LawFin Working Paper No. 22

Know Your Customer: Relationship Lending and Bank Trading

Rainer Haselmann | Christian Leuz | Sebastian Schreiber

Center for Advanced Studies on the Foundations of Law and Finance | House of Finance | Goethe University
Theodor-W.-Adorno-Platz 3 | 60629 Frankfurt am Main | Germany
www.lawfin.uni-frankfurt.de

Know Your Customer: Relationship Lending and Bank Trading*

Rainer Haselmann† Christian Leuz‡ Sebastian Schreiber§

August 2021

(Earlier Draft April 2021)

Abstract

In this study, we analyze the trading behavior of banks with lending relationships. We combine detailed German data on banks' proprietary trading and market making with lending information from the credit register and then examine how banks trade stocks of their borrowers around important corporate events. We find that banks trade more frequently and also profitably ahead of events when they are the main lender (or relationship bank) for the borrower. Specifically, we show that relationship banks are more likely to build up positive (negative) trading positions in the two weeks before positive (negative) news events, and also that they unwind these positions shortly after the event. This trading pattern is more pronounced for unscheduled earnings events, M&A transactions, and after borrower obtain new bank loans. Our results suggest that lending relationships endow banks with important information, highlighting the potential for conflicts of interest in banking, which has been a prominent concern in the regulatory debate.

*We would like to thank Patrick Augustin, Ray Ball, Luca Enriques, Anil Kashyap, Andreas Neuhierl, Dan Taylor, TObias Troeger, Antoinette Schoar, Joseph Weber, Michael Weber, Regina Wittenberg-Moerman, and Luigi Zingales as well as seminar participants at the University of Chicago for their helpful comments. The paper also benefited significantly from a fellow visit of Leuz at the Center for Advanced Studies Foundations of Law and Finance funded by the German Research Foundation (DFG) – project FOR 2774. The views expressed in this paper are those of the authors and do not necessarily reflect the views of Deutsche Bundesbank or its staff.

†Goethe University, CAS LawFin, and CEPR; haselmann@econ.uni-frankfurt.de.

‡University of Chicago and NBER; christian.leuz@chicagobooth.edu.

§Goethe University and Deutsche Bundesbank; schreiber@econ.uni-frankfurt.de.

1 Introduction

Banks are well-known to play an important role in the production of information in credit markets (e.g., James (1987), Lummer and McConnell (1989)). Their ability to screen, monitor, and form relationships with borrowers is critical for the provision of credit in the economy (e.g., Bernanke (1983), Petersen and Rajan (1994)). For instance, banks can serve as delegated monitors and mitigate incentive problems in lending (Diamond (1984)). However, banks could also take advantage of their privileged access to information and use it beyond their lending business.[1] In particular, the investment banking and brokerage arms of universal banks could have incentives to use borrowers' confidential information when selling securities to investors or trading in capital markets. Concerns about such conflicts of interest were a key reason for the separation of commercial and investment banks in the U.S. following the 1933 Glass Steagall Act (e.g., Kroszner and Rajan (1994)). After the financial crisis of 2008, banks' securities trading became again heavily debated and, in 2010, proprietary trading by banks was banned under the Volcker Rule. In Europe, a similar ban was proposed in the Liikanen report (Liikanen et al. (2012)), but never implemented.

Given these regulatory debates about bank trading, it is perhaps surprising that there are relatively few studies on banks' proprietary trading or direct evidence on the question of whether banks use private information that they acquire in the context of their lending relations when trading. Most studies focus on trading by institutional investors, i.e., mutual and hedge funds, that could obtain private information about borrowers by participating in loan syndicates or because they belong to the same financial conglomerate (e.g., Massa and Rehman (2008), Ivashina and Sun (2011), Massoud et al. (2011)). In this paper, we investigate proprietary trading of banks with lending relationships. Specifically, we examine whether banks trade more frequently and more profitably in stocks of their borrowers compared to other non-connected banks ahead of important corporate events.

Investigating the usage of private information within banks has been limited due to several empirical challenges. The first and primary challenge is that information flows cannot be directly observed. Therefore, an analysis requires granular data about banks' lending and also their trading activities. Second, banks may specialize in certain industries, firms or business models, in both their lending and their trading. Such expertise could result in lending to and more profitable trading in the same firm without any direct information flow from the lending function to the trading desk.

To overcome these challenges, we use the German credit register to determine lending relationships as well as new loans, and combine it with a novel dataset of banks' trading activities provided by the German

[1] At the same time, banks could use their private information to holdup borrowers and extract rents, e.g., Rajan (1992).

financial market supervisor (BaFin). This dataset contains every trade conducted by financial institutions on German exchanges and in the German OTC markets. We also build a comprehensive dataset of various corporate events for German firms. We then analyze bank trading around these corporate events, as profitable trading usually takes place when firms release new information (Cohen et al. (2008)). Our extensive database of corporate events helps with the second empirical challenge because it allows us to examine whether banks' trading behavior differs for events that are widely anticipated (e.g., earnings announcements that are scheduled in advance) and events that are unscheduled or harder to anticipate. For the latter, it is less likely that specialized bank expertise could explain trading ahead of the event. Thus, comparing banks' trading behavior across different types of corporate events provides insights into the underlying mechanism.

As in the U.S., insider trading is illegal in Germany Bhattacharya and Daouk (2002). The European Union's Market Abuse Regulation (MAR) prohibits the use of insider information for trading activities and its rules had to be implemented by all member states.[2] However, there are important exceptions when trading in the presence of inside information is allowed. For instance, market making activities are exempted and banks are allowed to trade in a stock even if some parts of the organization (e.g., lending) has inside information as long as internal arrangements (ethical walls) ensure that bank traders are not in possession of this information. These exceptions give rise to a grey zone. Another source of ambiguity is that banks have substantial discretion in declaring trades as proprietary trading versus market making. For this reason, we combine both categories and differentiate them from bank trades on behalf of clients.[3]

We first examine whether the relationship bank of a firm (defined as the largest lender or a lender that accounts for at least 25% of the firm's loans) trades more profitably than other, non-relationship banks in the two weeks prior to a corporate event. In order to do so, we consider the direction of trade in relation to the news released at the event. As the news and the return of a given event are the same for all banks, we focus on the number of shares bought or sold and the resulting trading imbalances, following Griffin et al. (2012). Our specifications include fixed effects for each corporate event and banks' industry specialization. We find that relationship banks purchase more shares and build up larger positive imbalances than non-relationship banks prior to events with positive news (i.e., positive market-adjusted returns). We also find relatively larger negative imbalances for relationship banks ahead of events with negative returns, although the results are often weaker for negative news events. The latter is perhaps not surprising as selling to benefit from

[2] The MAR (in §7) defines inside information as information that has not been made public, relates to a specific financial instrument and would have a significant impact on the price of the security if revealed. The definition of who is considered an insider is at least as broad in concept as it is under U.S. insider trading rules, although the latter have traditionally been enforced more stringently (Ventoruzzo (2014)).

[3] That being said, our results are not driven by this choice and hold if we exclude trades declared as market making from prop trading. On average, trades classified as prop trading (market making) account for about 69% (2%) of all trades and for 59% (18%) of all trading volume.

negative news requires banks to own shares prior to the event or, alternatively short-selling, which comes with institutional constraints. The differential strength of the results is also consistent with the literature on insider trades by corporate executives, which typically finds stronger results for insider purchases (e.g., Ke et al. (2003), Lakonishok and Lee (2001)).

To further aid the interpretation of our findings, we focus on unscheduled earnings-related events (pre-announcements, earnings guidance, certain dividend events). The results for such unscheduled events are more pronounced. We find that relationship banks build up significantly larger imbalances prior to positive (negative) events (0.19bp and -0.07bp of all shares outstanding, respectively). The effect sizes further increase when we restrict the analysis to events with larger market adjusted returns (above 2%). We also map out trading around such large-return events and find that, in the weeks after the event, relationship banks reverse the imbalances that they built up prior to the event. Again, the results are more pronounced for unscheduled events (in particular, those with positive news). We do not find significant imbalances of relationship banks for other time windows.

Evaluating the magnitude of the estimated effects is not straight forward given that not all relationship bank trades around corporate events are likely to be informed trades. We therefore focus on unscheduled earnings-related events that exhibit larger market-adjusted returns (>2%) and for which relationship banks build up substantial positions ahead of time (>0.5bp). For these instances, the relationship-bank effect on imbalances prior to positive events increases from 0.19bp to 0.85bp. The latter translates into an incremental position of €260,092. On average, relationship banks earn an additional trading profit of €3,890 per event. Compared to non-relationship banks' trading before events, we find that relationship banks earn an additional return of 0.92pp per event, essentially by trading more frequently in the "right" direction given the event return. To gauge the frequency of potentially informed trades, we define "suspicious trades" as cases in which a bank buys prior to a positive event and then sells right after the event (and vice versa for negative events). The unconditional probability of such a trade pattern in our data is 25.7% (requiring trading both prior to and after the event). For relationship banks, this probability increases by 5.7pp to 8.1pp, if we further restrict the analysis to cases, in which banks build up substantial positions prior to the event.

We refine our empirical design to better distinguish between two potential explanations for banks' profitable trading: lending relationships and bank specialization. First, we control for banks' specialization in certain industries during certain years by adding bank × industry × year fixed effects. The results indicate that banks' industry specialization in certain years does not explain our findings. Second, we consider that bank expertise could be firm specific. We therefore exploit changes in bank relationships. The idea is that building up bank expertise takes time and does not immediately disappear when the lending relationship ends. Thus, if bank specialization is the (joint) source of a bank's superior trading in a particular stock (and its loan to the firm), such trading should be longer lasting and not exactly coincide with the duration of the lending relationship. We therefore introduce bank $\times$ firm fixed effects. We find that these fixed effects only slightly attenuate the trading effects for relationship banks, which implies that banks have profitable positions around corporate events primarily when they are concurrently the relationship bank for a firm. To confirm this interpretation, we estimate the coefficient for "non-relationship periods" of relationship banks and show that it is insignificant.

Next, we perform a series of mechanism tests that shed light on potential information flows. First, we analyze corporate events that involve a borrower and a third party. But as we focus on trading in the third party, it is harder to explain with bank expertise. Specifically, we identify corporate events that involve two firms (e.g., legal dispute or merger), for which a bank is the relationship for one but not for the other. We then analyze bank trading in the unrelated firm around the joint corporate event. We find that the probability of a suspicious trade (as defined before) by a relationship bank increases by about 17pp around such events. Interestingly, however, we do not find that relationship banks are more likely to engage in suspicious trades around all other events of these unrelated firms. Thus, our finding for joint corporate events (involving borrowers) cannot be explained by a higher propensity to trade such unrelated firms generally.

Another way to explore the mechanism is to exploit that information flows differ across corporate events. For most events, new private information arises within firms, and we already differentiate between scheduled and unscheduled events. But there can also be external events that are unanticipated even by management. We therefore present results for different event categories. For earnings-related and M&A events, management is typically in the possession of private information prior to the release date and hence in those instances the lending relationship could give rise to information flows from the firm to the bank ahead of the event.[4] Consistent with these arguments, our results are much more pronounced for earnings guidance or M&A than for, say, legal events. These findings are suggestive that the information originates in borrowers and that banks trade on information obtained through their lending relationships.

We can also hone in on information flows by studying heterogeneity in the lending relationship and lending-related events. Larger loans likely require more monitoring and lead to more frequent interactions. Negotiating a new loan likely intensifies the communication between the firm and its lender as well. Thus, we examine whether the trading effects ahead of corporate events are stronger when the relationship bank's loan share is larger or when it recently granted a new loan to the borrower. We find that trading imbalances

[4] To monitor their loans, banks request regular performance updates from their borrowers (e.g., Minnis and Sutherland (2017)). M&A deals often involve new bank funding and hence conversations with the lending side of the bank. Literature reviews by Bhattacharya (2014) and Augustin and Subrahmanyam (2020) also suggest that concerns about informed trading often arise prior to earnings announcements and M&A transactions.

before positive news events increase in the loan share and in case a firm was recently granted a new loan from the relationship bank.

For our final mechanism exploration, we analyze whether the trading patterns themselves differ between relationship and non-relationship banks. We find that relationship banks build up imbalances with many (small) trades, rather than with a few big trades. This trading pattern is consistent with relationship banks trying to shroud orders to minimize price impact and detection. We continue to find this pattern when we include bank × firm fixed effects, which exploits relationship changes and implies that banks changes their trading behavior in a firm's stock once they become (or cease to be) the relationship bank to that firm.

