Information Content of Insider Trading in Germany – Three Empirical Essays

Dissertation

zur Erlangung des akademischen Grades

“Doctor Rerum Politicarum” (Dr. rer. pol.)

an der Fakultät Wirtschaftswissenschaften

der Technischen Universität Dortmund

vorgelegt von: Konstantina Fotini Kapsocavadis

geboren am: 08.12.1994 in Athen

Erstgutachterin: JProf. Dr. Nadine Georgiou

Zweitgutachterin: Prof. Dr. Christiane Pott

Datum der Einreichung: 22.06.2021

Datum der mündlichen Prüfung: 29.09.2021

Vorwort

Diese Dissertation wäre nicht möglich gewesen ohne die tatkräftige Unterstützung von wichtigen, mir nahestehenden Personen. Mein größter Dank gilt meinen Eltern Beate und Basile, die mir schon das Studium und nun die Promotion ermöglicht haben. Mir ist bewusst, dass ich mich sehr glücklich schätzen kann, Eltern wie euch zu haben. Selbstverständlich gilt mein besonderer Dank auch meinem Bruder Stefanos, für die Unterstützung und die vielen lieben Worte während der Erarbeitung meiner Dissertation. Ein ganz besonderer Dank gilt meinem Freund Kim, der mich stets aufgebaut und ermutigt hat.

Des Weiteren möchte ich mich bei meiner Doktormutter Dr. Nadine Georgiou für die Zusammenarbeit bedanken, wodurch die ersten beiden Beiträge entstanden sind.

Ich widme diese Dissertation meinen beiden Eltern:

Ευχαριστώ από καρδιάς.

Table of Content

List of Tables

List of Abbreviations

2SLS	2 Stage Least Square
AC	autocorrelation
ACF	autocorrelation function
Adj.	adjusted
ADL	autoregressive distributed lag model
AktG	Aktiengesetz
AP	affiliated person
AR	autoregression
ARIMA	autoregressive integrated moving average model
BaFin	Bundesanstalt für Finanzdienstleistungsaufsicht
CAR	cumulative abnormal return
CDAX	Composite DAX
CG	Corporate Governance
Coeff.	coefficient
CSP	Corporate Social Performance
CSR	Corporate Social Responsibility
DAX	Deutscher Aktienindex
DCGK	Deutscher Corporate Governance Kodex
Dep.	Dependent
D&O	director and officer
e.g.	exempli gratia
EB	executive board
EC	European Commission
EEC	European Economic Community
ESG	environmental, social, governance

et al.	et al
ETF	Exchange Traded Funds
ETP	Exchange Traded Product
EU	European Union
E.U.	European Union
EUR	Euro
FE	Fixed Effects
FPS	Francis, Philbrick and Schipper
FSAP	Financial Services Action Plan
F-Stat.	F-Statistics
G	governance
ISIN	International Securities Identification Number
ITA	insider trading activity
MAD	Market Abuse Directive
MAR	Market Abuse Regulation
MSCI	Morgan Stanley Capital International
MTF	multilateral trading facility
No.	Number
Obs.	observations
OLS	Ordinary Least Square
OTC	over-the-counter
OTF	organized trading facility
p.	page
PAC	partial autocorrelation
PACF	partial autocorrelation function
PDMR	persons discharging managerial responsibility

pp.	pages
Prob.	probability
p-value	probability value
SB	supervisory board
Sec.	section
SEC	Securities Exchange Commission
SOX	Sarbanes-Oxley Act
t-stat.	test-statistics
TPD	Transparency Directive
U.K.	United Kingdom
U.S.	United States
U.S.A.	United States of America
VIF	Variation Inflation Factor
WpHG	Wertpapierhandelsgesetz

List of Symbols

*	statistical significance at the 0.10 level
**	statistical significance at the 0.05 level
***	statistical significance at the 0.01 level
%	percent
&	and
α	regression cofficient
β	regression cofficient
ε	residual term
g	regression coefficient
i	firm index
j	identifier for a trade
k	time index for lag values
ln	natural logarithm
lag	lagged
m	market index
N	number of observations
p	time index for lag values
p	p-value
Q	Box-Pierce` Q statistics
R^2	coefficient of determination
t	time index
t	t-value

1. Introduction

There is a high level of attention paid to insiders' transactions because of their valuable inside information. In the context of the Covid-19 pandemic, Anginer et al. (2020) suggest that insiders successfully predicted the negative impact of the pandemic on their firms' stock prices as temporary. The reason for the substantial demand for insider trading information is that corporate insiders such as executives and directors know their firms better than an analyst ever could. Therefore, insider dealings can provide the capital market with useful information about future price movements of company shares, and in aggregate, with forecasts of future shares prices that are not available elsewhere (Anginer et al. 2020). These trades may reveal private information that is incorporated into new price quotes (Hasbrouck 1991).

Seyhun (1998) suggests that the stock price reaction subsequent to insider trades is not always conditional on a particular informational event. Rather, average market reaction following insider trading is a response to many different types of information asymmetries. Therefore, insiders' ability to time their trade may lead to abnormal returns. Moreover, Ke et al. (2003) present evidence that corporate insiders are already informed before earnings announcements are disclosed and thus may exploit their information advantage and gain abnormal returns. Campbell et al. (2021) show that abnormal insider trading activity occurs even one hour (or day) before the public release of information on potentially important corporate events.

Following prior research, the dissertation contains three studies examining first the influence of insider trading on corporate social responsibility engagement (Chapter 2), second the effect of the introduction of the Market Abuse Regulation (MAR) on the information content of insider trades (Chapter 3), and third the impact of aggregated insider trading on the predictability of market returns (Chapter 4) in Germany.

In the first paper of this dissertation "*The Effect of Insider Trading on CSR Engagement – Evidence from Germany*", we investigate the market efficiency of insider trading. We expect that if insider trades make financial markets more efficient and fairer, then firms with higher trading activity (number of insider trades, volume of trades, and number of traded shares) will exhibit higher values of corporate social responsibility performance. Several studies (see Dhaliwal et al. 2011, for an overview of CSR research) suggest that firms engaging in various CSR activities improve economic fairness and efficiency.

Consistent with Manne (1966), our results provide evidence for the market efficiency argument of insider trading activity. The coefficient estimates of all three insider-trading variables are positive and statistically significant. On the other hand, "bad" insider trading activity during the blackout period (30 days before earnings announcements) exhibits a negative association with CSR activities indicating that trades during the blackout period reduce market efficiency and fairness. After considering the timing of trading, we find evidence that executive board trades drive the negative effect of blackout dealings, whereas the positive effect of no-blackout dealings is mainly attributable to supervisory board trades. The net effect of dealings conducted by affiliated persons is positive. Further, we find that the introduction of the MAR reduces insiders' timing ability and thus the effect of bad insider trading on CSR performance. Moreover, we find potential window-dressing behavior for a subsample of firms with high levels of earnings management.

The second paper "*Information content of insider trades before and after the Market Abuse Regulation*" examines the informativeness of insider trades as captured by abnormal returns. Early studies on insider trading (Jaffe 1974, Seyhun 1986) confirm that insiders profit from their trades which implies that insider possess private information that is not impounded in stock prices at the time they trade. However, unlike Jaffe (1974), Seyhun (1986) cannot find evidence that outsiders can profit from public information about insider trading suggesting that the stock market is efficient also for insiders.

We investigate the information content of insider trading under the more timely and transparent disclosure regime introduced by the new EU Regulation on Market Abuse (MAR), Regulation, (EU) No 596/2014. Our findings indicate that abnormal returns by insider purchases are significantly lower in post-MAR versus pre-MAR period. The abnormal returns of insider sales are insignificant or significantly positive, indicating that insider sales do not include price-sensitive information. In addition, we show that mandated disclosure subsequent to MAR significantly decreases the information content of trades. The choice of trading venue (regulated market versus multilateral trading facilities and organized trading facilities) does not seem to have a different impact. However, the effect on the information content of insider trades depends on firm`s litigation risk. Only with an ex-ante high litigation risk, insiders refrain from information motivated trading resulting in a decrease of abnormal returns. Thus, the findings suggest that MAR regulation increases information transparency and discourages insider trading on private information, but the impact depends on firm`s litigation risk, high or low level of ex-ante litigation risk and on the trading venues (regulated markets versus alternative trading venues).

The third paper "*Aggregate Insider Trading Predictability and Market Returns: Evidence from German Data*", examines whether informed insider trades in aggregate predict market returns. Ahern (2020) reports that it is crucial to empirically assess which proxies for informed trading are valid. He summarizes that if material non-public information is short-lived, then autocorrelation in orders is a statistically and economically robust predictor of informed insider trading and hence for future returns. Therefore, this work employs an autoregressive framework, first introduced by Sims (1980) and used in many empirical works such as in Chowdhury et al. (1993) and in Lambe (2016) to investigate the predictive content of aggregate insider trading activity for market returns.

The findings show that aggregate insider trading predicts stock market returns, meaning that insiders have genuine market timing ability. I find that aggregate insider trading exhibits persistent and strong autocorrelation which suggests the arrival of new information to the markets and predictability in order flows of insider trading. The results suggest that insider-trading activity occurs at least three months before the change in market portfolio returns. The negative contemporaneous coefficient implies that corporate insiders reverse their trading direction after prices adjusted, which is a further evidence for the market timing ability of corporate insiders.

In sum, we find evidence that aggregate insider trading can predict market movements. The effect of aggregated insider trades to predict market prices is even higher when market transparency is stronger. Moreover, insiders' predictive ability becomes especially valuable during periods of significant market disruption such as the Covid-19 pandemic.

This dissertation contributes to current research by examining insider trading in Germany from 2004 to 2020. The first study exploits the interaction between CSR engagements and trading activities by corporate insiders and by investigating trading incentives of different insider groups like executive and supervisory board members. We confirm the positive impact of insider trades on market efficiency, however only if they occur outside the blackout period. Furthermore, the second study provides evidence that insider trades convey new information that is not inbounded in stock prices yet. However, the introduction of the MAR regulation in EU significantly decreases the information content of insider trading by enhancing information transparency and by tightening sanctions. The third study shows that aggregate insider trading is a precise indicator for future market returns, especially in periods of significant market disruption such as during the Covid-19 pandemic.

List of References

Ahern, K. R. (2020): Do Proxies for Informed Trading Measure Informed Trading? Evidence from Illegal Insider Trades, in: *The Review of Asset Pricing Studies*, 10 (3), 397–440.

Anginer, D., Donmez, A., Seyhun, N., & Zhang, R. (2020): Global Economic Impact Covid-19: Evidence from Insider Trades, *Working paper*, Simon Fraser University and University of Michigan.

Campbell, J. L., Twedt, B. J., & Whipple, B. C. (2021): Trading Prior to the Disclosure of Material Information: Evidence from Regulation Fair Disclosure Form 8-Ks, in: *Contemporary Accounting Research*, 38 (1), 412-442.

Chowdhury, M., Howe, J., & Liu, J. (1993): The relation between aggregate insider transactions and stock returns, in: *Journal of Financial and Quantitative Analysis*, 28 (1), 431-437.

Demsetz, H. (1986): Corporate Control, Insider Trading, and Rates of Return, in: *American Economic Review*, 76, 313–16.

Dhaliwal, D. S., Li, O. Z., Tsang, A., & Yang, Y. A. (2011): Voluntary nonfinancial disclosure and the cost of equity capital: The initiation of corporate social responsibility reporting, in: *The Accounting Review*, 86(1), 59-100.

Hasbrouck, J. (1991): Measuring the information content of stock trades, in: *Journal of Finance*, 46, 179-207.

Jaffe J., F. (1974): Special information and insider trading, in: *The Journal of Business*, 47(3), 410–428.

Ke, B., Huddart, S., Petroni, K. (2003): What insiders know about future earnings and how they use it: Evidence from Insider trades, in: *Journal of Accounting and Economics*, 35(3), 315-346.

Lambe, B. J. (2016): An unreliable canary: Insider trading, the cash flow hyphotesis and the financial crisis, in: *International Review of Financial Analysis*, 46, 151-158.

Manne, H.G. (1966): Insider trading and the stock market, in: *The Free Press*, New York.

Seyhun, H. N. (1986): Insiders' Profits, Costs of Trading, and Market Efficiency, in: *Journal of Financial Economics*, 16 (2), 189–212.

Seyhun, H. N. (1998): *Investment Intelligence from Insider Trading*, Cambridge, MA: MIT Press.

Sims, C. (1980): Macroeconomics and reality, in: *Econometrica*, 48 (1), 1-38.

2. The Effect of Insider Trading on CSR Engagement – Evidence from Germany

2.1 Introduction

We examine whether insiders' dealings drive corporate social responsibility (CSR) engagement. The regulatory environment of Germany allows us to analyse the trading behaviour of single insider groups and their effect on firms' CSR performance. We therefore distinguish between dealings of executive and supervisory board members as well as of their affiliated persons. Economic theory suggests that insider trading may be informative, since trades may increase the information content of capital markets (Manne, 1966; Carlton & Fischel 1983; Fernandes & Ferreira 2009). However, insider transactions may be also opportunistically motivated, if traders want to exploit their information advantage to receive abnormal gains (e.g. Sawicki & Shresha 2008; Jensen 2005; Strudler & Orts 1999; McGee 2009). Firms engaging in corporate social responsibility activities might strengthen business`s reputation and trust (Fombrun 1996; Chakravarthy et al. 2014) as well as decrease information asymmetries (Cho et al. 2013; Becchetti 2013; Dhaliwal et al. 2012). Insiders with less pronounced personal preferences regarding altruism and greed may trade more intensively and may not promote CSR activities. In this case, market efficiency and fairness would decline. However, if insiders trade in order to provide a signal about future prospects of a firm and to correct mispricing in the market, they are more inclined to engage in CSR activities, since CSR enhances information transparency and market fairness (Dhaliwal et al. 2011, 2012; Cui et al. 2015).

Prior empirical evidence shows that firms with high CSR ratings do not attempt to engage in unethical insider trading (Cui et al. 2015). Gao et al. (2014) refers on reputation motives, like social capital, whereas Lopatta et al. (2016) investigate the effect of CSR performance on asymmetric information. Both find that executives refrain from insider trading with high abnormal returns. Similarly, Lu et al. (2018) reveals a significantly negative association between CSR and insider trading for non-state-owned firms and for firms voluntarily disclosing CSR information in China. Overall, CSR consciousness seems to limit (opportunistic) insider trading and to decrease information opaqueness in the capital markets.

However, we also know from prior analytical and empirical literature that corporate insiders may influence real outcomes, by increasing production quantities (Chen & Jorgensen 2021), by disclosing more information prior trading (Bushman & Indjejikian 1995) or by strategically timing disclosure in order to increase trading profits (Cheng & Lo 2006). Moreover, Chen et al. (2013) find that insiders may put pressure on auditors for clean audit going-concern opinions after insider sales.

In order to extent previous literature on real outcomes of insider trading, we first examine whether insider trading also influences CSR engagement. In line with Bettis et al. (2000) and Cui et al. (2015), we use a non-directional measure of insider trading activity by pooling purchase and sales since we are interested in the overall level of insider trading and not in a specific trading direction. Second, we take advantage of the German two-tier board system that allows us to differentiate between dealings conducted by executive and supervisory board members as well as by persons in close relationship with these board members (affiliated persons). Prior studies reveal that insider information may also flow through social ties, like family members and friends. Karadas (2018), Koch and Westerholm (2014) and Dymke and Walter (2008) find out that affiliated persons (e.g. family members of politicians) gain significant abnormal returns. Third, we extent prior literature by examining an additional theoretical explanation, why insider trading may enhance CSR engagement. Executives might engage in CSR practices based on opportunistic incentives to cover up the impact of corporate misconduct (Hemingway & Maclagan 2004; Fritzsche 1991; Carroll 1979). We thus consider window-dressing behavior of insiders promoting CSR activities on firm level. Finally, we consider the introduction of the Market Abuse Regulation in July 2016, with announcement date in June 2014, which significantly tighten insider-trading regulation in Germany. The new regulation prohibits, among others, insider dealing during price-sensitive times (thirty days prior to earnings announcements), the so-called blackout period (Article 19 (11) MAR).

Based on the database of Director's Dealing Notification from the Federal Financial Supervisory Authority (*Bundesanstalt für Finanzdienstleistungsaufsicht, BaFin*) of Germany we investigate legal insider trading within the framework of Directive 2003/6/EC and Regulation (EU) No 596/2014 *(*Market Abuse Regulation, MAR). The final sample includes 610 firm-year observations of 90 listed firms from 2005 to 2018 in Germany.

Our findings show that insider trading increases CSR engagement, which may be explained by an information increasing motivation (outside the blackout period) of insiders. If we consider the timing of trading, we find evidence that bad insider trading (during the blackout period) decreases CSR, but only for the group of all insiders and for the executive board members. For the subgroup of supervisory board members, the coefficient is significantly positive for dealings outside the blackout period, indicating a CSR conscious behavior in line with an increase in market efficiency and fairness. Further, the analyses reveal that insider trading conducted by affiliated persons significantly increase the level of CSR performance.

However, we cannot make a statement regarding the underlying trading motivation, because after including the timing of trades the results become insignificant. After conducting several endogeneity tests, our findings remain robust.

The majority of empirical studies address insider-trading behavior in the U.S. We aim to contribute to this gap by investigating the impact of insider trading on CSR engagement in Germany. First, we investigate the change of the German securities trading regulation by the introduction of the MAR. We show that the MAR reduced the timing ability of insiders, thus mitigating the effect of bad insider trading on CSR performance by decreasing potential market inefficiency and unfairness. Second, the German two-tier board corporate governance system allows us to exploit trading incentives of different insider groups like executive and supervisory board members as well as their family members and affiliated firms. Third, we extent prior research of Cui et al. (2015), by considering an alternative explanation for a positive association between insider trading and CSR engagement. We introduce the concept of window-dressing, since prior literature suggests that executives may use the means of CSR to distract intentionally stakeholders from negative news.

The remainder of this work is organized as follows. Section 2.2 provides an overview of the insider trading legislation in Germany and the key characteristics of the German corporate governance system. Section 2.3 outlines prior literature and develops the hypotheses. Section 2.4 presents the sample selection and research design. Section 2.5 and Section 2.6 describe the univariate and multivariate as well as endogeneity-adjusted results of the empirical questions. Finally, Section 2.7 concludes the paper.

2.2 Regulatory Background

Insider Trading Regulation in Germany

Insider trading has been first regulated in the U.S. with the Securities Exchange Act of 1934 and the 1968 Williams Act Amendments. Due to this early regulation and excellent data availability, U.S. firms are prevalently examined in empirical research. In the European Union, the Directive 89/592/EEC has regulated insider trading since 1989.

It has been replaced by the Directive 2003/6/EC on insider dealing and market manipulation in 2003, which provides the basis for current domestic insider trading lation. In 1994, Germany implemented the Directive 89/592/EEC by introducing the German Securities Trading Act (*Wertpapierhandelsgesetz, WpHG*).[1] As a reaction on the Global Financial Crisis the Market Abuse Regulation (MAR) (*Regulation* (*EU*) *No 596/2014)* have been applied from July 2016, replacing the previous Market Abuse Directive 2003/6/EC (MAD). According to Section 13 WpHG (in the version applicable until 02, July, 2016) and Article 7 of MAR that replaced Section 13 WpHG insider trades denote trading activities, like selling and purchasing stocks, using private information about firms' prospects. Private information is information about not publicly reported circumstances which is expected to significantly affect the market price of the traded security paper after public announcement. Section 14 WpHG and Article 8 of MAR in combination with Article 14 of MAR prohibit insider trading on his own account or on the account of a third party. Article 19 Section 11 of MAR introduces a blackout period for the first time, which declares the prohibition of insider trading 30 days before the announcement of the interim (e.g., semi-annual) or annual financial report. The transactions reported to the *BaFin* are referred to as *legal* insider trading. In line with prior literature, only legal trading activities form the data basis of the following analyses.

Corporate Governance System in Germany

The two-tier board system is an important attribute of German listed firms, which divides management and control. It is regulated in *Aktiengesetz* (*AktG*), the German Stock Corporation Act and in *Deutscher Corporate Governance Codex (DCGK)*, the German Corporate Governance Codex. The executive board is responsible for the firms' management and for the development of

[1] Germany was the last major capital market adopting 1994 legislation prohibiting insider trading (see Pfeil 1996, p. 137). See also Bris (2005) for a comprehensive global study of insider trading regulation.

the firms' strategy as well as an appropriate risk controlling (Sec. 76 *AktG*, Figure 4.1 *DCGK*[2]). The supervisory board consists of owner and employee representatives (Sec. 96 *AktG*) that fulfill primarily a monitoring role (Sec. 111 *AktG*, Figure 5.1 *DCGK*). They further advise the executive board, oversee the accounting process as well as issue the audit assignment in order to reduce information asymmetries between management and shareholders.

Unlike the majority of the studies conducted on U.S. data, we are able to distinguish the trading activities of the executive and supervisory board members as well as of persons in close relationship with them and provide new insights into the impact of trading behavior on the level of CSR performance. The information about the insider groups are provided by the database of Director's Dealing Notification of the German Federal Financial Supervisory Authority. Thus, insider trades are defined as trading transactions of executive (EB) and supervisory board (SB) members as well as of affiliated persons of executive and supervisory board members (AP).

2.3 Literature Review and Hypothesis

Insider Trading

The costs and benefits of insider trading are widely discussed in finance and accounting research.[3] Insider trading is regarded as beneficial since it increases the information content of capital markets, improving in this way market efficiency (Manne 1966; Carlton & Fried 1983). Managers trading on private information provide a signal about the future prospects of a firm and correct mispricing in the market. As contrarian traders they trade against current investor expectations by identifying valuation errors on the market (Piotroski & Roulstone 2005).

2 The study refers to the *DCGK* of 2017, since our sample covers the years 2005 to 2018.

3 A wide literature strain deals with capital market effects of insider trading (e.g. Cornell & Sirri 1992; Aboody, Hughes, & Liu 2005; Del Brio & de Miguel 2010; Goncharov, Hodgson, Lhaopadchan, & Sanabria 2013).

Therefore, insider trading may increase the information content of stock prices (Carlton & Fischel 1983; Fernandes & Ferreira 2009).

However, insiders may strategically use their private information when trading. The underlying trading reasons may be opportunistically motivated, when traders exploit their information advantage and receive abnormal gains (e.g. Sawicki & Shrestha 2008). In line with the agency theory, insider trading moves wealth from uninformed shareholders to informed shareholders. The costly monitoring of these interest conflicts may destroy company`s value and reputation capital (Jensen 2005). In the same vein, Fernandes and Ferreira (2009) state that insider trading increases information asymmetries and may enhance adverse selection problems (Manove 1989), resulting in lower investments due to higher uncertainty risk. This decreases trading (Ausubel 1990) which is followed by a decline in liquidity (Leland 1992) and market price. The unequal access to insider information and the exploitation of private information may result in a violation of their fiduciary duty (Cui et al. 2015). According to Strudler and Orts (1999) and McGee (2009) insider trading may also encourage unethical greed and potential fraud.

Corporate Social Responsibility

CSR engagement might strengthen business`s reputation and trust, in terms of developing reputational and social capital (Fombrun 1996), reducing business`s cost and risks (Dhaliwal et al. 2011 and Dhaliwal et al. 2014), rebuild reputation e.g. after restatements (Chakravarthy et al. 2014), gaining competitive advantage, and improving business and society relations as well as reducing regulatory scrutiny (Fombrun & Shanley 1990; Maxwell et al. 2000; McWilliams et al. 2002; Carroll 2015). In this sense, also practitioners acknowledge the positive impact of CSR engagements, as Adam Friedman Associates (2012) show in a survey conducted with CSR executives at Fortune 1000 firms. Reputation plays a crucial role in the context of incomplete contracts and information asymmetries, since it may serve as an alternative mean to monitor and constrain opportunistic incentives (Klein & Leffler 1981; Kreps & Wilsong 1982). Although insider trading may be beneficial, its ethically negative connotation (Werhane 1991)[4] may damage the reputation of the company (Bettis et al. 2000) as well as the reputation of the members in the executive and supervisory board. First, the interests of executives and directors are linked to the reputation of their firm (e.g. job security, compensation, stock ownership), thus getting directly affected by negative news (Fama, 1980). In the context of CSR, executives will profit from a positive firm image (Hemingway & Maclagan 2004; Cespa & Cestone 2007). Christensen (2016) shows that CSR disclosure positively affects investors' perceptions of management intention and practice, even in cases of high-profile misconduct. Second, from an organizational point of view, the culture of a company can be characterized as a system of values describing favorable attitudes and conducts (O'Reilly & Chatman 1996).

In addition, literature suggests that CSR consiousness of firms may also be driven by the personal degree of altruism and greed of the management to behave in a social way (e.g., Benabou & Tirole 2006). According to this ethical argument, studies show that for example higher CSR commitment decreases the amount of earnings management (Kim et al. 2012), the level of tax aggressiveness (Lanis & Richardson 2012), and tax avoidance (Hoi et al. 2013). Similarily, Davidson et al. (2016) show that insiders which have a record of legal infractions exhibit a higher likelihood to trade on superior private information.

Insider Trading and Corporate Social Responsibility

Little research has been conducted on the association between insider trading and CSR performance. Cui et al. (2015) investigate the relation between CSR engagement and the number of insider transactions as well as the volume of insider transactions. Their insider group consists of managers, large shareholders (more than 10% of shares), and others who are required to report

4 See McGee (2009) and McGee and Yoon (2012) for an analysis of insider trading from an ethical point of view as well as Gaa, Nainar, and Shehata (2006), who investigate in an experimental setting whether market participants take economic decisions considering ethic factors.

their trades to the SEC. Their empirical evidence supports the fairness and ethical motives of CSR. Moreover, they find that firms with high CSR ratings do not attempt to engage in unethical or bad insider trading, in terms of insider trades executed during blackout periods. Cui et al. (2015) find also evidence for a significant reverse causal impact of insider transactions on CSR performance. Gao et al. (2014) refers on reputation motives, as social capital, suggesting that executives of CSR-conscious firms are more likely to refrain from insider trading with high abnormal returns. Consistent to prior literature, the authors assess firm`s CSR performance using a score reflecting various social ratings of social responsibility. They find that executives of firms with high CSR scores gain significantly less abnormal returns following insider trades and are less likely to trade prior to earnings announcements compared to executives of non CSR-conscious firms. Lopatta et al. (2016) investigate the association between asymmetric information of insider trading of managers as well as of directors and CSR performance in the U.S. They find that CSR practices reduce asymmetric information, increasing thereby the public available information and mitigating abnormal returns. Lu et al. (2018) reveals a significantly negative association between CSR and insider trading for non-state-owned firms and for firms voluntarily disclosing CSR information in China. Insider trading is measured by an indicator variable taking the value one if a listed company exhibits major asset reorganizations and thus generates insider information. In summary, previous empirical findings show that CSR consciousness seems to refrain from insider trading and decreases information opaqueness in the capital markets.

However, we also know from prior literature that corporate insiders affect real outcomes. Chen and Jorgensen (2021) argue that managers can influence real operating activities in way that is beneficial to them. They show based on an analytical model that managers choose higher production quantities than in case of no insider trading, resulting in lower firm profit but higher consumer surplus. With respect to voluntary disclosure, Bushman and Indjejikian (1995) show that insiders may decide to disclose information prior trading, thereby reducing information asymmetries. However, since equal access to information in the market is not achieved, insider may still exploit their information advantage. In line with this conjecture, empirical findings of Cheng and Lo (2006) indicate that insiders strategically choose disclosure by increasing disclosure of negative future forecasts in order to decrease share price. Chen et al. (2013) investigate whether managers' litigation concerns about insider selling affect the likelihood of firms receiving going-concern opinions. They find a negative relation between insider sales and auditor going-concern opinions suggesting that insiders may put pressure on auditors for clean audit going-concern opinions after insider sales.

Following the above insights that insiders are responsible for reporting choices, audit outcomes, strategical, and operational decisions, we extent previous literature on real outcomes by examining whether insider trading also influences CSR engagement. We assume that insiders with less pronounced personal preferences regarding altruism and greed may trade more intensively and not invest in CSR activities. However, if insiders trade in order to provide a signal about the future prospects of a firm and correct mispricing in the market, they are more inclined also to engage in CSR activities, since CSR enhances information transparency and market fairness.

In order to investigate these mechanisms, we try to differentiate between insider trading increasing market efficiency and insider trading decreasing market fairness. Although it is challenging, if not impossible, to capture the real underlying trading motivation of insiders, we rely on Cui et al. (2015) and define insider trading as "bad" insider trading, if the transactions have been conducted during a blackout period of thirty days before earnings announcements.[5] For the trading period before the introduction of MAR, we set the same *fictive* blackout period. The

[5] Since we do not have data about the exact time of insider trading or earnings announcement during the day, we include also the day of earnings announcement in the blackout period in order to capture likely intraday trades just before the earnings announcement and thus the possibility to gain abnormal returns.
We also verify our findings by using the (hand-collected) reporting date of the annual and the semi-annual reports for a small fraction of the sample. The positive association between trades outside the blackout period and CSR performance remain qualitatively robust. The association during blackout trades and CSR performance is negative, but not significant. Since, we replicated the analysis for a very small sample containing only 193 observations, the findings have to be interpreted with caution.

remaining transactions are assumed to enhance market efficiency and fairness. Based on this, we formulate the following hypotheses:

Hypothesis 1: If insiders are not CSR conscious and conduct transactions that make the financial market less efficient and unfair, then we expect a negative association between insider trading and CSR performance.

Hypothesis 2: If insiders are CSR conscious and conduct transactions that make information be released faster and the financial market be more efficient, then we expect a positive association between insider trading and CSR performance.

2.4 Data and Research Design

2.4.1 Sample Selection

We obtain insider trading information from the database of Director's Dealing Notification. The database contains transactions that are required to be reported to the German Federal Financial Supervisory Authority (*BaFin, Bundesanstalt für Finanzdienstleistungsaufsicht*). Moreover, insider trades which have been reported on a voluntary basis are also considered.[6] The database provides information about the company name as well as the professional and private role of the issuer (e.g. executive board member or supervisory board member), the ISIN (International Securities Identification Number), the transaction type, the transaction volume and the price, the trading venue as well as the date of trading, reporting and publishing. We collect financial statement information from Compustat.

[6] Voluntarily reported insider trades are transactions that do not exceed the total amount of EUR 5,000 until the end of the calendar year, and thus are not required to be reported to the *BaFin* (Section 15a (1) *WpHG* and Article 19 Section 8 of MAR).

We use the ESG scores of the Thomson Reuters database (former ASSET4) as a multidimensional empirical proxy of CSR performance. The ESG score is after the CSR

rating of MSCI (ESG STATS, former KLD) the most used CSR proxy in accounting and finance research (Bouten et al. 2017).

The database of Director's Dealing Notification contains 44,143 trading observations from 2005 to 2018 (Table 2.1). Consistent to Cheng and Lo (2006) as well as Huddart and Ke (2007), options are not included, since they do not capture trading incentives resulting from opportunistic or signaling purposes. Moreover, transaction types other than sales and purchases (e.g. capital increases and gifts) are also eliminated. In line with Stotz (2006), penny stocks[7] are excluded because they include noise (Conrad & Kaul 1993). After eliminating missing values, foreign trades[8], transactions with currencies other than Euro as well as implausible values with regard to trading, publishing and reporting day 29,548 observations and 869 companies remain. In line with Betzer & Theissen (2009), we further eliminate 305 block trades defined as insider trades with a volume larger than 5% of the shares outstanding.

For the purpose of our analyses, we summed up insider trading transactions on firm and year level. The resulting 2,740 firm-year observations contain the accumulated value of insider trades independent of the transaction type (sale or purchase). After eliminating missing values for defining the control variables and the CSR performance and after excluding financial institutes, the final sample consists of 610 firm-year observations (90 firms) for the period from 2005 to 2018 (Table 2.1). In order to distinguish between information increasing and bad insider trading, we add the earnings announcement date provided by Datastream (Refinitiv). Due to several missing data

7 Penny stocks are stocks with a market price below EUR 1 on the day of the transaction.

8 Transactions with foreign ISINs are excluded to prohibit a probable confounding effect due to a foreign legal environment.

values, the sample size reduces to 575 firm-year observations for the models including the blackout period.

Table 2.1 Sample Selection

Data Selection	Excluded Observations	Remaining Observations	Remaining Firms
Insider trades from 2005 to 2018		44,143	1,164
Less insider trades that are not sales or buys of shares	6,471	37,672	1,020
Less missing ISINs and foreign trades	5,335	32,337	908
Less currency other than Euro	612	31,725	908
Less implausible values regarding the date of trading, reporting and publishing	174	31,551	904
Less penny stocks	1,858	29,693	872
Less missing, values of price and number of shares	145	29,548	869
Control Variables/Dependent Variable merging	**Excluded Observations**	**Remaining Observations**	**Remaining Firms**
Less missing data in Compustat/Datastream	8,805	20,743	574
Less block trades and currency other than Euro (insider trades on transaction level)	305	20,438	469
Insider trades calculated on firm-year level	**17,698**	**2,740**	**469**
Less missing values for CSR performance on firm-year level	2,045	695	111
Less financial institutes	85	610	90
Final sample on firm-year level		**610**	**90**

2.4.2 Research Design

Similar to Cui et al. (2015), we run the following model to estimate the impact of insider trading behavior on CSR performance:

$$CSR\_PERF_{i,t} = \alpha_0 + \beta_1\, VOL_{i,t}/SHARES_{i,t}/FREQ_{i,t} + \beta_2\, SIZE_{i,t} + \beta_3\, RETURN_{i,t} + \beta_4\, DUMMYRNDR_{i,t} + \beta_5\, LEV_{i,t} + \beta_6\, ANALYST_{i,t} + \varepsilon_{i,t}. \quad (1)$$

We use the natural logarithm of the volume, the number of insider shares, and the frequency of insider transactions (Cheng & Lo 2006) because insider-trading measures are highly skewed. VOL is measured by the ln of (1 + annual Euro volume of insider transactions), SHARES is measured by the ln of (1 + annual number of insider shares traded) and FREQ is measured by the ln of (1 + annual number of insider transactions). We thereby differentiate between the volume, the shares and the frequency of insider trading conducted by the executive board (VOL_EB, SHARES_EB, FREQ_EB), the supervisory board (VOL_SB, SHARES_SB, FREQ_SB), and affiliated persons to executive and supervisory board members (VOL_AP, SHARES_AP, FREQ_AP). Because the number of persons affiliated to executive board members is too small (about 33%), we summarize these traders in one group with persons affiliated to supervisory board members. CSR performance (CSR_PERF) is defined by the ESG Score of the Thomson Reuters database (former ASSET4) that describes company’s ESG performance based on publicly disclosed data.

We defined the subsequent control variables at the end of fiscal year *t* (see appendix 2.1). In line with Jo and Harjoto (2011, 2012), we specify CSR_PERF as a function of firm size (SIZE), risk (RETURN), leverage (LEV) and the R&D expenditure ratio (DUMMYRNDR). The R&D expenditures are defined by an indicator variable taking the value 1 if expenditures are reported and 0 otherwise (Abody et al. 2000). In line with Jo and Harjoto (2012), we include analyst following (ANALYST) to control for external monitoring by analysts that may alleviate managerial myopia. This may enhance the long-term perspective of management and result in more active CSR engagement. The coefficient of interest is β_{1}, which indicates the impact of the volume, the traded shares and the frequency of insider trading conducted by executive and supervisory board members as well as by affiliated persons on CSR performance.

