She finds that insider trades move prices substantially. There are abnormal returns of 3% on average on insider trading days. Meulbroek controls for a potential selection bias. The detection of illegal insider trading may be biased, as unusual stock behavior might catch the regulator's interest in the first place. This is why the sample of detected insider trading cases could be biased in favor of insider trading cases which significantly affect stock behavior. However, Meulbroek argues many cases are detected on the basis of referrals which are unrelated to the magnitude of the price impact, such as referrals by brokers, former employees, fellow conspirators or ex-wives. These cases are unlikely to suffer from the selection bias as the likelihood of detection in such cases is independent of the actual price and volume impact of the insider trade. When analyzing this subsample, the results remain robust.

Keown and Pinkerton (1981) are among the first to empirically analyze runups prior to price-sensitive announcement. Based on unusual daily returns and weekly volume data on 192 takeover announcements between 1975 and 1978 they identify suspicious trading activities prior to takeover announcements. According to their results, 40 to 50% of the price impact of an acquisition announcement is already incorporated before the public disclosure.

Jarrell and Poulsen (1989) analyze abnormal return and volume behavior prior to 172 M&A announcements between 1981 and 1985. They draw attention to the problem that runups prior to price-sensitive announcements could also stem from rational market anticipation rather than insider trading. They find that unusual behavior prior to M&A announcement can be partially explained by observable information such as M&A rumors in the press and the foothold acquisition of the bidder. Their paper highlights the need to control for the extent to which the announcement is already anticipated by the market, in order to obtain a more accurate measure of insider trading.

Acharya and Johnson (2010) analyze a link between insider trading and the number of individuals who have access to inside information. They argue that there could either be a positive or a negative effect of the number of insiders on insider trading intensity: More insiders can lead to a higher likelihood of detection and punishment which could lead to less exploitation of inside information. Hence, there will be a negative relationship. However, if there is no connection between the likelihood of detection and the number of insiders, more insiders will lead to more insider activity. They empirically test the hypotheses with data on insider activity prior to bid announcements of private equity buyouts. As a number of insiders they use the number of financing participants of the transaction. As a measure of insider trading they use unusual behavior in return and volume 5 days prior to the announcement. They find that more equity participants are associated with suspicious stock and options trading activities.

To our best knowledge there is only one other paper which analyzes earnings announcements from the angle of information leakages. Cai et al. (2011) investigate whether Wall Street connections of the firm are associated with increased selective pre-disclosure of material, non-public information. They analyze whether Wall Street connections lead to earning announcements being less informative, where they measure the informativeness of an earnings announcement by the market reactions around the earnings announcements in the window of t-1 to t+1 around the announcement at t. The main hypothesis of Wall Street connections leading to more insider trading also implies that there will be higher runups prior to earnings announcements. The study of the runup as opposed to the market reaction - the approach we take in the present paper - would even present a more direct test of their hypothesis. However, it is unclear why the authors do not test this implication in their paper.

4.3 Data

4.3.1 Construction of the dataset

Detection sample: The detection sample is hand-collected from the archive of litigation releases from the website of the SEC.[7] Litigation releases are available from this database

[7] http://www.sec.gov/litigation/litreleases.shtml.

starting September 28, 1995. We collect insider trading litigation releases up to December 31, 2011. We search all litigation releases for cases of insider trading, i.e., trading on material, non-public information which constitutes a violations of SEC Rule 10b-5. A litigation release typically includes the following information: date of filing of the release, names of the defendants, the stock in which the defendant has traded, type of information on which the defendant has allegedly traded (e.g., takeover by another firm), date of the announcement of the public disclosure of the information (e.g., date of the takeover announcement), the association of the defendants with the firm, how the defendants learned from the information and whether the information has been tipped to others. In several cases, there is also information on the trading dates, the amount of shares or options traded and trading profits. Where available, we also use the complaints[8] to complement the information.

For the purpose of our empirical analysis, we are interested in the date where the detection of the insider trading incidence by the SEC becomes publicly available for the first time. As a default approach, we use the filing date of the litigation release as the detection date. The SEC investigates secretly and does not disclose any information on ongoing investigations. This is why the filing date of the litigation release usually coincides with the first disclosure of the insider trading case on behalf of the SEC. We run a press search using Factiva to search for a potential earlier release of the detection. Only in a few cases, we identify an earlier date. One may object that individuals associated with the firm are aware of the SEC investigations, because the firm is often asked to provide internal documents, e.g., information about all employees who have been involved in a takeover. In those cases, some employees receive earlier notice about the insider trading detection. In optimum, we would have to include the first date on which firm individuals become aware of the detection, i.e., the date at which the SEC informs individuals in the firm about the ongoing investigations in the matter of the insider trade. However, this information is private to the SEC and we do not have access to this information. Further, it is likely that only a small circle of individuals in a firm will be informed about the SEC investigations and this information is likely to spread within the firm in unknown cascades. Hence, we choose the date on which the information becomes publicly available, although we are aware that there might be some individuals who have received notice of the SEC investigations in advance. In some cases, there are several insider trading episodes in the

[8]In some cases, the SEC publishes the complaints for the insider trading episodes on their website. A complaint is a legal document which presents the facts and legal reasons for the litigation.

same firm. Only the first insider trading episode which is detected by the SEC is included in our sample.

Based on the information manually collected from the SEC website, we classify the insider trading cases to the following event categories which reveal the type of information on which the defendants have traded: M&A, earnings, fraud (accounting or financial fraud), announcements by the U.S. Food and Drug Administration, corporate finance measures (e.g., issue or repurchase of shares), analyst revisions, and other. The category other includes general business announcements or changes in personnel.

In many cases the stock of the firm is not listed anymore when the insider trading incidence is detected by the SEC. In several cases this is due to a takeover of the firm or other reasons for delisting (e.g., such as bankruptcy). If the firm has been taken over by another firm in the meantime, we include the acquiring firm in the sample. In a later robustness check, we investigate whether this adversely affects our results. In other cases of delisting, we exclude the observations from the sample.

Further, we classify the observations according to the source of leakage. Has the information been stolen, has the information leaked or is the source unknown? In cases of stolen information, we require that the defendant did not have access to the inside information through his job or did not receive any tips but has expropriated the inside information by illegally gaining access to it, e.g., by hacking into computers. Observations with an unknown source of leakage refer to the cases where the SEC has frozen accounts subsequent to extra-ordinarily large trading volumes in shares or options by one account prior to the announcement of price-sensitive information. The SEC has done so only in a small number of cases (see descriptive statistics below).

For the cases of information leakage, we classify the source further. How is the defendant related to the firm? The defendant has either traded on the information himself or he has tipped the information to a third party. The source of leakage may be identical to the individual that also traded on the information. Alternatively, the source of leakage has tipped the piece of material, non-public information to another party. In many cases, insider information is tipped to family members of friends, in an attempt to conceal the insider trading. We differentiate between the following categories: inside leakage, shareholder, director, professional service firm or other. The inside leakage category includes individuals which are directly employed by the firm, e.g., CEO, top executive (other executive members of the board except for the CEO), officer and executive not part of the management board, or employee. The category of professional service firm consists of individuals who have a fiduciary duty to the firm and its shareholders by advising the firm as a management consultant, investment bank or legal advisor. The category other includes individuals who have received the confidential information due to their employment with a supplier or a client. Furthermore, we classify the observations as crime of opportunity or organized crime. An insider trading episode is considered as organized crime if the defendants have traded in at least two episodes in different stocks. Otherwise, the observations are classified as crime of opportunity.

Firm characteristics and stock data: COMPUSTAT is used to collect information about the total assets, market capitalization, return on assets, leverage, Tobin's Q, book-to-market ratio, R&D expenditures and SIC code. Returns and trading volumes are from CRSP.

Sample of earnings announcements: We collect information on quarterly earnings announcements for the firms and corresponding analyst forecasts from IBES from 1993 to 2011. The following data is collected: date of the actual earnings announcement, number of analyst forecasts, actual earnings announced, mean and median of the analyst forecast consensus and the standard deviation of the analyst forecasts.

Control samples: Our objective is to compare the post detection change in insider trading with respect to detection targets with the effects on industry peers and remote firms. To this end, we select two control samples: a control sample of industry peers and a control sample of firms in industries in which there was not any detection event over the sample period. We identify the matched sample of industry peers as follows: From the universe of COMPUSTAT firms without any insider trading episodes we delete the ones for which there is no available data on CRSP and where we do not have IBES data on 8 or more earnings announcements. We use the following matching algorithm: For each insider trading episode in our sample, we select the firms with the same first 3 digits in terms of SIC code as the detection target. We then choose the 10 firms which are closest in terms of size in the month of the filing of the SEC detection. Among those, the firm that minimizes the distance in terms of book-to-market ratio is chosen as the matched control firm.[9] For each matched industry peer we also construct variables which describe

[9]Later in this paper, we control for a slightly different matching algorithm and more than one matched control firm.

the insider trading episode, such as the filing date, the event type of the insider trading case and the source of leakage by setting the values equal to the corresponding matched detection firm.

For the construction of the sample of firms in remote industries, we proceed as follows: Similar to the approach above, from the universe of COMPUSTAT firms without any insider trading episodes we delete the ones for which there is no available data on CRSP and where we do not have 8 or more earnings announcement data on IBES. As a next step, we identify the firms which are in 2-digit SIC code industries which have not experienced any detection event over the sample period. To each insider trading episode in our sample, we randomly assign a control firm from this set of firms. The values of variables describing the insider trading episode are set equal to the value of the matched episodes.

In sum, we have three different groups: the group of firms with an insider trading episode, a group of matched industry peers and a group of randomly assigned matched firms in remote industries. In the following analyses we refer to two samples which are defined as follows: The *treatment* sample consists of firms with an insider trading episode only. The *vicinity treatment* sample consists of firms in the neighborhood of the detection firm, that is the detection firm itself and industry peers.