To conclude our analysis, we conduct a number of robustness checks. Banks not only trade in borrowers' equities, but also in the options market. Option trades could offset what we document for equities or, conversely, be used for informed trading as well. We examine these possibilities, despite the fact that relatively few sample stocks have traded options. We do not find that prop trading in options offsets banks' equity trades. If anything, trading imbalances in options have a similar direction ahead of corporate events. Analyzing the net position of equities and options does not alter our results. Next, we analyze banks' trades on behalf of their clients. We do not find the same patterns in client trading. Lastly, we set up the analysis as a panel and include bank × event fixed effects. This analysis allows us to compare banks' imbalances right before an event relative to the average (or normal) imbalances within the same bank-event pair many weeks earlier. In this analysis, relationship banks continue to exhibit the same trading patterns around unscheduled events that we documented in our other analyses.

Our study contributes to two strands of the literature. First, our study relates to an important literature and ongoing policy debate about conflicts of interest in (universal) banks. The Glass-Steagall Act of 1933 was largely motivated by concerns about conflicts of interest that could arise when banks engage in commercial and investment banking activities. Private information from lending was central to these concerns. However, a number of influential studies presented evidence that questioned the concerns or the rationale for the separation of commercial and investment banking (e.g., Kroszner and Rajan (1994), Puri (1996), Kroszner and Rajan (1997)). The U.S. eventually repealed the Glass-Steagall Act in 1999. After the financial crisis in 2008, concerns about banks' speculative trading activities led to renewed calls to separate commercial and investment banking and resulted in the imposition of the Volcker Rule, which prohibits banks' proprietary trading in the U.S.[5]

Against this backdrop, we provide novel evidence on banks' proprietary trading in the context of a uni-

[5] While the Volcker Rule restricts banks' proprietary trading, it was not intended to restrict market-making activity (Bessembinder et al. (2018)). However, Duffie (2012) argues that market making is inherently a form of proprietary trading which makes it difficult for regulators to differentiate among the two.

versal banking system. The prevalence of universal banks in Germany should make conflicts of interest based on private information from lending more relevant, especially considering that German firms traditionally maintain strong ties with their main lenders or *Hausbanken* (Allen and Gale (1995)). Prior studies for the U.S., such as Massa and Rehman (2008) and Bodnaruk et al. (2009), present evidence of informed trading when mutual funds and banks belong to the same financial conglomerate. Their results suggest that mutual funds trade more and more profitably in firms that borrow from affiliated banks, suggesting that information obtained in one part of a financial conglomerate is used elsewhere to generate abnormal returns. Our study in turn focuses on information flows within banks, i.e., from banks' lending units to their trading desks.

Second, we contribute to a large literature studying the trading activities of privately-informed agents. Jegadeesh and Tang (2010) and Kedia and Zhou (2014) provide evidence for profitable trading prior to takeovers by target advisors and their affiliated dealers, respectively. Ivashina and Sun (2011) find that institutional investors (e.g., mutual funds, hedge funds, pension funds) that participate in loan syndication for a firm outperform other institutional investors in the same stock around major loan amendments. Massoud et al. (2011) show that hedge funds short-sell companies prior to loan origination or loan amendments when they are loan syndicate participants. In contrast, Griffin et al. (2012) use granular, trade-level data and find little evidence of connected trading ahead of takeovers or earnings announcements when analyzing client trading at and market making of investment banks that previously served as advisors in corporate transactions. Griffin et al. (2012) argue that their findings cast doubt on prior evidence on informed trading.

We add to this literature by studying banks and providing direct evidence on trading. There is substantial evidence that firms provide private information to banks, e.g., to facilitate loan contract monitoring (Minnis and Sutherland (2017)). However, the evidence that banks trade profitably on this information tends to be indirect, i.e., based on market-level outcomes such as returns, the (relative) price discovery in the CDS, secondary loan or stock markets, or syndicate participation (e.g., Acharya and Johnson (2007), Bushman et al. (2010), Carrizosa and Ryan (2017), Kang (2021)). To provide more direct evidence on trades or holdings, prior studies typically examine non-bank institutional lenders in loan syndicates, as they provide quarterly 13F filings. Our study combines granular trade-by-trade supervisory data with credit registry data, which allows us to directly observe banks' trading in individual stocks as well as their lending relationships with individual firms. Moreover, we can distinguish between banks' proprietary trading, market making and client trading, and study a comprehensive set of corporate events, both of which allows us to more fully understand bank trading in comparison to prior work that focused mostly on M&A deals or syndicated loan events.

2 Institutional Setting

In this section, we first delineate the legal rules governing banks' proprietary trading and market making activities during our sample period. Thereafter, we describe the legal and regulatory framework for insider trading in Europe.

The potential conflict of interest that arises when universal banks obtain confidential information about their borrowers and at the same time trade securities of these borrowers in the capital markets has featured prominently in the regulatory debate. Concerns about this and related conflicts played a central role in the separation of commercial and investment banks in the U.S. following the 1933 Glass-Steagall Act (e.g., Kroszner and Rajan (1994)). After being repealed in 1999 by the Gramm–Leach–Bliley Act, the Volcker rule in 2010 again banned proprietary trading by financial institutions but exempted market making activities.

In contrast to the U.S., commercial and investment banking activities have historically not been separated in Germany or in the EU. But as in the U.S., banks' security trading activities became heavily debated in Europe after the financial crisis of 2008. As a consequences, EU Internal Markets Commissioner Michel Barnier set up an expert group (known as the "Liikanen Group") to develop structural reforms of EU banking system to strengthen financial stability. The recommendations of this expert group, the so-called Liikanen report, *inter alia* proposed, among other things, the separation of commercial and retail banking activities from certain investment banking activities (Liikanen et al. (2012)). Another key element of this proposal was a ban of proprietary trading and market making by universal banks. The EU tried to institute this ban, but the proposal failed and no law was passed due to widely diverging positions of the EU member states on this matter.[6]

Following the rejection of the Liikanen recommendations, Germany unilaterally proposed a law governing banks' trading activities, the so-called Bank Separation Act (German Federal Ministry of Finance (2013)). This proposal was implemented in Article 2 of the German Banking Act and became effective on July 1, 2015. However, banks were given until July 1, 2016 to comply with the law. In principle, the Bank Separation Act introduced a ban on specific proprietary trading activities by banks whose trading activities exceed a set threshold defined in terms of trading volume.[7] Banks' above this threshold are not prohibited from trading, but have to direct these activities to a legally, organizationally and financially separate entity. Thus, a bank can continue to engage in proprietary trading as long as this activity is organized via a separate subsidiary

[6]For details on this proposal, see European Parliament (2014). For the different positions of the EU member states, see, e.g., Boersenzeitung (2015).

[7]A specific bank is considered to exceed this threshold if either trading activities of a given year exceed 100bn Euros, or, alternatively, trading activities sum up to more than 20 percent of its total assets and amount to at least 90bn Euros in the preceding three years (see Schelo and Steck (2013)).

of the bank.[8] Furthermore, the new Banking Act provides exceptions and discretion in classifying trading activities. For example, proprietary trading activities associated with a bank's hedging activities are exempt from this new regulation (Schaffelhuber and Kunschke (2015)). For these reasons, several legal scholars argue that the practical relevance of the Bank Separation Act when it comes to restricting proprietary trading is rather limited (e.g., Tröger (2016), Schaffelhuber and Kunschke (2015)). Consistent with these arguments, Table A2 shows that our sample banks' proprietary trading volume is only slightly lower in 2016 and 2017 than before the reform in 2015, and still *higher* than in 2012-2013.[9]

Next, We describe the legal restrictions on insider trading in Germany. Since Germany is part of the EU's single market, the single rulebook for EU financial markets applies in our setting. Here, insider trading is regulated under the Market Abuse Directive (MAD) as well as by the Market Abuse Regulation (MAR). The relevant passages of the statute, MAR Articles 7-14, define inside information as information that has not been made public, relates to a specific financial instrument and would have a significant impact on the price of a security if revealed. Once such information emerges inside a firm with publicly traded securities, trading based on this information is forbidden (MAR §14). Furthermore, the relevant information must be disclosed to the public immediately so as to maintain a level playing field among market participants. Thus, EU rules are based on the "equal access to information" theory (see Ventoruzzo (2014) for more details).

However, not all insider trades are illegal. In Article 9, the MAR lists situations, in which trading in the presence of inside information within a financial institution is not considered illegal. Trading is permitted if the bank has adequate and effective internal arrangements to ensure that its traders were not in possession of the inside information that is present in the bank (i.e., functioning 'ethical walls' need to be in place). Further, financial institutions may conduct security transactions in the 'normal course' of market making even in the presence of inside information. Finally, banks can discharge obligations incurred before the inside information was obtained and can also proceed with facilitating a takeover after it gained access to inside information. These exceptions give rise to a grey zone in which banks' trading could benefit from information obtained from their lending activities.

Insider trading has been regulated in the U.S. for a considerably longer time than in the EU. Broadly speaking, U.S. insider trading rules under the Securities Exchange Act of 1934 are quite similar when compared to current EU insider trading rules. However, the effectiveness of EU enforcement of its insider trading rules has been questioned (Ventoruzzo (2014)), whereas the SEC has a considerably longer record of credible enforcement (e.g., Bhattacharya and Daouk (2002)).

[8]The Liikanen report argued that such an organizational form requirement does not really constitute a restriction to banks' proprietary trading activities because the trading desk of a subsidiary would still benefit from the bank's funding costs in the same way a trading desk in the bank corporation would.

[9]The results on relationship trading presented below are present both before and after the reform.

3 Data and Descriptive Statistics

3.1 Bank Trading and Lending Data

We use two proprietary datasets on bank trading and lending for this study: one from the German Federal Financial Supervisory Authority (BaFin) and one from the German Central Bank (Deutsche Bundesbank). The principal dataset is the Securities Transactions Database maintained by BaFin. The German Security Trading Act (Wertpapierhandelsgesetz; WPHG) in conjunction with corresponding other regulation (WpHMV) requires each financial institution with a German banking licence (as defined by §9 of the WpHG), including subsidiaries of non-German banks, to report all its trades to BaFin. We have data from 2012 until 2017, when the WpHMV was replaced by EU regulation 600/2014 (Markets in Financial Instruments Regulation; MiFIR), requiring that banks report to the European Central Bank.

For each transaction, we have the security traded, date, time, price, volume, currency, an exchange code or indicator for OTC trades as well as a buy or sell indicator. Importantly, the dataset also includes short sales. In addition, we have information on the parties involved, i.e., an identifier for the reporting institution and, if applicable, identifiers for the client, counter-party, broker and intermediaries. Banks are further required to report for each trade whether (1) it acts on its own (proprietary trading), (2) it acts on behalf of a client but takes the security on its book (market making), or (3) it acts like a broker on behalf of a client without taking the security on its book. To account for the fact that market making is hard to disentangle from proprietary trading, as both involve taking a security on the bank book, we combine these two trade types under proprietary trading. By doing so, we do not rely on banks' trade classifications with respect to market making or proprietary trading.[10] We consider each bank with a separate BaFin identifier as a stand-alone entity in terms of trading.[11]

All trades are expressed in Euros (EUR). Trades in foreign currency are converted into EUR using daily exchange rates. For the most part, our analysis focuses on the equity markets, as they account for the vast majority of the trading volume on a given day. Moreover, not all firms have traded bonds or options. However, options could be important for banks' risk management.[12] Therefore, we also study option trades with the caveat that options do not exist for most sample firms and are often rarely traded.

Our second proprietary dataset is the German credit register maintained by Deutsche Bundesbank. This

[10]We re-run our analyses excluding trades classified as market making and obtain very similar results. See Section 6 and Table 10 for more details.

[11]There are three cases in our sample for which banks that belong to the same banking group have separate BaFin identifiers for some part of the sample period. When we manually aggregate these cases and net trades by banking group, results remain unchanged.

[12]Another reason to consider option trades is evidence that they are used for informed trading (Augustin et al. (2019)).

dataset allows us to identify and code banks' lending relationships. We have the identities of the lender and the borrower as well as the outstanding loan amount at the end of each quarter. Banks with a German banking license (i.e., including subsidiaries of non-German banks) have to report all loans above €1.5m (above €1m from Q1 2015 onward). Based on these data, we compute the loan share for each bank in each firm for each quarter, which then forms the basis for determining a firm's relationship bank(s).[13] We aggregate all loans to a given firm (identified by its main security) at the level of the banking group to also capture lending relationships by bank subsidiaries. Given the proprietary nature of the datasets, the credit register data and the securities transactions data are merged by Deutsche Bundesbank using a common bank identifier.