2.5 Descriptive Statistics and Univariate Analysis

Table 2.2 reports the summary statistics for the dependent and independent variables. These values include insider sales as well as purchases. For the whole sample the mean trading volume amounts to EUR 1,024,791. The median number of shares traded is 26,108, whereas the median insider trading frequency is about 6 times per year. The results of the insider trading activity of affiliated persons are particularly interesting. About 65% of the insider transactions are conducted by persons in close relationships with supervisory board members, whereas only 35% of the transactions refer to affiliated persons of executive board members. The average firm has total assets of about EUR 9,414 million and leverage (LEV) of about 87%. The mean number of analysts following is 24 and the mean firm’s return is about 11% similar to Schmidt et al. (2015). The average CSR performance amounts to about 61.

Table 2.2 Descriptive Statistics

Regression Variables					
Variable	Mean	Standard deviation	25% quartile	Median	75% quartile
CSR_PERF	61.47	17.29	48.49	65.05	75.48
VOL: ln (1+insider trading volume in EUR)	13.84	2.27	12.34	13.66	15.36
VOL: insider trading volume in EUR	1,024,791	-	228,661	855,978	4,685,578
VOL_EB	13.27	1.77	12.11	13.14	14.56
VOL_SB	12.06	2.04	10.70	11.90	13.25
VOL_AP	13.84	3.12	11.29	13.68	16.28
SHARES	10.32	2.33	8.77	10.17	11.82
number of shares traded	30,333	-	6,438	26,108	135,944
SHARES_EB	9.75	1.77	8.52	9.72	11.00
SHARES_SB	8.42	2.18	7.90	8.37	9.73
SHARES_AP	10.31	3.51	7.50	10.13	13.13
FREQ	1.86	0.82	1.10	1.80	2.40
insider trading frequency	6.42	-	3.00	6.05	11.02
FREQ_EB	1.60	0.71	1.10	1.61	2.08
FREQ_SB	1.26	0.60	0.69	1.10	1.61
FREQ_AP	1.42	0.86	0.69	1.10	1.80
SIZE: ln (total assets in EUR 1,000,000)	9.15	1.54	7.99	8.89	10.27
SIZE: total assets in EUR 1,000,000	9,414	-	2,951	7,259	28,853
RETURN in %	10.89	37.15	-11.84	8.03	34.12
D_R&D	0.78	0.42	1	1	1
LEV	0.87	1.01	0.34	0.65	1.07
ANALYST	23.90	8.76	18	25	30
GROWTH	2.45	1.96	1.24	1.97	2.88
ROE	0.11	0.14	0.07	0.12	0.17
ROA	0.04	0.05	0.01	0.04	0.06
DACC_SIZE	-0.002	0.08	-0.04	-0.005	0.03
DACC_IND	-0.002	0.08	-0.04	-0.007	0.03

For a definition of variables see Table 2.1 in the appendix. All variables are winsorized at the 1% and 99% percentiles. The number of firm-year observations is 610. The subsample with executive board trades includes 435 firm-years, with supervisory board trades 385 firm-years, and with persons in close relationship with board members 211 firm-years.

Table 2.3 Pearson Correlations

		1	2	3	4	5	6	7	8	9
1	CSR_PERF	1.0000								
2	VOL	0.1298 (0.0013)	1.0000							
3	SHARES	0.0517 (0.2023)	0.9288 (0.0000)	1.0000						
4	FREQ	0.0695 (0.0864)	0.5943 (0.0000)	0.5744 (0.0000)	1.0000					
5	SIZE	0.5856 (0.0000)	0.0268 (0.5087)	-0.0329 (0.4178)	0.0757 (0.0616)	1.0000				
6	RETURN	-0.0910 (0.0246)	0.0226 (0.5775)	0.0160 (0.6942)	-0.1088 (0.0071)	-0.0832 (0.0398)	1.0000			
7	LEV	0.0623 (0.1244)	0.0409 (0.3136)	0.1099 (0.0066)	0.0705 (0.0820)	0.2684 (0.0000)	-0.0403 (0.3201)	1.0000		
8	D_R&D	0.2652 (0.0000)	-0.0793 (0.5405)	-0.1432 (0.0004)	-0.0529 (0.1917)	0.1513 (0.0002)	-0.0271 (0.5036)	-0.1654 (0.0000)	1.0000	
9	ANALYST	0.4503 (0.0000)	0.0220 (0.5877)	-0.0266 (0.5127)	0.0228 (0.5744)	0.5220 (0.0000)	-0.0232 (0.5674)	-0.0526 (0.1949)	0.2799 (0.0000)	1.0000

For a definition of variables see Table A1 in the appendix. All variables are winsorized at the 1% and 99% percentiles. The number of firm-year observations is 610. Numbers in parentheses indicate p-values.

Pearson pair-wise correlations[9] of Table 2.3 indicate that the variable CSR_PERF is significantly positively correlated (1% significance level) with insider trading volume. The association with insider trading frequency is also positive and statistically significant. The correlation of traded shares and CSR performance is though positive but not significant. The results remain robust if we consider high values of insider trading volume, traded shares, and frequency. The correlations do not indicate severe multicollinearity. One of the highest correlations are between the variables SIZE and ANALYST (corr. = 0.5220) as well as SIZE and CSR_PERF (corr. = 0.5856).

2.6 Multivariate Results

2.6.1 Basic Regression: The Effect of Insider Trading on CSR Engagement

The following models are estimated using ordinary least-squares (OLS) regressions with industry and year fixed effects. The standard errors are adjusted for heteroscedasticity and clustered at firm level. All variables are winsorized at the 1st and 99th percentiles.

The results of Table 2.4 Column 1 show that higher insider trading volume significantly increases the level of CSR performance. We obtain robust results when using as alternative measures for insider trading the number of traded shares (SHARES, Table 2.4, Column 4) as well as the frequency of insider dealings (FREQ, Table 2.4, Column 7). The adjusted R^2 is about 45 % and the VIF is about 2.05 for all three measures. After introducing a one-year time lag for the directors' dealing variable, the coefficients for volumes (β_{VOL}=1.13) and shares (β_{SHARES}= 0.83) remain qualitatively consistent and significant at 1% and 5% level. In this way, we capture a likely effect of insider trading in *t-1* on CSR performance in *t*.

Since the coefficients are qualitatively small, we further examine whether high levels of insider trading volume may have a significant impact on CSR performance. VOL_high is a dummy

9 The Spearman correlations exhibit similar results.

variable taking the value 1 if equal or higher than the third quartile and 0 otherwise. We find that the coefficient of high trading volume is about five times larger than in the main model (Table 2.4, Column 3) which results in a significant increase of the CSR performance amounting to about 9.5% of the mean performance level. This finding remains also consistent with a high number of shares and high trading frequency (Table 2.4, Column 6 and 9). At first glance, the results indicate that more insider trading increases CSR engagement, which support the market efficiency-argument of Hypothesis 2.

In order to better distinguish between market efficiency enhancing and market efficiency decreasing trading, we follow Cui et al. (2015) and define a “bad” insider-trading variable based on the *timing* of trading. INSIDER_noBlackout measures the trading volume, the number of shares or the trading frequency outside the blackout period of thirty days before the earnings announcement, whereas INSIDER_Blackout includes the trading volume, the number of shares or the trading frequency during the blackout period. While transactions outside the blackout period are expected to accelerate news distribution, resulting in more efficient financial markets, transactions during the blackout period decrease the fairness and efficiency of the capital market. Both variables take the value 0 if there is no trading. In Germany, the legal prohibition of trading during the blackout period has been introduced with the MAR regulation in July 2016. Therefore, we define the same *fictive* blackout period for the pre-MAR time series. The results indicate that all insider-trading measures outside the blackout period are positive and statistically significant at 5%- or 10%-level.

Table 2.4 The Impact of Insider Trading on CSR Performance

INSIDER	VOL	VOL	VOL_high	SHARES	SHARES	SHARES_high	FREQ	FREQ	FREQ_high
Dep.Variable: CSR_PERF	Coeff. (p-value)	Coeff. (p-value)	Coeff. (p-value)	Coeff. (p-value)	Coeff. (p-value)	Coeff. (p-value)	Coeff. (p-value)	Coeff. (p-value)	Coeff. (p-value)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
INSIDER	1.1330*** (0.0024)		5.8416*** (0.0028)	0.8296** (0.0326)		4.5338** (0.0173)	1.4328* (0.0698)		0.9338 (0.5062)
INSIDER_ noBlackout		0.8754** (0.0142)			0.6800* (0.0698)			1.6070** (0.0400)	
INSIDER_ Blackout		-0.2230 (0.1081)			-0.3272* (0.0916)			-1.5633** (0.0329)	
SIZE	5.2132*** (0.0000)	5.1867*** (0.0000)	5.2016*** (0.0000)	5.3455*** (0.0000)	5.2843*** (0.0000)	5.3650*** (0.0000)	5.2402*** (0.0000)	5.1525*** (0.0000)	5.2478*** (0.0000)
RETURN	-0.0141 (0.5029)	-0.0106 (0.5735)	-0.0131 (0.5472)	-0.0118 (0.5719)	-0.0088 (0.6391)	-0.0130 (0.5366)	-0.0070 (0.7358)	-0.0044 (0.8175)	-0.0075 (0.7195)
D_R&D	7.9088** (0.0266)	8.6940** (0.0190)	7.7889** (0.0273)	7.3759** (0.0412)	8.3013** (0.0261)	7.4872** (0.0381)	7.1475* (0.0510)	8.2359** (0.0296)	6.9478* (0.0577)
LEV	-0.9480 (0.3899)	-1.5235 (0.1756)	-0.8125 (0.4747)	-0.9736 (0.4006)	-1.6131 (0.1576)	-0.9402 (0.4309)	-0.8846 (0.4557)	-1.5537 (0.1638)	-0.8206 (0.5025)
ANALYST	0.2881 (0.1532)	0.3666* (0.0872)	0.3101 (0.1338)	0.2971 (0.1463)	0.3802* (0.0837)	0.3015 (0.1492)	0.2974 (0.1568)	0.3933* (0.0750)	0.3041 (0.1522)
Intercept	-21.1164** (0.0259)	-16.0697* (0.0657)	-7.1340 (0.3413)	-14.5514 (0.1186)	-11.6464 (0.1795)	-7.2260 (0.3661)	-8.3228 (0.3144)	-7.4225 (0.3355)	-5.5055 (0.4903)
IND & YEAR FE	Included	Included	Included	Included	Included	Included	Included	Included	Included
N	610	575	610	610	575	610	610	575	610
Adj. R^2 in %	45.11	48.66	44.96	44.12	48.19	44.13	43.33	47.86	42.96
VIF (mean)	2.05	1.93	2.05	2.05	1.93	2.05	2.06	1.97	2.05
F-Stat.	10.43	12.33	11.57	9.38	12.35	9.49	9.28	12.42	9.14

*, **, and *** indicate significance at the 10%, 5%, and 1% level, using a two-tailed test. T-statistics are based on standard errors, which are adjusted for heteroscedasticity and clustering at firm level. Dep. variable stands for dependent variable and FE for fixed effects. VIF is the variation inflation factor. N presents the firm-year observations. For a definition of the control variables see Table 2.1 in the appendix.

An increase of the CSR performance is in line with the ethical argument and describes a CSR conscious behavior of insiders, resulting in efficient markets consistent to Hypothesis H2. However, the coefficient of bad insider trading during the blackout period is negative and statistically significant for frequency (β_{FREQ} = -1.5633) and shares (β_{SHARES} = -0.3272). In this case, a decrease of the CSR performance points out that firms with insider trading during blackout periods are less engaged in corporate social responsibility activities. This supports our market inefficiency Hypothesis H1. To sum up, our findings suggest that considering the *timing* of transactions is essential in order to conclude whether insiders are CSR conscious and conduct transactions that make information be released faster and the financial market be more efficient.

2.6.2 Endogeneity Analyses

Simultaneity Bias

Our empirical analyses may suffer from endogeneity concerns due to simultaneity bias. Insider trading may result in more CSR engagement in line with an increase in market fairness and efficiency. However, as Cui et al. (2015) show, enhanced CSR engagement may also increase insider trading. To adjust for this potential endogeneity bias, we estimate a simultaneous equation system using a three-stage least squares estimator in line with Jo and Harjoto (2011, 2012) and Cui et al. (2015). The two estimated regressions are the following:

$$VOL_{i,t}/FREQU_{i,t}/SHARES_{i,t} = \alpha_0 + \beta_1\, CSR\_PERF_{i,t} + \beta_2\, SIZE_{i,t} + \beta_3\, GROWTH_{i,t} + \beta_4\, RETURN_{i,t} + \beta_5\, ROE_{i,t} + \varepsilon_{i,t}. \quad (2)$$

$$CSR\_PERF_{i,t} = \alpha_0 + \beta_1\, VOL_{i,t}/FREQU_{i,t}/SHARES_{i,t} + \beta_2\, SIZE_{i,t} + \beta_3\, RETURN_{i,t} \quad \beta_4\, LEV_{i,t} + \beta_5\, Analyst_{i,t} + \beta_6\, DUMMYRNDR_{i,t} + \varepsilon_{i,t}. \quad (3)$$

Table 2.5 Endogeneity Analyses

Panel A: Simultaneity Bias						
Dep. Variable	VOL	CSR_PERF	SHARES	CSR_PERF	FREQ	CSR_PERF
	Coeff. (p-value)	Coeff. (p-value)	Coeff. (p-value)	Coeff. (p-value)	Coeff. (p-value)	Coeff. (p-value)
	(1)	(2)	(3)	(4)	(5)	(6)
CSR_PERF	0.0684** (0.018)		-0.0623** (0.028)		-0.0171* (0.07)	
VOL		4.7732*** (0.004)				
SHARES				9.3729** (0.037)		
FREQ						21.8285 (0.286)
SIZE	0.6424*** (0.003)	5.0091*** (0.000)	0.4311** (0.044)	5.8757*** (0.000)	0.1731** (0.015)	4.5370*** (0.0000)
GROWTH	0.3271*** (0.000)		0.2258*** (0.002)		0.0664*** (0.004)	
RETURN	0.0024 (0.520)	-0.0339 (0.152)	0.0036 (0.335)	-0.0521 (0.203)	-0.0011 (0.368)	0.0057 (0.868)
ROE	-1.1717 (0.169)		-1.8525** (0.017)		-0.3677 (0.126)	
LEV		-1.5190** (0.028)		-2.5679** (0.027)		-1.9011 (0.137)
ANALYST		0.2579*** (0.004)		0.3154*** (0.008)		0.3004*** (0.013)
D_R&D		10.7310*** (0.000)		11.5264*** (0.003)		9.9602** (0.030)
Industry FE	Included	Included	Included	Included	Included	Included
Year FE	Included	Included	Included	Included	Included	Included
N	610	610	610	610	610	610

Table 2.5 Endogeneity Analyses (cont'd)

Panel B: Reverse Causality			
Dep. Variable	VOL	SHARES	FREQ
	Coeff. (p-value) (1)	Coeff. (p-value) (2)	Coeff. (p-value) (3)
CSR_PERF_{t-1}	0.0281** (0.0289)	0.0191 (0.1417)	0.0028 (0.3372)
Control Variables	Included	Included	Included
Industry FE	Included	Included	Included
Year FE	Included	Included	Included
N	438	438	438
Adj. R^2 in %	3.44	2.79	9.45
VIF (mean)	2.13	2.10	2.10
F-Stat.	2.10	2.20	2.10
Prob. (F-Stat.)	0.0386	0.0066	0.0023

*, **, and *** indicate significance at the 10%, 5%, and 1% level, using a two-tailed test.

Panel A displays a simultaneous equation system using a three-stage least squares (3SLS) estimator in line with Jo and Harjoto (2011, 2012) and Cui et al. (2015). Columns (1), (3) and (5) contain the depended variables insider trading volume, shares and frequency, respectively. In Columns (2), (4) and (6) the dependent variables is CSR performance.

In Panel B the dependent variable is insider trading volume, shares, and frequency in t, respectively. In order to capture a likely reverse causality, the independent variable CSR performance captures the performance level in t-1. In the reverse causality model, the number of observations reduces to 438 due to the lag-specification of the CSR performance variable.

Results reported in Table 2.5, Panel A show that insider trading volume and number of traded shares are significantly associated with CSR performance. Insider trading frequency is though not significant in the 3SLS-model. In case of a potential simultaneous effect of CSR performance on insider trading, we find that firms with high CSR engagement also exhibit higher insider trading volumes, but lower number of traded shares and less insider trading frequency. Overall, after controlling for a potential simultaneity bias, our findings remain qualitatively similar to the main results in Table 2.4 and imply a positive association between insider trading and CSR performance.

Reverse Causality

Prior literature found evidence for a positive reverse association between insider trading and CSR performance (Cut et al. 2015). In order to address a likely reverse causality of CSR performance affecting the level of insider trading, we run the following regression with lagged values of CSR performance on insider trading volumes, traded number of shares, and the insider trading frequency.

$$VOL_{i,t}/FREQU_{i,t}/SHARES_{i,t} = \alpha_0 + \beta_1\, CSR\_PERF_{i,t-1} + \beta_2\, SIZE_{i,t} + \beta_3\, RETURN_{i,t} + \beta_4\, DUMMYRNDR_{i,t} + \beta_5\, LEV_{i,} + \beta_6\, ANALYST_{i,t} + \varepsilon_{i,t}. \quad (4)$$

The results in Table 2.5, Panel B show that only in terms of trading volumes, lagged CSR performance increases insider trading. The adjusted R^2, however, is only about 3.4% revealing a very low explanation power of the reverse model. The association between CSR performance and the number of traded shares and the trading frequency, respectively, are insignificant. We therefore do not expect reverse causality to interfere our main findings.

2.6.3 Distinction between Insider Groups

In the next step, we take a closer look on the single insider trading groups (Table 2.6). Prior literature mainly analyzed the trading behavior of managers and directors in one tier board systems. The German two-tier board system enables us to investigate precisely the trading behavior of different groups. We separate our sample in three subsamples including insiders of the executive and supervisory board, respectively, as well as persons in close relationship with members of these boards. The results of Table 2.6 Panel A show that a higher trading frequency of executive boards significantly increases the CSR engagement on firm level. In line with the market fairness Hypothesis H2, the positive association is highly significant at a 1%-level for trades conducted outside the blackout period. However, during the blackout period, the association of insider trading frequency and CSR performances decreases, which supports the market inefficiency Hypothesis H1. The negative influence also holds for the number of traded shares (Column 4). The timing of trades is thus relevant in order to distinguish properly the influence of directors' dealings on CSR activities.

Table 2.6 Distinction between Insider Groups

Panel A: Executive Board Members (EB)

EB	VOL	VOL	SHARES	SHARES	FREQ	FREQ
Dep. Variable: CSR_PERF	Coeff. (p-value) (1)	Coeff. (p-value) (2)	Coeff. (p-value) (3)	Coeff. (p-value) (4)	Coeff. (p-value) (5)	Coeff. (p-value) (6)
EB	0.7119 (0.1045)		0.3945 (0.4215)		1.6849** (0.0496)	
EB_noBlackout		0.4096 (0.1617)		0.3770 (0.2939)		2.6090*** (0.0009)
EB_Blackout		-0.2741 (0.1533)		-0.4725* (0.0561)		-4.8596** (0.0178)
SIZE	5.7949*** (0.0000)	5.4396*** (0.0000)	5.8739*** (0.0000)	5.4649*** (0.0000)	5.8041*** (0.0000)	5.3156*** (0.0000)
RETURN	0.0016 (0.9433)	0.0107 (0.6344)	0.0021 (0.9240)	0.0095 (0.6726)	0.0056 (0.7927)	0.0137 (0.5319)
D_R&D	6.2584* (0.0933)	7.2494* (0.0708)	6.1782* (0.0980)	7.1622* (0.0753)	6.1737* (0.0959)	7.1161* (0.0750)
LEV	-2.6770** (0.0114)	-2.3275** (0.0309)	-2.6942** (0.0114)	-2.3800** (0.0267)	-2.6191** (0.0128)	-2.3509** (0.0231)
ANALYST	0.1253 (0.5365)	0.1608 (0.5294)	0.1309 (0.5228)	0.1654 (0.5196)	0.1265 (0.5367)	0.1664 (0.5083)
Intercept	-4.2779 (0.6612)	1.8702 (0.8178)	0.1781 (0.9862)	3.2229 (0.7043)	1.8402 (0.8289)	4.9629 (0.5151)
IND & YEAR FE	Included	Included	Included	Included	Included	Included
N	435	397	435	397	435	397
Adj. R2 in %	45.55	47.59	45.16	44.55	45.48	48.51
VIF (mean)	2.07	2.13	2.08	2.13	2.08	2.13
F-Stat.	10.58	10.52	9.77	10.58	11.16	11.12

Table 2.6 Distinction between Insider Groups (cont'd)

Panel B: Supervisory Board Member (SB)

SB	VOL	VOL	SHARES	SHARES	FREQ	FREQ
Dep.Variable: CSR_PERF	Coeff. (p-value) (1)	Coeff. (p-value) (2)	Coeff. (p-value) (3)	Coeff. (p-value) (4)	Coeff. (p-value) (5)	Coeff. (p-value) (6)
SB	0.7806 (0.1257)		0.3672 (0.4571)		-0.6454 (0.6337)	
SB_noBlackout		0.7224** (0.0297)		0.6118* (0.0908)		0.1771 (0.9093)
SB_Blackout		0.0268 (0.8869)		-0.1426 (0.6175)		-1.5916 (0.5795)
SIZE	4.9504*** (0.0001)	4.3250*** (0.0001)	5.0108*** (0.0001)	4.4143*** (0.0001)	5.0389*** (0.0001)	4.4438*** (0.0001)
RETURN	-0.0079 (0.7718)	0.0074 (0.7695)	-0.0037 (0.8908)	0.0102 (0.6897)	-0.0006 (0.9828)	0.0164 (0.5188)
D_R&D	11.6964*** (0.0014)	11.4104*** (0.0025)	10.9473*** (0.0039)	10.8799*** (0.0044)	10.3441*** (0.0074)	10.2259*** (0.0089)
LEV	-2.4739* (0.0601)	-1.7046 (0.2669)	-2.4834* (0.0653)	-1.7048 (0.2731)	-2.4268* (0.0672)	-1.5880 (0.2945)
ANALYST	0.3294 (0.1696)	0.5267** (0.0391)	0.3459 (0.1440)	0.5409** (0.0362)	0.3529 (0.1319)	0.5389** (0.0392)
Intercept	-17.9238 (0.1446)	-12.2363 (0.1646)	-12.1479 (0.2923)	-6.3937 (0.5256)	-8.2139 (0.3571)	-2.4273 (0.7922)
IND & YEAR FE	Included	Included	Included	Included	Included	Included
N	385	329	385	329	385	329
Adj. R^2 in %	44.20	48.52	43.62	48.20	43.49	47.48
VIF (mean)	2.19	2.32	2.18	2.32	2.19	2.32
F-Stat.	8.28	8.30	8.24	8.00	8.75	8.23

Table 2.6 Distinction between Insider Groups (cont'd)

Panel C: Affiliated Persons (AP)

AP	VOL	VOL	SHARES	SHARES	FREQ	FREQ
Dep. Variable: CSR_PERF	Coeff. (p-value) (1)	Coeff. (p-value) (2)	Coeff. (p-value) (3)	Coeff. (p-value) (4)	Coeff. (p-value) (5)	Coeff. (p-value) (6)
AP	1.2160*** (0.0003)		0.9099** (0.0127)		2.0095* (0.0519)	
AP_noBlackout		0.2562 (0.4657)		0.2292 (0.5622)		-0.4742 (0.7246)
AP_Blackout		0.2975 (0.1907)		0.3558 (0.2692)		2.0088 (0.3752)
SIZE	5.9193*** (0.0000)	6.1446*** (0.0000)	6.1081*** (0.0000)	6.1910*** (0.0000)	5.9958*** (0.0001)	6.1426*** (0.0000)
RETURN	-0.0037 (0.8746)	-0.0132 (0.5996)	-0.0038 (0.8665)	-0.0136 (0.5872)	0.0006 (0.9794)	-0.0163 (0.5277)
D_R&D	10.6734*** (0.0053)	9.9645** (0.0237)	10.0723** (0.0109)	9.8983** (0.0253)	10.4006** (0.0121)	9.8164** (0.0289)
LEV	0.1528 (0.8855)	-0.7482 (0.5612)	-0.0395 (0.9710)	-0.8214 (0.5239)	-0.1039 (0.9260)	-0.9004 (0.4883)
ANALYST	0.2443 (0.2404)	0.1362 (0.5514)	0.2427 (0.2535)	0.1382 (0.5455)	0.2223 (0.3309)	0.1227 (0.5918)
Intercept	-13.0617 (0.2687)	-6.8666 (0.6149)	-6.9032 (0.5838)	-6.3687 (0.6455)	4.3145 (0.7393)	-2.2239 (0.8732)
IND & YEAR FE	Included	Included	Included	Included	Included	Included
N	211	184	211	184	211	184
Adj. R2 in %	50.34	47.08	48.93	47.02	46.92	46.76
VIF (mean)	2.54	2.30	2.56	2.30	2.54	2.30
F-Stat.	18.20	10.52	12.94	10.30	10.29	10.22

*, **, and *** indicate significance at the 10%, 5%, and 1% level, using a two-tailed test. T-statistics are based on standard errors, which are adjusted for heteroscedasticity and clustering at firm level. Dep. variable stands for dependent variable, EB for executive board, SB for supervisory board, AP for affiliated persons and FE for fixed effects. VIF is the variation inflation factor. N presents the firm-year observations. For a definition of variables see Table 2.1 in the appendix.

The alternative proxies for executive dealings are not significant (Column 1 to 3). The findings are consistent to the informational hierarchy theory (Seyhun 1986; Betzer & Theissen 2009) suggesting that insiders who are more engaged in the operative business of a firm have a better access to private information. Since executive board members are involved in the day-to-day operative business, they trade more often. In contrast, the association for dealings of supervisory board members is only significantly positive for trades with high volumes and with high number of shares outside the blackout period at 5% and 10% significance level (Table 2.6, Column 2 and 4 of Panel B).

With respect to our third insider group, recent literature states that insider information may also flow through social ties, for example family members and friends. Karadas (2018) find out that family members of insiders, like politicians of the U.S. Congress, gain significant abnormal returns. This likely indicates information sharing of insiders to persons in close relationship. Based on a network analyses, Ahern (2017) find out that insider traders gain significant abnormal returns, which can be explained by a person-to-person communication among investors. In a similar vein, Berkman, Koch and Westerholm (2014) investigate insider trading through the accounts of children. They reveal a significant outperformance on the buy and the sell side, suggesting that trading through the accounts of children seems to be more information and less liquidity driven. This is especially pronounced before major earnings announcements, large price changes, and takeover announcements. For Germany, Dymke and Walter (2008) investigate the link between insider trading and released ad hoc news, capturing in this way insider information that becomes public. They find that affiliated persons of the executive and the supervisory board gain comparably high profits by trading prior to ad-hoc news disclosures. Our analyses on the dealings conducted by affiliated persons of the executive and supervisory board suggests that, for all three trading specifications, the association between insider dealings and CSR engagement is significantly positive and explains approximately 50% (e.g. Column 1,3 and 5, Table 2.6, Panel

C) of the model. However, a closer investigation of the timing of the trades imply no significant effect. Consequently, we cannot make strong inferences about this insider subsample.

Overall, our findings in Table 2.6 demonstrate that the negative association between blackout trades and CSR engagement is driven by executives' dealings, whereas the positive influence of no-blackout trades on CSR activities is mainly attributable to the supervisory board. In case of affiliated persons, the results imply an aggregated positive effect on the level of CSR performance.

2.6.4 Market Abuse Regulation

Our sample period captures the enforcement of the Market Abuse Regulation (MAR) in July 2016 containing four main changes: (a) the extension of reporting requirements with respect to inside information (b) the reporting frame of insider trading transactions, (c) the introduction of the blackout period (also called closed period), and (d) the tightening of penalties. According to Article 17 Section 1 of MAR, issuers of securities are obliged to disclose inside information to the market as soon as possible. The ad hoc disclosure does not only apply to the regulated market but also to alternative trading venues such as multilateral trading facilities (MTF) and organized trading facilities (OTF). According to Section 15a WpHG, members of the executive and supervisory body as well as affiliated persons had to report their trading activities within five business days to the *BaFin*. The introduction of Article 19 (Section 1) of MAR reduces the timeframe to three days. Unlike in the U.S. and U.K., the German law according to *WpHG* did not consider blackout periods preventing insider trading. The new regulation however prohibits directors' dealings on private information during thirty days prior to earnings announcements (Article 19 Section (11) of MAR). The MAR further tightened sanctions in the event of a violation of disclosure obligations and insider law (Article 30 Section 2 point (i) and (j) of MAR). Insider dealings constitute now a criminal offence at least in serious cases and when committed intentionally (Article 3 Section 1 of Directive 2014/57/EU). In order to capture likely anticipation effects on the capital market (Christensen et al. 2016), we also consider the announcement date of the MAR, which was published in the Official Journal of the European Union on 12 June 2014.

We control for potential regulation effects by decomposing the sample into three time periods: the pre-MAR period including the years 2005 to 2013, the transition period between the announcement and the introduction of the MAR with the years 2014 and 2015, as well as the post-MAR period from 2016 to 2018. Table 2.7 illustrates the results of the sample decomposition. In the pre-MAR period (Table 2.7, Columns 1 and 3 of Panel A) the volume as well as the number of traded shares significantly increase CSR activities. In line with Hypothesis H2, the positive association is due to trades outside the blackout period (β_{VOL} = 0.7650, p-value = 0.04 and β_{SHARES} = 0.5836, p-value = 0.13).

However, in case of insider frequency, we find a market-inefficient trading behavior when trades take place outside the blackout period since CSR performance declines. Trades during the blackout period increase CSR performance, which is consistent with the window-dressing argument and suggests that insiders may want to mask their trading activities by engaging in CSR. Based on our analyses on different insider groups in Table 2.6, we know that executives are frequent traders. If we assume, that the results of the frequency measure in Table 2.7, Column 6, are mainly attributable to executives, then our findings imply, that executives are less aware about CSR and exploit their information advantage at the expense of other market participants in the pre-MAR period.

Table 2.7 The Introduction of the Market Abuse Regulation (MAR)

Panel A: Pre-MAR Period from 2005 to 2013

INSIDER	VOL	VOL	SHARES	SHARES	FREQ	FREQ
Dep.Variable: CSR_PERF	Coeff. (p-value) (1)	Coeff. (p-value) (2)	Coeff. (p-value) (3)	Coeff. (p-value) (4)	Coeff. (p-value) (5)	Coeff. (p-value) (6)
INSIDER	0.9391** (0.0162)		0.7106* (0.0586)		1.3832 (0.1521)	
INSIDER_ noBlackout		0.7650** (0.0428)		0.5836 (0.1295)		-1.5221* (0.0901)
INSIDER _Blackout		-0.2260 (0.1669)		-0.3110 (0.1718)		1.6889* (0.0688)
SIZE	6.3244*** (0.0000)	6.4359*** (0.0000)	6.4743*** (0.0000)	6.5549*** (0.0000)	6.4208*** (0.0000)	6.4896*** (0.0000)
RETURN	-0.0022 (0.9231)	-0.0000 (0.9997)	-0.0006 (0.9801)	0.0012 (0.9507)	0.0025 (0.9126)	0.0046 (0.8158)
D_R&D	6.4435* (0.0365)	7.3089* (0.0511)	5.9910* (0.0878)	6.9364* (0.0680)	5.5442 (0.1211)	6.5913* (0.0882)
LEV	-0.7650 (0.4941)	-1.5314 (0.1435)	-0.7658 (0.5092)	-1.6109 (0.1258)	-0.6624 (0.5727)	-1.5603 (0.1372)
ANALYST	0.1361 (0.5401)	0.1845 (0.4433)	0.1784 (0.3963)	0.1872 (0.4457)	0.1268 (0.5756)	0.1956 (0.4301)
Intercept	-2.9113* (0.7792)	-4.0593 (0.6821)	1.9264 (0.8487)	0.6773 (0.9482)	5.2355 (0.5955)	3.1729 (0.7471)
IND & YEAR FE	Included	Included	Included	Included	Included	Included
N	371	345	371	345	371	345
Adj. R^2 in %	46.06	44.86	45.37	45.53	44.83	44.05
VIF (mean)	2.10	2.12	2.11	2.13	2.11	2.12
F-Stat.	10.00	9.62	9.70	11.00	9.97	9.23

*, **, and *** indicate significance at the 10%, 5%, and 1% level, using a two-tailed test. T-statistics are based on standard errors, which are adjusted for heteroscedasticity and clustering at firm level. Dep. variable stands for dependent variable and FE for fixed effects. VIF is the variation inflation factor. N presents the firm-year observations. For a definition of the control variables see Table 2.1 in the appendix.

Panel A presents the results for the pre-MAR period from 2005 to 2013. Panel B contain the insider transactions during the transition period from 2014 to 2015. Panel C captures the firm-year observations in the post-MAR period from 2016 to 2018.

Table 2.7 The Introduction of the Market Abuse Regulation (MAR) (cont'd)

Panel B: Transition Period from 2014 to 2015

INSIDER	VOL	VOL	SHARES	SHARES	FREQ	FREQ
Dep.Variable: CSR_PERF	Coeff. (p-value) (1)	Coeff. (p-value) (2)	Coeff. (p-value) (3)	Coeff. (p-value) (4)	Coeff. (p-value) (5)	Coeff. (p-value) (6)
INSIDER	1.2382 (0.1247)		0.6784 (0.3950)		2.8025 (0.2003)	
INSIDER_ noBlackout		0.5576 (0.5167)		0.1183 (0.8946)		-6.0231*** (0.0008)
INSIDER_ Blackout		-0.8723** (0.0140)		-1.3707** (0.0105)		3.4580 (0.1583)
SIZE	5.0302*** (0.0022)	5.0864*** (0.0092)	5.0068*** (0.0031)	5.0242** (0.0126)	4.8825*** (0.0026)	5.1324*** (0.0077)
RETURN	-0.0040 (0.9524)	-0.0252 (0.7334)	0.0026 (0.9685)	-0.0163 (0.8189)	0.0148 (0.8245)	-0.0127 (0.8494)
D_R&D	14.9639** (0.0223)	-3.6002 (0.3019)	14.9439** (0.0209)	14.4376* (0.0543)	15.5495** (0.0172)	14.4437** (0.0493)
LEV	-4.4161* (0.0852)	-3.6002 (0.3019)	-4.4390* (0.0908)	-3.5787 (0.2993)	-4.6028* (0.0763)	-3.1180 (0.3522)
ANALYST	0.2999 (0.2585)	0.3067 (0.4171)	0.3232 (0.2381)	0.3426 (0.3749)	0.3142 (0.2386)	0.2840 (0.4184)
Intercept	-20.0618 (0.2754)	12.7509 (0.5298)	-4.6219 (0.7866)	28.6543 (0.1702)	-3.4876 (0.8140)	15.7681 (0.3498)
IND & YEAR FE	Included	Included	Included	Included	Included	Included
N	91	87	91	87	91	87
Adj. R^2 in %	42.29	44.86	40.67	45.53	41.42	44.05
VIF (mean)	2.10	2.12	2.03	2.13	2.10	2.11
F-Stat.	10.00	9.71	9.70	11.72	9.78	9.42

*, **, and *** indicate significance at the 10%, 5%, and 1% level, using a two-tailed test. T-statistics are based on standard errors, which are adjusted for heteroscedasticity and clustering at firm level. Dep. variable stands for dependent variable and FE for fixed effects. VIF is the variation inflation factor. N presents the firm-year observations. For a definition of the control variables see Table 2.1 in the appendix.