In total, many observations from the detection sample are lost due to missing data from COMPUSTAT, CRSP or IBES. In total we count 1,165 insider trading episodes detected by the SEC between 1995 and 2011. Restricting attention to the first announcement of insider trading within one firm, sufficient available information on the episode in the litigation release and the availability of CRSP data, our sample reduces to 625. The availability of COMPUSTAT data further reduces the sample to 573. The required availability of coverage by the IBES database further reduces the sample to 398 cases of insider trading episodes.

4.3.2 Descriptive statistics

Table 4.1 breaks down the insider trading episodes in our sample by time and type of information events. Exploiting foreknowledge of pending M&A announcements is the most common type of insider trading (35.9%). The second most common type is earnings announcements (23.1%), followed by announcements of the firm regarding corporate financing (15.3%). The average number of days between the event date (the date on which the information on which the defendants traded was disclosed) and the detection date (filing date of the SEC litigation release or if available earlier disclosure in the press) is 877.12 days (median 791.5). Of the 398 insider trading episodes, 298 observations include information on the original firm and stock in which the insider trading occurred, while in 100 cases, the firm has been acquired. In these cases, we use data on the acquiring firm.[10] Table 4.2 displays how the events are distributed across types of leakage sources. Source of leakage denotes the association between the tipper or trader accused of illegal insider trading and the firm. In 38 cases, the material, non-public information has been stolen. In 14 cases, the source of leakage is unknown at the time of detection by the SEC. There is information leakage in 346 cases. 121 of those include leakage of information by employees of the firm. 57 include leakage of information by shareholders and 21 of directors. In 123 cases, employees of professional service firms traded on non-material, public information or passed the information along to family or friends. Of the 398 insider trading episodes, 200 are classified as crime of opportunity and 198 as organized crime.

Table 4.1: Distribution of detection events

	M&A	Earnings	Fraud	FDA	Finance	Analyst revision	Other	Sum
1994	1	0	0	0	0	0	1	2
1995	2	1	0	0	0	0	0	3
1996	3	4	1	0	0	0	0	8
1997	1	2	1	3	0	0	1	8
1998	13	7	0	1	0	0	4	25
1999	14	0	1	0	0	0	9	24
2000	21	4	0	0	0	0	7	32
2001	9	4	2	0	0	0	1	16
2002	7	5	1	2	0	0	3	18
2003	8	6	2	1	0	0	1	18
2004	13	5	4	0	2	0	1	25
2005	5	17	1	5	7	0	11	46
2006	8	2	1	3	40	0	1	55
2007	7	14	0	1	11	16	0	49
2008	10	3	0	1	1	0	0	15
2009	15	8	1	2	0	0	7	33
2010	3	10	1	2	0	0	1	17
2011	3	0	0	0	0	0	1	4
Sum	143	92	16	21	61	16	49	398
In percent	35.9%	23.1%	4.0%	5.3%	15.3%	4.0%	12.3%	100.0%

The table reports the distribution of detection events over years and over different types of events on which material, non-public information has been misused. M&A denotes announcements of mergers and acquisitions, earnings denotes the announcement of quarterly or annual earnings, fraud denotes the announcement of financial or accounting fraud, FDA denotes announcements by the U.S. Food and Drug Administration, Finance denotes corporate financing policies (e.g., share buyback, capital increase). Analyst revisions refer to the update of analysts regarding buy or sell recommendations.

[10] We explicitly address potential differences with respect to the subsample of acquired firms in Section 6.

Table 4.2: Distribution of the source of leakage

Source of leakage			Number of cases
unknown			14
stolen			38
leakage			346
	inside leakage		121
		CEO	10
		top executive	10
		officer	57
		employee	44
	shareholder		57
	director		21
	professional service firm		123
		consultant	29
		legal advisor	21
		investment bank	73
	Other		24
Crime of opportunity			200
Organized crime			198

The table reports the sources of leakage of the material, non-public information which was exploited for insider trading. The source of leakage is labeled *unknown* if the SEC does not have information on how the defendants received access to the material, non-public information. Cases are classified as *stolen* if the defendant has illegally gained access to the private information. *leakage* denotes cases in which the defendants, i.e., the trader or the tipper, received the information as part of their employment. *inside leakage* denotes cases in which the trader or tipper is directly employed by the firm. This category is further broken down: *CEO* denotes Chief Executive Officer, *top executive* other executive board members excluding the CEO, *officer* includes executives below the executive board, and *employees*. *shareholder* denotes individuals with a substantial stake in the firm (at least 5%). *director* denotes non-executive members of the board. The category *professional service firm* includes employees of service firms with a fiduciary duty to the firm with the insider trading episode: *Consultant* stands for management consultants, *investment bank* for employees of investment banks who are advising the firm in matters of financing or mergers and acquisitions and *legal advisor* denote employees of law firms. An insider trading episode is classified as *crime of opportunity* if the defendants have exploited inside information with respect to one firm only. If they have committed insider trading in at least two different stocks, we classify the episode as *organized crime*.

Table 4.3 shows the summary statistics of the firm characteristics for the treatment sample, (Panel A), the sample of matched industry peers (Panel B) and the sample of randomly assigned control firms in remote industries (Panel C). A firm with an insider trading episode has a mean size of total assets of 8,097 million and a market capitalization of USD 7,374 million. The median values are much lower with 1,403 million and 1,589 million which indicates that the sample is skewed to the right. The mean Tobin's Q is 2.396, while the mean book-to-market ratio is 0.472. On average, the firms have a mean return on assets of 8.7% and R&D expenditures of 6.8%.

The table also reports the differences in means between the sample. Despite of the matching procedure, firms in the industry peer group are significantly smaller as compared to the treatment sample. They industry peers have a smaller Tobin's Q, a greater book-to-market ratio, are less profitable and have less R&D expenditures. There are two potential explanations for these differences: First, firms with certain characteristics could more likely to be involved with illegal insider trading activities. Second, if one assumes that illegal insider trading activities are equally distributed among all types of firms, it could be the case that the SEC does not treat all firms equally when deciding on the investigation and prosecution of insider trading episodes, but is biased towards focusing on certain types of firms. The resources to fund investigation and enforcement are constraint. [11] Investigating the reasons for the observed differences would go beyond the scope of this paper. In the following analyses, we control for the differences by using firm characteristics as control variables, including firm-fixed effects in the model and explicitly test how firm characteristics affect the impact of detection.

Table 4.4 shows summary statistics of the earnings information. On average, there are 10.8 analysts who issue quarterly earnings forecasts for one stock in the treatment sample. The mean standard deviation of the estimate is 3.1%. The mean absolute surprise ((actual earnings minus median of the forecasts)/share price) is 0.6%. If the actual earnings exceed the forecast (positive surprise), the surprise is 0.4%, whereas the surprise is -0.8% if the actual earnings fall short of the forecast consensus (negative surprise). There are significantly more analysts covering stocks in the treatment sample as opposed to stocks of industry peers or firms in remote industries. This difference can be attributed to the differences in size as shown in Table 4.3, because the number of analysts generally increases

[11] Kedia and Rajgopal (2011) find empirical evidence which points towards SEC enforcement preferences. According to their results, SEC enforcement is more likely with respect to firms which are geographically close to SEC offices.

Table 4.3: Firm characteristics

Variable	Mean	St. Dev.	Median	95% quantile	5% quantile
Panel A: treatment sample					
Total assets (in USDm)	8,097.306	14,720.860	1,403.257	53,747.250	42.131
Market capitalization (in USDm)	7,373.833	12,155.290	1,588.920	42,380.780	70.814
Tobin's Q	2.396	1.773	1.719	6.612	0.945
Book-to-market ratio	0.472	0.369	0.378	1.215	0.058
Return on assets	0.087	0.166	0.114	0.302	-0.267
R&D	0.068	0.101	0.023	0.287	0.000
Panel B: industry peer control sample					
Total assets (in USDm)	3,990.630	9,994.488	587.018	23,043.000	41.858
Market capitalization (in USDm)	3,527.729	7,691.392	746.515	17,966.620	60.998
Tobin's Q	2.292	1.664	1.715	5.973	0.917
Book-to-market ratio	0.486	0.367	0.400	1.192	0.076
Return on assets	0.080	0.167	0.115	0.272	-0.283
R&D	0.067	0.098	0.022	0.273	0.000
Panel C: remote firms control sample					
Total assets (in USDm)	1,791.924	3,565.729	626.571	7,872.000	62.777
Market capitalization (in USDm)	1,428.141	2,856.751	521.743	5,897.250	51.195
Tobin's Q	1.782	1.224	1.401	4.093	0.861
Book-to-market ratio	0.622	0.445	0.523	1.632	0.087
Return on assets	0.136	0.093	0.131	0.298	0.001
R&D	0.004	0.022	0.000	0.016	0.000
Difference in means:	A vs. B	A vs. C	B vs. C		
Total assets (in USDm)	4106.676***	6305.382***	2198.706***		
Market capitalization (in USDm)	3846.104***	5945.692***	2099.588***		
Tobin's Q	0.104***	0.614***	0.511***		
Book-to-market ratio	-0.014***	-0.150***	-0.136***		
Return on assets	0.008***	-0.049***	-0.056***		
R&D	0.002***	0.064***	0.062***		

The table reports summary statistics of firm characteristics of the detection group, the group of industry peers and the group of firms in remote industries. $Total\,assets$ is the total book value of the firm's assets. $Market\,capitalization$ is the market value of equity. $Tobin's\,Q$ denotes the market value of equity and debt divided by the book value of the firm's assets. $Return\,on\,assets$ denotes earnings before taxes and interest before depreciation divided by the book value of total assets. $R\&D$ is R&,D expenditures scaled by the book value of total assets. The table also indicates the differences in means between the detection group and the industry peers (A vs. B), the detection group and the group of remote firms (A vs. C) and the industry peer group and the group of remote firms (B vs. C). *, ** and *** indicate statistical significance at the 10%, 5% and 1% level based on a t-test with unequal variances.

with firm size. The dispersion of analysts as measured by the standard deviation of the estimates is larger for treatment firms as opposed to their industry peers. When we compare the treatment firms or the industry peers to the firms in remote industries we find that firms in remote industries seem to have a slightly smaller standard deviation of analyst estimates.