3.2 Compilation of Corporate Events

Publicly available datasets on corporate events differ on what they cover. We therefore combine several databases (Capital IQ, Eikon, IBES, Factset and Ravenpack) to compile a comprehensive set of corporate events for our sample firms. The combined database comprises events related to earnings announcements, financial reporting, management guidance, dividends, M&A transactions, board or executive changes, capital structure, legal issues, operating news (e.g., product releases) and bankruptcies. We cross-validate events and eliminate duplicates across databases, resulting in a sample of 39,992 corporate events. For each event, we compute the market-adjusted daily return by subtracting the DAX index return on a given day. Table 1, Panel A, provides frequency and return information for the different event categories. The largest number of events (11,484) fall into the earnings and financial reporting category. There are 6,808 management guidance events, 3,167 dividend events, 6,302 M&A events. The remaining categories contribute 12,231 corporate events. Bankruptcy events are rare in our sample. Judging from their market-adjusted returns, most events in our database constitute material news for investors. For all categories, the majority of the events exhibit (absolute) abnormal returns that exceed the median of the respective firm's daily abnormal returns over the sample period.

Next, we subdivide earnings events into regular earnings announcements (EAs), pre-announcements (prior to the regular earnings announcement date) and other financial reporting events (e.g., a firm reports monthly revenues for a specific segment or country). Among the earnings events, pre-announcements have the largest returns as firms usually pre-announce their earnings only if the earnings surprise is fairly large (Skinner (1994)). In comparison to EAs and pre-annoucements, other financial reporting events have relatively small

[13] We acknowledge that German firms could obtain loans from foreign banks without a German banking license, in which case we cannot code the relationship. However, such relationships would likely make it harder for us to find an effect and in that sense they work against us.

returns. We distinguish between management guidance (e.g., earnings or sales forecasts) that is provided at the EA, jointly with past earnings news, and guidance events when management provides stand-alone forecasts at other times. The latter is much less common than guidance at the EA. M&A events cover not only days when deals are consummated, but also announcements of intended or future deals as well as rumours about potential transactions, which why the category contains many events. We separately flag when the focal firm is the target of an M&A transaction or takeover. Legal events are mostly court rulings or instances when a firm is sued or sues another other firm. Operating events comprise a large number and broad set of firm news, including product announcements, capacity expansions, strategic alliances, many of which are less important, resulting in smaller returns.

An important distinction for our analysis is whether events are scheduled and therefore known to market participants ahead of time. For instance, we expect to sophisticated investors to collect information, perform analyses and trade ahead of corporate events. We therefore distinguish between scheduled events (e.g., conference calls, earnings announcements) and unscheduled events. For the latter, it is less clear that market participants expect the news or information to be released that day. As a first pass, we define “unscheduled earnings-related events” as pre-annoucements, stand-alone management forecasts and unscheduled dividends. The latter are defined as announcements of special dividends, stock dividends or dividend decreases. We do not include dividend increases because many firms maintain schedules that increase their dividends steadily.

The group of unscheduled earnings-related events is particularly relevant for our analysis. First, these events generally release material information to investors, as evidenced by their large stock market reactions. Second, we have a large number of these events, which allows us to construct powerful tests. Third, even for sophisticated investors, it should be more difficult to anticipate unscheduled events and to build positions ahead of them in a consistent fashion. Thus, successful trading around unscheduled events can be indicative of private information. Fourth, event overlap for unscheduled events is more limited. On days when firms hold conference calls or announce their earnings, they usually discuss many matters, including strategy, operational issues or new products, and they often provide guidance for the next year. Such event overlap makes it harder to sign the news, to define successful trading and to attribute the news to particular event categories.

3.3 Sample and Descriptive Statistics

To construct the corporate sample, we first compile all firms that are based and listed in Germany at some point between 2012 and 2017, which is the time period for which have banks' securities trading. We identify these firms by ISIN, keeping only ISINs that start with "DE". Non-German firms are not mapped by the

Bundesbank to the credit register. We exclude financial or bank stocks, identified by the Bundesbank SIC codes starting with 64, 65, 66 and 84 (except for 64G, which comprises non-bank financial service companies) because the lending relationships among banks (e.g., in the inter-bank market) are different from the ones that they have with non-financial, corporate borrowers. We drop firms for which we do not have any corporate events.[14] The resulting sample comprises 619 firms and constitutes the vast majority of publicly traded German stocks and a large part of the German corporate sector.

Table 1, Panel B, provides firm-level summary statistics for this sample. The average market capitalization of the sample firms is about €2.2bn, although the median firm is about half that size. About 40% of the firms are part of the German Prime Standard, which imposes more extensive reporting requirements. During our sample period, firms have on average 65 corporate events. The distribution of these events is highly skewed. Smaller firms have considerably fewer events, likely reflecting fewer reporting requirements (e.g., they do not have to report quarterly), fewer newsworthy events for these firms and less comprehensive database coverage of smaller firms.

For banks to enter the sample, they have to trade at least once per month in one of the 619 sample stocks between 2012 and 2017 and take the resulting positions on their books (i.e., prop trade or engage in market making for the stock). This restriction focuses the analysis on the subsample of banks with trading desks that frequently engage in prop trading, which in turn reduces the heterogeneity across banks. The resulting sample comprises 49 German and foreign banks with a German banking license. Fourteen of these banks do not make loans to the sample firms, i.e., they trade only and therefore are always in the control group. We define a lender as a relationship bank (in German called "Hausbank") if it is either the largest lender to a firm or accounts for at least 25% of the firm's loan share in the quarter prior to the respective firm having an event.[15] It is possible that a corporate borrower has more than one relationship bank. By coding the relationship variable for the quarter prior to an event ensures that a bank already has a lending relationship by the time the event occurs and hence it is at least conceivable that the bank is in possession of private information from the lending relationship. In our sample, 21 of the 49 sample banks are assigned as relationship bank to a firm at least once.

As shown in Panel C of Table 1, sample banks have on average a quarterly loan exposure of about €1.1bn against all sample firms. On average, a bank serves as relationship bank to 16 sample firms (prior

[14] We also exclude 17 firms because no sample bank trades their equity around any of their firm events.

[15] We do not code a bank as being a relationship bank for a given firm if i) the bank's lending volume is below €2m or ii) the lending volume in a quarter is at least 50% larger than in the two adjacent quarters, suggesting large fluctuations. The latter indicates that the firm maintains a current account at the bank rather than a long-term loan relationship. The former restriction intends to prevent variation in the relationship variable that arises simply because the outstanding loan balance fluctuates around the reporting threshold of €1.5m until 2015 and €1m after 2015. These restrictions do not alter our results.

to at least one event). However, both of these averages are highly skewed. The median bank has a loan exposure of €74m and is the relationship bank for one corporate borrower. Thus, a relatively small number of banks accounts for most of the lending relationships. The same is true for the trading activities, for which the majority of the Euro volumes stem from a relatively small number of banks. The median bank has a proprietary trading volume of about €3m per day, whereas the average volume is roughly €48m. The average sample bank engages in 2,261 prop trades across 48 sample stocks per day. The average trade size is €31,373. Focusing on the two weeks prior to a corporate event, banks engage in prop trading in 18% of the cases. Thus, prop trading prior to events is common but not the norm.

To analyze banks' prop trading around corporate events, we construct the dataset at the bank-event level. The resulting dataset has in principle 1,959,608 observations, i.e., 49 (banks) $\times$ 39,992 (events). As the respective event return is the same for all bank-event pairs, we focus on the number of shares banks trade ahead of the corporate events. We accumulate trades to determine the net trading position that a bank has built over the two weeks prior to an event. Following Griffin et al. (2012), we compute a trading imbalance for each of the 49 sample banks for the two weeks prior to the 39,992 corporate events, defined as $\frac{buys-sells}{shares\ outstanding} \times 10,000$. It is scaled by the respective firm's shares outstanding and expressed in basis points to make it comparable across firms and events. If a bank does not trade prior to the event, the imbalance is set to zero. The key variable of interest, *Relationship*, is also coded at the bank-event level and indicates that a bank is a relationship lender (as defined above) for a particular firm in the quarter before the event.

Panel D of Table 1 provides summary statistics for this bank-event dataset. When a bank is coded as a relationship bank, its loan share is on average about 39%. Imbalances characterize banks' proprietary trading ahead of corporate events, which differs considerably across events and banks. On average, imbalances are small and the median is zero because not all banks prop trade before every event. In fact, recall that only 18% of the events exhibit any prop trading by a bank in the two-week window. We further note that the distribution of imbalances exhibits extremely large observations on either end, reflecting a few out-sized trading positions. We therefore winsorize imbalances on both ends (at 1st and 99th percentile) to mitigate the influence of these observations. To get a sense for the magnitude of banks' trades ahead of events, we condition on prop trading in the [-14,-1] window prior to an event and consider the median negative (positive) imbalance, representing the first (third) quartile. The median negative (positive) imbalance conditional on trading is -0.23bps (0.26bps) of all shares outstanding. These median imbalances translate into €-positions of about -€0.08m (€0.11m). Multiplying imbalances with the respective event return provides the distribution of trading profits from these positions. Profits are generally small but again highly skewed in both directions. They are determined by the sign of the imbalance relative to the sign and magnitude of the event return.

We therefore compute in Panel E of Table 1 how often banks trade in the "right" direction, i.e., in the direction of the event return. If market-adjusted event returns are unpredictable and equally likely to be positive or negative, the baseline probability without private information or skill should be 50%. Consistent with this expectation, the probabilities of trading in the right direction shown in Panel E are close to 50%. The numbers indicate that it is difficult to consistently trade in the right direction ahead of corporate events, although the probability is slightly larger for relationship banks. Importantly, a larger probability could indicate expertise or skill due to research and financial analysis, and does not necessarily reflect the possession of private information. For instance, it is common for sophisticated investors to engage in extensive research prior to earnings announcements. It is noteworthy, however, that the likelihood of trading in the right direction further increases for relationship banks when we consider unscheduled events only. If anything, it should be more difficult to trade in the right direction for events that are not even scheduled.

4 Research Design

In this section, we describe our research design and empirical strategy to analyze whether banks with lending relationships trade more profitably in the stocks of their borrowers. We center the analysis on corporate events to focus on situations when new and previously private information is coming to the market. Importantly, profitable trading positions ahead of specific corporate events could arise for several reasons. One potential reason is that relationship banks obtain valuable information from their lending activities and this information somehow makes its way to the banks' trading desks and is used in prop trading. An important alternative explanation is that banks specialize in certain industries, business models or firms, both in lending and trading. This expertise could also explain why banks have lending relationships and trade more successfully ahead of corporate events. Below, we also discuss several empirical tests that are designed to shed light on these two alternative explanations.

4.1 Trading Imbalances around Corporate Events

Our main empirical model investigates whether relationship banks build larger and more profitable trading imbalances for the same corporate event than non-relationship banks. Formally, we estimate the following specification:

$$Imbalance_{be} = \beta_1 \times Relationship_{be} \times Pos_e + \beta_2 \times Relationship_{be} + \gamma_e + \gamma_{bs} + \epsilon_{be} \quad (1)$$

where $Imbalance_{be}$ is defined as $\frac{shares\ purchased\ -\ shares\ sold}{shares\ outstanding} \times 10,000$ by bank b in firm f's shares during the [-14,-1] day window prior to event e. That is, a value for the imbalance of 2 means that a bank in the two weeks prior to an event built up a net position amounting to 0.02% of all shares outstanding of a firm. In principle, our panel dataset is balanced because we code banks that do not trade before the event as having an imbalance of zero. However, in some specifications, we impose restrictions on the sample and require minimum absolute imbalances to focus the analysis on instances when banks have built up substantial positions ahead of corporate events.

The indicator variable $Relationship_{be}$ is equal to one if bank b is a relationship bank to firm f in the quarter prior to firm f's event e. Recall that a bank is classified as a relationship bank if it is either a firm's largest lender or its loan exposure accounts for at least 25% of the total loans to this firm. The indicator variable Pos_e is equal to one (zero) if the market-adjusted return of firm f stock in the [-1,+1] day window around its event e is positive (negative). In many tests, we focus on corporate events that are major news to the market and hence impose a minimum for the absolute abnormal return of 2%.