Panel A presents the results for the pre-MAR period from 2005 to 2013. Panel B contain the insider transactions during the transition period from 2014 to 2015. Panel C captures the firm-year observations in the post-MAR period from 2016 to 2018.

Table 2.7 The Introduction of the Market Abuse Regulation (MAR) (cont'd)

Panel C: Post-MAR from 2016 to 2018

INSIDER	VOL	VOL	SHARES	SHARES	FREQ	FREQ
Dep.Variable: CSR_PERF	Coeff. (p-value) (1)	Coeff. (p-value) (2)	Coeff. (p-value) (3)	Coeff. (p-value) (4)	Coeff. (p-value) (5)	Coeff. (p-value) (6)
INSIDER	1.4157** (0.0235)		1.2642** (0.0471)		21876 (0.2424)	
INSIDER_ noBlackout		1.0400** (0.0489)		1.0743* (0.0677)		-0.6555 (0.7033)
INSIDER_ Blackout		-0.1689 (0.5548)		-0.2614 (0.5033)		1.1742 (0.4245)
SIZE	2.2346 (0.1137)	2.5869* (0.0727)	2.2508 (0.1159)	2.5506* (0.0771)	2.0592 (0.1405)	2.5318* (0.0767)
RETURN	-0.0431 (0.2615)	-0.0401 (0.3270)	-0.0430 (0.2550)	-0.0395 (0.3262)	-0.0368 (0.3400)	-0.0383 (0.3605)
D_R&D	8.5126* (0.0704)	9.3905** (0.0367)	7.8966* (0.0928)	9.0089** (0.0461)	7.9293* (0.0929)	8.7374** (0.0486)
LEV	-1.3163 (0.3916)	-1.1415 (0.4864)	-1.5934 (0.3194)	-1.2881 (0.4404)	-1.9294 (0.2620)	-1.4956 (0.3994)
ANALYST	0.8304** (0.0111)	0.7609** (0.0161)	0.8875*** (0.0059)	0.8126*** (0.0095)	0.9279*** (0.0036)	0.8093*** (0.0094)
Intercept	8.2517 (0.4912)	11.3363 (0.3219)	13.6168 (0.2378)	13.6788 (0.2326)	24.0945** (0.0184)	23.4645** (0.0214)
IND & YEAR FE	Included	Included	Included	Included	Included	Included
N	148	143	148	143	148	143
Adj. R^2 in %	42.23	42.64	41.77	42.94	40.09	41.16
VIF (mean)	2.11	2.10	2.12	2.11	2.10	2.12
F-Stat.	10.54	9.70	9.70	10.71	9.72	9.49

*, **, and *** indicate significance at the 10%, 5%, and 1% level, using a two-tailed test. T-statistics are based on standard errors, which are adjusted for heteroscedasticity and clustering at firm level. Dep. variable stands for dependent variable and FE for fixed effects. VIF is the variation inflation factor. N presents the firm-year observations. For a definition of the control variables see Table 2.1 in the appendix.

Panel A presents the results for the pre-MAR period from 2005 to 2013. Panel B contain the insider transactions during the transition period from 2014 to 2015. Panel C captures the firm-year observations in the post-MAR period from 2016 to 2018.

Next, we investigate the transition period between the announcement and the introduction of MAR including the years 2014 and 2015. The association between all three proxies and CSR performance is positive but not statistically significant. A closer look on the trading timing reveals that only blackout trades with high volumes and with high number of shares significantly decrease CSR performance during the transition period. With regard to the frequency of insider trades, the negative coefficient outside the blackout period remains highly significant. However, the high coefficient must be interpreted with caution, since the observations reduce to 87 firm-years. Overall, the results suggest a self-serving and market inefficient trading behavior, which is reflected in low CSR awareness.

Last, we consider the post-MAR years from 2016 to 2018. The stricter trading regulation prohibiting trades within the blackout period may explain why we do not find a significant association between blackout trades and CSR performance. The results exhibit a significantly positive influence of the trading volume and number of traded shares on CSR performance. The frequency proxy is not significant any more, which implies that executives likely refrain from self-serving trading due to more market and media scrutiny as well as higher reputation and litigation risks after the MAR introduction.

To sum up, our findings reveal that changes of the securities trading regulation during the sample period significantly influences the association between insider trading and CSR engagement. The introduction of the MAR had a positive impact on restricting market-inefficient and unfair trading behavior. Therefore, a lack of consideration of the regulatory environment can result in wrong inferences.

2.6.5 Alternative Explanation: Window-Dressing

Prior literature suggests that executives may use the means of corporate social responsibility to intentionally whitewash and divert attention of firms’ stakeholders away from negative news.

CSR consciousness may thus result in window-dressing behavior, covering up the impact of corporate misconduct (Hemingway & Maclagan, 2004; Fritzsche, 1991; Carroll, 1979). To the extent that our findings do not result from insiders' motivation to increase fairness and efficiency of capital markets but from insiders wanting to mask their trading activities, window-dressing may explain the positive correlation between no-blackout trades and CSR performance. To address this alternative explanation, we investigate the influence of family firms and of firms exhibiting high levels of earnings management.

Family Firms: Anderson et al. (2017) investigate whether equity ownership structure affects the choice of outside directors. The results of U.S. public firms between 2001 and 2010 indicate that family firms are relatively more likely to appoint independent directors with prior experience or proficiency on other family firm boards, so called "family-friendly directors". They also show that the presence of these directors increases the likelihood of corporate misconduct. In the same vein, Anderson et al. (2017b) analyze the financial misconduct in family and non-family firms from 1978 to 2013. They find that family firms are about 6.6 times more likely to engage in financial misrepresentation and about 3-times more likely to be involved in federal enforcement actions than non-family firms are.

Based on these insights, we repeat our analyses for a subsample of family firms compared to a subsample of non-family firms. In line with Betzer and Theissen (2009), we define family firms as firms with a dominating shareholder being a family member and holding more than 25% of the equity. The data is collected from Hoppenstedt Aktienführer. We find a significantly positive association between insider trading and CSR performance only in the subsample of non-family firms, whereas the association in the subsample of family firms is insignificant (Table 2.8, Panel A). The effect is driven by dealings outside the blackout period and support the market fairness theory of Hypothesis H2 and not a likely window-dressing motivation of insiders.

Earnings Management: While some studies find that CSR performance decreases the level of earnings management (Labelle et al. 2010; Hong and Andersen 2011; Kim et al. 2012; Hummel & Ising 2015), others indicate a significant increase in earnings management (Prior et al. 2008; Gargouri et al. 2010). Koehn and Ueng (2009) find that firms forced to restate earnings seem to be using philanthropy either to divert attention away from these restatements or to buy good will from stakeholders after such restatements. In order to analyze, whether firms are inclined to enhance CSR performance in order to cover-up earnings management, we calculate discretionary accruals using two measures in line with the modified Jones (1991) model (Dechow, Sloan & Sweeney 1995). Most studies estimate discretionary accruals using industry membership as the criterion for selection estimation samples. Ecker et al. (2013) however show, that for non-U.S. data, industry-based estimation samples result in significant sample attrition, whereas estimation samples based on lagged assets perform equal well with less sample attrition. Based on these findings, we calculate DACC_IND using industry-based peers and DACC_SIZE using lagged assets-based peers.[10] The discretionary accruals are represented by the residual term of the following equation, based on cross-sectional regressions per industry cluster and size quartiles, respectively. Total accruals are calculated as change in working capital minus depreciation deflated by lagged total assets (Gassen & Fülbier 2015).:

$$TACC_t = \alpha_0 + \beta_1 (\Delta REV\text{-}\Delta REC_t) + \beta_2 PPE_t + \varepsilon_{i,t}. \qquad (5)$$

[10] According to Dechow et al. (1995), the estimation of discretionary accruals based on industry-year cluster shall contain at least 15 observations per cluster. However, we only use industry and size cluster, respectively, since the industry-year methodology would decrease our sample size tremendously.

Table 2.8 Window Dressing Behavior

Panel A: Family Firms versus Non-Family Firms

	Family Firms			**Non-Family Firms**		
INSIDER	VOL	SHARES	FREQ	VOL	SHARES	FREQ
Dep. Variable: CSR_PERF	Coeff. (p-value)	Coeff. (p-value)	Coeff. (p-value)	Coeff. (p-value)	Coeff. (p-value)	Coeff. (p-value)
	(1)	(2)	(3)	(4)	(5)	(6)
INSIDER_no Blackout	0.4159 (0.6430)	0.2912 (0.7292)	-1.6694 (0.6226)	1.2333*** (0.0053)	0.8728* (0.0703)	2.3761** (0.0163)
INSIDER_ Blackout	-0.5008 (0.1283)	-0.6355 (0.1320)	-1.4473 (0.3819)	-0.1508 (0.3182)	-0.2280 (0.2883)	-1.2087 (0.1112)
Control variables	Included	Included	Included	Included	Included	Included
IND & YEAR FE	Included	Included	Included	Included	Included	Included
N	96	96	96	354	354	354
Adj. R2 in %	58.47	58.27	58.08	50.30	49.16	49.10
VIF (mean)	2.10	2.20	2.10	2.00	2.01	2.00
F-Stat.	10.22	10.11	10.42	11.10	11.00	11.24

Panel B: Size-based estimation of discretionary accruals (DACC_SIZE)

	High DACC_SIZE			**Low DACC_SIZE**		
INSIDER	VOL	SHARES	FREQ	VOL	SHARES	FREQ
Dep. Variable: CSR_PERF	Coeff. (p-value)	Coeff. (p-value)	Coeff. (p-value)	Coeff. (p-value)	Coeff. (p-value)	Coeff. (p-value)
	(1)	(2)	(3)	(4)	(5)	(6)
INSIDER_no Blackout	0.7894* (0.0551)	0.4549 (0.2889)	2.5597** (0.0188)	1.3465*** (0.0022)	1.1956** (0.0103)	0.0270 (0.9812)
INSIDER_ Blackout	-0.5413*** (0.0031)	-0.7601*** (0.0018)	-3.0496*** (0.0011)	0.0106 (0.9621)	0.0214 (0.9463)	0.6553 (0.6423)
Control variables	Included	Included	Included	Included	Included	Included
IND & YEAR FE	Included	Included	Included	Included	Included	Included
N	220	220	220	219	219	219
Adj. R2 in %	53.98	53.28	53.92	53.19	52.73	50.31
VIF (mean)	2.13	2.22	2.10	2.21	2.20	2.21
F-Stat.	10.20	11.23	10.21	10.23	10.20	20.21

Table 2.8 Window Dressing Behavior (cont'd)

Panel C: Industry-based estimation of discretionary accruals (DACC_IND)

	High DACC_IND			**Low DACC_IND**		
INSIDER	VOL	SHARES	FREQ	VOL	SHARES	FREQ
Dep. Variable: CSR_PERF	Coeff. (p-value)	Coeff. (p-value)	Coeff. (p-value)	Coeff. (p-value)	Coeff. (p-value)	Coeff. (p-value)
	(1)	(2)	(3)	(4)	(5)	(6)
INSIDER_no Blackout	0.6516 (0.1481)	0.3428 (0.4804)	1.6176 (0.1743)	1.3359*** (0.0027)	1.1421** (0.0189)	0.6320 (0.5647)
INSIDER_ Blackout	-0.5209*** (0.0082)	-0.7422*** (0.0056)	-2.6356** (0.0107)	-0.0574 (0.7878)	-0.0465 (0.8762)	-0.2506 (0.8384)
Control variables	Included	Included	Included	Included	Included	Included
IND & YEAR FE	Included	Included	Included	Included	Included	Included
N	220	220	220	219	219	219
Adj. R2 in %	52.24	51.68	51.79	54.78	54.14	52.05
VIF (mean)	2.13	2.21	2.20	2.10	2.30	2.19
F-Stat.	11.34	12.43	11.34	11.23	12.48	12.46

*, **, and *** indicate significance at the 10%, 5%, and 1% level, using a two-tailed test.

Panel A displays the results of subsamples with family firms and without family firms. Family firms are defined as firms with at least one shareholder who holds more than 25% of the equity and if this largest shareholder is a family member.

Panel B and Panel C presents the results for firm with different levels of earnings management captured by discretionary accruals (DACC) in line with the modified Jones (1991) model (Dechow, Sloan & Sweeney, 1995). Size-based discretionary accruals are defined as High DACC_SIZE containing discretionary accruals greater or equal than the median value of size-based DACC and low DACC_SIZE includes discretionary accruals that are lower than median value ofsize-based DACC. Industry-based discretionary accruals are defined as High DACC_IND containing discretionary accruals greater or equal than the median value of industry-based DACC and low DACC_IND includes discretionary accruals that are lower to the median value of industry-based DACC.

Table 2.8, Panel B and C presents the results of the subsamples with high discretionary accruals (greater or equal median) and low discretionary accruals (lower median) capturing thereby the level of earnings management. We find a significantly positive association of no-blackout dealings and CSR performance for firms exhibiting *low* levels of earnings management for both discretionary accrual measures, which supports the fairness argument of Hypothesis H2 (for DACC_SIZE: Panel B, Columns 4-5; for DACC_IND: Panel C, Columns 4-5).

In contrast, for firms with *high* levels of size-based estimated discretionary accruals we find a significantly negative association between blackout dealings and CSR performance in line with the market inefficiency Hypothesis H1 (Panel B, Columns 1-3). The findings remain for all insider-trading specifications highly significant, also when estimating the discretionary accruals using industry-based peers (Panel C, Columns 1-3). In case of dealings outside the blackout period, only trading volume and trading frequency (Panel B, Column 1 and 3) exhibit a significantly positive association with CSR performance.

These findings are however not robust when estimating discretionary accruals using the industry-based sample. Nevertheless, the positive influence of insider dealings on the CSR performance in the subsample of firms with high levels of earnings management may be an indicator of window-dressing behavior, since these firms may be inclined to mask their dealings activities. Insider dealings conducted outside the blackout period can also be opportunistically motivated and beneficial for insiders by gaining abnormal returns, even though they may increase the information content of capital markets. Since insider trading may negatively affect business reputation, insiders may want to mask their trading activities by enhancing CSR engagement.

2.6.6 Additional Analyses

Omitted Variables

Our analyses may suffer from correlated omitted variables, which may affect both the insider trading behavior as well as the decision to engage in CSR activities. To address this potential bias, we first include two additional control variables capturing the financial performance of firms, the return of assets (ROA) and the return of equity (ROE). Our unreported results suggest that the main findings remain qualitatively robust, since the association of insider trading measures and CSR_PERF remains positive and statistically significant for all three measures. Insider trading volume, for example, exhibits a strongly significant positive coefficient of β_{VOL}=1.1384 (p-value=0.0022) after adding ROA and β_{VOL}=1.1471 (*p-value*=0.0021) after adding ROE.

Second, we control for corporate governance since governance mechanisms have an impact on the CSR orientation of firms as well as on the opportunity of insiders to undertake self-serving transactions. We measure corporate governance by firms' ownership structure, since equity distribution provides insights into the effectiveness of firms' monitoring mechanisms. The monitoring incentives of shareholders significantly affect the information asymmetries between insiders and the capital market and strongly depend on their underlying interests (Betzer & Theissen 2009). Conflicts between different principals, commonly referred to as principal-principal conflicts (La Porta et al. 1999; Dharwadkar et al. 2000; Young et al. 2008), can undermine the monitoring role of governance and facilitate opportunistic transactions by insiders (La Porta et al. 1998; Fidrmuc et al. 2006; Djankov et al. 2008; He & Rui 2016). With respect to the impact of equity structure on CSR activities, Dam and Scholtens (2013) show that firms with a higher ownership concentration rate, exhibit lower levels of CSR performance. Graves and Waddock (1994) find an insignificant relationship between social performance and the percentage of shares held by institutions, however, a positive association between CSR and the number of institutions. They interpret this result as "token investments", which means investing of small amounts in order to signal socially responsible awareness. In order to control for the potential effects resulting from the ownership structure of firms, we include a set of dummy variables for widely held firms, manager-controlled, family-controlled, and industry-controlled firms, in line with Betzer and Theissen (2009). If there is a dominating shareholder who holds more than 25% of the equity, a firm is classified as (a) family controlled if the dominating shareholder is a family member, (b) manager-controlled if the largest shareholder is a member of the executive board, and (c) industry-controlled if the largest shareholder is another non-financial firm. In case of firms where no single shareholder holds more than 25% the shares are considered to be widely held. Firms controlled by other dominating shareholders, in which the largest shareholder does not belong to one of the abovementioned groups, are the base case. Our results (untabulated) remain consistent after the inclusion of the equity structure and imply a positive association between insider trading and CSR performance. The coefficient of trading volume is β_{VOL}=1.3867 and highly significant at 1%-level, the coefficient on shares is β_{VOL}=1.0259 and the coefficient for frequency is β_{VOL}=1.893 with p-value=0.0137 and p-value=0.0851, respectively.

Mandatory CSR Disclosure

Our sample includes firms that voluntarily disclose CSR information, which is used in order to construct the CSR performance score. However, in 2017 the new EU Directive 2014/95/EU on non-financial information has been introduced in German law, requiring the mandatory disclosure of environmental, social, and governance policies, risks, and outcomes for all public interest entities.[11] The new disclosure requirement may influence firms' engagement regarding CSR issues. Although we focus on CSR performance and not on the decision process of disclosing this information or not, we exclude the year 2017 and 2018 for sensitivity purposes. The exclusion of the years with mandatory CSR disclosure (not tabulated) does not affect our findings of a significantly positive association between insider trading and CSR activities at a 1% significance level (e.g. insider trading volume: β_{VOL}=1.0356, p-value=0.0072).

Global Financial Crisis

The sample period contains the global financial crisis. Germany has been affected by the crisis in year 2008, with a huge drop of the *CDAX*-Index. Not tabulated results show a significant peak of insider purchases in 2008 followed by a strong decrease in subsequent years. Insider sales declined in 2008 and remain almost stable until 2009, exhibiting a further small decrease until 2010. The crash on international markets and the overreaction of investors may affect insider

[11] Public interest entities are companies which, due to the nature of their business, size, or number of employees are of significant public relevance, in particular companies whose securities are admitted to trading on a regulated market of a Member State, such as banks, other financial companies, and insurance undertakings (Article 2(13) Directive 2006/43/EC).

trading behavior and CSR consciosness. After excluding the years of the financial crisis our findings (not tabulated) remain robust.

2.7 Conclusion

We investigate real effects of insider trading and provide cross-sectional evidence regarding the impact of insider trading on CSR performance in Germany from 2005 to 2018. The two-tier board system of German public firms allows us to analyze the trading behavior of different insider groups, like executive and supervisory board members and persons in close relationship with them. In addition, we try to distinguish insider trading, which increases market efficiency and insider trading, which decreases market fairness. For this purpose, we distinguish between insider trades conducted outside the blackout period and insider transactions during the blackout period (so called “bad” insider trading) of thirty days before earnings announcements.

We assume that less CSR conscious insiders will trade more intensively and not promote CSR activities, which would decrease market efficiency and fairness. In contrast, insiders engaging in information increasing trading may increase also CSR performance, signaling in this way market fairness and ethical behavior. We find evidence that the timing of trading significantly affects the association between insider trading and CSR performance. Whereas trades outside the blackout period enhance CSR engagement, dealings during the blackout period decrease CSR performance. Our results show that executive board trades drive the negative effect of blackout dealings, whereas the positive effect of no-blackout dealings is mainly attributable to supervisory board trades. The net effect of dealings conducted by affiliated persons is positive. In order to exclude any alternative explanation about the positive association between insider trading and CSR performance, we try to control for window-dressing. Prior literature suggests that executives may use the means of corporate social responsibility to divert intentionally attention of firms’ stakeholders away from negative news. For firms engaging in strong earnings management, we cannot exclude that the results may be driven by window-dressing behavior to cover up negative insider-trading reputation. Moreover, after the introduction of the MAR regulation in 2016, we cannot find a negative impact of insider trading on CSR engagement anymore. The stricter regulation regime seems to have successfully restricted market-inefficient and unfair trading behavior.

Our analyses do not attempt to determine the optimal level of insider transactions or of CSR performance. Moreover, we cannot precisely measure the real underlying trading motivation of insiders or their personal CSR consciousness due to lack of private data. The sample size is quite small since we have to accumulate insider-trading transactions on firm-year level. Further, the sample includes not only firms that mandatorily disclose CSR information but also firms disclosing CSR information on a voluntary basis. This may result in a sample selection bias because firms which voluntary disclose CSR information may exhibit higher relative CSR performance scores. Despite these limitations, our results allow a better understanding of the association between insider trading and the influence on CSR engagement. By separating the insider groups, we investigate likely information flows within insiders and show how differently they affect CSR engagement on firm level. Future research may address these constraints and extent the analysis on an international sample, taking thereby into consideration cross-sectional differences on cultural and regulatory level.

List of References

Aboody, D., Lev, B. (2000): Information asymmetry, R&D, and insider gains, in: *Journal of Finance* 55, 2747-2766.

Aboody, D., Hughes, J., & Liu, J. (2005): Earnings Quality, Insider Trading, and Cost of Capital, in: *Journal of Accounting Research*, 43(5), 651-673.

Adam Friedman Associates (2012): New Findings on Corporate Social Responsibilly https://www.prweb.com/releases/2012/11/prweb10144917.htm.

Ahern, Kenneth R. (2017): Information networks: Evidence from illegal insider trading tips, in: *Journal of Financial Economics*, 125 (1), 26-47.

Anderson, R., Martin, G. S., & Reeb, D. (2017): Financial Misconduct and Family Firms, *Working Paper*, Temple University.

Anderson, R., C., Mehta, M., N., Reeb, D., M., & Zhao, W. (2017): Family-Friendly Directors, *Working Paper*, Temple University, University of Michigan, National University of Singapore, Renmin University of China.

Ausubel, L.M. (1990): Insider trading in a rational expactations economy, in: *American Economic Review*, *80* (5), 1022-1041.

Becchetti, L., Ciciretti, R., & Conzo, P. (2013): The Legal Origins of Corporate Social Responsibility, *CEIS Working Paper*, 291, Tor Vergata University.

Benabou, R., Tirole, J. (2006): Incentives and Prosocial Behavior, in: *The American Economic Review*, 96 (5), 1652-1678.

Berkman, H., Koch, P., & Wersterholm, J.P. (2014): Informed Trading through the Accounts of Children, in: *The Journal of Finance*, 69 (1), 363-404.

Bettis C.J., Coles, J.L., & Lemmon, M.L. (2000): Corporate policies restricting trading by insiders, in: *Journal of Financial Economics*, 57, 191-220.

Betzer, A., Theissen, E. (2009): Insider trading and corporate governance: The case of Germany, in: *European Financial Management*, 15, 402-429.

Bouten, L., Cho, C.H., Michelon, G., & Roberts, R.W. (2017): CSR Performance Proxies in Large-Sample Studies: "Umbrella Advocates", Construct Clarity, and the "Validity Police", *SSRN Working Paper*, Iseg School of Management, York University, University of Bristol, University of Central Florida.

Bris, A. (2005): Do Insider Trading Laws Work? in: *European Financial Management*, 11, 267-312.

Bushmann, R., Indjejikian, R. (1995): Voluntary disclosures and the trading behavior of Corporate Insiders, in: *Journal of Accounting Research*, 33 (2), 293-316.

Carlton, D.W., Fischel, D.R. (1983): The regulation of insider trading, in: *Stanford Law Review*, 35, 857-895.

Carroll, A. (1979): A three-dimensional conceptual model of corporate performance, in: *The Academy of Management Review*, 4 (4), 497-505.

Carroll, A.B. (2015): Corporate social responsibility: The centerpiece of competing and complementary frameworks, in: *Organizational Dynamics*, 44, 87-96.

Cespa, G., Cestone, G. (2007): Corporate Social Responsibility and Managerial Entrenchment, in: *Journal of Economics & Management Strategy*, 16 (3), 741-771.

Chakravarthy, J., deHaan, E., & Rajgopal, S. (2014): Reputation Repair After a Serious Restatement, in: *The Accounting Review*, 89 (4), 1329-1363.

Chen, C., Xiumin, M., & Xin, W. (2013): Insider Trading, Litigation Concerns, an Auditor Going-Concern Opinions, in: *The Accounting Review*, 88 (2), 365-39.

Chen, H., Jorgensen, B. N. (2021): Insider Trading, Competition and Real Activities Manipulation, in: *Management Science*, 1-19.

Cheng, Q., Lo, K. (2006): Insider trading and voluntary disclosures, in: *Journal of Accounting Research*, 44 (5), 815-848.

Cho, C.H., Guidry, R.P., Hageman, A.M., & Patten, D.M. (2012): Do actions speak louder than words? An empirical investigation of corporate environmental reputation, in: *Accounting, Organizations and Society*, 37 (1), 14-25.

Christensen, D.M. (2016): Corporate accountability reporting and high-profile misconduct, in: *The Accounting Review*, 91 (2), 377-399.

Christensen, H. B., Hail, L, & Leuz, C. (2016,): Capital-Market Effects of Securities Regulation: Prior Conditions, Implementation, and Enforcement, in: *Review of Financial Studies*, 29 (11), 2885-2924.

Conrad, J., Kaul, G. (1993): Long-Term Market Overreaction or Biases in Computed Returns? in: *The Journal of Finance*, 48 (1), 39-63.

Cornell, B., Sirri, E.R. (1992): The Reaction of Investors and Stock Prices to Insider Trading, in: *Journal of Finance*, 47 (3), 1031-1059.

Cui, J., Jo, H., & Li, Y. (2015): Corporate social responsibility and insider trading, in: *Journal of Bussines Ethics*, 130 (4), 869-887.

Dam, L., Scholtens, B. (2013): Ownership Concentration and CSR Policy of European Multinational Enterprises, in: *Journal of Business Ethics*, 118 (1), 117-126.

Davidson, R.H., Dey, A., & Smith, A.J. (2016): Executives´ Legal Records and Insider Trading Activities, in: *Chicago Booth Research Paper*, 16-12, *Fama-Miller Working Paper*.

Dechow, P., Sloan, R., & Sweeney, A. (1995): Detecting earnings management, in: *The Accounting Review*, 70, 193–225.

Del Brio, E.B., Miguel, A. (2010): Dividends and Market Signaling: an Analysis of Corporate Insider Trading, in: *European Financial Management*, 16 (3), 480-497.

Dhaliwal, D. S., Li, O. Z., Tsang, A., & Yang, Y. A. (2011): Voluntary nonfinancial disclosure and the cost of equity capital: The initiation of corporate social responsibility reporting, in: *The Accounting Review*, 86(1), 59-100.

Dhaliwal, D. S., Radhakrishnan, S., Tsang, A., & Yang, Y. G. (2012): Non-financial disclosure and analyst forecast accuracy: International evidence on corporate social responsibility disclosure, in: *The Accounting Review*, 87 (3), 723-759.

Dhaliwal, D., Li, O. Z., Tsang, A., & Yang, Y. G. (2014): Corporate social responsibility disclosure and the cost of equity capital: The roles of stakeholder orientation and financial transparency, in: *Journal of Accounting and Public Policy*, 33(4), 328-355.

Dharwadker, R., George, G., & Brandes, P. (2000): Privatization in emerging companies: An agency theory perspective, in: *Academy of Management Review*, 25 (3), 650-669.

Djankov, S., La Porta, R., Lopez-de-Silanes, F., & Shleifer, A. (2008): The law and economics of self-dealing, in: *Journal of Financial Economics*, 88, 430–465.

Dymke, B.M., Walter, A. (2008): Insider Trading in Germany – Do Corporate Insiders Exploit Insider Information? in: *Business Research*, 1 (2), 188-205.

Ecker, F., Francis, J., Olsson, P., & Schipper, K. (2013): Estimation sample selection for discretionary accruals models, in: *Journal of Accounting and Economics*, 56 (2), 190-211.

Fama, E.F. (1980): Agency Problems and the Theory of the Firm, in: *The Journal of Political Economy*, 88 (2), 288-307.

Fernandes, N., Ferreira, M.A. (2009): Insider Trading Laws and Stock Price Informativeness, in: *Review of Financial Studies*, 22 (5), 1845-1887.

Fidrmuc, J., Goergen, M., & Renneboog, L. (2006): Insider Trading, News Releases and Ownership Concentration, in: *Journal of Finance*, 61 (6), 2931-2973.

Fombrun, C., Shanley, M. (1990): What´s in a Name? Reputation Building and Corporate Strategy, in: *Academy of Management Journal*, 33 (2), 233-258.

Fombrun, C.J. (1996): *Realizing Value from the Corporate Image*, Harvard, Harvard Business School Press.

Fritzsche, D.J. (1991): A Model of Decision-making Incorporating Ethical Values, in*: Journal of Business Ethics*, 10, 841-852.

Füllbier, R. U., Gassen, J. (2015): Do creditors prefer smooth earnings?: Evidence from European private firms., in: *Journal of International Accounting Research*, 14 (2), 151-180.

Gaa, J. C., Nainar, S. M., & Shehata, M. (2006): Insider trading, ethical attitudes and culture: an experimental market analysis in: *International Journal of Business Governance and Ethics*, 2 (1-2), 84-100.

Gao, F.L., Lisic, L.L., & Zhang, I. (2014): Commitment to Social Good and Insider Trading, in: *Journal of Accounting and Economics*, 57, 149-175.

Gargouri, R.M., Shabou, R., & Francoer, C. (2010): The relationship between corporate social performance and earnings management, in: *Canadian Journal of Administrative Sciences*, 27 (4), 320-334.

Goncharov, I., Hodgson, A., Lhaopadchan, S., & Sanabria, S. (2013): Asymmetric trading by insiders - comparing abnormal returns and earnings prediction in Spain and Australia, in: *Accounting & Finance*, 53 (1), 163-184.

Graves, S.B., Waddock, S.A. (1994): Institititional Owners and corporate social performance, in: *Academy of Management Journal*, 37, 1034-1046.

He, Q., Rui, O. M. (2016): Ownership Structure and Insider Trading: Evidence from China, in: *Journal of Business Ethics*, 134, 553-574.

Hemingway, C., Maclagan, P.W. (2004): Manager´s Personal Values as Drivers of Corporate Social Responsibility, in: *Journal of Business Ethics*, 50, 33-44.

Hoi, C-K., Wu, Q., & Zhang, H. (2013): Is Corporate Social Responsibility (CSR) Associated with Tax Avoidance? Evidence from Irresponsible CSR Actitivities, in: *The Accounting Review*, 88 (6), 2025-2059.

Hong, Y., Andersen, M.L. (2011): The Relationship Between Corporate Social Responsibility and Earnings Management: An Exploratory Study, in: *Journal of Business Ethics*, 104 (4), 461-471.

Huddart, S., Kee, B. (2007): Information Asymmetry and Cross-sectional Variation in Insider Trading, in: *Contemporary Accounting Research*, 24 (1), 195-232.

Hummel, K., Ising, P. (2015): Earnings Management – Does Corporate Sustainability Performance Matter? University of Zurich, Department of Business Administration, *UZH Business Working Paper*, 358.

Jensen, M.C. (2005): Agency Costs of Overvalued Equity, in: *Financial Management*, 34 (1), 5-19.

Jo, H., Harjoto, M. (2011): Corporate governance and firm value: The impact of corporate social responsibility, in*: Journal of Business Ethics*, 103(3), 351–383.

Jo, H., Harjoto, M. (2012): The causal effect of corporate governance on corporate social responsibility, in: *Journal of Business Ethics*, 106 (1), 53-72.

Jones, J. (1991): Earnings management during import relief investigations, in: *Journal of Accounting Research*, 9 (2), 193-228.

Karadas, S. (2018): Family ties and informed trading: evidence from Capitol Hill, in: *Journal of Economics and Finance*, 42(2), 211-248.

Kim, Y., Park, M. S., & Wier, B. (2012): Is earnings quality associated with corporate social responsibility? in: *The Accounting Review*, 87, 761-796.

Klein, B., Leffler, K.B. (1981): The Role of Market Forces in Assuring Contractual Performance, in: *Journal of Political Economy*, 89 (4), 615-641.

Koehn, D., Ueng, J. (2010): Is philanthropy being used by corporate wrongdoers to buy good will? in: *Journal of Management and Governance*, 14 (1), 1-16.

Kreps, D.M., Wilsong, R. (1982): Reputation and imperfect information, in: *Journal of Economic Theory*, 27 (2), 253-279.

La Porta, R., Lopez-De-Silanes, F., & Shleifer, A. (1999): Corporate Ownership around the world, in: *Journal of Finance*, 54 (2), 471-517.

Labelle, R., Gargouri R.M., & Francoeur C. (2010): Ethics, diversity management and financial reporting quality, in: *Journal of Business Ethics*, 93, 335-353.

Lanis, R., Richardson, G. (2012): Corporate Social Responsibility and Tax Agressiveness: An Empirical Analysis, in: *Journal of Accounting and Public Policy*, 31, 86-108.

Leland, H.E. (1992): Insider trading: Should it be prohibited? in: *Journal of Political Economy*, 100 (4), 859-887.

Lopatta, K., Buchholz, F., & Kaspereit, T. (2016): Asymmetric Information and International Corporate Social Responsibility, in: *Business and Society*, 55(3), 458-488.

Lu, C., Zhao, X., & Dai, J. (2018): Corporate Social Responsibility and Insider Trading: Evidence from China, in: *Sustainability*, 10 (9), 1-17.

Manne, H.G. (1966): *Insider trading and the stock market*, New York,The Free Press.

Manove, M. (1989): The harm from insider trading and informed speculation, in: *The Quarterly Journal of Economics*, 104 (4), 823-845.

Maxwell, J.W., Lyon, T.P., & Hackett, S.C. (2000): Self-regulation and social welfare: The political economy of corporate environmentalism, in: *The Journal of Law and Economics*, 43 (2), 583-617.

McGee, R.W. (2009): Analyzing Insider Trading from the Perspectives of Utilitarian Ethics and Rights Theory, in: *Journal of Business Ethics*, 91, 65-82.

McGee, R.W., Yoon, Y. (2012): Insider Trading: An Ethical Analysis, in: *The International Journal of Finance*, 24 (1), 7070-7084.

McWilliams, A., Siegel, D.S., & Wright, P.M. (2002): Corporate Social Responsibility: Strategic Implications, in: *Journal of Management Studies*, 43 (1), 1-18.

O'Reilly, A., Chatman, J.A. (1996): Culture as social control: Corporations, cults, and commitment, in: *Research in organizational behavior: An annual series of analytical essays and critical reviews*, 18, 157-200.

Pfeil, U.C. (1996): Finanzplatz Deutschland: Germany Enacts Insider Trading Legislation, in: *American University International Law Review*, 11 (1), 137-193.

Piotroski, J.D., Roulstone, D.T. (2005): Do insider trades reflect both contrarian beliefs and superior knowledge about future cash flow realizations? in: *Journal of Accounting and Economics*, 39, 55-81.

Prior, D., Surroca, J., & Tribo, J. (2008): Are socially responsible managers really ethical? Exploring the relationship between earnings management and corporate social responsibility, in: *Corporate Governance*, 16 (3), 160-177.

Sawicki, J., Shrestha, K. (2008): Insider Trading and Earnings Management, in: *Journal of Business Finance & Accounting*, 35 (3-4), 331-346.

Schmidt, M.H., Stehle, R. (2015): Returns on German Stocks 1945 to 2013, in: *Credit and Capital Markets*, 48 (3), 427-476.

Seyhun, N. (1986): Insiders' Profits, Costs of Trading, and Market Efficiency, in: *Journal of Financial Economics*, 16 (2), 189-212.

Seyhun, H. N. (1998): *Investment Intelligence from Insider Trading*, Cambridge, MA: MIT Press.