Table 4.4: Summary of earnings announcements

Variable	Mean	St. Dev.	Median	95% quantile	5% quantile
Panel A: treatment sample					
Number of analyst estimates	10.796	8.022	9	26	1
Analyst dispersion	0.031	0.043	0.02	0.12	0
Surprise	0.006	0.015	0.001	0.029	0
Positive surprise	0.004	0.007	0.001	0.020	0.000
Negative surprise	-0.008	0.014	-0.002	0.000	-0.055
Panel B: industry peer control sample					
Number of analyst estimates	7.852	6.620	6	22	1
Analyst dispersion	0.028	0.041	0.01	0.11	0
Surprise	0.006	0.015	0.001	0.028	0
Positive surprise	0.004	0.006	0.001	0.020	0.000
Negative surprise	-0.009	0.014	-0.003	0.000	-0.055
Panel C: remote firms control sample					
Number of analyst estimates	5.533	4.504	4	16	1
Analyst dispersion	0.039	0.049	0.020	0.14	0
Surprise	0.007	0.015	0.002	0.034	0
Positive surprise	0.004	0.006	0.002	0.020	0.000
Negative surprise	-0.010	0.015	-0.004	0.000	-0.060
Difference in means:	A vs. B	A vs. C	B vs. C		
Number of analyst estimates	2.944***	5.263***	2.319***		
Analyst dispersion	0.003***	-0.008***	-0.011***		
Surprise	0.000	-0.001***	-0.001***		
Positive surprise	0.000	0.000***	0.000***		
Negative surprise	0.000	0.002***	0.001***		

The table reports summary statistics of the analyst forecasts of earnings announcements for the detection group, the group of industry peers and the group of firms in remote industries, the industry. *Number of analyst estimates* is the number of analysts who issue a forecast for a quarterly earnings announcement. *Analyst dispersion* is the standard deviation of the analyst forecasts with respect to one earnings announcement. *Surprise* is the absolute value of the difference between the actual earnings minus the median of analyst forecast scaled by the share price. *Positive surprise* (*negative surprise*) is the difference between the actual earnings minus the median of analyst forecasts scaled by the share price if the difference is strictly positive (negative). The table also indicates the differences in means between the detection group and the industry peers (A vs. B), the detection group and the group of remote firms (A vs. C) and the industry peer group and the group of remote firms (B vs. C). *, ** and *** indicate statistical significance at the 10%, 5% and 1% level based on a t-test with unequal variances.

4.4 Empirical strategy

4.4.1 Identification of insider trading

The goal of the present analysis is to analyze the effect of detection on subsequent exploitation of inside information in the neighborhood of the detection target, i.e., the detection firm itself and industry peers. Measuring insider trading activity directly is nearly impossible as this would require knowledge of the information set and transactions of all traders in a specific stock as pointed out by Acharya and Johnson (2010). Hence, empirical studies which aim at capturing insider trading activities have to rely on measures which are known to be monotonically related to insider trading. In the literature section above we have argued that unusual stock return behavior qualifies as a measure of suspicious trading activities.

For the purpose of testing the hypothesis that observed detection reduces insider trading activity, we choose a variable which is likely to be monotonically linked to the 'true' level of insider trading. We choose abnormal runups prior to quarterly earnings announcements. Part of the existing literature which analyzes the effects of regulation on insider trading (e.g., Ackerman et al. (2008) or Bris (2005)) uses abnormal returns prior to M&A announcements. For the purpose of the present paper, studying earnings announcements as opposed to M&A transactions is more appropriate for the following reasons: First, we seek to analyze the effect of detection *at the firm level*. Information about earnings announcements are available for many firms. Looking at M&A events, we would encounter a selection bias because the likelihood of undertaking or undergoing an M&A event is not exogenous. Second, earnings announcements occur on a quarterly basis, i.e., frequently and regularly. M&A events are less frequent and regular. In addition, the acquired firms are often delisted after the acquisition. Hence, we are able to compare insider trading activity before and after the detection event. Third, many different parties are involved in and have thus foreknowledge of M&A transactions. In addition to usual firm insiders, there are individuals associated with the acquirer, alternative bidders, alternative targets, consultants, investment banks, law firms etc. involved. Thus, it is less likely the case that the source of leakage stems from within the firms as opposed to earnings announcements, where the foreknowledge is more concentrated among individuals directly associated with the firm.

Further, the study by Jarrell and Poulsen (1989) argues that runups can both be caused by market anticipation and insider trading. With respect to earnings announcements we can account for market anticipation by controlling for the analyst forecast consensus. Thereby we can measure the surprise component of the announcement more precisely.

Similar to the approaches taken by Acharya and Johnson (2010) or Ackerman et al. (2008) we use runups prior to the announcement date, i.e., abnormal returns as a measure of insider trading. Cumulative abnormal returns (CAR) are constructed in a period before the earnings announcement day t. First, we estimate the parameters of the market model based on the daily returns in the estimation period from t-140 to t-30 by regressing daily returns on the market premium and a constant.[12] The parameters are then used to calculate expected daily returns for the event period t-20 to t+2. The daily abnormal return is obtained by subtracting the expected return from the actual return. To obtain CAR, we sum up the daily abnormal returns over the corresponding event window, where we use the window from t-5 to t-1 as the standard window of our analysis.

4.4.2 Regression

Our objective is to measure the effect of detection, our treatment, on runups as a measure of insider trading. To this end, we use a difference-in-differences method. According to this method, the effect of detection on insider trading is computed as a double difference: From the difference between the post and pre detection runups of the treatment sample we subtract the difference between the post and pre detection difference in runups of the control sample. This approach combines a cross-sectional and a time series perspective. Thereby, we avoid the potential problem of an omitted time trend which is affecting the groups simultaneously and sidestep the issue of unobserved heterogeneity between the groups. Since we would like to differentiate between the treatment effects on the close versus farther neighborhood of SEC detection, we look at two double differences and compare the pre-post differences of (1) the treatment group and the control group of remote firms and (2) the vicinity treatment group and the control group of remote firms. We run the following regression using data on the treatment sample and the two matched control samples:

[12]The factors are obtained from the Data Library of Kenneth French's website.

$$
\begin{aligned}
runup_{i,t} = {} & \beta_0 + \beta_1 \cdot vicinity\,treatment_i + \beta_2 \cdot treatment_i + \beta_3 \cdot post\,detection_{i,t} \\
& + \beta_4 \cdot post\,detection_{i,t} \cdot vicinity\,treatment_i + \beta_5 \cdot post\,detection_{i,t} \\
& \cdot treatment_i + \beta_6 \cdot surprise_{i,t} + \beta_7 \cdot analyst\,dispersion_{i,t} + \beta_8 \cdot X_{i,t},
\end{aligned} \tag{4.4.1}
$$

where $runup_{i,t}$ is the abnormal return of the firm's stock prior to the announcement of the earnings announcement of firm i in quarter t. It aims at capturing the extent of trading ahead of the upcoming earnings announcement. For the observations in which the analyst forecasts fall short of the actual earnings (negative surprises), we reverse the sign of the abnormal return. The dummy variable *vicinity treatment* is equal to 1 if the firm was subject to a detection event or if the firm is a matched industry peer. In other words, it is equal to 0 for the matched control firms in remote industries and 1 otherwise. The dummy variable *treatment* denotes a subset of *vicinity treatment*. It is set to 1 only if there is a detection event in the firm. The dummy variable *post detection* is set to 1 if the earnings announcement occurs after a detection event in the stock or 0 otherwise. We control for various other factors which are expected to affect the runup prior to an earnings announcement. The size of the runup is likely to depend on the information content of the earnings announcement. *Surprise* is the absolute difference between the actual earnings and the median forecast scaled by the share price. The variable controls for market anticipation and provides for an event-specific measure of asymmetric information with respect to the information content of the earnings announcement. We also control for the dispersion of analyst forecasts. The variable *analyst dispersion* is equal to the standard deviation of analyst forecasts. The higher the dispersion, the more uncertainty is there in the market regarding the upcoming earnings announcement. X stands for the vector of firm- and time-specific control variables. As control variables we use firm size (natural logarithm of market capitalization), Tobin's Q, R&D expenditures and return on assets. We also add firm-fixed effects to the model later. Thereby, we measure how the regression coefficients are driven by the variation over time within a given firm. When including firm-fixed effects we have to drop the variables *vicinity treatment* and *treatment* from the model specification because those variables are perfectly collinear to the firm intercepts. Standard errors are clustered at the firm level. Except for dummy variables, all independent variables are standardized.