We introduce the interaction between Pos_e and $Relationship_{be}$ to estimate differences in the trading patterns of relationship banks separately for positive and negative news events. Negative information is typically harder to use for traders because it either requires owning the stock ahead of the event or short-selling it, which comes with institutional constraints. The literature on insider trades by corporate executives also tends to find stronger results for insider purchases (e.g., Ke et al. (2003), Lakonishok and Lee (2001)). The primary coefficients of interest are β_1 and β_2. The former estimates the incremental imbalance for relationship banks in the two weeks prior to positive-return events relative to the average imbalance of non-relationship banks. The latter estimates the same incremental imbalance for negative-return events.

The model includes a series of fixed effects. In the main specification, we include fixed effects for each individual corporate event, γ_e, to control for the event return as well as any event-specific characteristics, such as differences in the extent to which an event and its return can be anticipated by all market participants. We further add bank $\times$ industry fixed effects, γ_{bs}, using the 3-digit industry classification by Deutsche Bundesbank, to account for any time-invariant bank- and industry-specific trading patterns. For instance, banks' prop trading desks and their research teams may specialize in certain industries and the resulting expertise differences (e.g., in the ability to forecast earnings) could also explain differences in trading patterns before major corporate events. We cluster standard errors at the bank level.

4.2 Mechanism Tests

In this subsection, we present empirical tests to distinguish between alternative explanations for why relationship banks build up profitable positions before corporate events of their borrowers. The main challenge is to differentiate between an explanation based on bank expertise for a specific industry, firm or business model and an explanation based on relationship information, especially considering that information flows cannot be observed.

We begin by exploiting time-series variation in lending relationships. During our sample period banks start new lending relationships and end existing ones. However, building up expertise takes time and does not disappear immediately when the lending relationship ends. Thus, if bank specialization is the (joint) source of a bank's superior trading in a particular stock (and its loan to the firm), such bank expertise should be longer lasting and not exactly coincide with the duration of the lending relationship. In contrast, private information from lending relationships is more closely tied to the relationship itself. Thus, we estimate the following specification:

$$\begin{aligned} Imbalance_{be} = {} & \beta_1 \times Relationship_{be} \times Pos_e + \beta_2 \times [Non - Rel.Periods_{be}] \times Pos_e + \beta_3 \\ & \times Relationship_{be} + \beta_4 \times [Non - Rel.Periods_{be}] + \gamma_e + \gamma_{bs} + \gamma_{bf} + \epsilon_{be} \end{aligned} \tag{2}$$

where $[Non - Rel.Periods_{be}]$ is a dummy variable that is equal to one for banks that are relationship bank to a firm at some point in the sample, but not currently (and zero otherwise). Relationship-specific fixed effects (i.e. bank $\times$ firm FEs) are indicated by γ_{bf}. In this specification, our main coefficient of interest β_1 compares trading imbalances around positive-return corporate events during times when the bank is a relationship lender with times when the bank is not a relationship lender to the *same* firm.[16] The coefficient β_2 indicates whether relationship banks also trade profitably in their borrowers when they do not have a significant loan outstanding to the firm. In addition, we estimate a model, in which we saturate specification (2) with time-varying bank-firm fixed effects (i.e., bank $\times$ firm $\times$ year).

Our second test focuses on indirect links between the relationship banks and firms. Specifically, we analyze corporate events that involve two firms (e.g., legal dispute or merger), for which a bank is the relationship for one but not for the other. We then analyze bank trading in the unrelated firm around the joint corporate event, for which profitable trading would be harder to explain with bank expertise. Specifically, we identify corporate events that involve two different sample firms: one firm (referred to as Firm F2) with a relationship bank (referred to as Bank B) and another firm (referred to as Firm F1) to which Bank B is not a relationship lender. We identify such cases by screening all event headlines for whether

[16] We put our focus on positive-return events in the mechanism tests as effects are more pronounced for such events (see Table 2).

another sample firm is mentioned. The majority of these cases consist of M&A events.[17] A typical example would be the following scenario: Firm F1 plans to take over Firm F2. While Bank B has no link to Firm F1, the bank could be informed about the M&A activity by its relationship borrower, Firm F2. The idea of the test is to examine Bank B's trading behavior in Firm F1 around its corporate events. More specifically, we compare the trading patterns of Bank B around Firm F1's corporate events that involve Firm F2, which is a borrower of Bank B, and those events of Firm F1 that do not involve such an indirect link. This test allows us to analyze bank trading in the same firm but for events when information from its lending relationship could be relevant versus when it is not. As we have relatively few of these third-party events and do not want a few large imbalances to drive the results, we employ the binary *suspicious trade* variable for this test.

5 Empirical Results

5.1 Relationship Banks' Trading around Corporate Events

In this section, we investigate relationship banks' trading behaviour around corporate events. Table 2, Panel A reports estimates of our main specification (1) that compares the profitability of the trades by relationship and non-relationship banks around corporate events. In addition, Table 2, Panel B examines the dynamics of these patterns over time.

As a starting point, we focus on all corporate events we introduced in Section 3.2. Relationship banks do trade more profitable around corporate events compared to non-relationship banks in the [-14,-1] window prior to a corporate event. While there is no statistical difference regarding the imbalances prior to corporate events associated with negative returns, relationship banks build up imbalances that are about 0.0325 bps larger than those of non-relationship banks prior to events associated with positive returns (Panel A, Column (1)). This effect is statistically significant on the 1% level and robust to controlling for industry specific specialization patterns of banks (i.e., by including bank $\times$ industry FEs) as shoen in Panel A, Column (2). Importantly, relationship banks most likely do not possess superior information on their borrowers for all corporate events. Corporates are generally required to report their earnings related news to their lender as a covenant of standard credit contracts. While investors with superior trading skills are potentially able to predict outcomes for scheduled earning announcements (EAs), the latter is considerably more difficult for unscheduled events that relate to earnings (pre-announcements, management forecasts and unscheduled dividend events). These characteristics as well as the fact that we have numerous observations of this event

[17] M&A events account for about 75% of all cases. Events when two firms form a strategic alliance (such events are part of the operating category) account for another 15%. The remainder is from miscellaneous categories.

category makes this type of events a natural candidate to exploit in greater detail. In Column (3) we therefore replicate the regression model of Column (2) restricting our sample to unscheduled earning-related (UE) events. Once we focus on this event category, the incremental imbalance relationship banks build up prior to positive return events increases from 0.03bps to 0.19bps. Interestingly, relationship banks also trade profitably around negative return UE events associated. Here, relationship banks build up an incremental negative imbalance equal to 0.07bps relative to non-relationship banks.

The fact that we find smaller effects for negative-return events in comparison to positive-return events is consistent with previous evidence on directors' dealings (Ke et al. (2003), Lakonishok and Lee (2001)). Further, building up a negative imbalance when a given bank has no prior holdings of the respective stock requires banks to short sell this particular stock. Doing so, tends to be more monitored compared to building up a long position.

Next, we split all unscheduled earnings-related events according to their absolute return (Panel A, columns (4)–(6)) to shed light on whether relationship trading is more pronounced for events with higher absolute returns. There is no evidence for relationship banks trading more profitably (by building up positions in the direction of the event return) when the absolute event return is below 2%, while for events with more than 2% absolute abnormal return, the effect again increases substantially. The fact that we do not observe different trading behavior for events with low abnormal return suggest that relationship banks only engage in a different trading strategy for those events associated with substantial abnormal returns. We also find smaller effects for events with more than 4% absolute return than for those between 2% and 4% which might be explained by traders of relationship banks being more cautiously, since such events potentially trigger supervisors' attention. In order to only keep relevant events with sufficiently large news content, we restrict our remaining tests to events that triggered an absolute abnormal return of at least 2%.

In Panel B, we focus on the dynamics of relationship banks' trading. To do so, we examine the imbalances of relationship and non-relationship banks around different time windows around unscheduled earnings-related events.[18] Focusing on events that have a minimum absolute return of 2%, we find that profitable positions are built up shorty before positive events and are reversed in the month afterwards. Importantly, we do not see comparable patterns when we zoom out further: In both the [-42,-29] day window and the [-28,-15] day window prior to an event, relationship banks trade comparably to non-relationship banks, i.e., do not built up significantly different imbalances. As already discussed, we then find relationship banks building up larger positive imbalances prior to positive events in the [-14,-1] day window. The build-up of a suspicious positions relatively closely prior to an event can be rationalized with investors wanting to minimize market risk. In the [+1,+14] day window and the [+15,+28] day window after positive events,

[18] We find comparable patterns for all corporate events, as shown in Table A4.

relationship banks' imbalances are by about 0.17bps and 0.12bps lower, respectively, than those of non-relationship banks. Interestingly, these two numbers set off relatively exactly the coefficient in the [-14,-1] window, +0.30bps, suggesting that the position built up prior to the event is entirely reversed within one month after the event. In the [+29,+42] day window, trading differences between relationship banks and non-relationship banks again vanish.

To better understand the magnitude of our observed imbalances, we present some further empirical analysis. Importantly, coefficients presented in Table 2 are based on averages of all corporate events or UE events. It is however unlikely that relationship banks posses superior information for all corporate events of their borrowers. In line with this observation we observe that banks trade only in some cases. In Table 3, once we consider those cases where a bank traded before an event, our coefficient of interest doubles in size (Column (1)). In Column (2) we further narrow our sample by only including those banks that built up substantial imbalances prior to an event. In those cases we observe that relationship banks build up an imbalance of 0.85 bps higher as compared to non-relationship banks.

In a next step, we translate our imbalance measure into an incremental position in Euro to better interpret the economic magnitude of our findings. In the two weeks prior to positive-return events, relationship banks on average build up positions that are about €160,000-€260,000 larger than non-relationship banks (Columns (3)-(4)). This can further be rephrased (by multiplication with the respective event return) into a per-event additional profit for relationship banks of €2,700-€3,900 (Columns (5)-(6)). While this number appears quite small at first glance, it must be interpreted in the context of our setting: The estimate represents an average across all events and also only takes into account the imbalance built up in the two weeks prior to an event. One further has to take into account that it is unlikely that every single position is informed. If this was the case in one out of ten cases, the coefficient we find would have to be multiplied by ten accordingly. To put these numbers into perspective (bear in mind however that the profits we estimate are incremental profits that relationship banks make compared to non-relationship banks), Meulbroek (1992) finds that the median profit gained by sentenced illegal trading defendants between 1980-1989 amounts to about $25,000.

In a next step, we use as dependent variable the trade direction interacted with the event return in order to obtain a return measure in percent. Once we consider substantial imbalances, we find that relationship banks earn an additional return of 0.92pp per event (by building up a position in the correct direction in the two weeks prior to an event more often) (Column (8)). Given that the mean (median) absolute return for unscheduled earnings-related events with at least 2% abnormal return is about 6.5% (4.6%), this represents an economically large increase.

Finally, we focus on cases where a bank traded in the right direction both before and after the event (i.e. bought in the two weeks prior to a positive event and sold in the two weeks afterwards, and vice versa for negative events) and refer to such cases as suspicious trades. A major advantage of this variable is the easy interpretation: while the unconditional sample probability of trading suspiciously is 25.68%,[19] there is an incremental probability of suspicious trading for relationship banks by 5.70pp-8.11pp, again suggesting that relationship banks systematically trade more profitable in their borrowers' stocks than non-relationship banks (Columns (9)-(10)).

5.2 Mechanism: Relationship Trading vs. Bank Specialization

We now aim to distinguish between alternative explanations for why relationship banks build up profitable positions before corporate events of their borrowers. As discussed in Section 4 we provide two different sets of tests. First, we saturate our main specification with fixed effects to exploit time-series variation regarding the formation of lending relationships. Second, we focus on third-party events.

A main challenge is to differentiate between banks building up expertise for a specific firm in contrast to banks transmitting information from the lending to the trading desk. To shed light on this issue, in Table 4 we add different types of fixed effects to our main specification. In comparison to the baseline regression in column (1), we add bank $\times$ year fixed effects in column (2) and bank $\times$ industry $\times$ year fixed effects in column (3) to account for the possibility that banks' trading experience is more pronounced in certain years or in certain years in certain industries, respectively. The results however indicate that both of these specialization cases do not explain our findings, as relationship banks still trade more profitable. Next, we exploit time-series changes in lending relationships by estimating specification (2). If bank specialization is the (joint) source of a bank's superior trading in a particular stock (and its loan to the firm), such trading should be longer lasting and not exactly coincide with the duration of the lending relationship. By introducing bank $\times$ firm fixed effects in Columns (4) and (5), our coefficient of interest is based on a comparison of trading imbalances around corporate events during times when the bank was relationship lender compared to times when the bank was not relationship lender to the *same* firm. As shown in Column (4), banks build up their profitable positions around corporate events only when they are the relationship bank for a firm. Column (5) further illustrates that the coefficient "non-relationship periods" of relationship banks is statistically insignificant and even has a negative sign. Finally, we account for time-varying bank-firm specialization by introducing bank $\times$ firm $\times$ year fixed effects. Even for this strict specification we observe that our coefficient is highly significant and even increases in magnitude (Column (6)).