Stotz, O. (2006): Germany's New Insider Law: The Empirical Evidence after the First Year, in: *German Economic Review*, 7 (4), 449-462.

Strudler, A., Orts, E.W. (1999): Moral Principle in the Law of Insider Trading, in: *Texas Law Review*, 78 (2), 374-438.

Young, M., Peng, M., W., & Ahlstrom, D. (2008): Corporate Governance in Emerging Ecomomies: A Review of the Principal-Principal Perspective, in: *Journal of Management Studies*, 45 (1), 196-220.

Werhane, P.H. (1991): The indefensibility of insider trading, in: *Journal of Business Ethics*, 10 (9), 729-73

Appendix 2.1: Definition of Variables

Variables	Definition
Insider Trading Variables	
VOL	Logarithm of accumulated insider trading volume on firm-year level: ln(1 + annual Euro volume of insider transactions). VOL_EB/SB/AF is the accumulated insider trading volume for the respective insider-trading group.
VOL_noBlackout	Logarithm of accumulated insider trading volume on firm-year level: ln(1 + annual Euro volume of insider transactions) if trading is not during blackout period. The variable takes the value 0 if there is no insider trading outside blackout period.
VOL_Blackout	Logarithm of accumulated insider trading volume on firm-year level: ln(1 + annual Euro volume of insider transactions) if trading is during blackout period. The variable takes the value 0 if there is no insider trading during blackout period.
VOL_high	Dummy variable taking the value 1 if the insider trading volume is equal or greater than the third quartile and value 0 otherwise.
FREQ	Logarithm of accumulated insider trading frequency on firm-year level: ln(1 + annual number of insider transactions).
FREQ_noBlackout	Logarithm of accumulated insider trading frequency on firm-year level: ln(1 + annual number of insider transactions) if trading is not during blackout period. The variable takes the value 0 if there is no insider trading outside blackout period.
FREQ_Blackout	Logarithm of accumulated insider trading frequency on firm-year level: ln(1 + annual number of insider transactions) if trading is during blackout period. The variable takes the value 0 if there is no insider trading during blackout period.
FREQ_high	Dummy variable taking the value 1 if the insider trading frequency is equal or greater than the third quartile and value 0 otherwise.
SHARES	Logarithm of accumulated insider trading shares on firm-year level: ln(1 + annual number of insider shares).
SHARES_noBlackout	Logarithm of accumulated insider trading shares on firm-year level: ln(1 + annual number of insider shares) if trading is not during blackout period. The variable takes the value 0 if there is no insider trading outside blackout period.
SHARES_Blackout	Logarithm of accumulated insider trading shares on firm-year level: ln(1 + annual number of insider shares) if trading is during blackout period. The variable takes the value 0 if there is no insider trading during blackout period.
SHARES_high	Dummy variable taking the value 1 if the insider trading shares is equal or greater than the third quartile and value 0 otherwise.

Appendix 2.1: Definition of Variables (cont’d)

Firm Characteristics	
CSR_PERF	Thomson Reuters ESG Score measuring a company’s relative ESG (Environment, Social and Governance) performance, commitment and effectiveness across 10 main themes (resource use, emissions, environmental product innovation, workforce, human rights, community, product responsibly, management, shareholders, and CSR strategy) based on company-reported data.
SIZE	Natural logarithm of the total assets at the end of fiscal year *t*.
RETURN	Total Stock Return (%) in *t*.
D_R&D	Dummy variable taking the value 1 if research and development expenditures divided by total sales are reported and the value 0 otherwise.
LEV	Long-term debt divided by total assets.
ANALYST	Number of analysts following the firm.
DACC_SIZE	Size-based estimation of discretionary accruals. Discretionary accruals, defined according to the modified Jones-Model.
DACC_IND	Industry-based estimation of discretionary accruals. Discretionary accruals, defined according to the modified Jones-Model.
TACC	Total accruals, defied by net income minus operating cash flow, deflated by lagged total assets.
REV	Change of revenues, deflated by lagged total assets.
REC	Change of accounts receivables, deflated by lagged total assets.
PPE	Property, plant and equipment, deflated by lagged total assets.
GROWTH	Market-to-book ratio at the end of fiscal year *t*.
ROE	Net income in *t* scaled by book value of equity.
ROA	Net income in *t* scaled by total assets.
Family	Dummy variable taking the value 1 if the firm is family controlled, if there is dominant shareholder holding more than 25% of the shares and the dominant shareholder is a family member.
Manager	Dummy variable taking the value 1 if the firm is manager controlled, if there is dominant shareholder holding more than 25% of the shares and the dominant shareholder belongs to the executive board.
Industry	Dummy variable taking the value 1 if the firm is industry controlled, if there is dominant shareholder holding more than 25% of the shares and the dominant shareholder is another non-financial firm.
Widely	Dummy variable taking the value 1 if no single shareholder holds more than 25% of the shares.
Others	Dummy variable taking the value 1 if the largest shareholder does not belong to any identifiable group.

3. Information Content of Insider Trades before and after the Market Abuse Regulation

3.1 Introduction

Regulation No 596/2014 on market abuse (MAR) aims to enhance investor protection and investors` trust in the market integrity.[12] MAR was published in the Official Journal of the European Union on 12 June 2014 and has direct application in the EU member states as of 3 July 2016. The directive on criminal sanctions for market abuse (2014/57/EU) complements the MAR that replaced the former Market Abuse Directive (MAD) 2003/6/EC.[13] The regulation introduces a regulatory framework on insider trading, unlawful disclosure of inside information, and market manipulation in order to enhance transparency in the capital markets (Article 1 of the MAR).

The concept of transparency is one of the most impactful regimes under MAR (Payne 2018). Article 17 of MAR stipulates pre-trades transparency requirements in terms of ex-ante ad hoc disclosure of inside information. The disclosure requirements prescribe the timely disclosure of inside information for financial instruments traded on regulated markets, and, opposite to MAD, ad hoc disclosure applies now also for instruments traded on trading platforms such as MTF (multilateral trading facilities) and OTF (organized trading facilities). Under Article 19(1) of the MAR corporate insiders must disclose their own transactions without undue delay tightening trading disclose requirements ex-post. Persons discharging managerial responsibilities have to announce their trading activities no later than three business days after the date of the transaction. In addition, MAR expressly prohibits corporate insiders to conduct any transactions on its own account or for the account of a third party during a "blackout" period of 30 calendar days before

[12] For a comparison of the Market Abuse Regulation and the regulation in the US, see Baum and Solomon (2019).

[13] For a presentation of Regulation (*EU)* No *596/2014 and Directive* 2014/57/EU as well as for their implications for German law, see Roeh and Beckmann (2016), p. 112-130. A German comprehensive commentary on the Market Abuse Regulation (MAR) and its implementing legislation is provided by Kloehn et al. (2018).

the announcement of an interim financial report or a year-end report (Article 19 Section 11 of MAR).

Further, MAR tightened up fines in the event of a violation of disclosure obligations and insider law, by relying on a mix of criminal penalties and administrative sanctions. For example, in 2019, the National Competent Authorities (NCAs) imposed a total of €88 million in fines related to 339 administrative and criminal actions under MAR. For Germany, 42 criminal sanctions and penalties of criminal sanctions amounting to EUR 5,523,750 were imposed in 2019 (ESMA, Annual Report 2019, pp. 3, 11). Insider dealings constitute now a criminal offence, at least in serious cases and when committed intentionally (Article 3 Section 1 of Directive 2014/57/EU). In addition, the new introduced "naming and shaming" - policy of disclosing detailed information about directors' dealings not only to the competent authority (in Germany the German Federal Financial Supervisory Authority, BaFin) but also on the website of the issuer for at least five years further increases market and media scrutiny as well as litigation risk (Article 34 of MAR in conjunction with § 125 WpHG).

We exploit the new transparency requirements and sanctions regime of the MAR to investigate whether the information content of insider trades changed in the pre- versus post-MAR period in Germany. We focus on the German market, even though MAR is effective for the entire European market, to avoid potential bias due to different legal origins in the EU. We expect MAR to have a significant effect on insiders` trading behavior.

Insider trades have information content if they lead to a change in investors` expectations and affect future returns (Beaver 1968; French & Roll 1986). Empirical research finds evidence that insiders gain significant abnormal returns indicating that they trade on private information not yet reflected in stock prices (Seyhun 1998; Lakonishok & Lee 2001 for the U.S.; Betzer & Theissen 2009; and King et al. 2015 for Germany; Fidrmuc et al. 2006 for the U.K.). Furthermore, insider trades are found to be associated with firm`s future earnings performance (Ke et al. 2003;

Piotroski & Roulstone 2005). Prior empirical studies investigating the influence of insider trading regulation are however inconclusive. Seyhun (1992) examined the impact of stricter insider trading regulation and higher enforcement during the 1980s in the U.S. and find increased excess returns and volumes of insider trades. In a similar vein, Brochet (2010) analysed the information content of Form 4 filings under Section 403 of the Sarbanes-Oxley Act of 2002 (SOX) and shows that abnormal returns and trading volumes around filings of insider purchases are significantly greater in the post-SOX than in the pre-SOX period. However, Gebka et al. (2017) as well as Prevoo and Weel (2010) find no systematic change in insider profits around the enactment of EU insider trading regulation Market Abuse Directive (MAD) in 2004. Especially for Germany, the coefficient of the MAD dummy is negative and strongly insignificant (Gebka et al. 2017).

Abnormal returns over a given event window proxy for the price-relevant information released to the market by the disclosure of insider trades that occur within this window (Huddart et al. 2007). To the extent that insiders trade on value relevant non-public information, their purchases (sales) will be positively (negatively) associated to firms' future cash flows. Huddart et al. (2001) find in their analytical model that public disclosure of insider trades accelerates price discovery as compared to the no-disclosure approach of Kyle (1985). Research in the U.S. shows that more timely dissemination of SEC filings is positively associated with the information content of insider trades (e.g., Carter and Soo 1999; Asthana and Balsam 2001; Brochet 2010). Theoretically, we would assume that the timelier notification of insider trades according to Article 19(1) of the MAR will increase abnormal returns. In contrast to the SOX regulation, the disclosure of insider trading has only been reduced from five to three days in Germany. Therefore, we do not expect this regulation change to have a similarly strong impact on the information content as compared to the findings of Brochet (2010). On the other hand, the extended ad hoc disclosure requirements according to Article 17 of the MAR will enhance pre-trade information dissemination on the market. In addition, consistent with the litigation avoidance hypothesis

(Skinner 1994; Kim & Skinner 2012), the stricter sanctions (Article 30 Section 1 of MAR) as well as the “naming and shaming”-policy (Article 17 of MAR) will increase scrutiny from investors, media, and regulators and thus may pre-empt insiders from trading based on private information. In line with this conjecture, we assume that insiders will gain lower abnormal returns in the post-MAR period. Still, since we cannot formulate a clear directional hypothesis, we leave the net change in information content of insider trading due to MAR as an empirical question.

On 2 July 2014, the European Union has enacted the MAR with a direct application as of 3 July 2016. Prior research suggests that capital markets often anticipate expected regulatory effects, even before the first firms adopt the new rules and after the regulation changes has been announced (Leuz & Wysocki 2016). Especially in case of EU regulations, the provisions apply automatically and uniformly to all countries (Article 288 of the Treaty on the Functioning of the European Union (TFEU)), in contrast to the country-level flexibility regarding the concrete implementation of EU directives, e.g. in case of penalties (see also Enriques & Gatti 2008). This may reinforce a possible anticipatory behavior since the regulation content is already known before implementation. Therefore, we expect that insiders anticipate the future regulatory changes and adjust their trading behaviour already in 2014.

Our results show that abnormal returns decrease after the MAR enactment on 2 July 2014, implying a decline in the information content of insider trading. The mean cumulative abnormal returns over a 20-day window amount to 2.55% (- 0.04%) for insider purchases (sales) before MAR and 1.24% (2.13%) for insider purchases (sales) after MAR. The differences in means are statistically significant at 1% level for insider purchases and at 10% level for insider sales. The empirical findings are consistent, but weaker, when using the MAR enforcement on 3 July 2016 as alternative treatment date. The empirical findings suggest that the information content of insider trades reduced in the post-MAR period, which may be explained by increased transparency resulting from the extended ad hoc disclosure as well as by enhanced market scrutiny and increased litigation risk. The effect is particularly pronounced for insider purchases, which are assumed to be driven by private information and less by portfolio rebalancing and liquidity needs like insider sales (Gebka et al. 2017).

Moreover, distinct analyses of single regulation provisions show no significant differences regarding the trading venue (regulated markets versus other trading facilities) or the trading time (within or outside the blackout period). Both *PostMAR*-interaction terms with MTF and OTF as well as with the blackout period are not significantly associated with abnormal returns. However, we find evidence that the level of litigation risk matters. Low ex-ante litigation risk moderates the disciplinary effect of the MAR on the information content of insider trades. Only for firms with high levels of litigation risk, abnormal returns remain significantly reduced after MAR.

Our study contributes to the literature of mandatory disclosure regimes not focusing on the U.S. market but rather on European jurisdictions complementing SOX-related research that documents changes in disclosure (e.g. Brochet 2019) and financial reporting (Cohen et al. 2008). Moreover, by focusing on Germany, we consider a country with a relatively high financial information opaqueness as captured by the Financial Information Score of Brochet (2019). He defines the Financial Information Score as the sum of the rankings of earnings quality, Big 4 auditors, analyst following, and international GAAP. Germany exhibits only a score of 2.89, compared to the U.S., the U.K., and France with values of 6.00, 6.00, and 4.07, respectively (Brochet 2019, pp. 348f.). Therefore, we expect not only to find a significant impact of the passage of MAR on the information content of German insider trades, but also a better understanding of the influence of disclosure regulations in environments with high information asymmetries.

This is the first study investigating the regulation effects of MAR on the German capital market. We show that a different regulatory environment for corporate insider trading subsequent to MAR triggers, opposite to MAD (Gebka et al. 2017), economically significant market reactions in Germany. We find evidence that higher information transparency of ad hoc disclosure and stricter sanctions reduce the information content of insider trades and likely restrict opportunistic insider behaviour. Moreover, our results contribute the literature on real effects of corporate disclosures and reporting that is still in its early stages (Leuz & Wysocki 2016).

The remainder of this paper is organized as follows. Section 3.2 describes the regulatory background in Germany and develops the research question based on prior literature. Section 3.3 introduces the research design. Section 3.4 and 3.5 present the empirical results on the information content of insider trading in the pre- and post-MAR period. Section 3.6 provides our robustness analyses. Section 3.7 concludes the paper.

3.2 Regulatory Background and Related Literature

3.2.1 Regulatory Framework

The EU acknowledges in the preamble of the MAR that "(a)n integrated, efficient and transparent financial market requires market integrity. (…) Market abuse harms the integrity of financial markets and public confidence in securities and derivatives." Therefore, by strengthening the disclosure regime and tightening penalties of insider trading, the EU aims to enhance market efficiency and transparency. Following Payne (2018), the prevalent theory underlying securities regulation is the semi-strong form of market efficiency. In this condition, all publicly available information about a stock is fully reflected in stock prices that instantly change when new public information is present (Fama 1970).

The MAR regulation applies in Germany from 3 July 2016 on, but has already been enacted and partly applied on 2 July 2014 (Article 39 Section 2 of MAR) replacing the earlier Market Abuse Directive (MAD) from 2004.[14] The MAR enforcement has been accomplished by amendments to the German Securities Trading Act of 1994 (*Wertpapierhandelsgesetz WpHG*).

[14] The MAD fundamentally changed the regulations on insider trading and significantly improved reporting standards (Dardas & Güttler 2011). Prior to the implementation of the MAD on 30 October 2004, insiders had to

Inside information is defined as an “information of a precise nature, which has not been made public, relating, directly or indirectly, to one or more issuers or to one or more financial instruments, and which, if it were made public, would be likely to have a significant effect on the prices of those financial instruments or on the price of related derivative financial instruments” (Article 7 Section 1 (a) of MAR). MAR prohibits insider dealing “where a person possesses inside information and uses that information by acquiring or disposing of, for its own account or for the account of a third party, directly or indirectly, financial instruments to which that information relates” (Article 8 Section 1 of MAR). An issuer with securities admitted to trading on an EU regulated market is according to Article 17 Section 1 of the MAR obliged to disclose inside information to the market as soon as possible adopting a concept of continuous disclosure (Payne 2018) and in a manner that enables fast access of the inside information by the public. This *ex-ante* disclosure provision intends to fulfill two functions. First, to increase investor protection by the means of market efficiency, and second, to prevent insider trading by ensuring a timely distribution of inside information to the market, mitigating insiders timing ability (Peyne 2018). The ad hoc disclosure requirement does not only apply to the regulated market but also to alternative trading venues such as multilateral trading facilities (MTF) and organized trading facilities (OTF).

In terms of an *ex-post* disclosure, any persons discharging managerial responsibilities and persons closely related to them have to report insider dealings to the issuer company and to the German Federal Financial Supervisory Authority (BaFin) promptly and no later than three days after the date of the transaction (Article 19 Section 1 of MAR). In the pre-MAR period, the

report their transactions "without delay" according to Directive 89/592/EEC. However, since the German supervisory authority did not further specify the regulation, considerable reporting delays were the result (Betzer & Theissen 2009). Moreover, prior to MAD, member states had wide discretion in implementing and enforcing insider trading laws, resulting in significant regulatory diversity across the EU.

disclosure requirement was five days (Article 15a WpHG in the version applicable until 2 July, 2016). Article 18 of MAR also requires the issuer to draw up a permanent insider list in prescribed format that can help to control the flow of insider information.

In addition, MAR expressly prohibits corporate insiders to conduct any transactions on its own account or for the account of a third party during a "blackout" period (also called closed period) of 30 calendar days before the announcement of an interim financial report or a year-end report (Article 19 Section 11 of MAR).[15]

The MAR further tightened sanctions resulting in higher litigation risk for insiders. Sanctions and penalties in the event of a violation of disclosure obligations and insider law amount to at least € 5 million for individuals and at least a maximum fine of € 15 million or 15% of annual turnover on group level for corporations (Article 30 Section 2 point (i) and (j) of MAR). Insider dealings constitute now a criminal offence at least in serious cases and when committed intentionally (Article 30 Section 1 of MAR).

3.2.2 Literature Review and Research Question

Insider trading profitability

Insider trading allows markets to quickly incorporate material information into stock prices, improving thus market efficiency and resources allocation (Manne 1966; Carlton & Fischer 1983; Demsetz 1986). However, empirical evidence shows also that insiders exploit their information advantages and receive abnormal gains. Pre-SOX studies based on U.S. data find evidence that insiders are better informed and earn abnormal returns (e.g. Jaffe 1974; Finnertry 1976; Seyhun 1986; Rozeff & Zaman 1998; Lakonishok & Lee 2001; Huddart and Ke 2007). For

[15] Betzer and Theissen (2009) find that German corporate insider trades occurring within 30 days before quarterly earnings announcements or within 60 days prior annual earnings announcement have an impact on prices measured by CAR (cumulate abnormal return) about twice as large in comparison to insider transactions outside these "blackout" periods.

U.K, Fidrmuc et al. (2006) find significantly positive cumulated abnormal returns for purchases of 1.65% and significantly negative cumulative abnormal returns for sales of -0.49% for a four-day window from 1991 to 1998.

For Germany, Rau (2004) investigates long-term abnormal returns following insider trading and finds significant abnormal profits in a time window of six months after the reporting day of insider transaction. Stotz (2006) shows that corporate insiders are contrarian traders and achieve on average an abnormal return of about 3% on average 25 days after buying a stock. According to Stotz (2006), outsiders mimicking insiders can realize nearly the same abnormal returns. Aussenegg and Ranzi (2018) infer that insider sales signal negative information about the firm value. Dymke and Walter (2008) find that corporate insiders trading prior ad hoc news disclosures realize high abnormal profits. Dickgiesser and Kaserer (2008) find strong evidence that corporate insiders in Germany exploit their informational advantage when trading in their own company`s stock and achieve significant excess profits. Unlike Stotz (2006), they show that outsiders cannot exploit information conveyed by insider trades to generate abnormal returns when taking in account transaction costs. Betzer and Theissen (2009) report abnormal returns for purchases (sales) of 1.02% (-0.94%) for a five days event window from 2002 to 2004. Dardas and Güttler (2011) report 21-days cumulative abnormal returns for purchases (sales) of 2.39% (-3.22%) between 2003 and 2009. In a similar vein, King et al. (2015) analyse German trades from 2002 to 2012 and find similar cumulative abnormal returns for purchases (sales) of 2.37% (-2.86%) over twenty days after the insider trading reporting date.

Impact of insider trading regulation on information content of insider trades

Brochet (2010) investigates the impact of the introduction of SOX on the U.S. capital market and finds evidence that insider purchases exhibit significantly higher abnormal returns after SOX. He attributes his findings on tighter ex-post disclosure requirements of insider dealings from up to 40 days (if transaction is conducted at the beginning of the month)[16] before SOX to two business days after SOX. Brochet (2010) infers that, ceteris paribus, the introduction of SOX positively affects the information content of insider purchases by accelerating the information content of Form 4. This is in line with Huddart et al. (2001), who find in their analytical model that public disclosure of insider trades accelerates price discovery as compared to the no-disclosure approach of Kyle (1985). Prior research in the U.S. also shows that more timely dissemination of SEC filings is positively associated with the information content (e.g., Carter & Soo 1999; Asthana & Balsam 2001). The costs of an increased litigation risk do not outweigh the benefits of the accelerate information provision.

In the European context, Prevoo and Weel (2010) investigate the effects of MAD on abnormal returns and volumes based on data from the Amsterdam Stock Market. They document that cumulative abnormal returns and volumes prior news announcement decreased in the post-MAD period. The differences in means between pre- and post-MAD are though not significant. Christensen et al. (2016) provide cross-country empirical evidence that stock market liquidity in the EU (including Germany) improves on a yearly basis by 0,1% to 0,2% of the total capitalization after the introduction of the MAD Regulation in 2004 and the Transparency Directive (TPD) in 2007. Gebka et al. (2017) find no systematic change in insider profits around the enactment of the MAD measured by shifts in Jensen`s alphas, indicating that MAD did not change the trading behavior of insiders and thus the information content of their trades. His empirical analysis includes also Germany in where the coefficient of the MAD exhibits a negative but insignificant coefficient. Watanabe et al. (2019) examined the impact of the introduction of the EU Transparency Directive on stock price informativeness captured by stock return synchronicity.

[16] According to Brochet (2010) "(u)ntil August 2002, the requirement had only been to file Form 4 with the SEC within ten days after the close of the calendar month in which the transaction had occurred." (p. 420).

Their findings reflect higher levels of firm transparency and more informative stock prices in the post-TPD period.

To sum up, prior empirical studies are inconclusive regarding the impact of regulation on trading outcomes. Research suggests that an ex post increase in information transparency by timely notification of insider transactions may accelerate price discovery in the market, increasing thereby the information content of directors' dealings. However, research also shows that information provided ex-ante by ad hoc disclosures is rapidly incorporated in the market (Fama et al. 1969) and increases market efficiency (Aharony & Swary 1980). Bank and Baumann (2015) investigated ad hoc disclosure in Germany and find that markets react efficiently, however prices need several days after disclosure to fully adjust. In line with these inferences, we assume that higher information dissemination before insider trades will be associated with lower information asymmetries thus decreasing insider trading informativeness. A further argument implies the litigation avoidance hypothesis (Skinner 1994; Kim and Skinner 2012) stating that stricter sanctions as well as the "naming and shaming"-policy introduced by the MAR, may present a costly devise for insiders pre-empting them from trading based on private information. In contrast to the SOX regulation, the notification requirement of insider trading has only been reduced from five to three days in Germany. Therefore, we do not expect the (transparency) argument of more timely dissemination of insider trade filings to outweigh the litigation risk argument and the ad hoc disclosure effects, as compared to the findings of Brochet (2010). Nevertheless, we cannot a priori suggest which provision will be prevalent in post-MAR period. We thus leave the net effect of the MAR on the information content of insider trading as an empirical question.

3.3 Research design

3.3.1 Definition of Abnormal Returns

In line with prior research, we use abnormal stock returns in order to measure the information content of insider trades (e.g., Karpoff 1986; Kim & Verrecchia 1991, Huddart & Ke 2007). Abnormal returns capture the average change in traders` beliefs, i.e. changes in the expectations of the market due to the announcement of an insider trading (Beaver 1968). We follow Betzer and Theissen (2009) and use the CDAX performance index as market index, which is a German broad, value-weighted index comprising all domestic shares listed in the Prime and General Standard segments at the Frankfurt Stock Exchange.

Abnormal returns during the event window are defined as

$$AR_{i,t} = R_{i,t} - (\alpha_i + \beta_i\, Rm_{i,t}) \qquad (1)$$

where $R_{i,t}$ and $R_{m,t}$ denote the return of stock i and the market, respectively, on day t. The parameters a_i and b_i are the intercept and the slope estimates of an Ordinary Least Squares (OLS) regression. We follow Kothari and Warner (1997) and use three different models to measure abnormal returns in order to exclude measurement bias:

(1) *Market-Adjusted Return Model:* In the context of the market-adjusted return model the intercept variable α_i and slope estimate β_i are constrained to zero and one, respectively (Kothari and Warner 1997).

(2) *Market-Model Regression:* The firm-specific parameters α_i and β_i are estimated by an OLS regression and are not prespecified. We follow MacKinlay (1997) and use an estimation window that comprises 120 trading days, in particular t-125 to t-6. Prior research provides evidence that an estimation window exceeding 100 days results in robust predicted returns not sensible any more to varying estimation periods (Armitage, 1995; Park, 2004; Aktas et al. 2007). Similar to Ahern (2009), we further

drop firms having less than 50 missing returns in the estimation period and 20 missing observations in the event period.

(3) *Four Factor-Model:* In line with Fama and French (1993) and Carhart (1997), we run a regression on four common factors to predict expected returns. Portfolios are formed based on the variables excess return on the market, size, book-to-market, and momentum.[17] The estimation window is the same as in the market-model and comprises 120 trading days. Similar to Brochet (2010), we measure abnormal returns by subtracting portfolio returns based on the market, size, book-to-market value, and momentum portfolios from individual stock returns to obtain daily abnormal returns AR_t.

3.3.2 Multivariate Regression Model

We use a standard short-window event-study to estimate the information content of insider trades (MacKinlay 1997). The window comprises 20-days, from day t_0 to day t_{+1}, where t_0 is the event day defined by the transaction date as reported in the database of Directors Dealing Notification.

To investigate the impact of the MAR introduction on the information content of insider trades, we run the following regression model similar to Lakonishok and Lee (2001), Ravina and Sapienza (2010), and Brochet (2010):

[17] The constructed MRF, SMB, HML and UMD factors data sets as well as market returns are obtained from Professor Stehle`s website at Humboldt-Universität zu Berlin (https://www.wiwi.hu-berlin.de/de/professuren/bwl/bb/daten/fama-french-factors-germany/fama-french-factors-for-germany), retrieved on 04.05.2020. SMB is the difference between the return on the portfolio of "small" stocks and "big" stocks; HML gives the difference between the return on the portfolio of "high" and "low"book-to-market stocks; UMD is the difference between the return on the portfolio of past one-year "winners" and "losers". *Monthly and daily data of Fama/French factors* are available from 1958 to 2016 and from 1990 to 2016, respectively.

$$CAR_{0,19} = \alpha_0 + \beta_1 PostMAR + \sum \beta_i\ Controls_{it} + \sum \beta_i\ Fixed\ Effects_i + \varepsilon_{i,t}. \qquad (2)$$

$CAR_{0,19}$ is the cumulative abnormal return over a 20-day window starting with t=0 on the transaction date. *PostMAR* is our main variables of interest and defined as an indicator variable equal to one for trades after MAR and zero otherwise. Since prior research (Leuz & Wysocki 2016, Christensen et al. 2016, 2013) suggests that capital markets often anticipate expected regulatory effects, even before the first firms adopt the new rules, and after the regulation changes have been announced, we use in the main model the announcement year 2014 as our treatment date. In sensitivity analyses, we repeat the model with the implementation year 2016 as an alternative treatment date. $Controls_{it}$ stands for a set of firm-level control variables. We include industry fixed effects to control for industry specific trends, which may influence trading behavior.

In line with Seyhun (1986), Rozeff and Zaman (1998), Lakonishok and Lee (2001), Cheng and Lo (2006), and Huddart and Ke (2007), we add *SIZE*, *GROWTH*, and *ROE* as dependent variables to control for trading strategies which may impair our results (Ravina & Sapienza 2010). Consistent with Seyhun (1986) and Lakonishok and Lee (2001), insiders purchase less stocks at large firms. For this reason, we expect that *SIZE* is negatively related to average abnormal returns earned by corporate insiders.[18] *SIZE* is defined as the natural logarithm of total assets at the end of fiscal year *t*. According to Rozeff and Zaman (1998), *GROWTH* is negatively (positively) associated with abnormal returns, due to reduction in purchase (increase in sales) when stocks change from value to growth categories. A high level of growth may be typical for large firms (Daniel and Titman 1997), which also may explain the negative association with abnormal returns of purchases. *GROWTH* is defined as the market-to-book ratio at the end of fiscal year *t*. We consider return on equity *(ROE)* to capture firms' recent performance and a potential contrarian

[18] As documented by prior research (e.g., Huddart, Ke and Shi, 2007), net number of purchases (frequency) and value of shares traded (volume) are positively related to price reactions, i.e., to abnormal returns.

trading strategy of insiders (Rozeff & Zaman 1998; Lakonishok & Lee 2001). In this case, the coefficient of *ROE* is expected to be negative. Return on equity is defined as net income in year *t* scaled by lagged book value of equity. Brochet (2010) complements the set of control variables[19] by including *TRADESIZE* and *R&D* expenditures. *TRADESIZE* is the number of shares traded in a given day calculated separately for purchases and sales and deflated by the number of shares outstanding. *TRADESIZE* captures whether larger insider dealings trigger a stronger market reaction upon executing (or reporting) the insider trade. *R&D* expenditures is defined as an indicator variable equal to one if the firm reported a non-zero *R&D* expense, and zero otherwise. *R&D* is expected to exhibit a positive (negative) association with abnormal returns in case of insider purchases (sales).

3.4 Data and Univariate Analyses

3.4.1 Sample Selection and Descriptive Statistics

Our sample covers insider-trading data from the database of Directors Dealing Notification provided by the German Federal Financial Supervisory Authority (BaFin). We gathered financial information data from Compustat, data on returns from Datastream (Refinitiv), and the ESG scores from ASSET4.

We select all insider purchases and sales between 2011 and 2018, which give us a minimum of two years of pre-and post-enactment (-implementation) of MAR. Consistent with Christensen et al. (2016), a longer time-series bevor 2011 and after 2018 is unlikely to affect our results because our findings are primarily identified from abnormal returns close to the treatment dates.

[19] We do not add *Loss* as performance variable according to Brochet (2010), because we have already included *ROE* (return on equity) as a performance indicator.

Table 3.1 Sample Selection

Panel A: Data Selection of Insider Trading Data			
Data Selection (2011-2018)	Remaining Observations	Purchases	Sales
Insider trades	15,286	10,652	4,634
Less no German ISIN	14,203	10,235	3,968
Less currency other than Euro	13,669	9,812	3,887
Less implausible values regarding dates	13,640	9,759	3,881
After cleansing process (less implausible values of volumes, penny stocks, prices)	12,844	9,366	3,478
Net transactions (per day cumulation)	9,073	6,687	2,351

Panel B: Data Selection regarding Variables			
Data Selection	Remaining Observations	Net Purchases	Net Sales
Less missing total return data from Datasteam	3,999	3,189	810
Less missing control variables data from Compustat			
Market Adjusted Return Model	3,516	2,790	726
Market Model	2,903	2,300	603
Four Factor-Model	1,148	853	295

Panel C: Distribution of Industries						
Industries	Remaining Observations		Net Purchases		Net Sales	
	N	%	N	%	N	%
Chemicals & Pharmaceutica	383	10.89	320	11.47	63	8.70
Durable Manufacturers	765	21.76	585	19.70	180	24.80
Transportation	204	5.80	176	6.31	28	3,86
Utilities & Retails	736	20.93	650	23.30	86	11.85
Computers & Services	735	20.90	515	18.55	220	30.30
Financial Institutes	693	19.71	544	19.50	149	20.52

N describes the number of observations.

Table 3.1, Panel A to C reports the data selection of insider trading. The initial sample consists of 15,286 transactions. After eliminating insider transactions of types other than share sales and purchases (e.g. capital increases and gifts, options), trades with low transaction price (penny stocks), transactions with trading volume more than 5% of total common shares outstanding (block trades), transactions with missing values, transactions with currencies other than Euros and implausible values regarding trading, publishing, and reporting day, our sample includes 12,844 insider transactions. Furthermore, multiple purchases (sales) trades of shares either by the same insider or by different insiders on the same reporting day have been aggregated in one purchase (sale) transaction on a given day. Net aggregated transactions (purchases minus sales of shares) on a given day are classified as purchases (sales) if the net transaction shares volume is positive (negative) (Betzer & Theissen 2009). The remaining sample of 9,073 of firm`s daily net trading positions consists of 6,687 purchases and of 2,351 insider sales. After merging the return data, the final sample comprises 3,999 insider transactions, if which 3,189 are purchases (1,090 before and 2,099 after MAR) and 810 are sales (362 before and 448 after MAR).

Table 3.1, Panel C reports the distribution across the industry sectors. In order to control for time invariant industry characteristics, we include industry fixed effects in our regression model. Most observations relate to firms from the manufactures industry (21.76%), the utilities and retails industry (20.93%), and the computers and services industry (20.90%).

Table 3.2 presents the descriptive statistics. The mean 20-day CAR of Table 3.2 Panel A is about 1.28 % over the total sample period. The average firm has total assets of about EUR 760 million, a mean market-to-book-ratio (*GROWTH*) of about 2.20, and a mean return on equity (*ROE*) of 0.06. Approximately 50% of the firms report research and development expenditures (*R&D*). The *TRADESIZE* is quite small with 0.03%, but comparable to findings of Brochet (2010: 0.09% for sales and 0.04% for purchases after SOX). Only 1.6% of the trades have been on average conducted on MTF and OTF venues. The mean corporate social responsibility performance index

(*CSR_PERF*) amounts to 62%. For the variable of interest in Panel B, we can see a clear decline of the 20-day cumulated abnormal return from 1.78 % before MAR to 0.98 % after MAR with a highly significant difference in means at 1% level.

Table 3.2 Descriptive Statistics and T-test

Panel A: Descriptive Statistics					
	Mean	Standard Deviation	25% quartile	Median	75% quartile
CAR$_{(0, 5)}$	0.0099	0.0586	-0.0185	0.0061	0.0331
CAR$_{(0, 19)}$	0.0128	0.0876	-0.0370	0.0073	0.0542
SIZE: ln (total assets in EUR 1,000,000)	6.5939	2.6718	4.9913	5.8618	8.3399
GROWTH	2.2046	2.5603	1.0285	1.5849	2.7368
ROE	0.0592	0.2474	0.0168	0.0936	0.1480
R&D	0.4966	0.5001	0	0	1
TRADE SIZE	0.0026	0.0247	0.0000	0.0001	0.0006
CSP_PERF	0.6169	0.4865	0	1	1
OTC	0.1362	0.3431	0	0	0
MTF/OTF	0.01577	0.1246	0	0	0

Panel B: T-test Statistics					
	Mean			N	
	Pre-MAR (1)	Post-MAR (2)	p-value for difference (1) - (2)	Pre-MAR	Post-MAR
CAR$_{(0, 5)}$	0.0112	0.0090	0.2947	1288	2228
CAR$_{(0, 19)}$	0.0178	0.0098	0.0000	1288	2228

*, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. T-statistics are reported for the differences in mean. All variables are winsorized at the 1% and 99% percentiles.