Table 4.5 displays the conditionals mean estimates from the difference-in-differences regression model. The sum $\beta_0 + \beta_1 + \beta_2 + \beta_3 + \beta_4 + \beta_5$ denotes the average runup for firms in the treatment group (i.e., detection targets) in the post detection period, while $\beta_0+\beta_1+\beta_2$ is the average runup for this group in the pre detection period. Hence, the pre-post difference between those average runups is $\beta_3 + \beta_4 + \beta_5$. The equivalent pre-post difference for the control group is β_3 $(= \beta_0 + \beta_3 - \beta_0)$. The double difference for the treatment effect of SEC detection is the difference between those pre-post differences, i.e., $\beta_4 + \beta_5$. In an analogous manner, the double difference with respect to the treatment effect on the farther vicinity of the detection target is β_4. The main coefficients of interest are, hence, β_4 and β_5. They test the main hypothesis that a detection event deters insider trading in the neighborhood of the firm. The coefficient β_4 captures the extent to which insider trading is deterred at the detection firm and peers in the same industry. However, the coefficient β_5 tests whether there is an additional deterrent effect at the level of the firm with the detection event. If there are spillover effects on industry peers, we expect β_4 to be negative and significant. If the deterrent effect for the detection firm is more pronounced as compared to the effect on industry peers, we expect a negative and significant β_5. If a detection event only impacts subsequent insider trading at the firm level, we expect β_4 to be insignificant and β_5 to be negative and significant.

Table 4.5: Conditional mean estimates from the difference-in-differences regression model

	Post detection	Pre detection	Difference
Treatment	$\beta_0 + \beta_1 + \beta_2 + \beta_3 + \beta_4 + \beta 5$	$\beta_0 + \beta_1 + \beta_2$	$\beta_3 + \beta_4 + \beta_5$
Vicinity treatment	$\beta_0 + \beta_1 + \beta_3 + \beta_4$	$\beta_0 + \beta_1$	$\beta_3 + \beta_4$
Control	$\beta_0 + \beta_3$	β_0	β_3
Difference treatment - control	$\beta_2 + \beta_4 + \beta_5$	β_2	$\beta_4 + \beta_5$
Difference vicinity treatment - control	$\beta_1 + \beta_4$	β_1	β_4

This table illustrates the conditional mean estimates of the difference-in-difference regression. This table is based on Roberts and Whited (2011), p. 39.

4.5 Empirical results

4.5.1 Impact of detection

Table 4.6 shows the results for the difference-in-differences regressions. Model (1) regresses runups on the difference-in-differences indicators, the earnings surprise and the dispersion of analyst forecasts. Model (2) adds control variable, whereas Model (3) additionally includes firm-fixed effects.

The results of Models (1), (2) and (3) show that a detection event reduces runups only with respect to treatment firms or firms in their neighborhood, but not with respect to remote firms. The coefficient of *post detection* is insignificant, while the one of *post detection* $*$ *vicinity treatment* is negative and statistically significant at the 1% level. The effect is also economically significant: It varies from -0.6% to -0.7%. However, the insignificance of the variable *post detection* $*$ *treatment* indicates that the detection effect on treatment firms does not differ from the effect on peers. These findings suggest that a detection event significantly reduces insider trading in the vicinity of the detection target. The spillover effect on industry peers is apparently strong, as this effect is statistically indistinguishable from the immediate effect in the same firm. The positive and significant coefficient of the dummy variable *vicinity treatment* indicates, that firms with a detection event and their peers have higher runups on average. However, the insignificant coefficient of *treatment* suggests that there is not any significant difference between the detection targets and their peers regarding the overall level of runups.

In Models (4) and (5) we look at positive and negative earnings surprises separately. A positive (negative) earnings surprise is an earnings announcement which beats (falls short of) the analyst forecast consensus which is defined as the median of the forecasts.[13] The runups for negative surprises have been multiplied with (-1), so we expect the independent variables to affect the runups in the same direction as compared to positive surprises. We observe that there is a significant deterrent effect with respect to positive surprises, but there is no effect on negative surprises. The positive coefficient of *post detection* in Model (4) indicates that runups of positive surprises are slightly higher for all three groups in the post detection period. The deterring effect of detection on detection targets and their peers is -0.9%. According to the results in Model (5) a detection event does not significantly affect insider trading prior to negative earnings announcements.

Models (6) and (7) show the results with respect to two subsets of the entire sample: Model (6) tests for differences in the treatment effect of a detection event between the group of detection targets and their industry firms. Model (7) compares the treatment effect between the group of detection targets and firms in remote industries. The results of Model (6) confirm the finding stated earlier that there is no statistically significant difference in the deterrent effect of detection between detection targets and their industry peers. Model

[13] The number of observations from (4) and (5) do not add up to the number of observations in Model (3) because we do not include observations where the variable surprise is equal to zero. In addition, we use several alternative thresholds to define positive and negative surprises. The results remain robust, when we use 0.0001 (-0.0001), 0.001 (-0.001), or 0.005 (-0.005) as alternative thresholds to define positive (negative) surprises.

(7) shows that compared to matched controls in remote industries, a detection event leads to significantly smaller runups in detection targets.

The magnitude of the runup is positively related to the variable *surprise*. The variable *size* is inversely related to the magnitude of the runup. A one standard-deviation increase in the natural log of firm size decreases the runup by between 0.8% and 1.2%. The coefficient of $Tobin's\,Q$ is positively associated with the magnitude of the runup. A one standard deviation increase leads to an increase in runups by between 0.5% to 0.7%. These findings are consistent with the notion that runups are higher in firms with higher asymmetric information. The coefficient of the variable *R&D* is only statistically significant at the 10% level in Model (3). In all other 5 specifications, the coefficient fails to be significant at conventional levels. *Return on assets* is inversely related to runups.

4.5.2 Source of leakage

The strength of the deterrent effect may be affected by the source of leakage. Trading ahead of earnings announcements is likely to stem from individuals who are closely related to the firm and have regular access to material, non-public information. We hypothesize that the deterrent effect is stronger when the caught individuals are closely related to the firm in which the insider trading occurred. This argument is based on the notion that individuals use experiences from their vicinity when updating their subjective probabilities of detection (see arguments in Section 2). Moreover, shareholders might be pressing to implement measures prohibiting future information leakages when they learn that there was an internal source of leakage. The regressions in Table 4.7 aim at testing whether the deterrent effect depends on the source of leakage. We build interaction terms between the dummy variable for the source of leakage and the variables *post detection*, $post\,detection * vicinity\,treatment$ and $post\,detection * treatment$.

We include the same control variables as in the previous regressions, however, for the sake of brevity we do not report the control variables in Table 4.7. Model (1) tests for differences between the cases where information has leaked as opposed to stolen information. All coefficients of the interaction terms with *stolen* are insignificant. Apparently, there is no significant difference between cases of stolen versus leaked information with respect to the deterrent effect. Model (2) tests whether there is a difference with respect to insider trading cases based on leakage from individuals who are employed by the firm (managers or

Table 4.6: Impact on runups

Dep. var.: runup (-5,-1)	(1) Basic b/t	(2) Control variables b/t	(3) Firm-fixed effects b/t	(4) Positive surprise b/t	(5) Negative surprise b/t	(6) No distant controls b/t	(7) No close controls b/t
Post detection (d)	-0.001	0.001	0.001	0.003*	-0.001	-0.006***	0.001
	(-0.73)	(0.75)	(0.84)	(1.69)	(-0.46)	(-5.39)	(0.68)
Postdetection*vicinity treatment	-0.007***	-0.006***	-0.007***	-0.012***	-0.001		
	(-4.21)	(-3.92)	(-4.51)	(-5.78)	(-0.19)		
Postdetection*treatment	-0.000	0.001	0.001	0.002	-0.003	0.001	-0.007***
	(-0.10)	(0.68)	(0.37)	(1.17)	(-1.04)	(0.37)	(-4.19)
Vicinity treatment (d)	0.006***	0.005***					
	(3.83)	(3.40)					
Treatment (d)	-0.001	0.002					
	(-0.40)	(1.29)					
Surprise	0.009***	0.006***	0.005***	0.005***	0.005***	0.004***	0.005***
	(17.06)	(10.83)	(8.41)	(5.69)	(7.31)	(6.01)	(7.96)
Analyst dispersion	-0.001***	0.000	0.000	-0.000	0.000	0.001	-0.000
	(-3.02)	(0.21)	(0.34)	(-0.10)	(0.35)	(1.47)	(-0.26)
Size		-0.008***	-0.010***	-0.012***	-0.008***	-0.010***	-0.011***
		(-19.68)	(-11.34)	(-9.90)	(-5.27)	(-10.11)	(-9.31)
Tobin's Q		0.005***	0.007***	0.007***	0.006***	0.007***	0.006***
		(10.90)	(11.28)	(9.76)	(5.91)	(10.97)	(8.47)
R&D		0.001	-0.002*	-0.002	-0.002	-0.001	-0.001
		(1.14)	(-1.70)	(-1.32)	(-1.20)	(-1.26)	(-1.07)
Return on assets		-0.003***	-0.004***	-0.004***	-0.003**	-0.004***	-0.004***
		(-5.29)	(-4.66)	(-4.10)	(-2.22)	(-4.69)	(-4.21)
Obs	44304	43646	43646	23157	15361	29370	31377
R-squared	0.035	0.078	0.149	0.177	0.195	0.155	0.145
Adj. R-squared			0.131	0.145	0.146	0.135	0.128

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

This table shows the results of the difference-in-differences regression. Models (3) to (7) include firm-fixed effects. Standard errors are clustered at the firm level. All variables except for dummy variables are winsorized at the 2% level and standardized. The dependent variable $runup\,(-5,-1)$ is the abnormal return of the firm's stock prior to the announcement of the earnings announcement from t-5 to t-1 prior to the announcement date at t. For the observations in which the earnings fall short of the analyst forecasts (negative surprise), we reverse the sign of the abnormal return. The dummy variable $vicinity\,treatment$ is equal to 1 if there is a detection event in the firm or if the firm is a matched industry peer of a firm with a detection event. The dummy variable $treatment$ denotes a subset of $vicinity\,treatment$. It is set to 1 only if there is a detection event in the firm. The dummy variable $post\,detection$ is set to 1 if the earnings announcement occurs after a detection event in the stock or 0 otherwise. $Surprise$ is the absolute difference between the actual earnings and the median forecast scaled by the share price. The variable $analyst\,dispersion$ is equal to the standard deviation of analyst forecasts. $Size$ is the natural logarithm of the market value of equity. $Tobin's\,Q$ denotes the market value of equity and debt divided by the book value of the firm's assets. $R\&D$ is R&D expenditures scaled by the book value of total assets. $Return\,on\,assets$ denotes earnings before taxes and interest before depreciation divided by the book value of total assets.

employees). The deterrent effect on the stock of a detection target is significantly stronger for cases of information leakage from the inside. The size of the incremental effect is -0.5% as suggested by the coefficient of the variable $post\,detection * treatment * stolen$. In total, the deterrent effect on detection targets is -1.3% as opposed to -0.8% for industry peers. However, this difference is only statistically significant at the 10% level.[14]

Model (3) tests the deterrent effect of cases involving professional service firms. We do not find any significant impact of the involvement of professional service firm employees on the deterrent effect with respect to detection targets or their peers. Model (4) tests whether there are differences between cases of crime of opportunity versus organized crime, i.e., cases where there has been trading on inside information with at least three different firms). The findings suggest that there is no significant differences among these two sources. In sum, there is only weak evidence that the source of leakage has an impact on the magnitude of the deterrent effect. The deterrent effect on the detection target seems to be slightly larger for episodes involving inside leakage.