[19] Note that in case of pure noise trading, this number would amount to exactly 25%, as the probability to trade in the proper direction is equal to 50% both pre and post event. The slightly higher number we find thus provides evidence for some sample banks trading systematically in the correct direction, even though suspicious trading is not very common.

Secondly, we present estimates of our "third-party" test. Focusing on corporate events where the information flow between the borrowing firm and the lender involves another (unrelated) firm, allows us to identify events for firms where banks do not do lending and trading at the same time. Estimates for this test are provided in Table 5. As explained in Section 4.2, we employ *suspicious trade* as dependent variable. The probability of engaging in a suspicious trading strategy increases by about 17.3pp for third-party relationship banks (Column (1)). The effect becomes even more pronounced when excluding events that do not overlap with other ones (e.g., when there is another non-third-party event by the same firm on the same day). To rule out that this effect is driven by banks generally trading exactly these stocks more profitable due to whatever reason, we examine the trading of these banks around all other events of the respective firms in columns (3)-(6) (Columns (5)-(6) focus on unscheduled earnings-related events only, for which we found the most pronounced effects). We obtain statistically and economically insignificant results in either case. That is, banks only trade profitably in non-relationship stocks when they could be in possession of private information via a third party.

5.3 Further Results: Event Categories, Relationship Strength and Frequency of Trades

Another way to explore the mechanism is to exploit that information flows differ across corporate events. For most events, new private information arises within firms, and we already differentiate between scheduled and unscheduled events in Table 2. But there can also be external events that are unanticipated even by management. If this is the case, there is no way management can transmit this information to the loan officer of the relationship bank. Thus, investigating the trading behavior around corporate events that are unexpected to firm management allows us to test for special expertise of the relationship banks trading.

We therefore split our corporate events into three categories: (i) events where the management has been in possession of the relevant information prior to the announcement and the information most likely had to be reported to the relationship bank (ii) events where the management has been in possession of the relevant information prior to the announcement, but the information had most likely not to be reported to the relationship bank, and (iii) events where the management was most likely not in possession of superior information prior to the corporate event. Events of the first category comprise unscheduled-earnings related events (and their subcategory unscheduled dividend events) as well as M&A events, in particular cases where a firm is a M&A target (this category is defined rather broad, e.g., takeover rumours and purchases of smaller stakes are also considered). Most loan contracts include covenants that require a firm to report such information to the relationship bank. Events of the second category comprise board events, which mostly are executive changes. While such events usually do not come surprising to the firm (e.g., when a new board member is presented or elected), such information is not provided to the relationship bank via interim financial reporting. However, the information still might be transmitted via informal meetings for instance. Events of the third category comprise legal events. These events are more often unanticipated by the firm itself: e.g., legal events comprise court ruling or cases where a firm suddenly learns that it is sued by another firm.

In Table 6, we provide estimates for these different event categories. Consistent with the above argumentation, we find statistically significant and economically pronounced effects for relationship banks trading profitably prior to UE events or M&A events. On the contrary, we find borderline significant effects for board events and no statistical significant evidence for relationship trading prior to legal events. These findings are suggestive that the information originates in borrowers and that banks trade on information obtained through their lending relationships.

Table 7 provides results that shed light on how the strength of potential information flows affects trading profitability. Concretely, Columns (1) and (2) suggest that the higher the loan share a relationship bank has to a firm, the more profitable it trades in the firm's equity. Columns (3)-(6) then differentiate the relationship variable into two cases, namely whether a new loan has been granted in the prior quarter or not. The idea here is that despite relationship banks continuously monitor their borrowers, the granting of a new loan triggers further information flow. As we do not observe individual loan contracts, but aggregate lending amounts per bank-firm-quarter, we follow Behn et al. (2016) and define a new loan as a case when the aggregate loan amount increased by at least 33%. We further impose thresholds, i.e. minimum amounts that the increase must amount to (in addition to the 33% requirement) such that we code a bank-firm-quarter observation as one with a new loan. Even with a modest new loan threshold of €2m, we find that relationship banks build up larger positions prior to positive unscheduled earnings-related events, not just relative to non-relationship banks but also relative to relationship banks when no new loan has been granted. The effect more than triples when only considering loans that amount to at least €50m in Column (4). This effect prevails when setting the new loan threshold in terms of at least 10pp loan share (i.e., if a new loan of €50m only lead to an increase in a bank's fraction at a firm's total lending of 5pp, we would not count this as a new loan) and even when further introducing bank × firm fixed effects. F tests for equality of new loan vs no new loan support this finding, as equality can be rejected on the 10% significance level in Columns (4)-(6).

In Table 8, we examine whether suspicious positions are rather built up using many smaller trades or few larger ones. We find that, after controlling for the size of the imbalance that is built up, the probability that a position is what we call a ”suspicious” one, increases in the number of trades for relationship banks.

Concretely, when a relationship bank builds up a position with more trades than the median number of trades an imbalance is built up with, this position turns out to be a suspicious one by an incremental 9.35pp-12.19pp (the latter with bank × firm FEs included). Such behaviour is consistent with trading much to shade the informed trades and to minimize price impact.

6 Robustness

Table 9 transforms the dataset from the bank × event level to the bank × event × time level such that we can benchmark a bank's trading behaviour right before an event to that of the same bank a longer time period prior to the same event. Even with this econometrically strict specification, which we saturate using bank × event fixed effects, the results in columns (1)-(3) suggest the previous results remain unchanged: in the two weeks prior to positive unscheduled earnings-related events, relationship banks build up larger imbalances. The position then is reversed in the following month. Column (4) shows the results when only including bank × event observations where a bank traded the stock a longer time before the event.

Table 10 in columns (1)-(2) examines option trades instead of equity trades. A priori, the role options can play is unclear: From a risk management perspective, options could be used to offset equity positions, i.e. make the results we find for equity trades vanish. On the other hand, a growing literature finds evidence for suspicious positions being built up prior to M&A events, as options allow to build up large positions more easily and cheaper (Lowry et al. (2019), Augustin et al. (2019)). The caveat in our setting is that in contrast to the US, options exist on less than 20% of our sample shares and are rather infrequently traded. While the results are statistically insignificant, the evidence rather points into the direction that relationship banks' option trades are also more profitable. Columns (4)-(6) shed light on clients' (equity) trades. While it might be the case that relationship banks pass on potential information to their clients or on the contrary arrange their profitable trades on the disadvantage of their clients Fecht et al. (2018), we again obtain a null finding. Columns (7) and (8) shows results when only considering trades classified as market making. The null finding here is ensuring in that our findings are not driven by client-initiated market making, but by proprietary trading.

Table 11 employs dependent variables other than the (winsorized) imbalance in order to shed further light on relationship trading around unscheduled earnings-related events with high news content (i.e., absolute returns of at least 2%). Magnitudes sharply increase when we do not winsorize the imbalance at the 1%/99% level (Columns (1)-(3)). As in Table 3, effects generally increase when restricting the sample to banks that built up larger imbalances prior to an event. We however stick to winsorizing in our main models as the skew for the imbalance variable is huge and we do not want that a few trades are responsible for our main results. In a next step, we replicate our main independent variable with a dummy variable indicating the trade direction, i.e., which is -1,0,+1 for negative, zero and positive imbalances, respectively. As shown in Columns (4)-(6), we find evidence for relationship banks trading in the direction of the event return prior to an event, in particular prior to positive events.

7 Conclusion

In this paper, we provide novel evidence that banks trade more profitably ahead of corporate events when they are a firm's main lender. Using a unique micro-level data set on individual trades, we observe that banks benefit of their privileged access to information beyond their lending business. Banks generate significantly higher returns when trading on relationship firms for unscheduled earnings events and after borrowers obtain new bank loans. According to the evidence presented, this pattern cannot be explained by banks' specializing in certain industries, firms or business models, in both their lending and their trading.

Our findings add to the debate on the separation of commercial and investment banking due to potential conflict of interest. In light of the presented results, opposition against Volcker and Liikanen type reforms is understandable, since the ability to trade securities of firms with a lending relationship is particular valuable to banks.

While the magnitude of profits associated with a relationship bank's incremental position per event seems to be moderate, it is important to keep in mind that there are many corporate events for many firms and that our estimates present averages across these. In practice however, it is unlikely that a relationship lender is in possession of private information for all of these trades. Thus, our presented magnitudes for the profits associated with a specific potentially informed trade is likely to be a lower bound.

References

Acharya, V. V. and Johnson, T. C. (2007). Insider trading in credit derivatives. *Journal of Financial Economics*, 84(1):110–141.

Allen, F. and Gale, D. (1995). A welfare comparison of intermediaries and financial markets in germany and the us. *European Economic Review*, 39(2):179–209.

Augustin, P., Brenner, M., and Subrahmanyam, M. G. (2019). Informed options trading prior to takeover announcements: Insider trading? *Management Science*, 65(12):5697–5720.

Augustin, P. and Subrahmanyam, M. G. (2020). Informed options trading before corporate events. *Annual Review of Financial Economics*, 12:327–355.

Behn, M., Haselmann, R., and Wachtel, P. (2016). Procyclical capital regulation and lending. *The Journal of Finance*, 71(2):919–956.

Bernanke, B. S. (1983). Non-monetary effects of the financial crisis in the propagation of the great depression. Technical report, National Bureau of Economic Research.

Bessembinder, H., Jacobsen, S., Maxwell, W., and Venkataraman, K. (2018). Capital commitment and illiquidity in corporate bonds. *The Journal of Finance*, 73(4):1615–1661.

Bhattacharya, U. (2014). Insider trading controversies: A literature review. *Annual Review of Financial Economics*, 6(1):385–403.

Bhattacharya, U. and Daouk, H. (2002). The world price of insider trading. *The Journal of Finance*, 57(1):75–108.

Bodnaruk, A., Massa, M., and Simonov, A. (2009). Investment banks as insiders and the market for corporate control. *The Review of Financial Studies*, 22(12):4989–5026.

Boersenzeitung (2015). Eu tut sich mit trennbankengesetz schwer. 27.5.2015.

Bushman, R. M., Smith, A. J., and Wittenberg-Moerman, R. (2010). Price discovery and dissemination of private information by loan syndicate participants. *Journal of Accounting Research*, 48(5):921–972.

Carrizosa, R. and Ryan, S. G. (2017). Borrower private information covenants and loan contract monitoring. *Journal of Accounting and Economics*, 64(2-3):313–339.

Cohen, L., Frazzini, A., and Malloy, C. (2008). The small world of investing: Board connections and mutual fund returns. *Journal of Political Economy*, 116(5):951–979.

Diamond, D. W. (1984). Financial intermediation and delegated monitoring. *The Review of Economic Studies*, 51(3):393–414.

Duffie, D. (2012). Market making under the proposed volcker rule. *Rock Center for Corporate Governance at Stanford University Working Paper*, (106).

Fecht, F., Hackethal, A., and Karabulut, Y. (2018). Is proprietary trading detrimental to retail investors? *The Journal of Finance*, 73(3):1323–1361.

Griffin, J. M., Shu, T., and Topaloglu, S. (2012). Examining the dark side of financial markets: Do institutions trade on information from investment bank connections? *The Review of Financial Studies*, 25(7):2155–2188.

Ivashina, V. and Sun, Z. (2011). Institutional stock trading on loan market information. *Journal of Financial Economics*, 100(2):284–303.

James, C. (1987). Some evidence on the uniqueness of bank loans. *Journal of Financial Economics*, 19(2):217–235.

Jegadeesh, N. and Tang, Y. (2010). Institutional trades around takeover announcements: Skill vs. inside information. In *AFA 2011 Denver Meetings Paper*.

Kang, J. K. (2021). Gone with the big data: Institutional lender demand for private information. *mimeo*.

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

Kedia, S. and Zhou, X. (2014). Informed trading around acquisitions: Evidence from corporate bonds. *Journal of Financial Markets*, 18:182–205.