Table 3.2 provides information on insider trading activity and firm characteristics before and after MAR regulation first applied on July 2, 2014. The sample captures the time period from 2011 to 2019 and comprises 2,790 firm day observations.

CAR$_{(0, 5)}$ are six-day abnormal returns on transaction date (t=0) predicted using the Market-Adjusted-Return Model. Similarly, *CAR$_{(0, 19)}$* are twenty-day abnormal returns on transaction date (t=0). *SIZE* is the natural logarithm of the total assets at the end of fiscal year *t*. *GROWTH* is defined as the market-to-book ratio at the end of fiscal year *t*. *ROE* is defined as net income in *t* scaled by lagged book value of equity. *TRADESIZE* is the number of shares purchased/sold by corporate insiders in a given day, divided by common shares outstanding. *R&D* expenditures is an indicator variable equal to one if the firm reported a non-zero R&D expense, and 0 otherwise.

3.4.2 Univariate analyses of pre- versus post-MAR CARs as of transaction dates for the enactment date 2014

In line with Christensen et al. (2016), we expect that insiders anticipate future regulatory changes and adjust their trading behavior. Therefore, we use the enactment date of MAR July 2, 2014 as the treatment date to identify changes in the information content of insider trading.

Insider Purchases

Table 3.3 Panel A presents univariate statistics about the distribution of CARs for insider purchases after the enactment of MAR on 2 July 2014. We focus here on the transaction dates since directors' dealings may trigger a price reaction already before the official notification and reporting of the trade.

The post-MAR 20-day cumulated abnormal returns are significantly lower at 1%-level for all three model specifications, indicating that the information content of insider trading decreased. The mean 20-day CARs amount to 1.18% - 1.24% after MAR versus 2.35% - 4.69% before MAR. King et al. (2015) and Gebka et al. (2017) find similar excess purchase returns for insiders of 2.73% in pre-MAR period. The cumulated abnormal returns one week after the insider transaction are however only in case of the Market-Model and the Four Factor-Model significantly lower. The findings in Table 3.3 Panel A suggest that the increased ad hoc disclosure requirements and the enhanced costs of the litigation risk outweigh the benefits of the increased transparency due to the shorter notification window, since insiders seem not to trade on non-public information. This is in contrast with empirical findings of Brochet (2010) for the U.S. market. He documents an increased abnormal return after insider purchases in the post-SOX period. The big SOX-change regarding the notification window (from up to 40 days to two days) compared to the MAR (from five to three days) may explain the different findings.

Table 3.3 Pre- versus post-MAR Cumulated Abnormal Returns (CAR) around Transaction Dates of Insider Purchases and Insider Sales: Enactment Date of MAR

Panel A: Enactment date of MAR on July 2, 2014 – Insider Purchases									
Abnormal Return Model	**Market-Adjusted Return Model**			**Market Model**			**Four Factor-Model**		
Days relative to transaction date	(1) Pre-MAR	(2) Post-MAR	(3) t-stat	(4) Pre-MAR	(5) Post-MAR	(6) t-stat	(7) Pre-MAR	(8) Post-MAR	(9) t-stat
0	0.0006^{+}	-0.0007^{+}	-0.06	0.0011^{+}	0.0005^{+}	0.4579	0.0037	-0.0001^{+}	2.1538**
[0,+1]	0.0029	0.0040	-0.67	0.0036	0.0034^{+}	0.2382	0.0072	0.0003^{+}	3.1116***
[0,+2]	0.0065	0.0060	0.2661	0.0070	0.0054	0.8315	0.0115	0.0005^{+}	4.3957***
[0,+5]	0.0144	0.0116	1.27	0.0156	0.0111	1.8585*	0.0222	-0.0089^{+}	3.5278***
[0,+19]	0.0255	0.0124	3.67***	0.0235	0.0118	2.9713***	0.0469	-0.0123^{+}	3.3027***
N	1,090	2,099		890	1,763		652	382	
Panel B: Enactment date of MAR on July 2, 2014 – Insider Sales									
Abnormal Return Model	**Market-Adjusted Return Model**			**Market Model**			**Four Factor-Model**		
Days relative to transaction date	(1) Pre-MAR	(2) Post-MAR	(3) t-stat	(4) Pre-MAR	(5) Post-MAR	(6) t-stat	(7) Pre-MAR	(8) Post-MAR	(9) t-stat
0	0.0026^{+}	0.0065	-1.36	0.0017^{+}	0.0060	-1.2661	0.0046^{+}	0.0052^{+}	-0.1190
[0,+1]	0.0020^{+}	0.0078	-1.44	-0.0008^{+}	0.0063	-1.5416	0.0038^{+}	0.0018^{+}	0.4613
[0,+2]	0.0112^{+}	0.0124	-1.29	-0.0028^{+}	0.0112^{+}	-1.3737	0.0039^{+}	0.0111^{+}	-0.8969
[0,+5]	-0.0024^{+}	0.0117^{+}	-1.62	-0.0089	0.0060^{+}	-1.4612	0.0055^{+}	0.0079^{+}	-0.2891
[0,+19]	-0.0041^{+}	0.0213	-1.77*	-0.0214	-0.0016^{+}	-1.1634	0.0065^{+}	0.1965	-3.1641***
N	362	448		305	370		237	93	

*, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. T-statistics are reported for the differences in mean. + Indicates that a mean is insignificantly different from zero at the 10% level. Table 3.3 presents mean abnormal returns following insider purchases after transaction dates before and after the enactment date of MAR on July 2, 2014. The sample includes insider purchases and sales from 2011 to 2018. Abnormal returns are calculated based on the Market-Adjusted Return Model, Market Model, and Four Factor-Model (Fama & French 1993, Carhart 1997). The Four Factor Model sample includes insider purchases and sales from 2011 to 2016 due to limited data availability of the Fama and French Factors in Germany.

Insider sales

Table 3.3 Panel B shows CAR distributions after insider sales. The abnormal returns are negative in pre-MAR period, but become positive after MAR. The difference in means is however only statistically significant for the mean 20-day CARs of the Market-Adjusted Model (Panel B, Column 3) on 10%-level and of the Four Factor-Model (Panel B, Column 9) on 1%-level. According to Cohen et al. (2012), a positive abnormal return after sales may be explained by so called “routine” trading, comprising trades due to personal liquidity and diversification motives. Our findings are in line with Brochet (2010), who also find that post-SOX abnormal returns after insider sales are higher than the pre-SOX abnormal returns. This indicates that in addition to liquidity needs the higher litigation risk and stronger market scrutiny following SOX and MAR result in less opportunistic behavior of insiders being less prone to sell their stocks ahead of bad news. Consistent with prior literature legal risk may be an important determinant of insider selling activity (Cheng & Lo 2006; Rogers 2008).[20]

3.4.3 Sensitivity analyses: Implementation date of the MAR in 2016 and reporting date of the insider trade

Implementation date of the MAR in 2016

We further assess the design validity of our main model using as an alternative treatment date the implementation date of the MAR on July 3, 2016. The findings show that the abnormal returns of insider purchases (Table 3.4, Panel A, Column 2 and 5) also decline after the entry-into-force date. However, the mean difference is only statistically significantly at 1% level for the Market-Adjusted Return Model. The 20-day CAR for insider purchases amounts to 2.01% for pre-MAR (Panel A, Column 1) and 1.13% for post-MAR (Panel A, Column 2). The results for the

[20] A further explanation for less information content in sales is the compensation structure of managers. Roulstone (2003) argues that an optimal compensation structure allows insider purchases rewarding managers for their success, but may restrict insider sales disciplining managers for their failures and compensating them by granting abnormal returns from insider sales in front of bad news. In Germany, the share of stock-based compensation components increased from 15 percent in 2009 to 52 percent in 2018 (Beck et al. 2020).

abnormal returns after insider sales (Table 3.4, Panel B) also indicate an increase after MAR. The difference in means is though not statistically significant (Column 3 and 6).

Table 3.4 Sensitivity Analyses of pre- versus post-MAR Cumulated Abnormal Returns (CAR) around Transaction Dates of Insider Purchases and Insider Sales: Implementation Date of MAR

Panel A: Implementation date of MAR July 3, 2016 – Insider Purchases

Abnormal Return Model	**Market-Adjusted Return Model**			**Market Model**		
Days relative to transaction date	(1) Pre-MAR	(2) Post-MAR	(3) t-stat	(4) Pre-MAR	(5) Post-MAR	(6) t-stat
0	0.0005+	-0.0018+	-0.80	-0.0006	0.0023+	-2.1058**
[0,+1]	0.0020	0.0052	-2.12**	0.0021	0.0050	-1.7161*
[0,+2]	0.0053	0.0071	-1.03	0.0050	0.0071	-1.1147
[0,+5]	0.0122	0.0129	-0.32	0.0120	0.0133	-0.5461
[0,+19]	0.0201	0.0133	3.67***	0.0178	0.0132	1.2148
N	1,682	1,507		1,463	1,190	

Panel B: Implementation date of MAR July 3, 2016 – Insider Sales

Abnormal Return Model	**Market-Adjusted Return Model**			**Market Model**		
Days relative to transaction date	(1) Pre-MAR	(2) Post-MAR	(3) t-stat	(4) Pre-MAR	(5) Post-MAR	(6) t-stat
0	0.0062	0.0027+	1.20	0.0053	0.0019	0.9740
[0,+1]	0.0065	0.0033+	0.80	0.0035	0.0023	0.2586
[0,+2]	0.0115	0.0015+	1.14	0.0075	0.0000	0.7017
[0,+5]	0.0062+	0.0044+	0.20	-0.0021	0.0017	-0.3548
[0,+19]	0.0056+	0.0167	-0.76	-0.0185	-0.0036	-1.2439
N	492	318		435	240	

*, **, and *** indicate significance at the 10%, 5%, and 1% level, respectively. T-statistics are reported for the differences in mean. + Indicates that a mean is insignificantly different from zero at the 10% level. This Table presents mean abnormal returns following insider sales after transaction dates before and after the implementation date of MAR on July 3, 2016. The sample includes insider purchases and sales from 2011 to 2018. Abnormal returns are calculated based on the Market-Adjusted Return Model, Market Model. The Four Factor Model sample includes insider purchases and sales from 2011 to 2016 due to limited data availability of the Fama and French Factors in Germany.

The weaker results of 2016 demonstrate that the change in information content of insider trades can be better identified when considering the anticipation effect in 2014. Following the announcement date, insiders seem to anticipate a stronger legal, market, and media scrutiny, adapting thus their trading behavior. This is especially pronounced for insider sales. While MAR has no impact on insider sales at implementation date in 2016, we find evidence that the information content of sales decreases after the announcement date in 2014 in terms of positive 20-day CARs.

Reporting date of insider dealings

In order to exclude any estimation bias due to the use of the transaction date, we repeat the univariate analyses using the reporting date of the insider dealing. The results are similar to the transaction dates, with significantly reduced abnormal returns after insider purchases and significantly increased abnormal returns after insider sales in the 20-day windows (untabulated results).

Non-Parametric Tests

In order to control for outliers as well as for the case that stock prices are not normally distributed, we run the non-parametric test according to Mann and Whitney (1947). The untabulated results indicate that the distributions are statistically different at 5% level, implying that abnormal returns are significantly different before and after the introduction of MAR.

3.5 Multivariate analyses

3.5.1 Basic results

Table 3.5 presents the multivariate regression results. The dependent variable comprises the cumulated abnormal returns over 20-days, CAR (0; +19). In line with Lakonishok and Lee (2001), we focus on the transaction date denoted as event date t_0 since the capital market reacts stronger around the insider transaction date than around the insider trading reporting date. Consistent to the univariate analyses, the treatment date is the enactment of the MAR in 2014.

Multivariate Results for Insider Purchases

The empirical findings in Table 3.5, Column 1 to 3 show that the *PostMAR* variable, capturing the value one for years after 2014 and zero otherwise, is highly significantly negative associated with 20-days CARs. The decrease of cumulated abnormal returns varies between - 5.49% and - 1.46%. The coefficient of *PostMAR* indicates a strong negative treatment effect on the information content of insider purchases also after controlling for alternative factors explaining abnormal returns.

The firm-specific control variables are partly significant and exhibit the expected signs. The coefficient estimate on *SIZE* is negative in all three models and highly significant at 1% level indicating lower abnormal returns with large firms (Seyhun 1986; Lakonishok & Lee 2001). The coefficient on *GROWTH* is also in line with prior findings and exhibits a negative sign. The coefficient of *ROE* is negative (-0.0355) and significant at 1% level (Column 2) showing that high abnormal returns are associated with less profitable firms (Lakonishok and Lee 2001; Betzer and Theissen, 2009). *TRADESIZE* is significantly positive related (Column 1 and 2) to abnormal returns indicating that the market reacts more strongly to larger insider trades (Brochet 2010).

Multivariate Results for Insider Sales

Table 3.5, Column 4 to 6 present the regression results of insider sales. The coefficients on *PostMAR* are not significant for the Market-Adjusted Return model and for the Market-Model regression. Only in case of the Four Factor-Model, the coefficient is significantly positive and thus in line with the univariate analyses. These findings are consistent with prior evidence on insider sales that tend to predict insignificant abnormal returns (Scott & Xu, 2004; Lakonishok & Lee, 2001).

Table 3.5 Information Content of Insider Trading after MAR Regulation

	Purchases			Sales		
Dep. Variable: $CAR_{0,19}$	**Market-Adjusted Return Model** Coeff. (p-value) (1)	**Market Model** Coeff. (p-value) (2)	**Four Factor Model** Coeff. (p-value) (3)	**Market-Adjusted Return Model** Coeff. (p-value) (4)	**Market Model** Coeff. (p-value) (5)	**Four Factor Model** Coeff. (p-value) (6)
PostMAR	-0.0146*** (0.000)	-0.0116*** (0.0039)	-0.0549*** (0.0000)	0.0068 (0.3512)	0.0048 (0.5841)	0.1321*** (0.0000)
SIZE	-0.0038*** (0.000)	-0.0021*** (0.0008)	0.0003 (0.8447)	0.0002 (0.9134)	0.0024 (0.1665)	0.0087 (0.1002)
GROWTH	0.0013* (0.063)	-0.0029*** (0.0002)	0.0020 (0.1749)	0.0027* (0.0521)	0.0039** (0.0178)	0.0001 (0.9791)
ROE	0.0047 (0.415)	-0.0355*** (0.0000)	-0.0089 (0.4284)	0.0124 (0.5739)	-0.0486** (0.0691)	-0.0497 (0.5849)
R&D	0.0009 (0.8290)	0.0033 (0.4817)	-0.0185*** (0.0364)	-0.0067 (0.4969)	-0.0006 (0.9603)	-0.1241*** (0.0007)
TRADESIZE	0.3024** (0.0104)	0.1888** (0.0350)	-0.0540 (0.9569)	0.2501*** (0.0000)	0.4137*** (0.0000)	0.3392 (0.1631)
Intercept	0.0544*** (0.0000)	0.0421*** (0.0000)	0.0685*** (0.0008)	0.0602*** (0.0024)	-0.0827*** (0.0002)	-0.0665 (0.4045)
Industry FE	Included	Included	Included	Included	Included	Included
N	2,790	2,300	853	726	603	295
R^2 in %	2.24	2.70	8.27	1.33	5.34	8.49

*, **, and *** indicate significance at the 10%, 5%, and 1% level, using a two-tailed test. T-statistics are based on standard errors, which are adjusted for heteroscedasticity and clustering at firm level.

Dep. variable stands for dependent variable on transaction date (t=0) and FE for fixed effects. N presents the insider trades observations. PostMAR is an indicator variable equal to 1 for insider trades on or after the enactment date of MAR on July 2, 2014 and 0 otherwise. SIZE is the natural logarithm of the total assets at the end of fiscal year t. GROWTH is defined as the market-to-book ratio at the end of fiscal year t. ROE is defined as net income in t scaled by lagged book value of equity. R&D is indicator variable equal to 1 if the firm reported a non-zero R&D expense in the most recent fiscal year, and 0 otherwise. TRADESIZE of insider trades is the number of shares traded, deflated by the number of shares outstanding on the same day. TRADESIZE is the sum of all transactions reported on the same trading date, but is calculated separately for purchases and sales.

Table 3.5 reports regression results with the 20-day abnormal returns (CAR0,19) around transaction date of insider trades as dependent variable. The sample includes transactions of corporate insiders from 2011 to 2018 for calculating abnormal returns according to the Market-Adjusted-return Model and the Market Model. The Four Factor-Model includes insider transactions from 2011 to 2016.

Since insider sales may also be liquidity driven, they include less price-sensitive information compared to insider purchases (Fidrmuc et al., 2006; Goncharov et al., 2013). In addition, sales are likely more exposed to higher litigation risk, pre-empting insiders from trading on private information (Billings & Cedergren, 2015).

Consistent with Rozeff and Zaman (1998) as well as Piotroski and Roulstone (2005), *GROWTH* is positively related to abnormal returns in line with insider trading based on contrarian beliefs. While the coefficients of *SIZE* are not significant, the coefficient on *ROE* is significantly negative in the Market-Model regression. *R&D* is negative and also significant for the Four Factor-Model, while *TRADESIZE* remains significant and positive for the Market-Adjusted Return Model and the Market Model.

3.5.2 Cross-sectional Analyses of Regulation Provisions

Our main findings reveal that the introduction of the MAR results in a significantly net decrease of cumulated abnormal returns of insider buys. We do not consider insider sales further because they seem not to contain price-relevant information after MAR. In order to understand the drivers of the net decrease in abnormal returns, we try to separate the effects of single regulation provisions.

Notification of insider trades

We do not conduct a separate analysis of the timelier notification of insider trades, because the reduction from five to three days is relatively small compared to the post-SOX change from up to 40 to two days. Further, 75% of the trades in the pre-MAR period have already been disclosed within three days. Therefore, we do not expect a predominant effect of this regulation provision. If though the two days reduction would significantly accelerate price discovery, then we should find either a positive effect or, if the provisions cancel each other out, no effect. The net decrease in abnormal returns in the post-MAR period confirms however our expectations.

Table 3.6 Analyses of Regulation Provisions

Regulations Provisions of MAR	**Ad hoc Disclosure**		**Blackout**		**Litigation Risk**	
Dep. Variable:	$CAR_{0,19}$		$CAR_{0,19}$		$CAR_{0,19}$	
Insider Purchases	(1) Coeff.	p-value	(2) Coeff.	p-value	(3) Coeff.	p-value
PostMAR	-0.0166***	0.0000	-0.0113***	0.0031	-0.0216**	0.0084
MTF/OTF	-0.0087	0.8867				
MTF/OTF*PostMAR	-0.0029	0.9653				
Blackout			-0.0862	0.9560		
Blackout*PostMAR			0.0782	0.6745		
Low_Litigation_Risk					-0.0297***	0.0044
Low_Litigation_Risk*PostMAR					0.0251**	0.0144
SIZE	-0.0037***	0.0000	-0.0032***	0.0000	-0.0003	0.8624
GROWTH	0.0008	0.3043	0.0005	0.5286	0.0061***	0.0008
ROE	0.0002	0.9702	-0.0072	0.2698	-0.0767***	0.0107
R&D	0.0040	0.3769	0.0079*	0.0861	0.0095	0.2377
TRADESIZE	0.4356***	0.0014	0.3033**	0.0109	-0.1478	0.5404
Intercept	0.0525***	0.0000	0.0465***	0.0000	0.0170	0.4229
Industry FE	Included		Included		Included	
N	2,410		2,212		770	
R^2 in %	2.46		2.11		2.54	

*, **, and *** indicate significance at the 10%, 5%, and 1% level, using a two-tailed test. T-statistics are based on standard errors, which are adjusted for heteroscedasticity and clustering at firm level.

Dep. variable stands for dependent variable on transaction date (t=0) and FE for fixed effects. N presents the insider trades observations. PostMAR is an indicator variable equal to 1 for insider trades on or after the enactment date of MAR on July 2, 2014, and 0 otherwise. SIZE is the natural logarithm of the total assets at the end of fiscal year t. GROWTH is defined as the market-to-book ratio at the end of fiscal year t. ROE is defined as net income in t scaled by lagged book value of equity. R&D is indicator variable equal to 1 if the firm reported a non-zero R&D expense in the most recent fiscal year, and 0 otherwise. TRADESIZE of insider trades is the number of shares traded, deflated by the number of shares outstanding on the same day. TRADESIZE is the sum of all transactions reported on the same trading date, but is calculated separately for purchases and sales. MTF/OTF is an indicator variable equal to 1 if a trade occurred in a multilateral trading facility or organized trading facility, and 0 otherwise. Blackout is an indicator variable equal to 1 if the trade occurs in a period of 30 calendar days before earnings announcement, and 0 otherwise. Low_Litigation_Risk is an indicator variable equal to 1 if greater or equal the mean of Thomson Reuther`s ESG index (CSR_PERF), and 0 otherwise.

Table 3.6 reports regression results with the 20-day abnormal returns (CAR0,19) around transaction date of insider trades as dependent variable. The sample includes transactions of corporate insiders from 2011 to 2018 for calculating abnormal returns according to the Market-Adjusted-Return Model.

Ad hoc Announcements

In order to capture the influence of the new reporting requirements of inside information, we first interact the variable *MTF&OTF* with *PostMAR* to capture the new ad hoc disclosure requirements for trading platforms, like multilateral (MTF) and organized trading facilities (OTF) (Article 17 Section 1 of the MAR).[21] At first glance, little has changed for firms issuing financial instruments in the regulated market that were already subject to the ad hoc obligation before MAR (BaFin 2016). However, several provisions, for example on dealing with rumors (Article 12 Section 1(c) of the MAR) have been supplemented and tightened for the regulated market. Therefore, we cannot a prior state which disclosure provision will mainly explain the negative effect on the information content of insider trades.

Table 3.6 Column 1 reports the results based on the Market Adjusted Return Model. The interaction term is not significant, suggesting that the new ad hoc disclosure requirements for other trading facilities do not have an incremental impact on the cumulated abnormal returns. Battalio et al. (2011) comes to a similar conclusion when analyzing short-term abnormal returns of OTC firms announcing their NYSE listing plans and thus facing new disclosure requirements. A comparison of the returns before and after the disclosure amendments did not exhibit significant differences. One reason could be that many OTC firms were already (voluntarily) reporting financial information to investors before the introduction of the regulation.

The impact of *PostMAR* remains negative (- 0.0166) and highly significant (p=0.0000) and is even higher than in the main model, indicating that insider purchases in the regulated market

[21] According to Article 17 Section 1 of the MAR, the public disclosure of inside information "(…) *shall apply to issuers who have requested or approved admission of their financial instruments to trading on a regulated market in a Member State or, in the case of instruments only traded on an MTF or on an OTF, issuers who have approved trading of their financial instruments on an MTF or an OTF or have requested admission to trading of their financial instruments on an MTF in a Member State*." First, we excluded OTC transactions from the ad hoc disclosure analysis, as they are not explicitly mentioned. However, OTC transactions (13.62%) are included in the main model as well as in the blackout and litigation analyses, because the duty to notify insider transactions also refers to OTC dealings (ESMA, 2015, recital 104, p. 43). Second, since we do not have data about approved instruments on an MTF or an OTF or about requests for admission to trade on an MTF, we assume for simplicity, that all reported trades of our sample conducted on an MTF or an OTF fulfill the requirements of Article 17 of the MAR.

still decrease the level of abnormal returns due to enhanced information transparency following MAR. When applying the Market Model, the (untabulated) results remain robust. However, in case of the Four Factor-Model, the interaction term exhibits a positive coefficient (+ 0.0338) significant on 10% level. The overall effect is still negative (- 0.0617 + 0.0338 = - 0.0279) but smaller than for trades within the regulated market. In sum, we can conclude that the introduction of the MAR decreases the abnormal returns of insiders trading in regulated markets as well as in other trading facilities.

Blackout Period

Article 19 Section 11 of MAR prohibits insider trading 30 calendar days before the announcement of an interim financial report or a year-end report. The MAR provisions aims to mitigate high abnormal profits of insiders by trading prior to the release of earnings news. Betzer and Theissen (2009) find for German insider trades in the pre MAR-period, that purchases occurring within the blackout period exhibit abnormal returns twice as large (amounting to 5.26%) as purchases outside the blackout period (1.96%). Bettis et al. (2000) investigate the effect of individual insider trading regulations introduced by single firms. They find evidence that blackout periods successfully reduce insider transactions and that the trading restriction is associated with a narrower bid-ask spread and thus less profitable trading. In order to analyze the blackout provision, we include an indicator variable capturing the value 1 if insider transactions occurred 30 calendar days before earnings announcements, and 0 otherwise. We interacted the variable with *PostMAR* in order to capture likely effects of the blackout period on informativeness of insider trades. Our results in Table 3.7 Column 2 show that the interaction term with the *BLACKOUT* variable is not significantly associated with the 20-day CARs of the Market-Adjusted Return Model. This is not surprising, since insider trading within this time period is prohibited. Insiders adapt their trading behavior in order to evade regulations and shift their trading outside the blackout period. Transactions conducted outside the blackout period after MAR are still negatively associated with the cumulated abnormal returns (- 0.0113, p-value = 0.0031), confirming the results of the main model. The findings (untabulated) remain robust when estimating the abnormal returns based on the Market Model and the Four Factor-Model.

Litigation Risk

Next, we try to separate the effect of higher litigation risk after the MAR introduction. We assume that the stricter MAR provisions in terms of tightened up fines in the event of a violation of disclosure obligations and insider law will more likely affect companies that have already a high litigation risk in the pre-MAR period. Litigation risk is commonly measured using an industry-based proxy referring on firms' membership in the biotechnology, computers, electronics, and retail industries (Francis, Philbrick & Schipper 1994a, 1994b). However, Kim and Skinner (2012) provide weak evidence in estimating litigation risk using firms' industry membership. They suggest considering also other firm characteristics like size, in order to improve models' predictive ability. Since we want to differentiate the effects of higher transparency and higher litigation risk, we decided not to use firms' size as a proxy. Large firms are more transparent and therefore exhibit lower abnormal returns than small firms with higher financial opacity. This interferes with the effect of higher litigation risk due to stronger market and media scrutiny, which also decreases abnormal returns. For this reason, we refer to recent literature suggesting that high levels of corporate social performance (CSP) reduces the likelihood of litigation. According to Baker and Griffith (2007), underwriters of directors' and officers' liability insurance focus on corporate governance quality to assess liability risk. In addition, Giese et al. (2021) show that, in the short term, governance is the dominant pillar in corporate social performance and significantly affects firm performance, because it strongly captures event risks, like fraud. Fauser and Utz (2021) find an insurance-like effect around class action lawsuit filings for firms with positive CSP in the US. It seems that CSP conveys information about firms' risk exposure and acts as a "reservoir of goodwill", signaling higher moral capital and thus moderating negative effects in times of corporate crisis. In a similar vein, Choi and Jung (2020) suggest that firms use corporate social responsibility to hedge for litigation risks.

In line with the abovementioned findings, we measure litigation risk using the environmental, social and governance (ESG) performance score of the Asset4 database. The indicator variable *Low_Litigation_Risk* takes the value 1 if the firm-level ESG score is greater or equal the sample mean, and zero otherwise. We are interacting the litigation risk variable in order to analyze whether firms with low pre-MAR litigation risk are affected less by the stricter MAR sanctions. Indeed, the incremental effect of firms with low levels of litigation risk is positive and highly significant at 5%-level. The overall effect becomes even positive (-0.0216 + 0.0251 = 0.0035), although very small, indicating that for firms with low litigation risk, the stricter MAR sanction do not decrease the cumulated abnormal returns of insider purchases. Only insiders in firms with high level of litigation risk (-0.0216) seem to refrain from information-based insider trading after MAR, which confirms the litigation avoidance hypothesis. However, the interaction term does not remain robust when applying the Market-Model and the Fama-French Model (untabulated results). In case of the Market Model, the *PostMAR*-variable is still negatively associated with cumulated abnormal returns (-0.0143), however not statistically significant (p-value=0.1600). Therefore, we cannot derive strong inferences based on the litigation risk analyses.

3.6 Robustness Analyses

Implementation date of the MAR in 2016

To verify our main results, we repeat the multivariate analyses using as event date the implementation date of July 3, 2016. The *PostMAR*-variable exhibit a significantly negative coefficient in the Market Adjusted Model, however with a smaller coefficient amounting to -0.0078. In case of the Market Model, the effect of the implementation date is negative though not significant.[22] Therefore, we conclude, that the regulation effect of the MAR is reasonably captured

[22] We could not conduct the analyses with the Fama French-Model for the implementation date 2016, since we do not have data of Fama/French factors for Germany after 2016.

in the main model specification, since the coefficients are attenuated as we move away from the enactment date in 2014.

Identification strategy: FSAP directives

Directives that have been announced and implemented during the sample period may confound our findings. In order to analyse the robustness of our identification strategy, we include two concurrent FSAP directives, which have been introduced after 2011 and after 2016, respectively. The Directive 2013/50/EU, announced on January 2014 and implemented on November 6, 2015, is the amendment directive of the European Union's Transparency Directive (TPD), 2004/109/EC, which regulates corporate reporting aiming to increase information transparency on capital markets. The Directive 2014/95/EU mandating the "disclosures of non-financial and diversity information" has been announced in April 2014 and came into force in March 2017. In both cases, the Directives require EU countries to fulfil a certain objective. However, the exact implementation into national law remains the responsibility of the individual EU countries (Christensen et al. 2016). According to Djankov et al. (2003), real effects of regulations may vary cross-sectional, since they do not depend only on the new rules but also on the implementation and enforcement mechanisms of single countries. Therefore, we do not assume that the capital markets already react on the announcement date, but first on the implementation date, because on the announcement date the single regulation provisions of the directives are not yet known.

In contrast, following Article 288 of the TFEU, EU regulations like the MAR are legal acts that are binding in their entirety and directly applicable in all EU countries. They do not need the transposition into national law, which may come along with different implementations on country-level. Thus, in case of the MAR, the capital market was already informed about the concrete content of the regulation when it was first announced.

First, we include in the model the announcement date of the MAR in 2014 (the event date of our main model) and the implementation date of the MAR in 2016 (Table 3.7, Column 1). Our main finding, that the information content of insider trades decreases in the post-2014 MAR period remains robust and is highly significant at 1%-level. The coefficient of the MAR implementation in 2016 though is insignificant.

In the next step, we add the implementation date of the TPD in 2015 as well as the implementation date of the CSR-Directive in 2017 (Table 3.7, Column 2). The *PostMAR*-coefficients remain highly significant for both event dates (2014 and 2016). However, the association after 2016 is smaller and less significant than after the announcement date 2014, which confirms our main results. The coefficient of the *Post_TPD* variable is insignificant, whereas we find a significantly increase of 20-days CARs for insider purchases after the introduction of the CSR-Directive. This may be explained by the low reporting quality of mandatory CSR reporting in the first implementation years, in terms of low comparability, low reliability and low relevance (European Commission 2020; Christensen et al. 2021; for an analysis of DAX 30 and DAX 160 firms, see Behncke & Wulf 2018, 2019) resulting in high opacity of non-financial information. In line with this, Georgiou and Maniora (2021) find that corporate insiders exploit their CSR information advantage and trade based on private CSR information, generating abnormal returns for insider purchases around the CSR report date.

Table 3.7 Robustness Analyses: Identification Strategy

	Insider Trading Purchases	
Dep. Variable	$CAR_{0,19}$	$CAR_{0,19}$
(Market-Adjusted-Return Model)	Coeff. (p-value) (1)	Coeff. (p-value) (2)
PostMAR (July 2, 2014)	-0.0173*** (0.0003)	-0.0203*** (0.0004)
PostMAR (July 3, 2016)	0.0037 (0.4232)	-0.0191** (0.0287)
Post_TPD (Nov. 6, 2015)		0.0080 (0.3310)
Post_CSR (March 31, 2017)		0.0213*** (0.0009)
SIZE	-0.0037*** (0.000)	-0.0038*** (0.0000)
GROWTH	0.0013* (0.0685)	0.0014* (0.0514)
ROE	0.0048 (0.4233)	0.0053 (0.3776)
R&D	0.0008 (0.8499)	-0.0001 (0.9711)
TRADE SIZE	0.3040** (0.0100)	0.3081*** (0.0089)
Intercept	0.0542*** (0.0000)	0.0539*** (0.0000)
Industry FE	Included	Included
N	2,790	2,790
R^2 in %	2.23	2.58

Table 3.7 reports OLS coefficient estimates and (in parentheses) t statistics based on robust standard errors that are clustered by firm. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, using a two-tailed test. T-statistics are based on standard errors, which are adjusted for heteroscedasticity and clustering at firm level. PostMAR (July 2, 2014) and PostMAR (July 3, 2016) are indicator variables equal to 1 for CARs beginning when MAR has become effective by EU, and when MAR has been implemented by Germany, respectively, and 0 otherwise. We also include indicator variables for other regulatory changes in the EU, i.e., the Directive Amending the Transparency Directive (TPD) 2013/50/EU implemented in Germany on November 6, 2015, and the CSR Reporting Law Directive 2014/95/EU implemented in Germany on March 2017. SIZE is the natural logarithm of the total assets at the end of fiscal year t. GROWTH is defined as the market-to-book ratio at the end of fiscal year t. ROE is defined as net income in t scaled by lagged book value of equity. R&D is an indicator variable equal to 1 if the firm reported a non-zero R&D expense in the most recent fiscal year, and 0 otherwise. TRADESIZE of insider trades is the number of shares traded, deflated by the number of shares outstanding on the same day. TRADESIZE is the sum of all transactions reported on the same trading date, but is calculated separately for purchases and sales. The abnormal returns are predicted using the Market-Adjusted-Return Model.

Overall, our results remain consistent after controlling for concurrent regulations during the announcement and implementation period of the MAR. Further the findings remain robust when estimating the abnormal returns with the Market Model and the Fama French-Model, implying that the tighter insider trading provisions decrease abnormal returns and thus the information content of insider purchases.

3.7 Conclusion

The study examines the information content of insider trades around the passage of the EU securities regulation MAR (Market Abuse Regulation) (EU) No 596/2014 in Germany. MAR is a far-reaching EU law dealing with insider trading, market abuse, and market manipulation. Theoretical and empirical research suggest that an increase in information transparency by ex-post timely disclosure of insider trades may increase the information content of trades and result in higher abnormal returns. However, in line with the litigation avoidance hypothesis, stricter sanctions as well as the "naming and shaming"-policy of the MAR may increase scrutiny from investors, media, and regulators and thus pre-empt insiders from exploiting private information. Moreover, ex-ante transparency provisions, like ad hoc disclosure of inside information, also mitigates the information content of insider trading due to decreased information advantages of corporate insiders.

Our results show that the MAR can have significant economic benefits by reducing information asymmetries on the capital market. We find, that the profitability of insider purchases significantly decreases in post-MAR period. The results of insider sales are insignificant or significantly positive, indicating that sales mainly reflect liquidity needs. After separating the effects of single regulation provisions, we find strong evidence that the reduced information content of insider trading after the introduction of the MAR is driven by the extended ad hoc disclosure requirements of the regulated market. Moreover, we find weak evidence that only in firms with high ex-ante litigation risk insiders refrain from informed trading in terms of lower abnormal returns.