4.5.3 Impact of firm cross-section

The deterrent effect is likely to be stronger for firms with a high ex ante risk of insider trading. The opportunity to make profits by trading ahead of price-sensitive announcements is larger for firms with high asymmetric information. Tables 4.8, 4.9 and 4.10 test whether the deterrent effect differs with respect to firm characteristics which are likely to be associated with asymmetric information, i.e., *size*, *R&D* and $Tobin's\,Q$.

First, we test whether there is an impact of firm size on the deterrent effect. In Model (1) of Table 4.8 we interact the difference-in-difference indicators with *size*, the natural logarithm of a firm's market value of equity. Model (2) interacts the indicators with dummy variables for small and large firms. We construct these dummies as follows: We sort the observations into terciles with respect to *size*. The results of Model (1) suggests that there is not any significant linear impact of the natural logarithm of size on the deterrent effect. The findings of Model (2) indicate that the runups of small firms are slightly larger in the post detection period for all firms in the sample, as suggested by the coefficient of $post\,detection * small$. However, the remaining interaction terms with the

[14] In non-reported results, we break down the source of inside leakage further. We do not find any significant differences between the impact of employees, top managers, shareholders or directors as the source of leakage on the deterrent effect.

Table 4.7: Source of information leakage and the impact of runups

Dep. var.: runup (-5,-1)	(1) b/t	(2) b/t	(3) b/t	(4) b/t
post detection (d)	0.001	0.004*	-0.001	0.002
	(0.98)	(1.92)	(-0.48)	(1.29)
Post detection*vicinity treatment	-0.007***	-0.008**	-0.007***	-0.007***
	(-4.23)	(-2.56)	(-3.41)	(-3.08)
Postdetection*treatment	0.001	0.001	0.001	-0.000
	(0.45)	(0.55)	(0.29)	(-0.01)
Post detection*stolen	-0.002	-0.005	0.000	
	(-0.45)	(-1.06)	(0.00)	
Post detection*vicinity treatment*stolen	0.001	0.001	0.001	
	(0.16)	(0.18)	(0.13)	
Post detection*treatment*stolen	-0.002	-0.003	-0.002	
	(-0.48)	(-0.57)	(-0.42)	
Post detection*inside leakage		-0.005*		
		(-1.80)		
Post detection*vicinity treatment*inside leakage		0.000		
		(0.02)		
Post detection*treatment		-0.001		
		(-0.24)		
Post detection*profservice			0.007**	
			(2.42)	
Post detection*vicinity treatment*profservice			-0.001	
			(-0.32)	
Post detection*treatment*profservice			0.000	
			(0.02)	
Post detection*crime of opportunity				-0.002
				(-1.01)
Post detection*vicinity treatment*crime of opportunity				-0.001
				(-0.23)
Post detection*treatment*crime of opportunity				0.002
				(0.50)
Obs	46646	46646	46646	46646
R-squared	0.149	0.149	0.149	0.149
Adj. R-squared	0.131	0.131	0.131	0.131

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

This table shows the results of the difference-in-differences regression. All regressions include firm-fixed effects. Standard errors are clustered at the firm level. All variables except for dummy variables are winsorized at the 2% level and standardized. The dependent variable $runup\,(-5,-1)$ is the abnormal return of the firm's stock prior to the announcement of the earnings announcement from t-5 to t-1 prior to the announcement date at t. For the observations in which the earnings fall short of the analyst forecasts (negative surprise), we reverse the sign of the abnormal return. The dummy variable $vicinity\,treatment$ is equal to 1 if there is a detection event in the firm or if the firm is a matched industry peer of a firm with a detection event. The dummy variable $treatment$ denotes a subset of $vicinity\,treatment$. It is set to 1 only if there is a detection event in the firm. The dummy variable $post\,detection$ is set to 1 if the earnings announcement occurs after a detection event in the stock or 0 otherwise. Cases are classified as $stolen$ if the defendant has illegally gained access to the private information. $insideleakage$ denotes cases in which the trader or tipper is directly employed by the firm. $professional\,service\,firm$ includes employees of service firms with a fiduciary duty to the firm with the insider trading episode (management consulting firm, investment bank or law firm).$crime\,of\,opportunity$ if the defendants have exploited inside information with respect to one firm only. We also include the following control variables. For brevity, we do not report the variables in the table. $surprise$ is the absolute value of the difference between the actual earnings minus the median of analyst forecast scaled by the share price. $size$ is the natural logarithm of the market value of equity. $Tobin's\,Q$ denotes the market value of equity and debt divided by the book value of the firm's assets. $R\&D$ is R&D expenditures scaled by the book value of total assets. $return\,on\,assets$ denotes earnings before taxes and interest before depreciation divided by the book value of total assets. $Surprise$ is the absolute difference between the actual earnings and the median forecast scaled by the share price. The variable $analyst\,dispersion$ is equal to the standard deviation of analyst forecasts. $Size$ is the natural logarithm of the market value of equity. $Tobin's\,Q$ denotes the market value of equity and debt divided by the book value of the firm's assets. $R\&D$ is R&D expenditures scaled by the book value of total assets. $Return\,on\,assets$ denotes earnings before taxes and interest before depreciation divided by the book value of total assets.

dummies for small and large firms are all insignificant.

Second, we analyze a potential impact of R&D on the deterrent effect. In an analogous manner to the procedure above, we interact a continuous measure for R&D, the R&D expenditures scaled by total assets, with the difference-in-differences indicators as well as binary variables for low and high R&D firms. To this end, we also sort firms into terciles according to their R&D expenditures. When we include the R&D variables in the analysis, the treatment effect of detection on detection targets and their peers disappears. In Model (1) of Table 4.9, the post detection runups are significantly smaller for all firms, i.e., for detection firms, their peers and firms in remote industry. This effect seems to increase with the R&D intensity, as indicated by the interaction variable *post detection* ∗ *R&D*. In Model (2), we do not observe any significant impact of the difference-in-differences indicators or their interactions with R&D. However, in both models the effect of detection on the post detection runups of firms in the *vicinity treatment* group disappears when we include interactions with *R&D*.

Third, we investigate whether $Tobin's\,Q$ affects the deterrent effect. In Model (1) of Table 4.10 we interact $Tobin's\,Q$ with the difference-in-differences indicators. We do not observe any evidence for a linear impact of this variable on the deterrent effect. Again, we sort firms into terciles according to their $Tobin's\,Q$ and form interaction variables of the top and bottom tercile with the difference-in-differences indicators. According to the results of Model (2), the deterrent effect is less pronounced for firms with a low value of $Tobin's\,Q$. This effect applies to the group of vicinity firms, i.e., the detection targets and their industry peers. Typically those firms have small growth prospects and, as a result, a rather low degree of information asymmetry. Apparently, the deterrent effect is smaller in environments with a rather low level of asymmetric information, because the opportunities for exploiting asymmetric information are smaller as compared to firms with medium or high levels of information asymmetry.[15]

[15]When we repeat the analyses above by sorting into quintiles instead of terciles, we find similar results. The results are not reported here but available upon request.

Table 4.8: Firm size and the impact of runups

Dep. var.: runup (-5,-1)	(1) runup (-5,-1) b/t	(2) runup (-5,-1) b/t
Post detection (d)	0.001	-0.001
	(0.69)	(-0.70)
Postdetection*vicinity treatment	-0.007***	-0.006**
	(-4.38)	(-2.56)
Postdetection*treatment	-0.000	0.000
	(-0.26)	(0.13)
Post detection*size	-0.002	
	(-1.20)	
Post detection*vicinity treatment*size	0.003	
	(1.30)	
Post detection*treatment*size	0.001	
	(0.90)	
Post detection*small		0.005*
		(1.84)
Post detection*vicinity treatment*small		-0.005
		(-1.23)
Post detection*treatment*small		-0.001
		(-0.24)
Post detection*large		0.002
		(0.98)
Post detection*vicinity treatment*large		0.000
		(0.06)
Post detection*treatment*large		0.000
		(0.07)
Surprise	0.005***	0.005***
	(8.46)	(8.39)
Analyst dispersion	0.000	0.000
	(0.33)	(0.35)
Size	-0.010***	-0.010***
	(-11.38)	(-11.38)
Tobin's Q	0.007***	0.007***
	(11.27)	(11.20)
R&D	-0.002	-0.002
	(-1.56)	(-1.57)
Return on assets	-0.004***	-0.004***
	(-4.64)	(-4.67)
Obs	43646	43646
R-squared	0.149	0.149
Adj. R-squared	0.131	0.131

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

This table shows the results of the difference-in-differences regression. All Models include firm-fixed effects. Standard errors are clustered at the firm level. All variables except for dummy variables are winsorized at the 2% level and standardized. The dependent variable $runup\,(-5,-1)$ is the abnormal return of the firm's stock prior to the announcement of the earnings announcement from t-5 to t-1 prior to the announcement date at t. For the observations in which the earnings fall short of the analyst forecasts (negative surprise), we reverse the sign of the abnormal return. The dummy variable $vicinity\,treatment$ is equal to 1 if there is a detection event in the firm or if the firm is a matched industry peer of a firm with a detection event. The dummy variable $treatment$ denotes a subset of $vicinity\,treatment$. It is set to 1 only if there is a detection event in the firm. The dummy variable $post\,detection$ is set to 1 if the earnings announcement occurs after a detection event in the stock or 0 otherwise. $Size$ is the natural logarithm of the market value of equity. $Small$ ($large$) is a dummy variable which is set to 1 if the firm is in the bottom (top) tercile in terms of size. $Surprise$ is the absolute difference between the actual earnings and the median forecast scaled by the share price. The variable $analyst\,dispersion$ is equal to the standard deviation of analyst forecasts. $Tobin's\,Q$ denotes the market value of equity and debt divided by the book value of the firm's assets. $R\&D$ is R&D expenditures scaled by the book value of total assets. $Return\,on\,assets$ denotes earnings before taxes and interest before depreciation divided by the book value of total assets.