Kroszner, R. S. and Rajan, R. G. (1994). Is the glass-steagall act justified? a study of the us experience with universal banking before 1933. *The American Economic Review*, pages 810–832.

Kroszner, R. S. and Rajan, R. G. (1997). Organization structure and credibility: Evidence from commercial bank securities activities before the glass-steagall act. *Journal of Monetary Economics*, 39(3):475–516.

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

Liikanen, E. et al. (2012). High-level expert group on reforming the structure of the eu banking sector. *Final Report, Brussels.*

Lowry, M., Rossi, M., and Zhu, Z. (2019). Informed trading by advisor banks: evidence from options holdings. *The Review of Financial Studies*, 32(2):605–645.

Lummer, S. L. and McConnell, J. J. (1989). Further evidence on the bank lending process and the capital-market response to bank loan agreements. *Journal of Financial Economics*, 25(1):99–122.

Massa, M. and Rehman, Z. (2008). Information flows within financial conglomerates: Evidence from the banks–mutual funds relation. *Journal of Financial Economics*, 89(2):288–306.

Massoud, N., Nandy, D., Saunders, A., and Song, K. (2011). Do hedge funds trade on private information? evidence from syndicated lending and short-selling. *Journal of Financial Economics*, 99(3):477–499.

Meulbroek, L. K. (1992). An empirical analysis of illegal insider trading. *The Journal of Finance*, 47(5):1661–1699.

Minnis, M. and Sutherland, A. (2017). Financial statements as monitoring mechanisms: Evidence from small commercial loans. *Journal of Accounting Research*, 55(1):197–233.

Petersen, M. A. and Rajan, R. G. (1994). The benefits of lending relationships: Evidence from small business data. *The Journal of Finance*, 49(1):3–37.

Puri, M. (1996). Commercial banks in investment banking conflict of interest or certification role? *Journal of Financial Economics*, 40(3):373–401.

Rajan, R. G. (1992). Insiders and outsiders: The choice between informed and arm's-length debt. *The Journal of Finance*, 47(4):1367–1400.

Schaffelhuber, K. and Kunschke, D. (2015). Das sogenannte trennbankengesetz–zwang zur verlagerung bestimmter handelsaktivitäten und geschäfte mit stark gehebelten investmentvehikeln auf ein gruppenangehöriges finanzhandelsinstitut. In *Bankenrating*, pages 387–403. Springer.

Schelo, S. and Steck, A. (2013). Das trennbankengesetz: Prävention durch bankentestamente und risikoabschirmung. *Zeitschrift für Bankrecht und Bankwirtschaft*, 25(4):227–244.

Skinner, D. J. (1994). Why firms voluntarily disclose bad news. *Journal of Accounting Research*, 32(1):38–60.

European Parliament (2014). Regulation of the european parliament and the council on structural measures improving the resilience of eu credit institutions.

German Federal Ministry of Finance (2013). German act on ringfencing and recovery and resolution planning for credit institutions and financial groups. *BGBl 1*, I:p.3090.

Tröger, T. (2016). Strukturreform im finanzsektor–das trennbankengesetz als untauglicher versuch der verwirklichung von nachhaltigkeitszielen im aufsichtsrecht. *Nachhaltigkeit im Bankensektor. Konzepte, Rechtsfragen, Kulturwandel, Köln, Otto Schmidt*, pages 139–61.

Ventoruzzo, M. (2014). Comparing insider trading in the united states and in the european union: History and recent developments. *ECFR*, 11:554.

Table 1: Descriptive Statistics

Panel A: Corporate Events

Event Category	N	Return Distribution		% > p50
		p25	p75	
Earnings	11,484	-0.0204	0.0242	62
Earnings announcement	8,238	-0.0213	0.0249	62
Pre-announcement	1,978	-0.0233	0.0289	68
Other financial reporting	1,268	-0.0131	0.0150	55
Guidance	6,808	-0.0233	0.0257	67
Guidance at EA	5,400	-0.0231	0.0257	67
Stand-alone forecast	1,408	-0.0248	0.0261	67
Dividends	3,167	-0.0155	0.0233	62
Unscheduled dividend events	316	-0.0255	0.0223	69
M&A	6,302	-0.0113	0.0181	57
Firm is target	1,811	-0.0104	0.0230	57
Board/Executives	2,015	-0.0137	0.0149	53
Capital structure	3,239	-0.0161	0.0182	57
Legal	600	-0.0156	0.0119	59
Operating	6,361	-0.0101	0.0135	53
Bankruptcy	16	-0.4862	-0.0851	94

Panel B: Non-Financial Firms (Borrowers)

	N	Mean	p1	p25	p50	p75	p99
Market capitalization (€m.)	619	2,217	1.02	25.45	93.50	508.58	50,369
Number of shares outst. (m.)	619	63.36	0.05	3.97	9.72	31.81	1,069
Firm is in Prime Standard	619	0.39	0	0	0	1	1
Number of events per firm	619	64.61	1	11	40	92	485
Number of UE-events per firm	619	6.41	0	1	4	10	26

Panel C: Banks - Lending Relationships and Proprietary Trading

	N	Mean	Median	SD
Average loan exposure to sample firms (€m.)	49	1,118	74	2,365
Number of firms for which a bank is relationship bank	49	15.96	1	37.25
Number of different sample stocks traded per day	49	48.07	14.01	81.22
Number of prop trades in sample stock per day	49	2,261	149	7,307
Trading volume in sample stocks per day (€m.)	49	47.50	3.27	135.95
Average trade size (€)	49	31,373	25,225	28,174
Fraction of events with trading in [-14,-1] window	49	0.18	0.09	0.22

Panel D: Descriptives Statistics at the Trade-Level

	N	Mean	p1	p25	p50	p75	p99
Relationship bank	1,959,608	0.0153	0	0	0	0	1
Loan share if rel. bank	29,915	0.3906	0.11	0.23	0.31	0.47	1
Imbalance [-14,-1] in bps. cond. on trading	361,363	0.0600	-19.80	-0.23	0.00	0.26	24.70
Position [-14,-1] in €m cond. on trading	361,363	1.10	-26.19	-0.08	0.00	0.11	36.74
Profit [-14,-1] in € cond. on trading	361,363	4,145	-373,372	-1,132	0.00	1,174	412,109

Panel E: Probability of Trading in the "Right" Direction

		P(Correct)
	Expected Prob	50.00%
All events	Non-rel banks	49.99%
	Rel banks	51.32%
UE events	Non-rel banks	50.13%
	Rel banks	53.53%

Panel A provides descriptive statistics for the 619 non-financial sample firms (or borrowers) in which sample banks trade.
Panel B provides descriptive statistics for the sample banks, their lending relationships and proprietary trading. More granular bank-level statistics cannot be provided due to data confidentiality.
Panel C provides the frequency of corporate events by event category as well as statistics for the returns to these events. Earnings announcements refer to regular quarterly/half-yearly/yearly earnings reports. Pre-announcements refer to a firm announcing key financial reporting information before the official earnings announcement. Stand-alone forecasts comprise all management guidance that is not jointly issued with an earnings announcement. Unscheduled dividend events comprise special dividends, stock dividends and dividend decreases. *% > p50* indicates the fraction of events with an above-median *absolute* return, indicating a large stock price reaction. If for instance the median absolute return of a firm throughout 2012-2017 is 2.5% and 60% of this firm's EAs have an absolute return of >2.5%, the value would be equal to 60%. After obtaining this value for each firm and event category, we calculate a weighted (by the number of events per firm) average per event category.
Panel D provides descriptive statistics at the bank-event level based on our main dataset. It consists of 1,959,608 (=49 banks x 39,992 events) observations.
Panel E shows the probability of trading in the right direction (i.e., building up a positive position in the two weeks prior to an event with positive return or vice versa) conditional on trading. We differentiate between relationship banks vs non-relationship banks and between all events vs unscheduled earnings-related events only. All variable definitions are in Appendix A1.

Table 2: Relationship Trading

Panel A: Equity Trading Imbalances by Relationship Banks around Corporate Events

Dependent variable:	Imbalance [-14,-1]					
	(1)	(2)	(3)	(4)	(5)	(6)
Relationship	0.0220	0.0019	-0.0691***	-0.0297	-0.1154	-0.0796
	(0.81)	(0.12)	(-3.59)	(-0.41)	(-1.46)	(-0.73)
Relationship x Pos	0.0325***	0.0303***	0.1910***	0.0282	0.3495**	0.2389***
	(3.71)	(3.44)	(3.46)	(0.24)	(2.26)	(4.47)
Event FE	yes	yes	yes	yes	yes	yes
Bank x SIC FE	no	yes	yes	yes	yes	yes
Events	All	All	UE	UE	UE	UE
Abs. Event Return	-	-	-	<2%	2%-4%	>4%
Observations	1,500,772	1,500,772	194,236	79,282	47,775	66,591
Adj. R^2	0.0034	0.0047	0.0050	0.0126	0.0066	0.0040

Panel B: Unscheduled Earnings-Related Events Mapped Out Over Time

Dependent variable:	Imbalance					
	[-42,-29]	[-28,-15]	[-14,-1]	[+1,+14]	[+15,+28]	[+29,+42]
Relationship	0.0342	0.0158	-0.0966**	0.0627	0.0491	0.0047
	(0.62)	(0.44)	(-2.30)	(1.01)	(0.68)	(0.22)
Relationship x Pos	-0.0013	-0.0594	0.2983***	-0.1663**	-0.1219**	0.0109
	(-0.01)	(-0.90)	(3.53)	(-2.28)	(-2.13)	(0.34)
Event FE	yes	yes	yes	yes	yes	yes
Bank x SIC FE	yes	yes	yes	yes	yes	yes
Abs. Event Return	>2%	>2%	>2%	>2%	>2%	>2%
Observations	114,709	114,709	114,709	114,709	114,709	114,709

Panel A examines whether relationship banks build up larger imbalances prior to positive events (and vice versa for negative events). UE stands for unscheduled earnings-related events and refers to pre-announcements, stand-alone forecasts and unscheduled dividend events. When working with all events, we keep only one event per firm-day in order to avoid double-counting. Panel B maps out bank trading around unscheduled earnings-related events in two-week time windows before and after the events. We estimate and report a separate regression with imbalances computed over the respective time window indicated. All variable definitions are in Appendix A1. We include one fixed effect for each event (Event FE) and one fixed effect for each bank x 3-digit industry code (Bank x SIC FE). Bank × SIC FE refer to fixed effects at the bank × 3-digit industry level. T-statistics with standard errors adjusted for clustering at the bank level are reported in parentheses. *, ** and *** indicate statistical significance at the 10%, 5% and 1%-level (two-tailed), respectively.

Table 3: Trading Profits and "Suspicious Trades"

Dependent variable:	Imbalance		€-Position		€-Profit		Return x Direction		Suspicious Trade	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Relationship	-0.1917*	-0.1864	-22,436	38,926	2,724***	3,890***	0.0073***	0.0092***	0.0570**	0.0811***
	(-2.01)	(-1.45)	(-0.51)	(0.51)	(6.27)	(3.61)	(3.75)	(4.14)	(2.66)	(3.34)
Relationship x Pos	0.6066***	0.8505***	160,306***	260,092*						
	(5.11)	(5.03)	(2.77)	(1.82)						
Event FE	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Bank x SIC FE	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Abs. Event Return	>2%	>2%	>2%	>2%	>2%	>2%	>2%	>2%	>2%	>2%
Abs. Imbalance	>0	>0.5bp	>0	>0.5bp	>0	>0.5bp	>0	>0.5bp	>0	>0.5bp
Observations	15,899	7,214	15,899	7,214	15,899	7,214	15,899	7,214	13,450	4,374

This table presents results for alternative dependent variables and estimates the trading profits of relationship banks. The sample is restricted to unscheduled earnings-related events with large absolute returns (>2%) and then further restricts the analysis to non-zero imbalances and absolute imbalances exceeding 0.5bp, respectively. Thus, we present results for two restricted samples for each dependent variable. Suspicious Trade is a dummy equal to 1 if a bank builds up a positive imbalance in the two weeks before a positive event and a negative imbalance in the two weeks after a positive event (vice versa for negative events). Given the coding of the indicator, we use only bank-event observations when a bank trades in the two weeks before and after the event (irrespective of direction). All variable definitions are in Appendix A1. We include one fixed effect for each event (Event FE) and one fixed effect for each bank x 3-digit industry code (Bank x SIC FE). T-statistics with standard errors adjusted for clustering at the bank level are reported in parentheses. *, ** and *** indicate statistical significance at the 10%, 5% and 1%-level (two-tailed), respectively.