Our study does not provide evidence on the costs of MAR. Further, our analyses include only German insider trading data, implying a small sample size, especially in the context of the litigation risk analysis. Despite these limitations, our results allow a better understanding of the implications of the introduction of MAR, especially with regard to different trading venues and firms' level of litigation risk. Future research may address these constraints and extent the analysis on an international sample, taking thereby into consideration countries' regulatory environment.

List of References

Ahern, K. (2009): Sample Selection and Event Study Estimation, in: *Journal of Empirical Finance,* 16(3), 466-482.

Ahorny, J., Swary, I. (1980): Quarterly Dividend Earnings Announcements and Stakeholder Returns: An Empirical Analyses, in: *Journal of Finance*, 35, 1-12.

Aktas, N., De Bodt, E., & Cousin, J. G. (2007): Event studies with a contaminated estimation period, in: *Journal of Corporate Finance*, 13(1), 129-145.

Armitage, S. (1995): Event study methods and evidence of their performance, in: *Journal of Economic Surveys*, 8(4), 25-52.

Asthana, S., Balsam, S. (2001): The effect of EDGAR on the market reaction to 10-K filings, in*:* *Journal of Accounting and Public Policy*, 20 (4-5), 349-372.

Aussenegg, W., Jelic, R., & Ranzi, R. (2018): Corporate Insider Trading in Europe. Journal of International Financial Markets, in: *Institutions & Money*, 54, 27-42.

Baker, T., Griffith, S. (2007): Predicting corporate governance risk: evidence from the directors' and officers' liability insurance market. in: *The University of Chicago Law Review*, 74, 487–544.

Bank, M., Baumann, R., H. (2015): Market efficiency under ad hoc information: evidence from Germany, in: *Financial Markets and Portfolio Management*, 29, 173-206.

Battalio, R., Hatch, B., & Loughran, T. (2011): Who benefited from the disclosure mandates of the 1964 Securities Acts Amendments?, in: *Journal of Corporate Finance*, 17, 1047-1063.

Baum, I., Solomon, D. (2019): When Should You Abstain? A Call for a Global Rule of Insider trading, in: *University of Cincinnati Law Review*, 88 (1), 66-100.

Beaver, W., (1968): The information content of annual earnings announcements, in: *Journal of Accounting Research*, 6, 67-92.

Beck, D., Friedl, G., Schäfer, P. (2020): Executive compensation in Germany, in: *Journal of Business Economics*, 90, 787-824.

Behnke, N., Wulf, I. (2018): Erste Berichts- und Prüfungssaison der nichtfinanziellen Berichterstattung – Empirische Analyse der DAX30-Unternehmen, in: *KoR*, 12, 570-580.

Behnke, N., Wulf, I. (2019): Erste Berichts- und Prüfungssaison der nichtfinanziellen Berichterstattung – Eine empirische Analyse der DAX160-Unternehmen für das Geschäftsjahr 2017, in: *KoR*, 1, 21-31.

Bettis J.C., Coles J.L., & Lemmon M.L. (2000): Corporate policies restricting trading by insiders, in: *Journal of Financial Economics*, 57(2), 191–220.

Betzer, A., Theissen, E. (2009): Insider trading and corporate governance: The case of Germany, in: *European Financial Management*, 15, 402-429.

Billings, M.B., Cedergren, M. C. (2015): Strategic silence, insider selling and litigation risk, in: *Journal of Accounting and Economics*, 59, 119-142.

Brochet, F. (2019): Aggregate insider trading and market returns: The role of transparency, in: *Journal of Business Finance & Accounting* ,46 (3-4), 336-369.

Brochet, F. (2010): Information Content of Insider Trades before and after the Sarbanes-Oxley Act, in: *The Accounting Review*, 85(2), 419-446.

Carhart, M. M. (1997): "On Persistence in Mutual Fund Performance", in: *The Journal of Finance*, 52(1), 57-82.

Carlton, D.W., Fischer, D.R. (1983): The regulation of insider trading, in: *Stanford Law Review*, 35, 857–895.

Carter, M. E., Soo, B. (1999): The relevance of Form 8-K reports, in: *Journal of Accounting Research*, 37 (1), 119–132.

Cheng, Q., Lo, K. (2006): Insider trading and voluntary disclosures, in: *Journal of Accounting Research*, 44 (5), 815–848.

Choi, S., Jung, H. (2020): Effects of the litigation risk coverage on corporate social responsibility, in: *Applied Economic Letters*, published online first: https://www.tandfonline.com/doi/full/10.1080/13504851.2020.1854443

Christensen, H. B., Hail, L., & Leuz, C. (2016): Capital-Market Effects of Securities Regulation: Prior Conditions, Implementation, and Enforcement, in: *Review of Financial Studies*, 29 (11), 2885-2924.

Christensen, H. B., Hail, L., & Leuz, C. (2021): Mandatory CSR and Sustainability Reporting: Economic Analysis and Literature Review, ECGI Working Paper Series in Finance N° 623/2019.

Cohen, D. A., Dey, A., & Lys, T. Z. (2008): Real and Accrual-Based Earnings Management in the Pre- and Post-Sarbanes-Oxley Period, in: *The Accounting Review*, 83(3), 757–787.

Cohen, L., Malloy, C., & Pomorski, L. (2012): Decoding inside information, in: *Journal of Finance*, 67(3), 1009–1043.

Daniel, K., Titman, S. (1997): Evidence on the characteristic of cross sectional variation in stock return, in: *The Journal of Finance*, 1, 1–33.

Dardas, K., Güttler, G. (2011): Are directors' dealings informative? Evidence from European stock markets, in: *Financial Markets and Portfolio Management*, 25, 111-148.

Demsetz, H. (1986): Corporate Control, Insider Trading, and Rates of Return, in: *American Economic Review*, 76, 313–16.

Dickgiesser, S., Kaserer, C. (2008): Market Efficiency Reloaded: why insider trades do not reveal exploitable information, *CEFS working paper series*, No. 2008-04, Center for Entrepreneurial and Financial Studies (CEFS), Munich.

Djankov, S., Glaeser, E., La Porta, R., Lopez-de-Silanes, F., & Shleifer, A. (2003): The new comparative economics, in: *Journal of Comparative Economics*, 31, 595–619.

Dymke, B., Walter, A. (2008): Insider Trading in Germany – Do Corporate Insiders Exploit Inside Information? in: *BuR – Business Research*, 1, 188-205.

Engelland, A. (2016): Ad-hoc-Publizität: Änderungen durch die neue Marktmissbrauchsverordnung, in: *BaFinJournal*, https://www.bafin.de/DE/PublikationenDaten/BaFinJournal/AlleFachartikel/alle_fachartikel_node.html, 07/2016.

Enriques, L., Gatti, M. (2008): Is there a uniform EU securities law after the Financial Services Action Plan? In*: Stanford Journal of Law, Business and Finance*, 14, 43–81.

ESMA, Annual report 2019, https://www.esma.europa.eu/sites/default/files/library/esma70-156-3537_annual_report_on_mar_administrative_and_criminal_sanctions_2020.pdf, 03.12.2020.

European Commission (2020): Summary Report of the Public Consultation on the Review of the Non-Financial Reporting Directive 20 February 2020, Ref. Ares (2020)3997889 - 29/07/2020https://www.consob.it/documents/46180/46181/Ares%282020%293997889_summary_report.pdf/bf9a64eb-3b24-4ade-bc5e-c7a1e238ca89

Fama, E.F., Fisher, L., Roll, R. (1969): The Adjustment of Stock Prices to New Information, in: *International Economic Review*, 10(1), 1-21.

Fama, E.F. (1970): Efficient Capital Markets: A Review of Theory and Empirical Work, in: *The Journal of Finance*, 25, 383-417.

Fama, E.F., French, K.R. (1993): Common risk factors in the returns on stocks and bonds, in: *Journal of Financial Economics*, 33(1), 3-56.

Fauser, D. V., Utz, S. (2021): Risk Mitigation of Corporate Social Performance in US Class Action Lawsuits, in: *Financial Analyst Journal*, 77 (2).

Fidrmuc, J., Goergen, M., & Renneboog, L. (2006): Insider Trading, News Releases and Ownership Concentration, in: *Journal of Finance*, 61 (6), 2931–2973.

Finnerty, J. E. (1976): Insiders and Market Efficiency, in: *The Journal of Finance*, 31 (4), 1141–1148.

Francis, J., Philbrick, D., & Schipper, K. (1994): Shareholder Litigation and Corporate Disclosures, in: *Journal of Accounting Research*, 2 (2), 137–164.

French, K.R., Roll, R. (1986): Stock return variances: The arrival of information and the reaction of traders, in: *Journal of Financial Economics*, 17(1), 5-26.

Gebka, B., Korczak, A., Korczak P., & Traczykowski J. (2017): Profitability of Insider Trading in Europe: A Performance Evaluation Approach, in: *Journal of Empirical Finance*, 44, 66-90.

Georgiou, N., Maniora, J. (2021): Do Insiders Trade on (Private) Corporate Social Responsibility Information? *Working Paper*, TU Dortmund und HHU Düsseldorf.

Giese, G., Lee, L.-E., & Nagy Z. (2021): Deconstructing ESG Ratings Performance: Risk and Return for E, S, and G by Time Horizon, Sector, and Weighting, in: *The Journal of Portfolio Management*, 47 (3), 1-18.

Goncharov, I., Hodgson, A., Sanabria, S., & Lhaopadchan, S. (2013): symmetric Trading by Insiders – Comparing Abnormal Returns and Earnings Prediction in Spain and Australia, in: *Accounting & Finance*, 53 (1), 163-184.

Huddart, S., Ke, B. (2007): Information Asymmetry and Cross-sectional Variation in Insider Trading, in: *Contemporary Accounting Research*, 24 (1), 195 – 232.

Huddart, S., Ke, B., & Shi., C. (2007): Jeopardy, non-public information, and insider trading around SEC 10-K and 10-Q filings, in: *Journal of Accounting and Economics,* 43, 3–36.

Huddart, S., Hughes, J., & Levine, C. (2001): Public disclosure and dissimulation of insider trades, in: *Econometrica* 69, 665-81.

Jaffe J., F. (1974): Special information and insider trading, in: *The Journal of Business*, 47(3), 410–428.

Karpoff, J. M. (1986): A Theory of Trading Volume, in: *Journal of Finance*, 41: 1069-87.

Ke, B., Huddart, S., & Petroni, K. (2003): What insiders know about future earnings and how they use it: Evidence from Insider trades, in: Journal of Accounting and Economics, 35(3), 315-346.

Kloehn, L., Brellochs, M., & Schmolke, K. (2018): Martkmissbrauchsverodnung: Verordnung (EU) Nr. 596/2014 über Markmissbrauch, München 2018.

Kim, I., Skinner, J. D. (2012): Measuring Securities Litigation Risk, in: *Journal of Accounting & Economics*, 53 (1), 290-310.

Kim, O., Verrecchia, R., E. (1991): Trading volumes and price reactions to public announcements, in: *Journal of Accounting Research*, 26, 302-21.

King, J., Schmidt, M. H., & Stehle, R. (2015): Do Insiders and Their Imitators Trade Profitably? Index-Specific Evidence from Germany (August 24, 2015). Available at SSRN: https://ssrn.com/abstract=2620169 or http://dx.doi.org/10.2139/ssrn.2620169

Kothari, S.P., Warner, J.B. (1997): Measuring long-horizon security price performance, in: *Journal of Financial Economics*, 43, 301-339.

Kyle, A.S. (1985): Continuous auctions and insider trading, in: *Econometrica*, 53, 1315-1335.

Lakonishok, J., Lee, I. (2001): Are insider trades informative? in: *Review of Financial Studies*, 14 (1), 79–111.

Leuz, C., Wysocki, P. D. (2016): The economics of disclosure and financial reporting regulation: Evidence and suggestions for future research, in: *Journal of Accounting Research*, 54 (2), 525-622.

Mackinlay, A. C. (1997): Event Studies in Economics and Finance, in: *Journal of Economic Literature*, 35, 13-39.

Mann, H. B., Whitney, D. R. (1947): On a test of whether one of two random variables is stochastically larger than the other. in: *Annals of Mathematical Statistics*, 18, 50–60.

Manne, H.G. (1966): Insider trading and the stock market, in: *The Free Press*, New York.

Park, N. (2004): A guide to using study methods in multi-country settings, in: *Strategic Management Journal*, 25(7), 655-668.

Payne, J. (2018): Disclosure of Inside Information. The Transparency of Stock Corporations in Europe (R Veil and V Tountopoulos, eds., Forthcoming), European Corporate Governance Institute (ECGI) - Law *Working Paper* No. 422/2018, Oxford Legal Studies Research Paper No. 8/2019, Available at SSRN: https://ssrn.com/abstract=3244401

Piotroski, J., Roulstone. D. (2005): Do insider trades reflect both contrarian beliefs and superior knowledge about future cash flow realizations? in: *Journal of Accounting and Economics*, 39, 55–81.

Prevoo, T., Weel, B. (2010): The Effects of a Change in Market Abuse Regulation on Abnormal Returns and Volumes: Evidence from the Amsterdam Stock Market, in: *De Economist*, 158 (3), 237-293.

Rau, M. (2004): Directors' Dealings am deutschen Aktienmarkt. Deutscher Universitats-Vertag; Auflage: 2004 (1. Januar 2004).

Ravina, E., Sapienza, P. (2010): What Do Independent Directors Know? Evidence from Their Trading, in: *The Review of Financial Studies*, 23(3), 962-1003.

Roeh, L., Beckmann, M. (2016): Germany, in: *The Securities Litigation Review*, 2nd edition, Chapter 9, 112-130.

Rogers, J. L. (2008): Disclosure quality and management trading incentives, in: *Journal of Accounting Research*, 46 (5), 1265–1296.

Roulstone, D. (2003): The relation between insider-trading restrictions and executive compensation, in: *Journal of Accounting Research*, 41(3), 525–551.

Rozeff, M.S., Zaman, M.A. (1998): Overreaction and insider trading: Evidence from growth and value portfolios, in: *The Journal of Finance*, 53(2), 701–716.

Scott, J., Xu, P. (2004): Some Insider Sales Are Positive Signals, in: *Financial Analysts Journal*, 60 (3), 44-51.

Seyhun, H. N. (1986): Insiders' Profits, Costs of Trading, and Market Efficiency, in: *Journal of Financial Economics*, 16 (2), 189–212.

Seyhun, H. N. (1992): The Effectiveness of the Insider-Trading Sanctions, in: *Journal of Law and Economics*, 35, 149-182.

Seyhun, H. N. (1998): Investment Intelligence from Insider Trading (MIT Press, Cambridge, MA).

Skinner, D. (1994): Why firms voluntarily disclose bad news, in: *Journal of Accounting Research*, 32, 38-60.

Stotz, O. (2006): Germany's New Insider Law: The Empirical Evidence after the First Year, in: *German Economic Review*, 7, 449-462.

Watanabe, O. V., Imhof, M., & Tartaroglu, S. (2019): Transparency Regulation and Stock Price Informativeness: Evidence from the European Union's Transparency Directive, in: *Journal of International Accounting Research*, 18 (2), 89-113.

Appendix 3.1: Definition of Variables

Variables	Definition
Insider Trading Abnormal Return Variables	
$CAR_{(0, 5)}$	Six-day cumulated abnormal return on transaction date (t=0).
$CAR_{(0, 19)}$	Twenty-day cumulated abnormal return on transaction date (t=0).
PostMAR	Indicator variable equal to 1 for insider trades on or after the enactment date of MAR on July 2, 2014.
Firm Characteristics	
SIZE	Natural logarithm of the total assets at the end of fiscal year *t*.
GROWTH	Market-to-book ratio at the end of fiscal year *t*.
ROE	Net income in *t* scaled by book value of equity.
R&D	Dummy variable taking the value 1 if research and development expenditures divided by total sales are reported and the value 0 otherwise.
TRADE SIZE	The number of shares purchased/sold by corporate insiders in a given day, divided by common shares outstanding.
Additional Variables	
MTF/OTF	MTF/OTF is indicator variable equal to 1 if a trade occurred in a multilateral trading facility or organized trading facility, and zero otherwise.
MTF/OTF*PostMAR	Is an interaction term between the variables MTF/OTF and PostMAR.
Low_Litigation_Risk	Dichotomous variable equal to one greater or equal the mean of Thomson Reuther`s ESG index, and zero otherwise.
Low_Litigation_Risk *PostMAR	Is an interaction term between the variables Low_Litigation_Risk and PostMAR.
Blackout	Dichotomous variable equal to one if the trade occurs in a period of 30 calendar days before the announcement of a year-end report.
Blackout*MAR	Is an interaction term between the variables Blackout and PostMAR.
Post_TPD	Binary indicator variable for the regulatory change in the EU, i.e., the Directive Amending Transparency Directive (TPD) 2013/50/EU, taking the value 1, if the trade occurs after the implementation date by Germany on November 6, 2015.
Post_CSR	Binary indicator variable for the regulatory change in the EU, i.e., the CSR reporting law Directive 2014/95/EU, taking the value 1, if the trade occurs after the implementation date by Germany on March 2017.

4. Aggregate Insider Trading Predictability and Market Returns: Evidence from GermanData

4.1 Introduction

This work investigates the predictive content of aggregate insider trading for market returns employing German data.[23] Aggregate insider trading refers to the sum of all transactions by corporate insiders across all firms in the sample in time *t*. Prior research shows that aggregate managerial decision variables such as aggregate equity issuance or aggregate insider trades, predict market stock returns (Baker et al. 2006). Managers likely can time not only the idiosyncratic component of their returns but also the systematic (market) component (Baker and Wurgler 2000). Following findings of empirical studies using U.S. data, insiders` aggregated purchasing predicts market returns (Seyhun 1988, 1992; Lakonishok and Lee 2001; Jiang and Zaman 2010) (and with more recent data in a cross-country work, Brochet 2019).

However, the U.S. studies show mixed results. For instance, Seyhun (1988) finds a significant association between standardized aggregate insider buying and future market returns, while Chowdhury et al. (1993) only find weak effect of aggregated insider trades on future stock market movements. Moreover, findings by Lambe (2016) for the U.K. market suggest that this relationship is not present. For this reason, it is important to test the robustness of results from the U.S. market for other markets. Especially in Germany, the stock market is characterized by (1) very small number of free float stocks in comparison to about 80% in the U.S., (2) much lower number of retail investors (5.2% of the population are shareholders) and much more institutional investors than in in the U.S. (about 84.5% of all constituents in Germany have one shareholder with a stake of more than 25%) (Finter et al. 2012). Also, worth noting is (3) the speciality of the governance structure with the two-tier boards (supervisory and executive board) in German

[23] Generally, term “insiders” designates directors, officers, and beneficial owners of more than 10 percent. In this study, corporate insiders are defined according EU Market Abuse Regulation (MAR) as persons discharging managerial responsibilities (PDMR) and "persons closely related”.

companies. These German specific features might lead to different reaction of stock market returns to aggregate insider trading activity. The main research question in this study is as follows: Do aggregate insider trades have predictive content for market returns in Germany?

This paper seeks to address this question employing an extensive sample 2004-2020 (however, I keep data of 2020 only for Covid-19 investigation since it has been a special period) for insider trades from Germany. For the tests, I use an autoregressive framework consistent with Seyhun (1988), and Chowdhury et al. (1993). This is one of the first studies that investigates the insider trading predictability for market returns under the aspects of market disruptions (Covid-19) and regime change (MAR). Moreover, I also investigate the predictability of insider trading on firm-level as counterpart of aggregate trading because I conjecture that firm-level trades contain a transitory element that is diversified away at the market level. This might lead to differences in stock price predictability by insider trading (Seyhun 1988).

The impact of informed insider trading on market returns and the autocorrelation of insider trades are the primary factors determining the model`s dynamics in this paper. This is consistent to Seyhun (1988), and Chowdhury et al. (1993). By pushing stock prices towards the fundamental values of assets, informed trades cause a positive relation between informed insider trading activity and stock returns (Huang and Stoll 1997). Moreover, serial correlations in insider trading may also be driven by information-based trading such as strategic splitting of trading by corporate insiders. These trades should contain superior knowledge about firms' future cash flows, consistent with the multi-period model of Kyle (1985). Following Kyle (1985), insiders have the opportunity to trade multiple times on the same information causing serial correlation in trades. Gu et al. (2021) provide the empirical evidence that insiders strategically disguise trading by splitting trades over time to escape trading competition leading to trades clustering.

In addition, serial correlation in insider trades may arise because of systemic errors (assumptions of investors sentiment and limits to arbitrage) predicted by "behavioral finance" literature which provides evidence for bias such as overreacting, underreacting, overconfidence, and myopic loss aversion (Bernard and Thomas 1990; Baker and Wurgler 2007).[24] This sentiment including myopic loss aversion might lead to mispricing that can also cause autocorrelation in trading.[25] Therefore, behavioral biases and strategic informed insider tradings are suggested to cause autocorrelations in aggregate insider trading.

Given these research results, if autocorrelation in trades is driven by private information, then the effect on stock returns should be considered genuine, since it is the result of economic forces (Campbell et al. 1997).

Yet, if insiders trade only on firm-specific information, the idiosyncratic private information at aggregated, as argued by Lucas (1977), will be "averaged out", and no impact on market returns will be observed. However, the phenomenon of predicting the market by aggregate insider trading can arise through two channels. One channel is the *cash flow hypothesis*, and the second channel is *mispricing*, both assumptions documented in Seyhun`s studies (1988, 1990, 1992), and Anginer et al. (2020). In the former case corporate insiders trade on their superior information about fundamentals of their firms being not strictly idiosyncratic to their companies but also based on changes in market-wide factors that are not yet reflected in their firms` stock prices. In the latter case they trade on superior knowledge of true value of their firms` fundamentals after having identified the extent of market-wide mispricing when markets over- or underreact to

[24] Baker and Wurgler 2007 define investors sentiment as beliefs about future flows and investment risks which are not satisfied by the fundamental facts in hand (propensity to speculate). In addition, limits to arbitrage makes it difficult for market participants to force prices to fundamentals as certain stocks are costly and risky to arbitrage against sentimental investors (these are mainly stocks such as young, small, unprofitable, or extreme growth stocks).
[25] For the Sentiment intuition behind the concept of myopic loss aversion see Benartzi and Thaler (1995).

a market-wide shock, such as changes in oil prices, the present coronavirus (Covid-19) pandemic or other macroeconomic shocks.

However, stock prices react positively to insider trading activity but require several quarters to fully reflect the private information of insider trades (Lakonishok and Lee 2001), suggesting that a trade`s full price impact arrives only with a protracted lag (Hasbrouck 1991). This delayed adjustment to private information is a significant evidence of autocorrelation in insider trades (Hasbrouck 1991; Campbell et al. 1993; Chordia et al. 2002; Chordia and Subrahmanyam 2004; Bouchaud et al. 2009). If autocorrelation in insider trading is expected, then this would generate intertemporal correlation in price pressures which gives rise to a positive predictive relation between serial correlation in trades and future returns (Chordia and Subrahmanyam 2994).

Moreover, Elliott et al. (1984) suggest a directional reversal of a speculative position by insiders following public announcement. If insiders run a profitable trading strategy based on private information, preceding a public announcement of corporate news, then they may reverse their trading following public disclosure. Insider buying may be reduced (delayed) after public announcement of good news following by return increasing (market adjustment) that will be reflected in a negative coefficient on standardized purchasing trading variable. This reversal of trading direction indicates also the tendency of insiders to contrarian trading and trading on market mispricing.

My first key result is that quarterly aggregate insider trading activity is serially and positively correlated. The estimates pattern is *remarkably persistent*: 0.64, 0.45, 0.36, and 0.28 for the first four quarter lags suggesting some degree of predictability in the autocorrelation evolution. The autocorrelation values are statistically significant as shown in Bx-Pierce` Q statistic test, that is the Prob>Q value of less than 0.05.

My second result is that quarterly aggregate insider trading is a precise predictor for market movements. The estimated coefficient for the contemporaneous term of insider trading shows a highly significant negative impact on market returns of -0.61, while the estimate for the first lagged quarter is strongly significant positive of 0.35.[26]

These findings suggest first that since insiders` trades precede the market moving, insiders' trading based on superior information about future cash flows appears to predict the market return during the next 3 months. Second, contemporaneously standardized aggregate purchases are significantly negative related to market returns indicating that insiders reverse their trading direction after realization of market adjustments. The results suggest that while non-insider purchases tend to follow the market price increase (biased adjust), insider buying tends to exhibit contrarian pattern against market increase and mispricing and by doing so, may reflect predictability for the market return. Third, the significant relation between serial correlation in insider trades and *future* market returns suggests that serial correlation is driven mainly by private (new) information.

Opposite to remarkable market predictability of aggregate trading, firm-level trades show positive but insignificant market predictability (positive coefficients on quarters lags 1 to 3) suggesting that they are less persistent than aggregate trades. Firm-level trades seem to contain a strong transitory, idiosyncratic information component that gets diversified away at market-level.

Moreover, the predictability power of insider trading varies reasonably with market transparency as shown in my test, before and after the introduction of EU Market Abuse Regulation (MAR) 2016. In addition, similar to Anginer et al. (2020), I investigate insider trading around the onset of the Covid-19 pandemic beginning at February 20, 2020. The findings indicate

[26] The effects of order flow imbalance (i.e., difference between buy and sell orders during a given period) on the German stock market appear to be contrary to these findings: the contemporaneous effect of estimated order imbalances on individual stock returns is strongly positive, and the lagged impact negative (Hanke and Weigerding 2015). Chordia et al. 2002 find similar results for the NYSE market.

that insiders` predictive ability became especially strong and identifying market overreaction during the crash time period February 20, 2020 to March 20, 2020 of significant market disruption.

In addition, my findings contribute to the existing literature in several points. This paper extents prior literature, as research does not disentangle the potential sources for predictability of aggregate insider trading. The findings in this paper can establish, that insider in aggregate, trade against mispricing (i.e., contrarian trading) and with superior knowledge representing distinct trading scenarios for forecasting market returns. This evidence could be relevant to the ongoing debate over the insider trading effect on market efficiency. Moreover, this work contributes to the research in modern financial economics by using serial correlation in insider trading driven by informed traders to generate predictability. However, in the spirit of Campbell et al. (1997), economic research is still far from having a complete understanding of the nature and sources for these rational microstructure factors - serial correlations in trades driven by new information about cash flows and mispricing, and to explain the striking lead-lag effects.

The work proceeds as follows. Section 4.2 provides the institutional background and hypothesis development for the analyses. Section 4.3 describes the model design. Section 4.4 provides the data sources. Section 4.5 delivers the descriptive statistics, describes time-series properties of aggregate insider trading, and provides the main results. Sections 4.6 and 4.7 explore predictability variation of insider trading subsequent market transparency increase and subsequent mispricing due to fads during market disruption.[27] Section 4.8 provides robustness checks and section 4.9 concludes.

[27] Seyhun (1992) uses the term 'fads' in reference to movements in market returns unexplained by observable macroeconomic factors. I use the term 'fads' as a synonym of Investors sentiment referring to Baker and Wurgler (2007). See also footnote 24 in this work.

4.2 Insider Trading Regulation and Hypothesis Development

4.2.1 Institutional Background

Regulation has to consider the fundamental trade-off in the insider trading effects on information and liquidity (Fox et al. 2018). Indeed, the early 2000s brought about fundamental regulatory changes that have facilitated numerous reporting requirements for informed trades, and especially for insider trades, and the timely disclosures (i.e., two to three days after trading date) of insider trades. These mechanisms for timely dissemination of information, but also for further discouragement of trading on material non-public information should ensure market liquidity. This is in line with theoretical and empirical findings, which support the regulators` view by showing that disclosure of insider trading and material firm-specific information accelerates price discovery and reduces abnormal returns, relative to no disclosure regime (Huddart et al. 2001).

Such requirements have been introduced by section 403 of the Sarbanes-Oxley Act (SOX) in 2002 in the U.S., the Market Abuse Directive (MAD) in 2004 in the E.U., and the Market Abuse Regulation (MAR) 2016, (Regulation (EU) No 596/2014). Decisive for this work is the passage of MAR that reflects a significant shock to transparency at market-level, including the significant change in disclosure requirements for inside information und insider transactions within the investigation period of the sample 2004 to 2019. The obligation to disclose inside information contained in the directly applicable MAR Regulation concerns provisions such as “ad hoc disclosure” of inside information that directly affects the issuer of financial instruments (Article 17 of the MAR), and prohibition of insider dealing and of unlawful disclosure of inside information that only indirectly affects the issuer (Article 8 and 14 of the MAR).

Using the passage of MAR July 3, 2016 as an exogenous variable, I investigate whether such market-level transparency effects the association between the aggregate insider trading and market returns to the extent on which insider trading predict market returns. In addition, the results could shed further light on the effect of time series variation in transparency on the predictive power of aggregate insider trades.

4.2.2 Literature Review and Hypothesis Development

Corporate insiders have been shown to trade at firm-level on superior knowledge about future earnings realizations and contrarian beliefs (Piotroski and Roulstone 2005).[28] In particular, empirical evidence documents the ability of insiders to forecast future stock prices in their own stocks three-to-nine quarters in advance of breaks in a strand of consecutive earnings increases (Ke et al. 2003). Seyhun, (1988, 1992), Rozeff and Zaman (1998), and Lakonishok and Lee (2001) present evidence on aggregate level, that insiders` knowledge about both firms` fundamentals and contrarian trading contributes to predictive ability of aggregate insider trades.

Serial correlation properties: informed trading and behavioral finance

Empirical predictions which relate stock market returns to private information and trading, explore how stock markets react to aggregate insider trading, mirroring serial correlations in insider trading (e.g., Lorie and Niederhoffer 1968; Seyhun 1988).

Autocorrelations (serial correlation properties) in trades may arise due to the *random arrival of private information* i.e., the trade comes from an informed trader (Kelly and Steigerwald 2004). In a similar spirit, serial correlation in trades can be caused by *strategic order splitting* of informed trading originally showed by Kyle (1985), where Kyle`s lambda measures the impact of informed trading on return.

In the imperfect competition model of Kyle (1985), an insider has the opportunity to trade multiple times on the same information. In similar vein, the entry and exit of informed traders in

[28] In this work, inside information is defined as an "information of a precise nature, which has not been made public, relating, directly or indirectly, to one or more issuers or to one or more financial instruments, and which, if it were made public, would be likely to have a significant effect on the prices of those financial instruments or on the price of related derivative financial instruments" (Article 7 Section 1 (a) MAR).

response to the random arrival of private information implies that trades are serial correlated (Kelly and Steigerwald 2004). Covrig and Ng (2004) provide the empirical evidence that institutional traders who are more likely to be informed traders generate correlated trades. That is because informed insiders tend to split their trades in more time periods increasing gradual their stock positions to conceal their private information and maximize their profits. Thus, arrivals (even independent) of new private information generate trades in the current and in the future periods (He and Wang 1995), causing serial correlation in trading.

In addition, similar to Daniel et al. (1998) who present evidence for investors overreaction, Luo et al. (2020) build on *overconfidence and scepticism* of investors to explain trading activity following corporate announcements. Because of investors underreaction, scepticism “stretches out” the effect of positive cash flow news to the market. A similar investor sentiment could arise when *myopic loss aversion* is the behavioral bias of investors that is a combination of a greater sensitivity to losses than to gains and a tendency to evaluate outcomes frequently (Benartzi and Thaler 1995). This investor sentiment is consistent with behavioral finance models such as in Bernard and Thomas (1989, 1990), and Barberis et a. (1998). Investors do not seem to understand the time series properties of earnings or, in this paper, the serial correlation of trading. Similarly, Lakonishok and Lee (2001), and Daniel et al. (1998) provide evidence that the market initially ignores insiders` material information. Baker and Wurgler (2007) present evidence that investors sentiment causes overvaluation, i.e., mispricing.

As a result, stock prices may not reflect firm fundamentals. In this case, the predictability of stock returns could reflect the correction of sentiment-induced mispricing of companies by insiders (Baker and Wurgler 2007). Insiders are in possession of private information about the true value of their firms. Therefore, their trading decisions may reveal their views about the mispricing of their companies. If investors’ sentiment leads to correlated mispricings across companies, aggregate insider trades may contain a systematic sentiment component (Seyhun 1998).

In sum, serial series in trading may be driven by *strategic trading of informed traders or*, similar, *random arrival of private information,* and *behavioral bias*. These effects can be part of the same process by which new information is being incorporated into stock prices. Duration and magnitude of price adjustments may be predicted based on trading activity, which is in turn positively related to informed traders.

Empirical evidence

Seyhun (1988) suggests that aggregation in insider trades can cancel out firm-specific information components and reinforce the common response on market-wide factors increasing the stock price predictive power of insider trades.

Especially, in several papers, Seyhun (1988, 1992) demonstrates a persistent evidence of a positive serial correlation in insider trades, as well as a strong positive association between aggregate insider activity and subsequent market returns. Chowdhury et al. (1993) extended the analysis of Seyhun (1988) by re-examining the study using a vector autoregressive regression frame with results that contradict those of Seyhun (1988). Chowdhury et al. (1993) show results suggesting that aggregate insider trades cannot predict market returns because the main impact arises from market return to insider trading. In contrast to Chowdhury et al. (1993), and similar to Seyhun (1988), the works of Lakonishok and Lee (2001), Baker et al. (2006) and Jiang and Zaman (2010) deliver a positive predictive content of insider trades in aggregate.

Recently a study with an international sample of 32 equity markets by Brochet (2019) confirms the earlier findings of Lakonishok (2001). However, Brochet (2019) shows the predictability of aggregate insider trading for market returns is inversely related to market transparency in the different markets. In the metaphoric imagery in Zhu et al. (2014), the positive correlation between aggregate insider transactions and market returns based on China data is described as “Swimming ducks forecast the coming of spring”, suggesting that this positive relationship should be expected. Moreover, findings by Lambe (2016) for the U.K. market suggest that, unlike the U.S. and China, the relationship is not present. Instead, aggregate insider trading shows that insiders are more likely driven by public perception than by private information, with Lambe`s (2016) metaphor of "an unreliable canary" alluding to the above statement by Zhu et al. (2014).

Furthermore, Seyhun (1988) reports reversal of aggregate insider trading direction after the realization of stock price movements. The evidence suggests that the market will overreact to the news because myopic trader do not reflect the extent to which the news are already "priced in" (Brunnermeier 2005). Insiders recognize the market mispricing and trade against the market adjustment. That suggests the superior information content of insider trades about firms' future cash flows dominates the mispricing resulting from informational inefficiencies. Thus, insider trading is expected to retain its predictive ability.

Given the serial correlation and the forecasting ability of aggregate insider trading recognized in the literature that is based on both firm fundamentals and mispricing, this study examines the predictive content of aggregate insider trading with data from Germany 2004 to 2019. In addition, this study investigates whether and to which extent market transparency induced by MAR introduction effects the market return predictability of insider trades. Prior studies find evidence that firm- and market-level financial information and governance transparency effect informativeness of firm-level insider trading activity (Frankel and Li 2004; Huddart and Ke 2007; Dai et al. 2016; Fidrmuc et al. 2013; Gebka et al. 2017). Borchert (2019) shows a negative effect of market transparency on predictability of aggregate insider trades. Brochet measures overall transparency by an aggregated proxy of factors for financial information transparency, investor protection and governance transparency. Furthermore, prior studies find evidence that insiders` predictive information is especially valuable during periods of high level of uncertainty and market volatility caused by unprecedented market disruption subsequent to global crisis and pandemics such as the Covid-19 pandemic early spring 2020 (Seyhun 1990; Anginer et al. 2020).