Table 4.9: R&D and the impact of runups

Dep. var.: runup (-5,-1)	(1) runup (-5,-1) b/t	(2) runup (-5,-1) b/t
Post detection (d)	-0.004**	-0.001
	(-2.23)	(-0.42)
Postdetection*vicinity treatment	-0.002	-0.004
	(-1.10)	(-1.14)
Postdetection*treatment	0.001	0.002
	(0.62)	(0.85)
Post detection*R&D	-0.009***	
	(-3.55)	
Post detection*vicinity treatment*R&D	0.004	
	(1.33)	
Post detection*treatment*R&D	0.001	
	(0.30)	
Post detection*low R&D		0.003
		(0.88)
Post detection*vicinity treatment*low R&D		0.001
		(0.19)
Post detection*treatment*low R&D		-0.002
		(-0.49)
Post detection*high R&D		-0.005
		(-0.81)
Post detection*vicinity treatment*high R&D		-0.001
		(-0.14)
Post detection*treatment*high R&D		-0.003
		(-0.67)
Surprise	0.005***	0.005***
	(8.54)	(8.40)
Analyst dispersion	0.000	0.000
	(0.28)	(0.27)
Size	-0.010***	-0.010***
	(-11.17)	(-11.24)
Tobin's Q	0.007***	0.007***
	(11.08)	(10.82)
R&D	0.000	-0.001
	(0.03)	(-1.44)
Return on assets	-0.004***	-0.004***
	(-4.48)	(-4.47)
Obs	43646	43646
R-squared	0.150	0.150
Adj. R-squared	0.132	0.132

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

This table shows the results of the difference-in-differences regression. All Models include firm-fixed effects. Standard errors are clustered at the firm level. All variables except for dummy variables are winsorized at the 2% level and standardized. The dependent variable $runup\,(-5,-1)$ is the abnormal return of the firm's stock prior to the announcement of the earnings announcement from t-5 to t-1 prior to the announcement date at t. For the observations in which the earnings fall short of the analyst forecasts (negative surprise), we reverse the sign of the abnormal return. The dummy variable *vicinity treatment* is equal to 1 if there is a detection event in the firm or if the firm is a matched industry peer of a firm with a detection event. The dummy variable *treatment* denotes a subset of *vicinity treatment*. It is set to 1 only if there is a detection event in the firm. The dummy variable *post detection* is set to 1 if the earnings announcement occurs after a detection event in the stock or 0 otherwise. *R&D* is R&D expenditures scaled by the book value of total assets. *High R&D* (*low R&D*) is a dummy variable which is set to 1 if the firm is in the top (bottom) tercile in terms of R&D expenditures. *Surprise* is the absolute difference between the actual earnings and the median forecast scaled by the share price. The variable *analyst dispersion* is equal to the standard deviation of analyst forecasts. *Size* is the natural logarithm of the market value of equity. *Tobin's Q* denotes the market value of equity and debt divided by the book value of the firm's assets. *Return on assets* denotes earnings before taxes and interest before depreciation divided by the book value of total assets.

Table 4.10: Tobin's Q and the impact of runups

Dep. var.: runup (-5,-1)	(1) runup (-5,-1) b/t	(2) runup (-5,-1) b/t
post detection (d)	0.000	0.001
	(0.04)	(0.82)
Postdetection*vicinity treatment	-0.007***	-0.010***
	(-3.76)	(-4.79)
Postdetection*treatment	0.001	0.002
	(0.40)	(0.81)
Post detection*Tobin's Q	-0.003	
	(-1.62)	
Post detection*vicinity treatment*Tobin's Q	-0.000	
	(-0.13)	
Post detection*treatment*Tobin's Q	-0.001	
	(-0.57)	
Post detection*low Q		-0.000
		(-0.22)
Post detection*vicinity treatment*low Q		0.007**
		(2.38)
Post detection*treatment*low Q		-0.002
		(-0.57)
Post detection*high Q		-0.000
		(-0.03)
Post detection*vicinity treatment*high Q		-0.001
		(-0.33)
Post detection*treatment*high Q		-0.001
		(-0.52)
Surprise	0.005***	0.005***
	(8.39)	(8.29)
Analyst dispersion	0.000	0.000
	(0.35)	(0.35)
Size	-0.010***	-0.010***
	(-10.88)	(-10.74)
Tobin's Q	0.008***	0.007***
	(11.96)	(11.28)
R&D	-0.002	-0.002
	(-1.48)	(-1.53)
Return on assets	-0.004***	-0.004***
	(-4.48)	(-4.42)
Obs	43646	43646
R-squared	0.149	0.149
Adj. R-squared	0.132	0.131

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

This table shows the results of the difference-in-differences regression. All Models include firm-fixed effects. Standard errors are clustered at the firm level. All variables except for dummy variables are winsorized at the 2% level and standardized. The dependent variable $runup\,(-5,-1)$ is the abnormal return of the firm's stock prior to the announcement of the earnings announcement from t-5 to t-1 prior to the announcement date at t. For the observations in which the earnings fall short of the analyst forecasts (negative surprise), we reverse the sign of the abnormal return. The dummy variable $vicinity\,treatment$ is equal to 1 if there is a detection event in the firm or if the firm is a matched industry peer of a firm with a detection event. The dummy variable $treatment$ denotes a subset of $vicinity\,treatment$. It is set to 1 only if there is a detection event in the firm. The dummy variable $post\,detection$ is set to 1 if the earnings announcement occurs after a detection event in the stock or 0 otherwise. $Tobin's\,Q$ denotes the market value of equity and debt divided by the book value of the firm's assets. $High\,Tobin's\,Q$ ($low\,Tobin's\,Q$) is a dummy variable which is set to 1 if the firm is in the top (bottom) tercile in terms of $Tobin's\,Q$. $Surprise$ is the absolute difference between the actual earnings and the median forecast scaled by the share price. The variable $analyst\,dispersion$ is equal to the standard deviation of analyst forecasts. $Size$ is the natural logarithm of the market value of equity. $R\&D$ is R&D expenditures scaled by the book value of total assets. $Return\,on\,assets$ denotes earnings before taxes and interest before depreciation divided by the book value of total assets.

4.6 Robustness

4.6.1 Fraction as an alternative measure

We use an alternative approach to measure insider trading prior to earnings announcements. As an alternative measure for information leakage prior to the public announcement we calculate the variable $fraction$ as the runup prior to the announcement (CAR(-10,-1)/CAR(-10,2)), similar to the approach by Ackerman et al. (2008). This variable seeks to measure the fraction of information which has been impounded into prices before the announcement relative to the total price effect of the earnings announcements. When fraction is smaller than 0, we set it to 0 and when it is larger than 1, we set it equal to 1. The rationale for this robustness check stems from the critique that the observed deterrent effect may not be due to less insider trading activity, but due to a smaller information content of earnings announcements in general. Scaling the runup by a measure for the overall information content, which in our case is approximated by the abnormal return in the time window from -10 to 2 days around the earnings announcement, addresses this objections.

Table 4.11 shows the results from the regressions. We use the same model specifications as before with the difference-in-differences indicators, characteristics of the earnings announcement and firm characteristics as independent variables. We merely exchange the dependent variable and use $fraction$ instead of the runup. The coefficient of the variable $post\,detection * vicinity$ is negative and statistically significant. The effect remains robust to the inclusion of control variables in Model (2) and the inclusion of firm-fixed effects in Model (3). Post detection the fraction of the market response impounded already before the announcement is reduced by between -3.6% and -3.1%. This effect prevails for the stock of the detection firm as well as the stocks of firms in the direct neighborhood, that is industry peers. There is no significant difference between the direct effect on the detection and the indirect spillover effect on peers.