Table 4: Mechanism: Relationship Trading vs. Bank Specialization

Dependent variable:	Imbalance [-14,-1]					
	(1)	(2)	(3)	(4)	(5)	(6)
Relationship x Pos	0.2983***	0.3065***	0.3973***	0.2589***	0.2575***	0.4995***
	(3.53)	(3.65)	(3.04)	(3.19)	(3.23)	(3.06)
Non-Rel. Periods x Pos					-0.0620	
					(-0.54)	
Event FE	yes	yes	yes	yes	yes	yes
Bank x SIC FE	yes	no	-	-	-	-
Bank x Year FE	no	yes	-	no	no	-
Bank x SIC x Year FE	no	no	yes	no	no	-
Bank x Firm FE	no	no	no	yes	yes	-
Bank x Firm x Year FE	no	no	no	no	no	yes
Events	UE	UE	UE	UE	UE	UE
Abs. Event Return	>2%	>2%	>2%	>2%	>2%	>2%
Observations	114,709	114,856	111,720	110,936	110,936	78,645

This table estimates the relationship bank effects for different fixed effect structures by exploiting variation in banks' relationships. The sample is restricted to unscheduled earnings-related events with large absolute returns (>2%). Non-Rel. Periods is a binary indicator marking the non-relationship periods of a bank-firm pair, when the bank is a relationship bank for the respective firm at some point over our sample period. All variable definitions are in Appendix A1. We include one fixed effect for each event (Event FE) and one fixed effect for each bank x 3-digit industry code (Bank x SIC FE). In the Columns (1) - (6), we vary the bank level fixed effects, using industry or firm as well as year, to exploit variation in banks' lending relationships. T-statistics with standard errors adjusted for clustering at the bank level are reported in parentheses. *, ** and *** indicate statistical significance at the 10%, 5% and 1%-level (two-tailed), respectively.

Table 5: Mechanism: Third Party Trading

Dependent variable:	Suspicious Trade					
	(1)	(2)	(3)	(4)	(5)	(6)
RB third party trades	0.1733**	0.2998***				
	(2.20)	(3.13)				
Other RB trades			-0.0072	-0.0057	-0.0136	-0.0114
			(-0.67)	(-0.53)	(-0.59)	(-0.68)
Event FE	yes	yes	yes	yes	yes	yes
Bank x SIC FE	yes	yes	yes	yes	yes	yes
Events	All	All	All	All	UE	UE
Abs. Event Return	>2%	>2%	>2%	>2%	>2%	>2%
Overlap excluded	no	yes	no	yes	no	yes
Observations	764	536	76,066	63,432	13,450	9,063

This table provides results for examining third party trading. That is, when firm F1 has an event where firm F2 is also involved, we check whether firm F2's relationship bank B traded profitably/suspiciously in firm F1's stock. In columns (2), (4) and (6), we exclude those events that overlap with (i.e. occur on the same firm-day as) other, non-third party events. All variable definitions are in Appendix A1. We include one fixed effect for each event (Event FE) and one fixed effect for each bank x 3-digit industry code (Bank x SIC FE). T-statistics with standard errors adjusted for clustering at the bank level are reported in parentheses. *, ** and *** indicate statistical significance at the 10%, 5% and 1%-level (two-tailed), respectively.

Table 6: Mechanism: Relationship Trading by Event Category

Dependent variable:	Imbalance [-14,-1]					
	UE	M&A	M&A target	Unsch. Div	Board	Legal
Relationship x Pos	0.1778***	0.1514***	0.2197**	0.3830**	0.0949	0.0971
	(2.82)	(2.91)	(2.08)	(2.40)	(1.50)	(0.53)
Event FE	yes	yes	yes	yes	yes	yes
Bank x SIC FE	yes	yes	yes	yes	yes	yes
Overlap excluded	yes	yes	yes	yes	yes	yes
Abs. Event Return	>2%	>2%	>2%	>2%	>2%	>2%
Observations	86,240	92,708	36,848	6,615	27,489	7,350

This table provides results for different event categories: UE (unscheduled earnings-related events), M&A, M&A when the respective firm is a target, unscheduled dividend events (special dividends, stock dividends, dividend decreases), Board and Legal events, respectively. For each even category, we only consider events that do not overlap, i.e. occur jointly with an event from another event category. Unsch. Div refers to unscheduled divided-related events (special dividends, stock dividends and dividend decreases). All variable definitions are in Appendix A1. We include one fixed effect for each event (Event FE) and one fixed effect for each bank x 3-digit industry code (Bank x SIC FE). T-statistics with standard errors adjusted for clustering at the bank level are reported in parentheses. *, ** and *** indicate statistical significance at the 10%, 5% and 1%-level (two-tailed), respectively.

Table 7: Mechanism: Information Flows, Bank Monitoring and New Loans

Dependent variable:	Imbalance [-14,-1]					
	(1)	(2)	(3)	(4)	(5)	(6)
RB Loan Share x Pos	0.5365***	0.5234***				
	(3.86)	(3.37)				
Relationship NL x Pos			0.4500**	1.5898**	0.7441***	0.8136***
			(2.05)	(2.01)	(3.30)	(2.76)
Relationship NoNL x Pos			0.2767***	0.2744***	0.2772***	0.2310***
			(3.50)	(3.14)	(3.32)	(2.88)
Event FE	yes	yes	yes	yes	yes	yes
Bank x SIC FE	yes	-	yes	yes	yes	-
Bank x Firm FE	no	yes	no	no	no	yes
New Loan Threshold	-	-	€2m	€50m	10pp	10pp
Abs. Event Return	>2%	>2%	>2%	>2%	>2%	>2%
Events	UE	UE	UE	UE	UE	UE
Observations	114,709	110,936	114,709	114,709	114,709	110,936
P-value of Test for Equality	-	-	0.3917	0.0975*	0.0239**	0.0432**

This table examines the trading effects for relationship banks as a function of their loan share or after having recently granted a new loan. The sample is restricted to unscheduled earnings-related events with large absolute returns (>2%). In Columns (1)-(2), RB Loan Share is the loan share, defined as the lending by a bank divided by the firm's total lending, of the relationship bank. In Columns (3) - (6), we examine cases where a relationship bank also granted a new loan in the previous quarter. We always define a new loan as an increase in loan exposure from a bank to a firm by at least 33%. On top of that, we require the new loan to amount to at least €2m, €5m or 10pp of a firm's total loan exposure in Columns (3), (4) and (5)-(6), respectively. All variable definitions are in Appendix A1. We include one fixed effect for each event (Event FE) and one fixed effect for each bank x 3-digit industry code (Bank x SIC FE). Bank × Firm FE refers to bank-firm pair fixed effects. T-statistics with standard errors adjusted for clustering at the bank level are reported in parentheses. *, ** and *** indicate statistical significance at the 10%, 5% and 1%-level (two-tailed), respectively.

Table 8: Mechanism: Trade Frequency

Dependent variable:	Suspicious Trade			
	(1)	(2)	(3)	(4)
Relationship x ln(Trades)	0.0255**			
	(2.49)			
Relationship x Trade-Dummy		0.0935**	0.1362***	0.1219***
		(2.45)	(2.97)	(2.77)
Control for Imbalance Size	yes	yes	yes	yes
Event FE	yes	yes	yes	yes
Bank x SIC FE	yes	yes	yes	-
Bank x Firm FE	no	no	no	yes
Events	UE	UE	UE	UE
Abs. Event Return	>2%	>2%	>2%	>2%
Trade-Dummy Threshold	-	P50	P75	P50
Observations	13,450	13,450	13,450	12,794

This table examines whether relationship banks build up their positions using many small trades or a few large trades. The sample is restricted to unscheduled earnings-related events with large absolute returns (>2%). Ln(Trades) is the natural log of the number of trades a bank carries out in the stock of a firm in the [-14,-1] window. Trade-Dummy is set to one if the number of trades over the [-14,-1] window exceeds a predefined threshold of the number of trades distribution. We control for the size of the imbalance multiplied by the relationship dummy on the right-hand size. All variable definitions are in Appendix A1. We include one fixed effect for each event (Event FE) and one fixed effect for each bank x 3-digit industry code (Bank x SIC FE). Bank × Firm FE refers to bank-firm pair fixed effects. T-statistics with standard errors adjusted for clustering at the bank level are reported in parentheses. *, ** and *** indicate statistical significance at the 10%, 5% and 1%-level (two-tailed), respectively.

Table 9: Robustness: Panel Analysis at the Bank x Event x Time Level

Dependent variable:	Imbalance			
	(1)	(2)	(3)	(4)
Relationship x Pos x [-28,-15]	-0.0636	-0.1266	-0.1430	-0.0728
	(-0.83)	(-0.78)	(-0.61)	(-0.77)
Relationship x Pos x [-14,-1]	0.3138***	0.6845***	1.2749***	0.5621***
	(3.42)	(4.81)	(7.25)	(3.36)
Relationship x Pos x [+1,+14]	-0.1437*	-0.2485	-0.3048	-0.1627
	(-1.97)	(-1.51)	(-1.30)	(-1.07)
Relationship x Pos x [+15,+28]	-0.1148***	-0.3021***	-0.5348***	-0.3806***
	(-2.81)	(-3.68)	(-4.07)	(-4.01)
Bank x Event FE	yes	yes	yes	yes
Events	UE	UE	UE	UE
Abs. Imbalance	-	>0	>0.5	>0 in [-84,-71]
Abs. Event Return	>2%	>2%	>2%	>2%
Observations	918,848	122,416	56,277	122,480

This table presents results from panel regressions using eight two-week windows around corporate events (i.e., [-84,-71], [-70,-57],.., [+15,+28]). For each bank and event, we compute an imbalance in the usual fashion. Thus, the analysis is at the Bank × Event × Time Level. We separately estimate coefficients for four time windows centered around the event, and the effects are estimated relative to the imbalances in the [-84,-29] windows. The sample is restricted to unscheduled earnings-related events with large absolute returns (>2%). In Columns (2) - (4), we further condition on bank prop trading by requiring non-zero or larger absolute imbalances. In Column (4), we impose the trading condition only long before the event, i.e., in the [-84,-71] window. All variable definitions are in Appendix A1. We include a fixed effect for each bank-event pair (Bank × Event FE). T-statistics with standard errors adjusted for clustering at the bank level are reported in parentheses. *, ** and *** indicate statistical significance at the 10%, 5% and 1%-level (two-tailed), respectively.

Table 10: Robustness: Options Trading and Client Trading

Dependent variable:	Imbalance [-14,-1]							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Relationship x Pos	0.0115	0.1757	0.3441***	0.0414	0.0009	0.2901**	0.0157	0.1336
	(0.90)	(1.33)	(3.22)	(1.24)	(0.02)	(2.08)	(0.53)	(0.88)
Event FE	yes	yes	yes	yes	yes	yes	yes	yes
Bank x SIC FE	yes	yes	yes	yes	yes	yes	yes	yes
Securities	Options	Options	Eq.+Opt. Netted	Equity	Equity	Equity	Equity	Equity
Trade Classification	PropMM	PropMM	PropMM	Clients	Clients	PropMM - Clients	MM	MM
Abs. Imbalance	-	>0	-	-	>0	-	-	>0
Abs. Event Return	>2%	>2%	>2%	>2%	>2%	>2%	>2%	>2%
Observations	114,709	2,130	114,709	114,709	37,512	114,709	114,709	14,418

This table examines banks' proprietary options trading as well as banks' equity trading on behalf of clients. The sample is restricted to unscheduled earnings-related events with large absolute returns (>2%). Column (1) shows results when computing imbalances for equity options. Column (2) conditions on trading by restricting the sample to observations from banks with non-zero imbalances. In Column (3), we combine banks' positions in the stock and the options market when computing imbalances. Column (4) shows the results when using client trades to compute imbalances (instead of prop trades). Column (5) again conditions on trading. In Column (6), we compute banks' prop trading imbalances relative to their client imbalances (by subtracting the latter from the former). While we usually net proprietary trading and market making, Columns (7) and (8) show results when only considering market making. All variable definitions are in Appendix A1. We include one fixed effect for each event (Event FE) and one fixed effect for each bank x 3-digit industry code (Bank x SIC FE). T-statistics with standard errors adjusted for clustering at the bank level are reported in parentheses. *, ** and *** indicate statistical significance at the 10%, 5% and 1%-level (two-tailed), respectively.