Based on the review of theoretical and empirical research, I formulate the hypotheses in *Null* format as follows:

1. *Insider trades are driven neither by new information nor by investor sentiment. Therefore, there is no serial correlation of insider trading.*
2. *Aggregate insider trading is less persistent than insider trading at firm-level.*
3. *Aggregate insider trading does not predict market returns.*
4. *Aggregate insider trading has less predictive content in case of more market transparency and in periods of significant market disruptions.*

4.3 Research Design and Variables Definition

4.3.1 Insider Trading Variables

I focus on market`s reaction on quarterly insider trading activity (Brochet 2019), though also monthly data is used to check for robustness of my results (Seyhun 1988).

The standardized insider trading activity (ITA), is measured as *Insider Trading Purchases Frequency Ratio.* This is consistent to Seyhun (1988), Lakonishok and Lee (2001), Piotroski and Roulstone (2005), and Brochet (2019), who use variations of the purchases ratio methodology for the overall market (market-level). I define three *standardized* proxies for *Insider Trading Purchases Frequency Ratio*. *Frequency* thereby captures the number of transactions. First, I define the purchases ratio for the overall market (market-level), the so called aggregated “PurchasesRatio$_{gg}$”, which captures the number of purchases during quarter t scaled by number of purchases plus number of sales during quarter t. The second proxy is “PurchasesRatio_firm” measured as firm-level quarterly insider trading purchases frequency divided by frequency of purchases plus sales on firm-level. The third proxy is an equal-weighted measure “PurchasesRatio$_{ew}$”. Equal weighted ratios are calculated quarterly for each firm (firm-quarter) and then averaged. The equal-weighted series are, in contrast to the first measure, averages of “PurchasesRatio_firm” ratios in quarter t.[29]

In addition to the three forementioned trading measures being used in the regressions also a fourth insider trading proxy “Insider Direction” is used for investigating insiders` predictability during Covid-19 pandemic crash. Insider Direction is calculated as total insider trading that is purchases minus sales scaled by total insider trades (for more details see Table 4.7). Moreover, the proxy “Buy (t-1)” is a dummy variable and corresponds to groups of firms where the Insider Direction variable is greater than zero during the crash period of Covid-19 in 2020.

4.3.2 Research Design

Autocorrelations in Trades

Similar to Seyhun (1988), I employ an autoregressive framework, first introduced by Sims (1980) and used in many empirical works such as in Chowdhury et al. (1993), and Lambe (2016) to investigate the predictive content of aggregate insider trading activity for the market returns. To begin with, I check for autocorrelation in the trades, i.e. the correlation between the insider trade and its previous values. This approach is also useful for making predictions about future

[29] It is worthful to note, that the coefficient on aggregate insider trading captures the incremental stock returns per unit of insider buying ratio. Thus, it is not possible to say whether aggregate insider trading shows abnormal profits or not as there is no single purchases or sales “event” that I can identify in aggregate, relatedly to event studies examining firm-level returns following individual insider trades like Fidrmuc et al. (2013).

behaviour. Following Box and Pierce (1970), Autocorrelations (AC) or serial correlation can be detected by plotting the model residuals versus time using the correlogram method (Auto Correlation Function ACF):

$$\mu\ (\varepsilon_t\ /\ \varepsilon_{t-1}, \ldots, \varepsilon_{t-k}) \qquad (1)$$

where ε_t are residuals (sample autocorrelation function of the residuals). Moreover, Partial Autocorrelations (PAC) stand for checking the necessary order of autoregressive (AR) model.

Autoregressions

The *autoregressive process* for insider trading frequency builds on simple and multiple autoregression model (AR) functions similar to Kothari et al. (2006).

Simple regressive model

$$ITA_t = a + b_k\, ITA_{t-k} + e_t \qquad (2a)$$

Multiple regressive method

$$ITA_t = a + b_k\, ITA_{t-1} + b_k\, ITA_{t-k} + \ldots + b_k\, ITA_{t-k} + e_t \qquad (2b)$$

The multiple regression estimates autoregressive coefficients with all lags together as regressors to predict current trades, while the simple regression reports simple correlations for lags varying from $k = 1$ to 4 quarters in the past.

The slopes b_k represent the degree of autoregression in insider trading frequency that shows the expectation formed from linear projection on the trading history, and e_t is error term.

Forecasting Regression: Market Return and Insider Trades

A common empirical framework is a rational expectations model discussed by Mankiw and Shapiro (1986), where there is serial correlation of the forecasting variable. Therefore, following Seyhun (1998), I regress market return R_t on contemporaneous and lagged terms of the standardized aggregate buying:

$R_t = a + b_k\ ITA_{t-0} \ldots + b_k\ ITA_{t-k} + e_t$ (3)

The forecast variable market return, R_t is regressed on contemporaneous insider trading activity (ITA) in t = 0 and four lags varying from k = 1 to 4 quarters in the past. Quarter k = 0 shows the contemporaneous relation between insider trading and returns. The disturbance term e_t shows innovation in the public information, and b_k are the trade coefficients reflecting managers` genuine market timing ability.

4.4 Sample Selection

The insider trades in the sample are from the database of Director's Dealing Notification. The database contains transactions that are required to be reported to the German Federal Financial Supervisory Authority (*BaFin, Bundesanstalt für Finanzdienstleistungsaufsicht*). The sample covers the period from 2004 to 2020.

After a cleansing process, I drop approximately 30% of the trades in the Bafin data of originally 49,901 insider trades from 2004 to 2019. The final sample then contains 33,376 insider transactions from which 22,761 are purchases and 10,615 are sales (Table 4.1, Panel A). The aggregate series for the analyses are the insider trades accumulated of 64 observations on quarterly level and 192 monthly based. Depending on the number of lags the observations decrease while using autoregressive models. For the firm quarterly accumulation 2,639 observations remain.

The data selection, and time periods for Covid-19 pandemic follows Anginer et al. (2020). After a cleansing process, similar to the before mentioned sample, for the Covid-19 sample in 2020 remain 2,556 insider trades and 937 firm day insider directions (Table 4.1, Panel B), from which 232 (untabulated results) occur during the crash period, which means that 25% of the observations in 2020 fall into the crash period. That shows the high trading activity during crash period of one month.

I obtain stock market data from Datastream (Refinitiv), and accounting variables such as market capitalization, book equity, size, and leverage data from Compustat.

Table 4.1 Sample Selection

Panel A: Data Selection of Insider Trading Data			
Data Selection (2004-2019)	Observations	Purchases	Sales
Insider Trades	49,901	27,795	22,106
Less no German ISIN	41,539	24,699	16,840
Less currency other than Euro	39,978	24,201	15,777
After cleansing Process (less implausible values of volumes, dates, penny stocks, prices, trading direction)	33,376	22,761	10,615
Final Data on aggregated level	Quarterly aggregated	Monthly Aggregated	Firm Quarterly level
Number of Observations	64	192	2,639
Panel B: Subsample Covid-19			
Data Selection 2020	Observations after cleansing process	Firm-day level	Firm-level crash period
Number of Observations	2,556	937	72

The table describes the composition of the final data set for insider trading 2004-2020. Panel A shows the data during period time 2004-2019 for the main analysis, and Panel B reports the final observations for the special Covid-19 period 2020.

Insider Direction measures the direction of insider trades, calculated as total insider trades that are purchases minus the total that are sales scaled by total insider trades (see also Table 4.7).

4.5 Results

4.5.1 Descriptive Statistics

Table 4.2 summarizes statistics for insider trading activity. The table shows the different portfolios, classified into *CDAX*, *insider trading sample*, and *Covid-19* sample, from which data is used. Additional to the entire sample, portfolios are partitioned as bottom and top terciles ranked by *Size* and book to market ratio (*B/M ratio)* (Table 4.2, Panel B).

The insiders in Germany tend to be net buyers (see average purchases frequency of 67.80%, Table 4.2, Panel A), though executives receive more than 50% compensation in stocks and options (Beck et al. 2020). This may indicate that compensations are more often options than shares. The mean firm value of insider direction proxy during the crash period time of Covid-19 February 20, 2020 to March 20, 2020 is about 83%. This positive value of insider direction proxy indicates that insiders carried out much more purchases than sales during the crash period time of Covid-19. In conjunction with the high trading frequency (25% of firm day insider directions 2020 occurred during crash period), the proxies suggest a superior trading activity during crash period.

Table 4.2 Panel A shows further interesting facts. First, profitability of CDAX portfolio since 2004 has been fairly high, average quarterly CDAX index return is 2.40%, and somewhat higher than corresponding average trading sample return of 1.40%. The difference is most likely an evidence that insider trading activity is related negatively (positive) to profitability (loss) (Huddert and Ke 2007). The trading sample has an average purchases frequency of 67.80% in quarter indicating that insiders buy more often than they sell. In comparison, Brochet (2019) finds a mean purchases ratio of 58,1% for his international cross-country sample.

Table 4.2 Descriptive Statistics: Summary Statistics for Returns and Insider Trades proxies

Panel A: Insider Trading Sample

Portfolio	N	Returns	Purchases Ratio_ firm	Purchases $Ratio_{gg}$	Purchases $Ratio_{ew}$	Insider Direction
CDAX						
Mean	540	0.024	-	-	-	-
Std. Dev.	51	0.092	-	-	-	-
Insider trading sample 2004-2019	850					-
Mean quarterly	98	0.014	0.91	0.678	0.90	-
Std. Dev.	35.01	0.225	0.20	0.143	0.068	-
Insider Trade sample 2020 Covid-19 year	192					
Mean daily	4	-	-	-	-	0.9338
Std. Dev.	3.61	-	-	-	-	0.2440
Insider Trade sample Covid-19: Firm - crash period	72	-	-	-	-	0.8270

Panel B: Subsample

Portfolio	N	$PurchasesRatio_{gg}$
Small stocks	300	
Mean	21	0.73
Std. Dev.	12.26	0.18
Large stocks	124	
Mean	19	0.62
Std. dev.	7.87	0.20
Low-B/M stocks	258	
Mean	17	0.55
Std. dev.	6.64	0.20
High-B/M stocks	286	
Mean	22	0.76
Std. dev.	17.38	0.18

The table presents time-series average and standard deviation of quarterly market stock returns, and aggregate insider trading measured by *PurchasesRatio*$_{gg}$ for various stock portfolios, and *PurchasesRatio*$_{ew}$ that are calculated as averages of firm-level insider trading on equity ratios in quarter. *PurchasesRatio_firm* are firm-level insider trades on equity ratios in quarter. In addition, total trading activity is measured at firm-quartet-level by *Insider Direction* for the Covid-19 year 2020. Except of the number of firms N in each portfolio, all variables should be interpreted in percent since they are measured in ratios. Returns are equal to the return of CDAX. The portfolio values are measured in two ways: The "aggregate" series is simply the cross-sectional sum of insider trades frequency (number of purchases divided by total number of trades in quarter) for all firms in the sample over the quarter *t*. "Equal weighted" series for purchases ratio frequency are averages of firm-level ratios in quarter *t.* Insider Direction measures the direction of insider trades, calculated as total insider trades that are purchases minus the total that are sales scaled by total insider trades (see also Table 4.7).

Pre-crash, crash, and post-crash refer to the periods January 1st to February 19th, February 20th to March 20th, and March 21st to April 30th, 2020, respectively.

„Small stocks" and "Large stocks" are the bottom and top firm terciles ranked by market capitalization "Low-B/M stocks" and "High-B/M stocks" are the bottom and top terciles ranked by book to market value

Second, the sample includes firms with wide cross-sectional variation in size and book-to-market ratio. In Table 4.2 Panel B, I report the statistics for the top and bottom terciles of stocks ranked by size measured by firm capitalizing and B/M – ratio. Small stocks and stocks with low B/M – ratio have mean trading activity of 73% and 55%. The mean trading activity for large stocks is 62% and 76% for high B/M – ratio companies, respectively.

4.5.2 Serial Correlations and Forecasts for Insider Trades H1 and H2

Autocorrelation in insider trades (Correlograms)

Table 4.3 explores the autocorrelation of aggregate insider trading by using the correlogram method. Reported are autocorrelations (AC) and partial autocorrelations (PAC). The serial correlation of trade is thereby a robust predictor of informed insider trading (Ahern 2020).

The pattern of autocorrelations is computed employing two alternative measures PurchasesRatio$_{gg}$ and PurchasesRatio$_{ew}$. The coefficients detect the presence of an autocorrelation process in time series in the data suggesting information content, respectively, predictive content in insider trading. Using the autocorrelation function (ACF) given by: Corr(PurchasesRatio$_{gg\ t}$, PurchasesRatio$_{gg\ t-k}$), the estimates for aggregate insider trading (AC) are representative: 0.64, 0.45, 0.36, 0.28, and 0.26 at five lags. This series of coefficients suggest significant autocorrelations. The Box-Pierce` Q statistics (Prob>Q value = 0.0000) at any *k* are less than 0.05 satisfying the required critical value of test statistics (Mankiw and Shapiro 1986). Thus, I reject the null hypothesis 1 based on the 5% critical value.

Table 4.3 Correlograms: Serial Correlations of Insider Trading measures, 2004-2019

Insider trading measure	Lag *k*	**Trading frequency (purchases ratio)**			
		AC	PAC	Q	Prob>Q
$\text{PurchasesRatio}_{gg}$					
	1	0.6401	0.6421	27.471	0.0000
.	2	0.4544	0.1483	41.538	0.0000
	3	0.3643	0.0591	50.727	0.0000
	4	0.2825	0.0580	56.346	0.0000
	5	0.2584	0.1773	61.126	0.0000
$\text{PurchasesRatio}_{ew}$					
	1	0.7250	0.7294	35.242	0.0000
	2	0.6888	0.3781	67.569	0.0000
	3	0.5573	-0.0421	89.078	0.0000
	4	0.5202	0.0718	108.13	0.0000
	5	0.4786	0.1664	124.53	0.0000

The table explores serial correlations in aggregate insider trading measured by PurchasesRatiogg and PurchasesRatioew using the correlogram method. The output includes autocorrelation (AC) coefficient and partial correlations (PAC). Box-Pierce` Q statistics tests the null hypothesis that all correlation up to lag k are equal zero.

In addition, aggregate insider trading is highly correlated (slope on first Lag = 0.64 and lower coefficients for the subsequent lags) indicating last quarters trading contains much information for the current quarter's trading. The autocorrelation decays fairly slowly. They are also persistent as they are positively autocorrelated for several quarters (at least five) and show no sign of a long-term reversal. As a result, trades errors are correlated through time based on ACF model, suggesting that lagged insider trades predict future insider trades. This indicates that lagged insider trades may forecast market returns in the current period.

Furthermore, the PAC identifies the economically significant order of an autoregression model at lag 4. The autocorrelation coefficient falls at lag 4 on the low coefficient of 0.06, and after that, there is no decaying estimate. Thus, in subsequent analysis, a high-degree AR (4) process could be useful.[30] In comparison, Seyhun (1988) uses three lags as to small slope on his third lag of 0.03.

Following Table 4.3, the pattern of serial correlations of the second insider trading proxy $PurchasesRatio_{ew}$ are very similar. Additionally, because of the significant series correlations in quarterly standardized aggregate insider purchasing the hypothesis 1 can be rejected. The results also suggest that aggregate insider trades should be well suited in terms of their persistence to test whether they can predict market returns. Furthermore, the strong autocorrelation in quarterly standardized aggregate insider purchasing is consistent with both information driven clustering and/or serial correlation due to mispricing.

Simple and multiple regression estimates

Next, I run simple and multiple autoregressions at firm- and aggregated-level using regression methods (2a) and (2b). I compare firm-level insider trading measure to aggregate insider trading, as I expect firm-level trades to contain idiosyncratic information components which get diversified away on market level, and therefore show less predictability than trades in aggregate. Table 4.4 reports the results. Panel A, presents at firm-level, the simple and multiple correlations for four lags. Firm-level regressions are derived from Fama and MacBeth (1973) procedure, i.e. I

[30] Ivanov and Kilian, (2005) report that too many lags could increase the error in the forecasts.

estimate a cross-sectional coefficient each quarter and show the time-series average of the coefficient estimates from the cross-sectional regressions.

Table 4.4 Autoregressions of Quarterly Insider Trading activity, 2004-2019

Insider trading measure	Lag k	**Simple regressions (1)**			**Multiple regressions (2)**		
		(1) Slope	(2) t-stat	(3) Adj. R^2	(4) Slope	(5) t-test	(6) Adj. R^2
Panel A. Firm-level							
Dep. Variable	**PurchasesRatio_firm**						
	1	0.0191*	1.9754	0.03	0.0269**	2.3741	0.10
.	2	-0.0148*	-1.7237	0.03	-0.0208*	-1.9181	
	3	-0.0078	-1.1592	0.02	-0.0124	-1.3012	
	4	-0.0050	-0.6068	0.02	-0.0047	-0.4708	
Panel B. Aggregate							
Dep. Variable	**$\text{PurchasesRatio}_{gg}$**						
	1	0.64^{***}	7.3557	0.47	0.52***	3.87	0.38
	2	0.47^{***}	4.8378	0.28	0.12	0.71	
	3	0.39^{***}	3.7407	0.19	0.01	0.05	
	4	0.31^{***}	2.9166	0.13	0.05	2.70	

Simple regressions (1): PurchasesRatioggt = a + bk PurchasesRatiogg t-k + et

Multiple regressions (2): PurchasesRatiogg t = a + b1 PurchasesRatiogg t-1 …+ bk PurchasesRatiogg t-k + et

Model (1) includes reports simple correlations stemmed from regressions for lags k = 1-4, and model (2) shows multiple regression estimates including all k lags together. Panel A reports the time-series average of slopes (coefficients) for individual firms i, obtained from a Fama and MacBeth (1973) cross-section regression: PurchasesRatio_firmi = a + b1 PurchasesRatio_firm t-1,i ..+ bk PurchasesRatio_firm t-k,i + et,i (simple and multiple regressions)

where t = 1, . . ., T is measured in quarters, i = 1, . . ., N indicates the cross section of firms, purchases ratio t, i is the purchases ratio for firm i at quarter t, et, i is the firm- specific (idiosyncratic) residual. Firm-level reported autocorrelation coefficients are the time series average autocorrelation slopes, bk of the coefficient estimates from the cross-sectional regressions. There are 2,639 firm-level observations.Panel B reports estimates from aggregate insider trades portfolios, obtained from time-series regressions. Aggregate numbers equal the cross-sectional sum of trading frequency in quarter t. There are 60 quarterly grouped observations for each series.

*, **, and *** indicate significance at the 10%, 5%, and 1% level, using a two-tailed test. T-statistics are based on standard errors, which are adjusted for heteroscedasticity and clustering at firm-level.

The firm-level correlations in insider trades are positive at the first lag and negative at the following three lags from lag 2 to lag 4.: 0.019, - 0.015, - 0.008, - 0.005, respectively. The findings are very similar to the negative autocorrelation of order flows of "illegal" insider trades in Ahern (2020) that are by definition informed trades. The estimates from the multiple regression are closed to these results (Table 4.4, Panel A, Column 4). This variation in the sign of estimated coefficients most plausibly reflects changes in the ratio of informed to momentum traders (i.e., opposite to contrarian, momentum traders buy stocks when prices are rising and sell stocks when prices are falling), with negative correlation in lag 2 to lag 4 when momentum traders predominate, probably affecting higher price increase (Ahern 2020), and with positive correlation in first lag when informed traders predominate.

Table 4.4, Panel B reports results for autoregression on aggregate. All five simple coefficients are positive and significant at 1% level. In particular, the estimates are 0.64, 0.47, 0.39, and 0.31. The value for Adj. R^2 is reasonable of 47% (for the first lag) to 13% (lag t-4) indicating correlation in quarterly trading not only in statistical but also in substantive sense. The estimates in aggregate are more persistent than at firm-level. Comparing Panels A and B, firm-level insider trading activity seems to contain a transitory, firm-specific component which averages out at the market-level (Lucas 1977).

Table 4.4, Panel B (Column 4), reports the results for the multiple regressions estimates including all four lags together. Consistent with Seyhun (1988), the coefficient on first-lag is positive of 0.52 and high significant at 1% level (t = 3.88), whereas higher degrees coefficients, though positive, are not different from zero. These results suggest that insider trading in quarter *t* and insider trading in quarter *t-1* tend to proxy for each other, i.e., current insider trading can forecast insider trades in subsequent periods suggesting that autoregressions in insider trades are well suited for predicting market returns. In addition, their correlations are remarkably more persistent than the correlation in trades on firm-level. Therefore, hypothesis 2 can be rejected.

4.5.3 Market Reactions to Insider Trading: The Predictive Content of Insider Trades H3

Table 4.5 presents the results from the regression model (3). Panel A, reports Fama-MacBeth procedure on firm-level insider trading. The firm-level insider trading significantly reduces market return in quarter k = 0 at 5% level (t-statistics of -2.16). The effects of past firm-level insider trading in lag one, lag two and lag three are positive, however statistically insignificant, indicating that the firm-level insider trading autocorrelation only limitedly predicts market returns. This may be explained by the transitory, idiosyncratic components of firm-level insider trading. Thus hypothesis 3 can be rejected.

In contrast, lagged aggregate insider trading capturing the systematic market-wide information component of trading is significantly associated with market returns in t (Table 4.5, Panel B), which is in line with Seyhun (1988). For t=0 the association between aggregate insider trading and market return is negative of -0.61, and significant at 1%-level, suggesting a likely overreaction of the market. Insiders recognize this market mispricing and trade accordingly, i.e., against market adjustment. Consistent with Seyhun (1988, 1992) my results suggest a reversal in the direction of standardized aggregate insider trading. Insiders increase their purchases prior the rise in market returns, which is reflected in a positive coefficient on lag t-1. However, they decrease their purchases following increases of market returns in the current period, which is reflected in a negative contemporaneous coefficient for quarterly aggregate insider trading in t.

Previous literature argues that contrarian trading is based on insiders' awareness of current investor sentiment and mispricing (e.g. Piotroski et al. 2005). Then, predictability of market returns could reflect the correction of these fads and mispricings by insiders (Baker and Wurgler 2007). However, to the extent that contrarian trades against mispricing also reflect superior information about future cash flows, this needs to be interpreted with caution (e.g., Piotroski et al. 2005). In this case, insiders use their private information about future cash flows to differentiate between underreaction and overreaction, they will trade accordingly adjusting their trading direction. Thus, my results concerning the negative relation to current returns could also reflect that insiders reverse their trading direction in anticipation of future earnings.

Table 4.5 Quarterly Market Returns and Insider Trading activity, 2004-2019

Insider trading measure	Lag *k*	**Dep. Variable: Return**		
		Slope	t-stat	Adj. R^2
Panel A. Firm-level		$R_{t,i} = a_t + b_0$ PurchasesRatio_firm $_{t-0,i}$….+ b_k PurchasesRatio_firm $_{t-k,i}$ + $e_{t,i}$		
PurchaseRatio_firm				
	0	-0.0659**	-2.1654	0.14
	1	0.0116	1.0829	
	2	0.0035	0.3043	
	3	0.0029	0.3096	
	4	-0.0024	-0.2806	
Panel B. Aggregate		$R_t = a + b_0$ PurchasesRatio$_{gg\ t-0}$…+ b_k PurchasesRatio$_{gg\ t-k}$ + e_t		
PurchasesRatio$_{gg}$				
	0	-0.61***	-6.09	0.37
	1	0.35***	3.07	
	2	-0.05	-0.41	
	3	0.09	0.81	
	4	-0.06	-0.61	

The Table reports the slope estimate, t-stat, and adjusted R2 when quarterly market returns Rt are regressed on quarterly insider trades measured by the purchase ratio:

Panel A reports the time-series average of slopes (coefficients) for individual firms i, obtained from a Fama and MacBeth (1973) cross-section regression:

Rt,i = at + b0 PurchasesRatio_firm t-0,i….+ bk PurchasesRatio_firm t-k, i + et,i

Panel B reports estimates from aggregate insider trades portfolios, obtained from time-series regressions.

Rt = a + b0 PurchasesRatiogg t-0…+ bk PurchasesRatiogg t-k + et

Aggregate numbers equal the cross-sectional sum of purchases scaled by the total number of trades in quarter t. Regressions lags varies between k = 0-4. There are 60 quarterly grouped observations for each series. There are 2,639 firm-level observations.

*, **, and *** indicate significance at the 10%, 5%, and 1% level, using a two-tailed test. T-statistics are based on standard errors, which are adjusted for heteroscedasticity and clustering at firm-level.

However, for t-1 the association becomes significantly positive (t=3.07), indicating that market returns reflect insider´s information with delay. In this case, the delay amounts to one quarter, similar to Seyhun's (1988) findings of at least two months. Economically, the coefficient estimates for *k=1* is 0.35. A two-standard-deviation positive shock to purchases ratio is associated with 10% increase in stock market prices in the next quarter (standard deviation on *k=1* in Table 4.5, Panel B, is 0.14, i.e., 2x0.14x0.35=9.8%).

This result strongly indicates that lagged standardized quarterly buying can predict market returns because insider can trade on their private information of the future cash flows of their firms. Similar to Piotroski et al. (2005), I assume that the variable market return in the *next* quarter is unbiased (albeit inefficient). Following my findings that lagged insider trading is positively related to returns in the *next* quarter, insiders use their private information and buy in advance of a future strong performance. When the market adjusts one quarter later, insider trades in aggregate appear to predict market returns in the three months prior to the market adjustment. Thus, insider trading driven by informational advantage about future cash flows seems to forecast the market. Altogether, mispricing and private information about firms` future cash flows might drive trading predictability, thus hypothesis 3 can also be rejected.

Moreover, consistent with Seyhun (1988), and Chordia et al. (2002), I find that lagged insider trading becomes insignificant when not accompanied by their contemporaneous counterparts (untabulated results). The explanation of Seyhun (1988) is that the estimated coefficient on current trades is negative and since the estimated coefficient on lag *k=1* is positive, omitting the contemporaneous trading term reduces the significance of lagged coefficients.

To sum up, the findings suggest that changes in insider`s purchases activity occurs at least one quarter before the changes in market returns which is consistent with findings in Seyhun (1988) that insiders trading on their future cash flows predict the market at least two months before.

Moreover, insiders may trade on mispricing in the current period as to my findings above, correcting thereby mispricing that might reflect the predictability of market returns.

4.6 The Impact of Information Transparency: Pre MAR versus Post MAR H4

Brochet (2019) documents a negative correlation between predictability of aggregate insider trading, and country-level financial information transparency and investor protection in a cross-sectional analysis between countries.

I test the effect of market-level transparency on the connection between aggregate insider trading and market returns using the introduction of MAR (Market Abuse Regulation by EU) July 3, 2016 and the announcement of MAR July 2, 2014 in Germany that reflects a transparency shock. MAR induces a series of financial information transparency, including a significant increase in the timeliness of insider trading and insider information disclosures. MAR stands also for a broader view of transparency in form of stronger governance like investor protection and governance provisions such as blackout periods.

In average, pre-MAR market transparency is less pronounced in the German market compared to the Anglo-Saxon markets (Australia, Canada, New Zealand, U.K., U.S.) and to the French market. Following the transparency data in Brochet (2019), the calculated Financial Information Score in Germany is 2.89 and, in the U.K., U.S.A. and France 6.00, 6.00 and 4.07, respectively (sample period: 2004-2012). The Governance Scores exhibit similar results. Thus, I expect a strong impact by the passage of MAR on the predictability of aggregate insider trades in Germany. I re-run my main tests by splitting the sample in a pre-and post-MAR period using both, the announcement date on July 2, 2014 and the enactment date on July 3, 2016. I therefore investigate, based on four sub-periods, whether the predictive content of aggregate insider trades changed after the passage of MAR. Table 4.6 exhibits surprising findings. Thus hypothesis 4 can be rejected.

Table 4.6 Monthly Aggregate Insider Trades and Future Returns: Transparency and MAR

Insider trading measure	MAR enouncement 2, July, 2014 Dep. Variable: Market return		MAR enactment 3, July, 2016 Dep. Variable: Market return	
	(1) Pre-MAR coeff (tstat)	(2) Post-MAR coeff (tstat)	(3) Pre -MAR coeff (tstat)	(4) Post -MAR coeff (tstat)
PurchasesRatio$_{\mathbf{gg\ t}}$	-0.14*** (-4.09)	-0.15*** (-3.20)	-0.14*** (-4.76)	-0.15*** (-2.53)
PurchasesRatio$_{\mathbf{gg\ t-1}}$	0.05* (1.65)	0.12** (2.59)	0.06** (2.13)	0.12** (2.04)
Intercept	0.06*** (3.23)	0.03 (0.64)	0.06*** (3.29)	0.03 (0.61)
N	125	66	149	42
Adj. R^2	0.13	0.18	0.14	0.17

This table reports regression results of Market returns Rt regressed on PurchasesRatiogg for lagged aggregate insider trades around passage of MAR. The regression specification is OLS. The sample includes transaction of corporate insider from 2004 to 2019.

Rt = a + bk PurchaseRatiogg t-1 + …bk PurchasesRatiogg t-k + et

MAR enactment 3, July, 2016, and MAR enouncement 2, July, 2014 are alternative treatment dates.

N presents the insider trades observations, monthly aggregated. Regressions lags varies between k = 1-2.

*, **, and *** indicate significance at the 10%, 5%, and 1% level, using a two-tailed test. T-statistics are based on standard errors, which are adjusted for heteroscedasticity and clustering at firm-level.

Following the significant estimate on lag t-1 of 0.05 and 0.12 before and after MAR (Column 1 and 2), respectively, that reflects the predictive ability of insiders in the distinct periods, the predictive content of insider trading increases in the period of higher market transparency after MAR. The findings remain robust, if I use the enactment date of MAR in 2016 (Table 4.6).

4.7 Insiders` Trading Predictability during Market Disruption: Evidence around the onset of the Covid-19 Pandemic H4

Most recent empirical research employing U.S. and international data (Canada, Italy, Spain and South Korea) shows that insiders were successful in predicting short-term market reactions in the post-crash period of the Covid-19 pandemic from March 21, 2020 to April 30, 2020 (Anginer et al. 2020). This may be especially true for insiders that have personal connections to China, where the pandemic first started (Anginer et al. 2020). There are large numbers of interconnections between agents (e.g., boardroom network), functioning as potential distribution of firm-idiosyncratic information about their future cash flows throughout the market (Larcker et al. 2013). Network economics deliver evidence, that network structures influence aggregation of such firm-specific information, and generate sizable aggregate effects (Bramoulle` et al. 2016; Alatas et al., 2016; Acemoglu et al. 2012). Anginer et al. (2020) find, that U.S. companies with insiders who are net buyers during the pandemic crash-period in late February 2020 to late March 2020 achieved on average 3.3% to 4.7% higher returns in the post-crash period compared to other firms.

I examine whether insider trading in Germany during the crash period may convey information about the timing and direction of expected recovery after the Covid-19 pandemic crash. In particular, abnormal purchases during the crash period would suggest that insiders believe the impact of pandemic to be transitory and thereby predicting high returns during the post-crash period. Considered are trades over the period from January 2019 to December 2020. The period around the onset of the Covid-19 pandemic is following Anginer et al. (2020) subdivided into the pre-crash time period from January 1, 2020 to February 19, 2020; the crash time period from February 20, 2020 to March 20, 2020; and the post-crash time period from March 21, 2020 to April 30, 2020. During the crash time period the German market (DAX) declined by 28%, very similar to the U.S. market that decreased during the same period by 35% (Anginer et al. 2020). Similar to Anginer et al. (2020), insider trading is measured by using a proxy for the direction of insider trading (*Insider Direction*), calculated as total insider trades that are purchases minus total insider sales scaled by total insider trades (for more details see Table 4.7). I calculate also the insider trading variables for the same date ranges in prior year 2019 to control for potential seasonality bias (Cohen et al. 2012).

The analysis takes place in two stages. In the first step (Table 4.7 Column 1 and 2), the dependent variable, Insider Direction, is the presentence of net buyers in a given period. I use dummy indicators for the three pandemic periods mentioned above: value of one for trades in the pre-crash period, and zero otherwise; value of one for trades in the crash period, and zero otherwise; and value of one for trades in the post-crash period, and zero otherwise. If corporate insiders disagree with the rapid stock price reaction during Covid-19 crash period, which reduced market indices, I expect them to anticipate market`s overreaction. Under the assumption, that firm`s future financial prospects are better than the market prices reveal, insiders are expected to buy stocks during the crash period.

In the second step (Table 4.7, Column 3 and 5), firm returns in the post-crash time period (R_t) are regressed on $\textit{Insider Direction}_{t-1,}$ (i.e. calculated as total insider trades that are purchases minus the total that are sales scaled by total insider trades) and $\textit{Buy}_{t-11}$, (i.e. firm purchases) respectively, during crash time period. This is done in order to detect any predictability of insider trades, and whether insiders` private information became especially valuable during the significant market disruption in the crash period.

Consistent with Lakonishok and Lee (2001), and Anginer et al. (2020), I control for a set of firm characteristics, which may influence the insider trading behavior during the crash sub-periods. The control variables include firm size (*SIZE*) defined as the natural log of firm market value; growth (*GROWTH*), calculated as the ratio of the market value of equity divided by the book value of equity, and leverage (*LEV*) that captures total liabilities divided by shareholders` equity. The variables are winsorized at the top and bottom 0,1% to eliminate potential effects of extreme values.

Table 4.7 Insider Trading during the Covid-19 crash and Cross-sectional Return regression

Insider trading measure	**Dep. Variable: Insider Direction**		**Dep. Variable: $returns_t$ (post-crash)**		**Dep. Variable: $returns_t$ (post-crash)**	
	(1) Slope 2020	(2) Slope 2019	(3) Slope	(4) t-stat	(5) Slope	(6) t-stat
Pre-crash	0.0443	0.0229				
crash	0.0655***	-0.0742***				
Post-crash	0.0928***	0.0117				
Insider Direction $_{t-1}$			0.5247***	2.89		
Buy (t-1)					0.6100**	2.0390
SIZE	0.0189***	0.0027	0.0034	0.08	0.0081	0.1913
GROWTH	0.0226***	-0.0002	0.0975	1.29	0.0946	1.2181
LEV	0.0122***	-0.0118**	-0.0214	-0.23	0.0088	0.0929
Intercept	0.9206***	0.9748***	-0.0270	-0.05	-0.1886	-0.3283
Industry FE	yes	yes	yes		yes	
N	937	655	72		72	
Adj. R^2	0.2007	0.0205	0.0903		0.0329	

This table reports an alternative proxy for insider trading (Insider Direction) and the effects of different periods pre-crash, crash and post-crash period around the onset of the Covid-19 pandemic at beginning of year 2020. Moreover, it shows the cross-sectional regression results of Market returns in the post-crash period per firm regressed on insider direction in the crash-period per firm. Insider Direction is calculated as total insider trades that are purchases minus the total that are sales scaled by total insider trades (Anginer et al. 2020):

$$\text{Insider Direction}i,t = \frac{\sum Buy\ i,j,t - \sum Sell\ i,j.t}{\sum Buy\ i,j,t + \sum Sell\ i,j,t}$$

where Buy is dummy indicator that takes a value of one if a trade j at firm i has made a purchase in time period t. Similarly, in case of Sell. Pre-crash, crash, and post-crash refer to the periods January 1st to February 19th, February 20th to March 20th, and March 21st to April 30th, 2020, respectively. For the return regressions, the post-crash period has been extended to August 20th, 2020 to capture all market recovery. The results for the dependent variable, Insider Direction, are reported also for the same "pseudo"-periods in 2019. Buy(t-1) correspond to groups of firms where the Insider Direction variable is greater than zero during crash period.

Firm size (SIZE) is the natural log of total assets; Market-to-book value (GROWTH)) is calculated as ratio of market value of equity divided by book value of equity; leverage (LEV) is long-term debt divided by total assets. VIF is the variation inflation factor. Industry FE control for industry fixed effects; N presents the insider trades observations.