4.6.2 Alternative pre-event windows

We use alternative event windows prior to the earnings announcement day to calculate the runup: (-10,-1), (-3,-1) and (-2,-1). Table 4.12 reports the results of the main regression with firm-fixed effects for these alternative event windows. In sum, the results remain

Table 4.11: Information impounded before the announcement

Dep. var.: Fraction of runup	(1) Pooled b/t	(2) Pooled b/t	(3) Pooled b/t
Post detection (d)	-0.053***	-0.053***	-0.041***
	(-5.43)	(-5.43)	(-3.71)
Postdetection*vicinity treatment	-0.036***	-0.031**	-0.031**
	(-2.59)	(-2.22)	(-2.17)
Postdetection*treatment	0.004	0.002	0.016
	(0.29)	(0.13)	(1.20)
Vicinity treatment (d)	0.023**	0.025**	
	(2.39)	(2.46)	
Treatment (d)	0.004	0.013	
	(0.46)	(1.37)	
Surprise	0.018***	0.009***	-0.005
	(5.32)	(2.67)	(-1.59)
Analyst disperson	-0.003	-0.002	-0.002
	(-1.49)	(-0.72)	(-0.94)
Size		-0.019***	-0.101***
		(-5.30)	(-13.56)
Tobin's Q		-0.004	0.025***
		(-1.39)	(6.38)
R&D		-0.004	-0.017**
		(-0.90)	(-2.40)
Return on assets		-0.015***	0.004
		(-3.85)	(0.74)
Obs	46492	45783	45783
R-squared	0.010	0.014	0.079
Adj. R-squared			0.060

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

This table shows the results of the difference-in-differences regression. Model (3) includes firm-fixed effects. Standard errors are clustered at the firm level. All variables except for dummy variables are winsorized at the 2% level and standardized. $fraction$ is defined as CAR(-10,-1) divided by CAR(-10,2). The dummy variable $vicinity\,treatment$ is equal to 1 if there is a detection event in the firm or if the firm is a matched industry peer of a firm with a detection event. The dummy variable $treatment$ denotes a subset of $vicinity\,treatment$. It is set to 1 only if there is a detection event in the firm. The dummy variable $post\,detection$ is set to 1 if the earnings announcement occurs after a detection event in the stock or 0 otherwise. $Surprise$ is the absolute difference between the actual earnings and the median forecast scaled by the share price. The variable $analyst\,dispersion$ is equal to the standard deviation of analyst forecasts. $Size$ is the natural logarithm of the market value of equity. $Tobin's\,Q$ denotes the market value of equity and debt divided by the book value of the firm's assets. $R\&D$ is R&D expenditures scaled by the book value of total assets. $Return\,on\,assets$ denotes earnings before taxes and interest before depreciation divided by the book value of total assets.

robust to alternative pre-event windows. The coefficient of the variable *post detection* $*$ *vicinity treatment* is statistically significant at the 1% level in all six regressions. The economic magnitude ranges from -1.1% for the (-10,-1) window to 0.5% for the (-3,-1) window.

Table 4.12: Alternative pre-event windows

Dep. var.: runup	(1) (-10,-1) b/t	(2) (-3,-1) b/t	(3) (-2,-1) b/t
Post detection (d)	0.002	-0.000	0.001
	(1.22)	(-0.09)	(0.80)
Postdetection*vicinity treatment	-0.011***	-0.005***	-0.006***
	(-4.74)	(-3.93)	(-5.09)
Postdetection*treatment	0.003	0.001	0.002**
	(1.18)	(0.49)	(2.05)
Surprise	0.008***	0.004***	0.003***
	(10.80)	(8.67)	(8.30)
Analyst dispersion	-0.000	0.000	-0.000
	(-0.48)	(0.01)	(-0.46)
Size	-0.013***	-0.009***	-0.008***
	(-9.97)	(-11.49)	(-12.93)
Tobin's Q	0.009***	0.006***	0.005***
	(10.81)	(12.87)	(13.42)
R&D	-0.003**	-0.002**	-0.002***
	(-2.04)	(-2.14)	(-3.45)
Return on assets	-0.007***	-0.003***	-0.003***
	(-5.43)	(-4.95)	(-5.85)
Obs	43645	43649	43650
R-squared	0.153	0.148	0.146
Adj. R-squared	0.135	0.130	0.128

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

This table shows the results of the difference-in-differences regression. All Models include firm-fixed effects. Standard errors are clustered at the firm level. All variables except for dummy variables are winsorized at the 2% level and standardized. The dependent variable *runup* is the abnormal return of the firm's stock prior to the announcement of the earnings announcement over different windows prior to the announcement date at t: from t-10 to t-1, t-3 to t-1 and t-2 to t-1. For the observations in which the earnings fall short of the analyst forecasts (negative surprise), we reverse the sign of the abnormal return. The dummy variable *vicinity treatment* is equal to 1 if there is a detection event in the firm or if the firm is a matched industry peer of a firm with a detection event. The dummy variable *treatment* denotes a subset of *vicinity treatment*. It is set to 1 only if there is a detection event in the firm. The dummy variable *post detection* is set to 1 if the earnings announcement occurs after a detection event in the stock or 0 otherwise. *Surprise* is the absolute difference between the actual earnings and the median forecast scaled by the share price. The variable *analyst dispersion* is equal to the standard deviation of analyst forecasts. *Size* is the natural logarithm of the market value of equity. $Tobin's\,Q$ denotes the market value of equity and debt divided by the book value of the firm's assets. *R&D* is R&D expenditures scaled by the book value of total assets. *Return on assets* denotes earnings before taxes and interest before depreciation divided by the book value of total assets.

4.6.3 Excluding acquired firms

In several cases, the firm on whose stock the insider trading occurred is acquired by another firm in between the insider trading event and the detection. Earnings announcement runups cannot be calculated if the stock has been delisted. Instead, in the analyses above we include the acquiring firm in the sample and compare their earnings announcement runups before and after the detection event. In Model (1) of Table 4.13 we exclude the cases of acquired firms. The results are very similar to the basic results. The coefficient of the dummy $post\, detection * vicinity\, treatment$ is -0.7% and is statistically significant at the 1% level.

4.6.4 Excluding M&A or fraud

In Model (2) of 4.13 we exclude the cases from the sample where the insider trade took place in advance of the announcement of M&A events. Model (3) excludes cases of trading ahead of the announcement of corporate fraud. The deterrent effect of detection on detection targets and their peers remains robust to these subsamples.

4.6.5 Alternative control sample

In the basic specifications, we only include one matched control firm for each treatment firm. In Model (4) we include up to 3 control firms from the same industry (according to the 3-digit SIC code). From the 10 firms in the same 3-digit SIC code, we pick up to 3 firms (if available) which are closest in terms of book-to-market ratio. The results remain robust to this alternative specification. In Model (5) we select the matched sample of industry peers using a slightly altered matching algorithm. We select the closest firm in terms of book-to-market ratio from the five firms which are closes in terms of size. The main effect also prevails in this sample.

4.6.6 Minimum number of analysts

Lastly, Model (6) of Table 4.13 only includes earnings announcements in the sample where there are at least 5 analyst forecasts for the quarterly earnings announcement available. The precision of analyst consensus as a proxy for market expectations is likely to increase with the number of analysts who are analyzing the firm and issuing forecasts. The results remain robust to this subsample. The results also remain robust to different thresholds which are not reported here, such as 3 or 7 analyst forecasts.

Table 4.13: Alternative robustness checks

Dep. var.: runup (-5,-1)	(1) Excl. acquired b/t	(2) Excl. fraud b/t	(3) Excl. M&A b/t	(4) Up to 3 controls b/t	(5) Alternative matching b/t	(6) Min. 5 analysts b/t
Post detection (d)	0.001	0.001	0.001	0.001	0.001	-0.002
	(0.68)	(0.71)	(0.69)	(0.86)	(0.63)	(-0.84)
Postdetection*vicinity treatment	-0.007***	-0.007***	-0.009***	-0.007***	-0.009***	-0.006*
	(-4.07)	(-4.21)	(-4.61)	(-4.75)	(-4.25)	(-1.73)
Postdetection*treatment	-0.002	0.001	0.001	0.000	0.002	0.002
	(-0.88)	(0.45)	(0.49)	(0.09)	(1.06)	(0.72)
Surprise	0.005***	0.005***	0.004***	0.005***	0.005***	0.007***
	(7.03)	(7.78)	(5.70)	(10.13)	(9.22)	(6.39)
Analyst disperson	0.000	0.000	0.000	0.000	0.000	0.000
	(0.45)	(0.55)	(0.44)	(0.03)	(0.04)	(0.91)
Size	-0.011***	-0.010***	-0.012***	-0.011***	-0.010***	-0.008***
	(-10.32)	(-11.19)	(-10.34)	(-13.67)	(-9.69)	(-4.92)
Tobin's Q	0.007***	0.007***	0.007***	0.007***	0.006***	0.006***
	(10.30)	(11.26)	(9.09)	(13.66)	(8.68)	(6.96)
R&D	-0.002	-0.002	-0.002	-0.003***	-0.001	-0.001
	(-1.45)	(-1.56)	(-1.60)	(-3.14)	(-0.90)	(-0.34)
Return on assets	-0.003***	-0.004***	-0.003***	-0.004***	-0.004***	-0.004***
	(-3.45)	(-4.74)	(-3.57)	(-5.58)	(-4.29)	(-3.49)
Obs	35379	43698	29994	64378	40316	22758
R-squared	0.149	0.148	0.146	0.147	0.150	0.156
Adj. R-squared	0.130	0.130	0.127	0.129	0.132	0.131

t statistics in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

This table shows the results of the difference-in-differences regression. All Models include firm-fixed effects. Standard errors are clustered at the firm level. All variables except for dummy variables are winsorized at the 2% level and standardized. The dependent variable $runup\,(-5,-1)$ is the abnormal return of the firm's stock prior to the announcement of the earnings announcement from t-5 to t-1 prior to the announcement date at t. For the observations in which the earnings fall short of the analyst forecasts (negative surprise), we reverse the sign of the abnormal return. The dummy variable $vicinity\,treatment$ is equal to 1 if there is a detection event in the firm or if the firm is a matched industry peer of a firm with a detection event. The dummy variable $treatment$ denotes a subset of $vicinity\,treatment$. It is set to 1 only if there is a detection event in the firm. The dummy variable $post\,detection$ is set to 1 if the earnings announcement occurs after a detection event in the stock or 0 otherwise. $Surprise$ is the absolute difference between the actual earnings and the median forecast scaled by the share price. The variable $analyst\,dispersion$ is equal to the standard deviation of analyst forecasts. $Size$ is the natural logarithm of the market value of equity. $Tobin's\,Q$ denotes the market value of equity and debt divided by the book value of the firm's assets. $R\&D$ is R&D expenditures scaled by the book value of total assets. $Return\,on\,assets$ denotes earnings before taxes and interest before depreciation divided by the book value of total assets.