Table 11: Robustness: Alternative Dependent Variables

Dependent variable:	Imbalance no Wins.			Direction		
	(1)	(2)	(3)	(4)	(5)	(6)
Relationship	-0.2863**	-1.0687**	-0.3019	-0.0418***	-0.0871*	-0.0524
	(-2.28)	(-2.39)	(-0.39)	(-2.95)	(-1.70)	(-1.07)
Relationship x Pos	0.8076**	2.2352***	3.7098***	0.1334***	0.2788***	0.1836***
	(2.42)	(2.92)	(3.06)	(8.79)	(5.30)	(3.93)
Event FE	yes	yes	yes	yes	yes	yes
Bank x SIC FE	yes	yes	yes	yes	yes	yes
Abs. Event Return	>2%	>2%	>2%	>2%	>2%	>2%
Abs. Imbalance	-	>0	>0.5bp	-	>0	>0.5bp
Observations	114,709	15,899	7,214	114,709	15,899	7,214

This table presents results for further alternative dependent variables. The sample is restricted to unscheduled earnings-related events with large absolute returns (>2%) and then further restricts the analysis to non-zero imbalances and absolute imbalances exceeding 0.5bp, respectively. Thus, we present results for three restricted samples for each dependent variable. All variable definitions are in Appendix A1. We include one fixed effect for each event (Event FE) and one fixed effect for each bank x 3-digit industry code (Bank x SIC FE). T-statistics with standard errors adjusted for clustering at the bank level are reported in parentheses. *, ** and *** indicate statistical significance at the 10%, 5% and 1%-level (two-tailed), respectively.

Appendix

A Tables

Table A1: Variable Appendix

Panel A: Relationship Variables

Variable Name	**Definition**
Average loan exposure to sample firms (€m.)	Total quarterly loan exposure per bank to all our sample firms, averaged across all quarters between 2012 and 2017.
Number of firms for which a bank is relationship bank (#)	Number of sample firms for which a bank is coded as having a *Relationship* for at least one event between 2012 and 2017.
Relationship (Indicator)	Set equal to one if a bank is the largest lender or has a loan share of at least 25% (of a firm's total borrowing) to a firm in the quarter prior to an event.
RB Loan Share (Ratio)	Loan amount provided by a relationship bank to a firm divided by the firm's total borrowing (from any bank in the German credit register).
Non-Rel. Periods (Indicator)	Binary indicator marking the non-relationship periods of a bank-firm pair, when the bank is a relationship bank for the respective firm at some point over our sample period.
RB third party trades (Indicator)	Set equal to one for firm F2's relationship bank B prior for an event by firm F1 where firm F2 also is mentioned, i.e. where B might be in possession of private information about F1 via F2.
Other RB trades (Indicator)	Set equal to one for firm F2's relationship bank B prior for an event by firm F1 where firm F2 is not involved.
Rel. NL and *Rel. No NL* (Indicators)	Rel. NL (Rel. No NL) is set equal to one for relationship banks when they granted a new loan (no new loan) in the quarter prior to the event. We define a new loan as an increase in lending from a bank to a firm by at least 33% from one quarter to the next.

Panel B: Trade Variables

Variable Name	**Definition**
Number of different sample stocks traded per day (#)	Indicates how many different sample stocks each bank prop trades per day. We obtain one number per bank by taking the average across all trading days throughout our sample (2012-2017).
Number of prop trades in sample stock per day (#)	Indicates how many prop trades in sample stock each bank carries out per day. We obtain one number per bank by taking the average across all trading days throughout our sample (2012-2017).
Trading volume in sample stocks per day (€m.)	Daily prop trading volume in sample stocks. We obtain one number per bank by taking the average across all trading days throughout our sample (2012-2017).
Average trade size (€)	Average bank-level prop trade size. We obtain one number per bank by taking the average of all trading days throughout our sample (2012-2017).
Fraction of events with trading in [-14,-1] window (Fraction)	Fraction of events in the two weeks prior to which a bank prop traded the respective stock.
Imbalance (basis points)	$\frac{shares\ purchased - shares\ sold}{shares\ outstanding} \times 10,000$ over the two weeks prior to an event. We indicate once we calculate imbalances for other time windows, securities or trading parties in some tests. Winsorized at 1%/99% unless indicated otherwise.
€-Position (€)	$(shares\ purchased\ -\ shares\ sold) \times price$ over the two weeks prior to an event. Winsorized at 1%/99%.
€-Profit (€)	$(shares\ purchased - shares\ sold) \times price \times$ *(market-adjusted event return)* over the two weeks prior to an event. Winsorized at 1%/99%.

Panel B: Trade Variables (Continued)

Variable Name	**Definition**
Trade in Right Direction (Indicator)	Set equal to 1 if a bank builds up a positive imbalance in the two weeks before a positive event (vice versa for negative events). Given the coding of the indicator, we use only bank-event observations when a bank trades in the two weeks before the event (irrespective of direction).
Suspicious Trade (Indicator)	Set equal to 1 if a bank builds up a positive imbalance in the two weeks before a positive event and a negative imbalance in the two weeks after a positive event (vice versa for negative events). Given the coding of the indicator, we use only bank-event observations when a bank trades in the two weeks before and after the event (irrespective of direction).
Return $\times$ *Direction* (Number)	Combining the market-adjusted event return and the trade direction essentially estimates the additional return that relationship banks earn around corporate events by trading more frequently in the direction of the event return (Ivashina and Sun (2011)).
ln(Trades) (Number)	The natural log of the number of trades a bank carries out in the stock of a firm in the [-14,-1] window.
Trade-Dummy (Indicator)	Set equal to one if the number of trades over the [-14,-1] window exceeds a predefined threshold of the number of trades distribution (concretely, we use p50 and p75 as threshold).
P(Trade) (Indicator)	Set equal to one if a bank prop traded the stock of a firm in the two weeks prior to an event.
Direction (-1,0 or +1)	Set equal to $-1/0/+1$, indicating negative, zero and positive two-week imbalances, respectively.

Panel C: Firm and Event Variables

Variable Name	**Definition**
Market capitalization (€m.)	Market capitalization per firm averaged over the sample period (2012-2017).
Number of shares outst. (m.)	Number of shares outstanding per firm averaged over the sample period (2012-2017).
Firm is in Prime Standard (Indicator)	The Prime Standard is a segment of the German stock market, which mandates higher disclosure and reporting standards.
Number of events per firm (#)	Number of corporate events per sample firm over the sample period (2012-2017).
Number of UE-events per firm (#)	Number of UE corporate events per sample firm over the sample period (2012-2017). UE refers to unscheduled earnings-related events, comprising pre-announcements, stand-alone management forecasts and unscheduled dividend events.
Pos (Indicator)	Set equal to one for events with market-adjusted returns larger than zero.
[-28,-15], [-14,-1], [+1,+14], [+15,+28] (Indicators)	Set equal to one for the respective time windows around an event.

Table A2: Prop Trading Volume over Time

Year	Prop Trading Volume in €bn
2012	496
2013	512
2014	553
2015	787
2016	544
2017	636

This table shows the total prop trading volume in sample stocks by sample banks per year. Note that since we simply add up all sample banks' trading volumes per year, a trade is double-counted when two sample banks prop-trade with each other.

Table A3: Probability of Trading in the Right Direction

Dependent variable:	Trade in Right Direction					
	(1)	(2)	(3)	(4)	(5)	(6)
Relationship	0.0129***	0.0065	0.0490**	0.0019	0.1224***	0.0663***
	(3.07)	(1.32)	(2.24)	(0.06)	(3.17)	(4.63)
Event FE	yes	yes	yes	yes	yes	yes
Bank x SIC FE	no	yes	yes	yes	yes	yes
Events	All	All	UE	UE	UE	UE
Event Return	-	-	-	<2%	2%-4%	>4%
Observations	275,488	275,320	28,611	12,488	7,167	8,493

This table examines trading in the right direction prior to an event, i.e. building up a positive (negative) position in the two weeks prior to an event with positive (negative) return. When considering all events, we keep only one event per firm-day in order to avoid double-counting. UE stands for unscheduled earnings-related events. All variable definitions are in Appendix A1. We include one fixed effect for each event (Event FE) and one fixed effect for each bank x 3-digit industry code (Bank x SIC FE). T-statistics with standard errors adjusted for clustering at the bank level are reported in parentheses. *, ** and *** indicate statistical significance at the 10%, 5% and 1%-level (two-tailed), respectively.

Table A4: Mapping out Bank Trading around Corporate Events

Dependent variable:	Imbalance					
	[-42,-29]	[-28,-15]	[-14,-1]	[+1,+14]	[+15,+28]	[+29,+42]
Relationship	0.0255	-0.0040	-0.0126	0.0788*	0.0268	-0.0118
	(1.12)	(-0.35)	(-1.08)	(1.69)	(1.25)	(-0.68)
Relationship x Pos	-0.0143	-0.0046	0.0500***	-0.0913*	-0.0369*	0.0342
	(-0.82)	(-0.31)	(4.97)	(-1.99)	(-1.93)	(1.50)
Event FE	yes	yes	yes	yes	yes	yes
Bank x SIC FE	yes	yes	yes	yes	yes	yes
Abs. Event Return	>2%	>2%	>2%	>2%	>2%	>2%
Observations	662,186	662,186	662,186	662,186	662,186	662,186

This table examines bank trading around corporate events, mapping out the effect for relationship banks in two-week time windows before and after the events. We estimate and report a separate regression with imbalances computed over the respective time window indicated. Results are for all events, keeping only one event per firm-day in order to avoid double-counting. All variable definitions are in Appendix A1. We include one fixed effect for each event (Event FE) and one fixed effect for each bank x 3-digit industry code (Bank x SIC FE). T-statistics with standard errors adjusted for clustering at the bank level are reported in parentheses. *, ** and *** indicate statistical significance at the 10%, 5% and 1%-level (two-tailed), respectively.

Table A5: Panel Analysis for Positive and Negative Events

Dependent variable:	Imbalance			
	(1)	(2)	(3)	(4)
Relationship x [-28,-15]	0.0185	0.0255	0.0097	0.0224
	(0.51)	(0.34)	(0.09)	(0.63)
Relationship x [-14,-1]	-0.1215***	-0.2800***	-0.4909***	-0.1921**
	(3.94)	(-4.57)	(-4.14)	(-2.01)
Relationship x [+1,+14]	0.0704	0.0683	0.0709	0.0370
	(1.32)	(0.58)	(0.39)	(0.41)
Relationship x [+15,+28]	0.0458	0.0884	0.0656	0.1671
	(0.82)	(0.71)	(0.82)	(1.37)
Relationship x Pos x [-28,-15]	-0.0636	-0.1266	-0.1430	-0.0728
	(-0.83)	(-0.78)	(-0.61)	(-0.77)
Relationship x Pos x [-14,-1]	0.3138***	0.6845***	1.2749***	0.5621***
	(3.42)	(4.81)	(7.25)	(3.36)
Relationship x Pos x [+1,+14]	-0.1437*	-0.2485	-0.3048	-0.1627
	(-1.97)	(-1.51)	(-1.30)	(-1.07)
Relationship x Pos x [+15,+28]	-0.1148***	-0.3021***	-0.5348***	-0.3806***
	(-2.81)	(-3.68)	(-4.07)	(-4.01)
Bank x Event FE	yes	yes	yes	yes
Events	UE	UE	UE	UE
Abs. Imbalance	-	>0	>0.5	>0 in [-84,-71]
Abs. Event Return	>2%	>2%	>2%	>2%
Observations	918,848	122,416	56,277	122,480

This table presents results from panel regressions using eight two-week windows around corporate events (i.e., [-84,-71], [-70,-57],.., [+15,+28]). For each bank and event, we compute an imbalance in the usual fashion. Thus, the analysis is at the Bank × Event × Time Level. We separately estimate coefficients for four time windows centered around the event, and the effects are estimated relative to the imbalances in the [-84,-29] windows. The sample is restricted to unscheduled earnings-related events with large absolute returns (>2%). In Columns (2) - (4), we further condition on bank prop trading by requiring non-zero or larger absolute imbalances. In Column (4), we impose the trading condition only long before the event, i.e., in the [-84,-71] window. All variable definitions are in Appendix A1. We include a fixed effect for each bank-event pair (Bank × Event FE). T-statistics with standard errors adjusted for clustering at the bank level are reported in parentheses. *, ** and *** indicate statistical significance at the 10%, 5% and 1%-level (two-tailed), respectively.