*, **, and *** indicate significance at the 10%, 5%, and 1% level, using a two-tailed test. T-statistics are based on standard errors, which are adjusted for heteroscedasticity and clustering at firm-level.

Table 4.7 reports the results. First, the trading behavior around the Covid-19 pandemic is investigated. The first column shows that the dummy variable pre-crash is not significant, indicating no opportunistic sales behavior of insiders before the market crash. Contrary, a significantly negative effect would have been expected, which would reflect (opportunistic) insider sales in the pre-cash period. However, after the market decline in the late February 2020 and March 2020, insiders purchased stocks in their own firms leading to high abnormal purchases, i.e., a positive slope of 0.0655 that is highly significant at 1% level. The adjusted R^2 is fairly high about 20%. These abnormal purchases suggest that according to the beliefs of corporate insiders in aggregate, the financial crisis has only transitory impact on the stock market. Other studies like Niemann and Rünger (2017) find, that the insider trading behavior was similar to my results during the crash (last quarter 2008 to first quarter 2009) in the finance crisis from 2008 to 2009. Insiders bought in total in the last quarter 2008 nine times more stocks than in the last quarter 2007, and 34 times more than in the last quarter of 2009 suggesting that according to the beliefs of corporate insiders, the financial crisis has only transitory impact on the stock market. Insiders have predicted successfully the future development of the market, since three months later (second quarter 2009) the market began to recover. Consistent with Anginer et al. (2020), corporate insiders continue to buy shares through April 2020 signaling further recovery. Furthermore, the second column reports the results for the same periods one year before i.e., 2019. The coefficient on pseudo pre-crash dummy predictor 2019 is not significant, like in 2020. However, there is a remarkable difference between the estimates for the pseudo crash-period and pseudo post-crash periods in 2019, and the Covid19-period in 2020. The coefficient of the pseudo crash dummy in 2019 is significantly negative amounting to -0.07 in contrast to the positive and highly significant estimate of the crash-dummy in 2020 (Table 4.7, Column1). The coefficient of the pseudo post-crash predictor in 2019 is not significant, suggesting the seasonality trends to not drive the results of 2020.

The findings also show that around the onset of the Covid-19 pandemic, insider purchases are more pronounced for larger firms, high levels of leverage, and for growth firms. The increase in insider purchases in the Covid-19 crash period 2020, especially among insiders at growth firms and firms with high levels of leverage, may be more vulnerable than in other firms. This is due to liquidity problems caused by ongoing economic difficulties because of the Covid-19 pandemic, strongly suggesting that corporate insiders expected the effect of their firms` stock price to decline due to pandemic to be temporary.

Second, I examine the effect of insider transactions on returns. For this purpose, I extend the post-crash period to August 20th, 2020, since at this date the German market (DAX) closed at a level of 12,945 almost reaching the level before the crash time period. Based on cross-sectional regressions of post-crash firm-level returns (R_t) on insider trading variables on firm-level and firm characteristics computed during the crash period, the results suggest that firm's *Insider Direction* during the crash period is positively correlated to returns during the post-crash period. The coefficient amounts to 0.52 with a t-value of 2.89, indicating a strong economical and statistical significance. The finding is consistent with the conjecture that insiders purchase securities in anticipation of good future news.

However, hypothesis 4 can be rejected, that refers to the argument that insider` private information becomes especially valuable during periods of significant market disruptions.

The effect is even stronger when I use the Buy_{t-1} variable, an indicator variable that corresponds to positive values of Insider Direction. The coefficient on Buy_{t-1} is 0.61 and significant at 5% level (Table 4.7, Column 5). Consistent with Anginer et al. (2020), I find evidence, that insider trading was informative during the covid-19 crash. Moreover, according to my aforementioned results, their trading behavior (high abnormal buying) in aggregate during Covid-

19 crash period conveys also valuable information about the macroeconomic outlook, like future market development of market stock prices.

4.8 Robustness Checks

In the following, I conduct a battery of robustness tests. The tests contain controls for lagged returns and Granger-causality. Further, I consider alternative definitions for aggregate insider trading and repeat the analyses based on monthly regressions, different sub-periods, and for size-sorted portfolios.

4.8.1 Predictability after controlling for Lagged Market Returns: Bivariate Regression Model and testing for Granger-causality

To verify the robustness of my results, I follow Chowdhury et al. (1993), and employ a bivariate regression model. Furthermore, I test for Granger causality whether the direction of causality is from trades to market return, or inversely (Granger 1969, 1980). Also, in line with Rozeff and Zaman (1998), as well as Piotroski and Roulstone (2005), lagged market returns explaining insider trading, may capture likely investor sentiment beliefs. In this way I can investigate the extent to which insiders probably trade against mispricing (i.e., on the basis of contrarian beliefs).

Table 4.8, Column 1 shows that the primary factors determining the model`s dynamic adjustment are the positive effect of lagged insider trades on market returns and the positive serial correlation of trades. Panel A reports the time series properties of aggregate insider purchases ratio after controlling for lagged returns. Consistent with Seyhun (1988), the results show a significant positive first-order serial correlation coefficient of 0.38 (t-value = 2.22), while the higher order of autocorrelation coefficients are insignificant. This suggests that aggregate purchases ratio by insiders appear as first-order autoregressive processes (Seyhun 1998).

Table 4.8 Quarterly Market Returns and Insider Trading activity, Bivariate regression.

Dep. Variable	Lag *k*	PurchasesRatio$_{gg\ t}$(bi)		Market returns (g_i)		
		(1) Slope	(2) t-stat	(3) Slope	(4) t-stat	(5) Adj. R^2
Panel A. PurchasesRatio$_{gg\ t}$						
	0					
.	1	0.38**	2.22	-0.24	-1.31	0.43
	2	0.26	1.46	0.19	1.07	
	3	-0.10	-0.52	-0.08	0.44	
	4	0.24	1.64	0.43***	2.78	
Panel B. Market Returns						
	0	-0.57***	-5.28			
	1	0.35**	2.52	0.08	0.58	0.38
	2	-0.20	-1.33	-0.25*	-1.82	
	3	0.28*	1.91	0.17	1.22	
	4	-0.15	-1.24	-0.06	-0.43	
Granger causality test: using OLS						
F(4, 50)	2,70					
Prob > F	0.0412					

The table reports the slope estimate, t-stat, and adjusted R2 when quarterly market return (R) is regressed on quarterly insider, and on lagged Market returns, und when insider trading is regressed on lagged insider trading and lagged market return. There are 60 quarterly observations for each series.

The model allows very generally a resolution between trade innovation (private information) and quote revision innovation (public information). The regression specification is OLS.

PurchasesRatiogg t = a +b1PurchasesRatiogg t-1 ...+b4PurchasesRatiogg t-k + g1Rt-1 …+ g4Rt-k + et (Panel A)

Rt = a + b0PurchasesRatiogg t-0 …+ b4 PurchasesRatiogg t-k + g1Rt-1 …+ g4Rt-k + et (Panel B)

Panel A reports estimates from aggregate insider trades. Panel B reports estimates from market returns. Regressions lags varies between k = 0-4. *, **, and *** indicate significance at the 10%, 5%, and 1% level, using a two-tailed test. T-statistics are based on standard errors, which are adjusted for heteroscedasticity and clustering at firm-level.

After adjusting for lagged market returns, the estimates in return regression (Table 4.8, Panel B, Column 1) are -0.57 (contemporaneous) and 0.35 for the first lag of insider trades (significant at 1% and 5% level, respectively), and confirm the results in the main model (Table 4.5, Panel B). As Table 4.8 reports, the estimate at third lag is with a value of 0.28 also economically and as to its t-statistics (p value = 0.0600) also statistically significant.

Two other findings are noteworthy. First, as Table 4.8 reports for the return specification (Panel B), by running the Granger-Causality test, the Prob>F = 0.0412 is significant, that implies, I can reject the null hypothesis that all coefficients on lagged insider trading are equal to zero. Therefore, insider trading Granger-cause market return indicating that aggregate insider trading can predict the market. Furthermore, since insider trading is not associated with past returns, it is less likely to reflect mispricing and investor sentiment that are suggested to capture more public (market-wide) information such as market returns. The result is consistent to Toth et al. (2015) who find that the order splitting by informed traders is the dominant cause for autocorrelation in order flows, rather than the herding behaviour of investors (investor sentiment). At the same time, the findings in Table 4.8, Panel B suggest market efficiency, as the results show that the autocorrelation in return is less, consistent with an efficient market in Chordia et al. (2002) and LeBaron and Yamamoto (2007).

However, it should not be concluded that mispricing can play a minor role. As to the result of the main forecasting regression in this work, the negative contribution of mispricing in current period (negative contemporaneous coefficient in the return regression, Table 4.5) is required to examine the predictability of lagged aggregate purchases for market returns. Only after including the relation between returns and current insider trading in the regression, which is mainly driven by mispricing, the findings provide positive and significant coefficient estimates for lagged insider trades.

4.8.2 Alternative Insider Trading Variable

For sensitivity purposes, I use an alternative variable to capture aggregate insider trading. $PurchasesRatio_{ew}$ is calculated as quarterly averages of firm-level insider purchases ratio. Due to the PAC coefficient computed in Table 4.3, only 2 lags are necessary for this analysis.

Table 4.9 Quarterly Market Returns and Insider Trading activity (alternative proxy)

Variables	Lag *k*	**Autoregression insider trading** Dep. Variable: $PurchasesRatio_{ew}$ (1)		**Return reaction to Insider trading** Dep. Variable: Market return (2)		**Return reaction to Insider trading; lagged return** Dep. Variable: Market return (3)	
		Slope	t-stat	Slope	t-stat	Slope	t-stat
$PurchasesRatio_{ew}$							
	0			-0.74***	-2.81	-0.74***	-2.70
	1	0.44***	3.66	0.55**	2.03	0.56*	1.97
	2	0.38***	3.19	-0.14	-0.53	-0.15	-0.54
Market return							
	0						
	1					0.02	0.16
Adj. R^2		0.59		0.12		0.10	

The table reports the slope estimate, t-stat, and adjusted R2 when quarterly market returns R is regressed on alternative quarterly insider trade in aggregate PurchasesRatioew series that are calculated as averages of firm-level insider trading ratios in quarter. There are 62 quarterly observations for each series. Firm-level numbers are equal to monthly averages of individual firms (the measures are calculated for each firm, then averaged). Aggregate numbers equal the sum of trading values divided by sum of firms in portfolio:

Rt = a + bk PurchasesRatioew t-0 ..+ bk PurchasesRatioew t-k + et (specification 2)

Rt = a + bk PurchasesRatioew t-0 … + bk PurchasesRatioew t-k + g1Rt-1 (specification 3)

Rt is regressed on trading quarter t that shows the contemporaneous relation between insider trading and returns, and on two trading lags.The first model (1) shows the coefficients of the trades autoregression, and specification (3) reports the estimates on lagged trading after controlling for lagged return Rt-1. Regressions lags varies between k = 0-2.

*, **, and *** indicate significance at the 10%, 5%, and 1% level, using a two-tailed test. T-statistics are based on standard errors, which are adjusted for heteroscedasticity and clustering at firm-level.

Table 4.9 presents the results, which are similar to the main findings of Table 4.3 and Table 4.4. The coefficients of the autoregression-model amount to 0.44 for lag t-1 and 0.38 for lag t-2 (Column 1). The t-statistics are 3.66 and 3.19 respectively. In the return regression (Column 2), the significant slopes at t=0 and t-1 are -0.74 and 0.55 indicating stronger results than in the main model. After controlling for lagged market returns (Column 3) the association between aggregate insider trading and market returns remain robust.

4.8.3 Monthly Market Returns and Insider Trading Activity, 2004-2019

Table 4.10 replicates the analysis using monthly data and reports the autoregression pattern of insider trades and then the influence of aggregate trading on market returns. The number of observations increases from 60 quarter-observations to 187 monthly observations. The monthly specification is consistent to Seyhun (1988), who aggregates insider trading information on monthly basis.

The time-series properties of aggregate insider trading are positively autocorrelated for five months (0.61, 0.57, 0.52, 0.39, and 0.42), with Box-Pierce` Q statistics of Prob>Q value = 0.0000. Thus, the autocorrelations are significantly different from zero. The monthly market-level return regression in Table 4.10 also matches my previous quarterly results. Monthly market returns are contemporaneously negative correlated with insider trades (coefficient: -0.19, p-value=0.0000) with adjusted R^2 value of 15%. Further, consistent with Seyhun (1988) lagged trading (t-1 and t-2) exhibits predictive power for future monthly returns with positive and statistically significant slopes. The coefficients of the third to the fifth monthly lag are not significant. Overall, the results suggest that lagged insider trading is significantly positive associated with future market returns, thus also on monthly basis insider trading predicts the market returns.

Table 4.10 Monthly Market Returns and Insider Trading activity ($PurchasesRatio_{gg}$)

Insider trading measure	Lag *k*	1) Correlation Series Insider Trading				2) Insider trading autoregression			3) Dep. Variable: Market Return		
Purchases Ratio$_{gg}$		AC	PAC	Q	Prob> Q	Slope	t-stat	Adj. R^2	Slope	t-stat	Adj R^2
	0								-0.19***	-6.17	0.15
.	1	0.61	0.61	71.94	0.0000	0.34***	4.80	0.46	0.05*	1.65	
	2	0.57	0.34	135.72	0.0000	0.25***	3.31		0.05*	1.76	
	3	0.52	0.20	189.32	0.0000	0.18**	2.43		0.05	1.55	
	4	0.39	-0.04	219	0.0000	-0.07	-1.01		-0.02	-0.79	
	5	0.42	0.11	254.5	0.0000	0.11	1.60		0.00	-0.11	

The Table reports the slope estimate, t-stat, and adjusted R2 when monthly market returns R is regressed on monthly insider purchases frequency:

Rt = a + bkPurchasesRatiogg t-0…+bk PurchasesRatiogg t-k + et

k = Lag. Month k = 0 shows the contemporaneous relation between insider trading and returns. Regressions lags varies between k = 0-5.

The Table presents reports estimates from aggregate insider trades portfolios, obtained from time-series regressions. There are 187 monthly observations for the series.

*, **, and *** indicate significance at the 10%, 5%, and 1% level, using a two-tailed test. T-statistics are based on standard errors, which are adjusted for heteroscedasticity and clustering at firm-level.

4.8.4 Size Portfolios (25% Top Stocks and 25% Bottom Stocks)

Table 4.11 presents the analysis results separately for big and small firms, defined as the top and bottom terciles of stocks ranked by market capitalisation and book-to-market ratio respectively. At aggregate level, correlations are significantly positive at lags t-1 to t-2 for both small and large firms (Columns 1 and 2). The large-stock portfolio ranked by market capitalization has a first-order autocorrelation of 0.35. However, the large-stock portfolio sorted by the book-to-market ratio exhibits a first-order and a second-order correlation of 0.38 and 0.31 respectively. The findings for the small-stock portfolio are 0.47 first-order correlation and second-order correlation 0.25 for market capitalization. For the small-stock portfolio of book to market ratio the first-order correlation is 0.35, respectively.

The return regressions in Column 3 and 4 of Table 4.11 suggest interesting differences across groups. Large stocks provide strong evidence that market returns and concurrent insider trading are negatively correlated. The coefficient for the large-stocks (ranked by market capitalization) is significantly negative (-0.34) for k=0 (t-statistic: -6.27), but significantly positive (0.11) for k=1 (t-statistic: 1.77). However, findings for small-stocks (ranked by market capitalization) for k=1 are not significant suggesting that aggregate insider trades do not predict market returns for small firms. Whereas this result remains consistent for small stocks when using book-to-market to differentiate between the groups, the estimates of large stocks show that for k=2 the aggregate insider trade still significantly predicts market returns. Given that insider trading activity increases in the size of firm (Seyhun 1986; Huddart and Ke 2007), these findings are consistent with prior results that higher information-based trading frequency induces both larger stock price impact and stronger positive correlation in trade direction (Chung et al. 2005; Kelly and Steigerwald 2004). The results also suggest that smaller companies may be associated with greater mispricing (greater underreaction) of economy-wide information due to higher market uncertainty about the impact of firm-specific information about future cash flows and ongoing returns (Veenman 2013). Therefore, it might be difficult for insiders to recognize and trade on these mispricings that would rise the possibility of predictability.

Table 4.11 Size portfolios: Quarterly Market Returns and Insider Trading activity ($PurchasesRatio_{ggt}$), 2004-2019

Portfolio	Lag k	Insider trading autoregressions: $PurchasesRatio_{gg}$						Dep. Variable: Market Return					
		(1) Small stocks			(2) Large stocks			(3) Small stocks			(4) Large stocks		
		Slope	t-stat	Adj. R^2	Slop	t-test	Adj. R^2	Slope	t-stat	Adj. R^2	Slope	t-stat	Adj. R^2
Market Capitalization													
	0							-0.10	-0.87	-0.06	-0.34***	-6.27	0.38
.	1	0.47***	3.55	0.36	0.35**	2.37	0.13	0.03	0.26		0.11*	1.77	
	2	0.25*	01.69		-0.05	-0.30		-0.06	-0.50		-0.02	-0.35	
	3	-0.11	-0.61		0.09	0.61		0.01	0.06		0.08	1.42	
	4	-0.04	-0.25		0.17	1.15		-0.08	-0.66		0.05	0.81	
	5	0.02	0.15		0.01	0.07		0.05	0.56		-0.05	-0.92	
Book-to-market													
	0							-0.23***	-3.11	0.13	-0.42***	-4.54	0.25
	1	0.35**	2.58	0.12	0.38***	2.98	0.33	0.11	1.40		0.03	0.30	
	2	0.14	0.97		0.31**	2.46		-0.12	-1.53		0.17*	1.95	
	3	0.03	0.19		-0.12	-1.00		0.07	0.85		-0.10	-1.24	
	4	-0.17	-1.19		0.23*	1.88		-0.06	-0.81		0.04	0.46	
	5	0.10	0.71		-0.17	-1.54		0.01	0.07		0.01	0.07	

The sample is split into large and small portfolios, defined as the top and bottom terciles of firms ranked by market capitalization and Book-to-market ratio. Regressions lags varies between k = 0-5. There are 59 quarterly observations for each series.The left panel shows autocorrelations of quarterly insider trades and the right panel reports coefficients estimates from the specification:

$R_t = a + b_k PurchasesRatio_{gg\ t-0} \ldots + b_{k\ t-k} + e_t$, where R_t is the quarterly market return.

Table reports estimates for aggregate insider trading measured by $PurchasesRatio_{gg}$. For more information see Tables 4.3 and 4.4. *, **, and *** indicate significance at the 10%, 5%, and 1% level, using a two-tailed test. T-statistics are based on standard errors, which are adjusted for heteroscedasticity and clustering at firm-level.

4.9 Conclusion

The empirical evidence in this paper may shed new light in the relation between insider trading and market return predictability using non-U.S. data. The paper provides evidence that aggregate insider trading activity forecasts stock market returns. However, the predictive content of aggregate insider trading activity varies with the level of market transparency. High market transparency such as after MAR increases the predictive power of insider trades. In addition, using the Covid-19 pandemic as an external shock, I find that insiders` private information is especially valuable during mispricing periods caused by market fads and market sentiments during market disruptions such as the Covid-19 crash.

Moreover, my findings suggest that insider purchases trading behavior is contemporaneously negative correlated with market returns. This indicates that insiders reverse their trading direction after realization of market movement. Following my results, the insiders recognize the mispricing of the market and trade in anticipation of future cash flows of their firms in a contrarian direction. In sum, the primary dynamics of the market return predictability by aggregate insider trading are determined by the impact of informed insider trading on market returns and by the autocorrelation of insider trades.

A caveat in this paper is, that it recognizes that informed traders and trading by insiders on mispricing are the underlying forces for market price predictability, but the evidence does not irrefutably support a causal effect of mispricing. However, much remains to be done in terms of spelling out this dynamic framework, but the potential payoffs of an improved understanding of serial correlations in trading, mispricing, and informed trading in conjunction with market-wide information are substantial. Maybe, more empirical research in this market microstructure could provide explanations for effects on market prices and return predictability, that are not explained by the neoclassic financial theory for estimating fundamental market betas, which do not account for informed traders and investors sentiment.

List of References

Acemoglu, D., Carvalho,V. M., Ozdaglar, A., & Tahbaz-Salehi, A. (2012): The Network Origins of Aggregate Fluctuations, in: *Econometrica*, Journal of the econometric society 80, 1977-2016.

Ahern, K. R. (2020): Do Proxies for Informed Trading Measure Informed Trading? Evidence from Illegal Insider Trades, in: *The Review of Asset Pricing Studies*, 10 (3), 397–440.

Alatas, V., Banerjee, A., Chandrasekhar, A. G., Hanna, R., & Olken, B. A. (2016): Network Structure and the Aggregation of Information: Theory and Evidence from Indonesia: Dataset, in: *American Economic Review*, 1663-1704.

Anginer, D., Donmez, A., Seyhun, N., & Zhang, R. (2020): Global Economic Impact Covid-19: Evidence from Insider Trades, *Working paper*, Simon Fraser University and University of Michigan: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3624403.

Baker, M., Taliaferro, R., & Wurgler, J. (2006): Predicting Returns with Managerial Decision Variables: Is There a Small-Sample Bias, in: *The Journal of Finance*, 61 (4), 1711-1730.

Baker, M., Wurgler, J. (2000): The equity share in new issues and aggregate stock returns, in: *Journal of Finance*, 55, 2219–2257.

Baker, M., Wurgler, J. (2007): Investor Sentiment in the Stock Market, in: *Journal of Economic Perspectives-Volume*, 21(2), 129-152.

Barberis, N., Shleifer,A., & Vishny, R. (1998): A model of investor sentiment, in: *Journal of Financial Economics*, 49, 307–343.

Beck, D., Friedl, G., & Schäfer, P (2020): Executive compensation in Germany, in: *Journal of Business Economics*, 90, 787-824.

Benartzi, S., Thaler, R. H. (1995): Myopic Loss Aversion and the Equity Premium Puzzle, in: The Quarterly Journal of Economics 110 (1), 73-92.

Bernard, V. and Thomas, J. (1989): Post-earnings-announcement drift: delayed price response or risk premium? in: *Journal of Accounting Research*, 27, 1–36.

Bernard, V., Thomas, J. (1990): Evidence that stock prices do not fully reflect the implications of current earnings for future earnings, in: *Journal of Accounting and Economics*, 13, 305–340.

Bouchaud, J-P, Doyne Farmer, J., & Lillo, F. (2009): How markets slowly digest changes in supply and demand, in T. Hens, and K. Schenk-Hoppe, eds.: *Handbook of Financial Markets: Dynamics and Evolution* (Elsevier).

Box, G. E. P., Pierce, D. A. (1970): Distribution of Residual Autocorrelations in Autoregressive-Integrated Moving Average Time Series Models, in: *Journal of the American Statistical Association*, 65 (332), 1509-1526.

Bramoulle`, Y., Galeotti, A., & Rogers, B.W. (2016): The Oxford Handbook of The Economics of Networks, Oxford University Press 2016, NY 10016.

Brochet, F. (2019): Aggregate insider trading and market returns: The role of transparency, in: *Journal of Business Finance & Accounting*, 46 (3-4), 336-369.

Brunnermeier, M. K. (2005): Information Leakage and Market Efficiency, in: *Review of Financial Studies*, 18, 417-457.

Campbell, J. Y., Grossman, S. J., & Wang, J. (1993): Trading Volume and Serial Correlation in Stock Returns, in: *The Quarterly Journal of Economics*, 108 (4), 905- 939.

Campbell, J. Y., Lo, A. W., & MacKinlay, A. C. (1997): *The Economics of Financial Markets*, Princeton University Press, Princeton New Jersey.

Chordia, T., Subrahmanyam, A., (2004): Order imbalance and individual stock returns: Theory and evidence, in: *Journal of Financial Economics*, 72, 485-518.

Chordia, T., Roll, R., & Subrahmanyam, A., (2002): Order imbalance, liquidity, and market returns, in: *Journal of Financial Economics*, 65, 111-130.

Chowdhury, M., Howe, J., & Liu, J. (1993): The relation between aggregate insider transactions and stock returns, in: *Journal of Financial and Quantitative Analysis*, 28 (1), 431-437.

Chung, K. H., Li, M., & McInish, T. H. (2005): Information-based trading, price impact of trades, and trade autocorrelation, in: *Journal of Banking & Finance*, 29 (7), 1645-1669.

Cohen, L., Malloy, C., & Pomorski, L. (2012): Decoding inside information, in: *The Journal of Finance*, 67 (3), 1009–1043.

Covrig, V., Ng, L., 2004. Volume autocorrelation, information, and investor trading, in: *Journal of Banking and Finance*, 28, 2155-2174.

Dai, L., Fu, R., Kang, J.-K., & Lee, I. (2016): Corporate governance and the profitability of insider trading, in: *Journal of Corporate Finance*, 40, 235–253.

Daniel, K., Hirshleifer, D., & Subrahmanyam, A. (1998): Investor psychology and security market under- and overreactions, in*: Journal of Finance*, 53, 1839–1885.

Elliott, J., Morse, D., Richardson, G. (1984): The association between insider trading and information announcements, in: *Rand Journal of Economics* 15 (4), 521-536.

Fama, E. F., MacBeth, J. (1973): Risk, returns and equilibrium: empirical tests, in: *Journal of Political Economy*, 71, 607-636.

Fama, E. F., French, K. R. (1988): Permanent and temporary components of stock prices, in: *Journal of Political Economy*, 96, 246-273.

Fidrmuc, J., Korczak, A., & Korczak, P. (2013): Why does shareholder protection matter for abnormal returns after reported insider purchases and sales? in: *Journal of Banking and Finance*, 37, 1915–1935.

Finter, P., Niessen-Ruenzi, A., & Ruenzi, S. (2012): The impact of investor sentiment on the German stock market, in: *Zeitschrift für Betriebswirtschaft*, granger82, 133-163.

Fox, M. B., Glosten, L. R., & Rauterberg, G. V. (2018): Informed Trading and Its Regulation, in: *J. Corp. L.*, 43 (4), 817-98.

Frankel, R., Li, X. (2004): Characteristics of Firm`s Information Environment and the Information Asymmetry between Insiders and Outsiders, in: *Journal of Accounting and Economics*, 37, 229-259.

Gebka, B., Korczak, A., Korczak P., & Traczykowski J. (2017): Profitability of Insider Trading in Europe: A Performance Evaluation Approach, in: *Journal of Empirical Finance*, 44, 66-90.

Granger, C. W. J. (1969): Investigating causal relations by econometric models and cross-spectral models, in: *Econometrica*, 37, 424–438.

Granger, C. W. J. (1980): Testing for Causality: A Personal Viewpoint, in: *Journal of Economic Dynamics and Control*, 2, 329-352.

Gu, D., Liu, X., Sun, H., & Zhao, H. (2021): Strategic insider trading: Disguising order to escape trading completion, in: Journal of Corporate Finance 67, Forthcoming.

Hanke, M., Weigerding, M. (2015): Order flow imbalance on the German stock market, in: *Business Research*, 8, 213-238.

Hasbrouck, J. (1991): Measuring the information content of stock trades, in: *Journal of Finance*, 46, 179-207.

He, H., Wang, J. (1995): Differential information and dynamic behavior of stock trading volume, in: *Review of Financial Studies 8*, 919–972.

Huang, R. D., Stoll, H. R. (1997): The components of the bid-ask spread, in: *Review of Financial Studies 10(4)*, 995–1034.

Huddart, S., Hughes, J. S., & Levine, C. B. (2001): Public disclosure and dissimulation of insider trades, in: *Econometrica*, 69 (3), 665–681.

Huddart, S., Kee, B. (2007): Information Asymmetry and Cross-sectional Variation in Insider Trading, in: *Contemporary Accounting Research*, 24 (1), 195 – 232.

Ivanov, V., Kilian, L. (2005): A Practioner´s Guide to Lag Order Selection For VAR Impulse Response Analysis, in: *Studies in Nonlinear Dynamic & Economics*, 9 (1), 1-34.

Jiang, X., Zaman, M. (2010): Aggregate insider trading: contrarian beliefs or superior information? in: *Journal of Banking and Finance*, 34, 1225–1236.

Ke, B., Huddart, S., Petroni, K. (2003): What insiders know about future earnings and how they use it: Evidence from insider trades, in: Journal of Accounting & Economics 35 (3), 315–346.

Kelly, D. L., Steigerwald, D. G. (2004): Private Information and High-Frequency Stochastic Volatility, in: *Steadies in Nonlinear Dynamics & Economics*, 8 (1),1-28.

Kothari, S. P., Lewellen, J., & Warner, J. B. (2006): Stock returns, aggregate earnings surprises, and behavioral finance, in: *Journal of Financial Economics*, 79 (3), 537-568.

Kyle, A.S. (1985): Continuous auctions and insider trading, in: *Econometrica*, 53, 1315-1335.

Lakonishok, J., Lee, I. (2001): Are insiders' trades informative? in: *Review of Financial Studies*, 14, 79–111.

Lambe, B. J. (2016): An unreliable canary: Insider trading, the cash flow hyphotesis and the financial crisis, in: *International Review of Financial Analysis*, 46, 151-158.

Larcker, So, E.C., Wang, C.C.Y. (2013): Boardroom centrality and firm performance, in: *J. Account. Econ*, 55, 225–250.

LeBaron, B., Yamamoto, R. (2007): Long-memory in an order-driven market, in: *Physica A*, 383, 85-89.

Lorie, J.H., Niederhoffer, V. (1968): Predictive and statistical properties of insider trading, in: *The Journal of Law and Economics*, 11 (1), 35–53.

Lucas, R. E. (1977): Understanding Business Cycles, in: *Carnegie–Rochester Conference Series on Public Policy*, 5 (1), 7–29.

Luo, J., Subrahmanyam, A., & Titman, S. (2020): Momentum and Reversals When Overconfident Investors Underestimate Their Competition, in: *The Review of Financial Studies*, Forthcoming, 34(1), 351-393.

Mankiw, N. G., Shapiro, M. (1986): Do we reject too often? Small sample properties of tests of rational expectations models, in: *Economics Letters*, 20, 139–145.

Niemann, R., Rünger, S. (2017): The Impact of the Introduction of a Final Withholding Tax on Holding Periods of Share Investments – an Empirical Investigation of Directors`Dealing in Germany, in: *Schmalenbachs Zeitschrift für betriebswirtschaftliche Forschnung*, 69 (1), 41-80.

Piotroski, J., Roulstone. D. (2005): Do insider trades reflect both contrarian beliefs and superior knowledge about future cash flow realizations? in: *Journal of Accounting and Economics*, 39, 55–81.

Rozeff, S. M., Zaman, M. A. (1998): Overreaction and insider trading: Evidence from growth and value portfolios, in: *Journal of Finance*, 53.

Seyhun, H. N. (1986): Insiders' profits, costs of trading, and market efficiency, in: *Journal of Financial Economics*, 16 (2), 189–212.

Seyhun, H. N. (1988): The information content of aggregate insider trading, in: *Journal of Business*, 61, 1–24.

Seyhun, H. N. (1998): Investment Intelligence from Insider Trading, MIT Press, Cambridge, Mass.

Seyhun, H. N. (1990): Overreaction or fundamentals: Some lessons from insiders' response to the market crash of 1987, in: *The Journal of Finance*, 45 (5), 1363–1388.

Seyhun, H. N. (1992): Why does aggregate insider trading predict future stock returns? in: *Quarterly Journal of Economics*, 107 (4), 1303–1331.

Sims, C. (1980): Macroeconomics and reality, in: *Econometrica*, 48 (1), 1-38.

Toth, B., Palit, I., Lillo, F., Farmer, J. D. (2015): Why is equity order flow so persistent? in: *Journal of Economic Dynamics and Control*, 51, 218-239.

Veenman, D. (2013): Do Managers Trade on Public or Private Information? Evidence from Fundamental Valuations, in: *European Accounting Review*, 22 (3), 427-465.

Zhu, C., Wang, L., & Yang, T. (2014): "Swimming ducks forecast the coming of spring" – The predictability of aggregate insider trading on future market returns in the Chinese market, in: *China Journal of Accounting Research*, 7 (3), 179–201.

Appendix 4.1: Definition of Variables

Variables	Definition
Insider Trading Frequency Ratio	
$\text{PurchasesRatio}_{gg}$	Accumulated insider purchases frequency (count) on quarter (monthly) level for all firms scaled by purchases plus sales transactions quarter (monthly) level for all firms.
$\text{PurchasesRatio}_{ew}$	Firm-level quarterly insider trading purchases frequency divided by frequency of purchases plus sales on firm-level quarterly and then averaged.
PurchasesRatio_firm	Firm-level quarterly insider trading purchases frequency divided by frequency of purchases plus sales on firm-level quarterly.
Insider Trading Direction	
$\text{Insider Direction}_{i,t}$	Direction of insider trades, calculated as total insider trades that are purchases minus the total that are sales scaled by total insider trades, on firm-level (i) per period (t) day, month or crash period of Covid-19 in 2020 (see also Table 4.7).
$\text{Insider Direction}_{i,t-1}$	Direction of insider trades, calculated as total insider trades that are purchases minus the total that are sales scaled by total insider trades, per firm and day in the crash period of Covid-19 in 2020.
Buy (t-1)	Buy (t-1) is a dummy variable and corresponds to groups of firms where the Insider Direction variable is greater than zero during the crash period of Covid-19 in 2020.
Firm Characteristics	
SIZE	Natural logarithm of the total assets at the end of fiscal year *t*.
GROWTH	Market-to-book ratio at the end of fiscal year *t*.
LEV	Long-term debt divided by total assets.
Market Cap	The number of outstanding shares multiplied by the current market value of one share.
Book-to-market	Book-to-market ratio at the end of fiscal year *t*.
Stock Market returns	
R_t	Quarterly (Monthly) market returns of CDAX.
$R_{t,\,i}$	Quarterly firm-level returns.
$\text{returns}_{\,t}$	Firm-level returns cumulated on firm-level for the post-crash period of Covid19 in 2020.

5. Conclusion

This dissertation employs an empirical strategy to investigate the information content of insider trading. The analysis is based on the basic premise that insiders, while possessing private information, trade for many reasons and perform a variety of roles. By identifying information motivated trades (trades outside blackout periods) and examining their interest positive interaction to Corporate Social Responsibility (CSR), we show that legal insider trading contributes to market efficiency and fairness.

Further, we find substantial abnormal returns (most in cases of purchases) that indicates valuable content of information in insider trades. MAR regulation though mitigates the informativeness of insider trading, the impact appears mostly for trades of firms with high level of litigation risk. In addition, the MAR effect on trades in alternative trading venues is weak.

Last, in exploiting the predictability of aggregate insider trading, this work demonstrates that insider trades in aggregate deliver us a precise predictor for future market returns, at least three months before the market moves. The stock market price predictivity effect of aggregate insider trades is even higher when market transparency is stronger (in the period after MAR introduction). Following to the results of this work, insiders' predictive ability becomes especially valuable during periods of significant market disruption such as during Covid-19 pandemic.

Collectively, the results suggest that purchases convey information about future cash flows and for market returns. Investors, market regulators, and all active participants in securities markets should treat these trades as credible signals when forming forecasts returns and stock valuations at firm levels, but also predictions for market moves. Together, these implications are consistent with Manne (1966), who first argues that insider trades could benefit society in the sense of more market efficiency and fairness by inserting (rapidly) material private insiders` information into stock prices. Thus, the findings are relevant to the ongoing debate over the impact of insider trades on pushing prices towards fundamental values. This is an interesting area for further exploration.