4.7 Discussion

4.7.1 Mechanical relationship

One may object that the observed drop in the post detection runups is purely mechanical for the following reason: It could be argued that the pre detection runups are greater simply because they include the insider trading episode. First, a pure mechanical relationship is unable to explain why we observe a significant drop in the runups of industry peers. Second, if this criticism holds and the observed relationship was purely mechanical, then the effect would disappear if we exclude the runups from insider trading episodes from our sample. Only 23.1% of the insider trading episodes in our sample include earnings announcements as the event on which material, non-public information has been exploited. In Table 4.14 we report the results of the difference-in-differences regression in which we exclude all insider trading episodes involving earnings announcements.[16] The results suggest that the treatment effect on detection targets and their industry peers persists in this subsample. This finding casts doubt on the objection that the treatment effect is purely mechanical.

4.7.2 Alternative explanations

The main hypothesis developed in Section 2 is that a reduction in trading ahead of earnings announcements is caused by the update of subjective detection probabilities of individuals with access to private information. One could argue that there are alternative factors which drive the main findings. SEC detection could raise the shareholders' concerns about adverse selection costs. As a consequence, they could exert pressure on the management to improve efforts to prevent the exploitation of inside information. There are two ways in which firms could respond to those demands: improve the dissemination of information to the market or improve internal compliance mechanisms.

After a detection event firms may improve their disclosure of information to the market which leads to more accurate prices to begin with. Under this assumption, the decrease in the price runups is due to more informative prices. First, although the channel through

[16] It would actually be sufficient to exclude the runups for the quarterly earnings announcement which were involved in a detected insider trading episode. However, the SEC litigation releases do not always provide precise information about the respective quarter. As an alternative approach, we therefore eliminate all observations (detection firms and also their matched control firms) for which the respective insider event type is earnings announcements.

Table 4.14: Impact on runups excluding earnings announcements

Dep. var.: runup (-5,-1)	(1) b/t
Post detection (d)	0.001
	(0.58)
Postdetection*vicinity treatment	-0.006***
	(-3.42)
Postdetection*treatment	0.000
	(0.13)
Surprise	0.005***
	(7.78)
Analyst disperson	0.000
	(0.32)
Size	-0.010***
	(-9.83)
Tobin's Q	0.006***
	(8.99)
R&D	-0.001
	(-1.12)
Return on assets	-0.004***
	(-3.96)
Obs	32446
R-squared	

t statistics in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

This table shows the results of the difference-in-differences regression. The Model includes firm-fixed effects. Standard errors are clustered at the firm level. All variables except for dummy variables are winsorized at the 2% level and standardized. The dependent variable $runup\,(-5,-1)$ is the abnormal return of the firm's stock prior to the announcement of the earnings announcement from t-5 to t-1 prior to the announcement date at t. For the observations in which the earnings fall short of the analyst forecasts (negative surprise), I reverse the sign of the abnormal return. The dummy variable *vicinity treatment* is equal to 1 if there is a detection event in the firm or if the firm is a matched industry peer of a firm with a detection event. The dummy variable *treatment* denotes a subset of *vicinity treatment*. It is set to 1 only if there is a detection event in the firm. The dummy variable *post detection* is set to 1 if the earnings announcement occurs after a detection event in the stock or 0 otherwise. *Surprise* is the absolute difference between the actual earnings and the median forecast scaled by the share price. The variable *analyst dispersion* is equal to the standard deviation of analyst forecasts. *Size* is the natural logarithm of the market value of equity. $Tobin's\,Q$ denotes the market value of equity and debt divided by the book value of the firm's assets. *R&D* is R&D expenditures scaled by the book value of total assets. *Return on assets* denotes earnings before taxes and interest before depreciation divided by the book value of total assets.

which SEC detection affects insider trading is different, this alternative explanation is still consistent with the interpretation of less insider trading activity. Second, improved dissemination of information to the market implies that analysts should make more accurate forecasts. This implication is empirically testable. We compare analyst dispersion and accuracy of analyst forecasts for the vicinity treatment sample (detection targets and their industry peers) pre and post detection in Table 4.15. Post detection we observe an increase of the average number of analyst by 1.3. The difference is statistically significant at the 1%. We observe a greater dispersion among analysts' opinions after a detection event (difference in means: 1.2%). Further, analyst forecasts seem to be less accurate post detection as suggested by a significant increase in the magnitude of surprises (difference in means: 0.3%).[17] These observations cast doubt on the notion that firms have improved their communication with the market after a detection event.

Table 4.15: Analyst estimates pre and post detection

Variable	Mean	St. Dev.	Median	95% quantile	5% quantile
Panel A: vicinity treatment pre detection					
Number of analyst estimates	7.466	6.628	5	21	1
Std. dev. of estimate	0.026	0.042	0.010	0.1	0
Surprise	0.006	0.016	0.001	0.027	0
Positive surprise	0.004	0.008	0.001	0.019	0.000
Negative surprise	-0.008	0.015	-0.002	0.000	-0.052
Panel B: vicinity treatment post detection					
Number of analyst estimates	8.814	7.136	7	23	1
Std. dev. of estimate	0.038	0.051	0.020	0.15	0
Surprise	0.009	0.020	0.002	0.048	0
Positive surprise	0.006	0.009	0.002	0.030	0.000
Negative surprise	-0.012	0.018	-0.004	0.000	-0.055
Difference in means					
Number of analyst estimates	1.347***				
Std. dev. of estimate	0.012***				
Surprise	0.003***				
Positive surprise	0.002***				
Negative surprise	-0.004***				

This table shows descriptive statistics of analyst estimates of quarterly earnings announcement for the sample of firms with detection events before and after the detection event. *Number of analyst estimates* is the number of analysts who issue a forecast for a quarterly earnings announcement. *Analyst dispersion* is the standard deviation of the analyst forecasts with respect to one earnings announcement. *surprise* is the absolute value of the difference between the actual earnings minus the median of analyst forecast scaled by the share price. *Positive surprise* (*negative surprise*) is the difference between the actual earnings minus the median of analyst forecasts scaled by the share price if the difference is strictly positive (negative). *, **, *** denote statistical significance at the 10%, 5% or 1% level respectively based on a t-test with unequal variances.

[17] When we compare the figures for the treatment group, we find comparable results: The number of analysts increases by 1.4, the standard deviation of the analyst forecasts increases by 1.2% and the magnitude of surprises increases by 0.3%.

Moreover, the firm subject to a detection event could improve efforts to prevent insider trading through internal policies. Examples for better prevention are limiting the access to confidential information, requiring pre clearance of any transaction by the compliance department or increasing awareness by issuing a code of conduct. These actions are likely to lead to reductions in insider trading activities. The consequences of an update of the subjective detection probability and improved internal control mechanisms are observationally equivalent. We could disentangle these two explanations if we had information on changes in internal compliance mechanisms subsequent to the detection event. This information is not publicly available and costly to collect. Based on the analysis in this paper, we cannot disentangle an update in probabilities from improved compliance mechanisms.

4.7.3 Representativeness

One may object that trading ahead of earnings announcements is not representative for the general amount of insider trading in a given stock. We do not account for a complete picture of all insider trading activities in a given firm. Insider trading can take place well in advance of the announcement of price-sensitive information and it also can take place with respect to many different types of news events. A comprehensive analysis of insider trading based on an exhaustive set of news announcements is difficult because of the high frequency of news production. With respect to many types of those news (such as personnel changes or investment activities) it is difficult to assess the value implications ex ante and to construct a proxy for market expectations. Therefore, it is difficult to jointly analyze all different types of news announcements. Our analysis just captures a small aspect by focusing on the trading ahead in the 10 days prior to an earnings announcement.

Further, one can criticize that post detection individuals with private information trade smarter in such a way that they reduce the market impact of their transactions. E.g., the individuals who seek to exploit private information place their trades in smaller chunks or over a larger period of time. The observation of smaller runups before earnings announcement after a detection event may not be due to actual decreases insider trading but differences in the strategies to exploit insider trading. This potential change in insider trading strategies cannot be observed. Our results are, hence, limited to the finding SEC detection reduces insider trading activities prior to earnings announcements.

4.8 Conclusion

The present paper explores the consequences of the public detection of insider trading by the SEC. Using runups prior to earnings announcement as a measure of insider trading activity, we compare insider trading before and after the event of SEC detection using a difference-in-differences approach. We hypothesize that SEC detection leads to an update of the subjective probabilities of getting caught among individuals in the vicinity of the defendants. As a consequence of this update, expected cost of insider trading increase which reduces the observed level of insider trading.

In sum, we find that post detection earnings announcement runups prior are significantly lower. Subsequent to detection, runups over the time window of t-5 to t-1 around the earnings announcement are reduced by 0.7% for firms with a detection event and their industry peers. We do not find any significant difference between the impact on the detection targets and impact on their peers. There is weak empirical support that the effect on the detection targets is stronger for cases of inside leakage. This finding corroborates the hypothesis that individuals base their subjective probabilities on experiences gained by themselves and their close vicinity. The empirical results support the hypothesis that individuals with the ability to trade on private information update their subjective detection probabilities after they observe an SEC detection event in their vicinity. As a result, they are less likely to exploit their possession of material, non-public information. Our results portray a positive picture of SEC enforcement by indicating that enforcement actions against insider trading are effective in reducing future insider trading activities.

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