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Know Your Customer: Informed Trading by Banks*

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Abstract

This study analyzes information production and trading behavior of banks with lending relationships. We combine trade-by-trade supervisory data and credit-registry data to examine banks' proprietary trading in borrower stocks around a large number of corporate events. We find that relationship banks build up positive (negative) trading positions in the two weeks before events with positive (negative) news, even when these events are unscheduled, and unwind positions shortly after the event. This trading pattern is more pronounced in situations when banks are likely to possess private information about their borrowers, and cannot be explained by specialized expertise in certain industries or certain firms. The results suggest that banks' lending relationships inform their trading and underscore the potential for conflicts of interest in universal banking, which have been a prominent concern in the regulatory debate for a long time. Our analysis illustrates how combining large data sets can uncover unusual trading patterns and enhance the supervision of financial institutions.

Keywords: Universal banks, bank regulation, big data, proprietary trading, Volcker Rule, insider trading, market supervision

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1 Introduction

Banks 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 credit provision and mitigating incentive problems in lending (e.g., Bernanke (1983), Diamond (1984), Petersen and Rajan (1994)). However, banks could also take advantage of their privileged access to information and use it beyond their lending business.[1] Universal banks, in particular, could 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)). Over time, these concerns waned and banks were allowed to combine these activities under one roof. The debate was reignited by the 2008 financial crisis and resulted in the Volcker Rule, which bans proprietary trading by U.S. banks. In Europe, the Liikanen Report proposed a similar ban (Liikanen et al. (2012)), but the EU chose instead to require universal banks to have organizational structures (e.g., ethical walls) that mitigate conflicts of interest arising from combined investment and corporate banking.

We know little about the effectiveness of such organizational structures, banks' internal information flows and the use of private information obtained from clients in trading. One simple reason is that bank proprietary trading data are rarely available. Most studies focus instead on institutional investors (e.g., mutual and hedge funds), for which we can obtain trading or holdings data. These institutions could also obtain private information about borrowers by participating in loan syndicates or because they belong to financial conglomerates (e.g., Massa and Rehman (2008), Ivashina and Sun (2011), Massoud et al. (2011)). Our paper differs from these studies in that we can investigate proprietary trading by universal banks, which in turn allows us to assess the effectiveness of their organizational structures when it comes to information flows and conflicts of interest.

[1] On the lending side, banks could also use their private information to holdup borrowers and extract rents (e.g., Rajan (1992)).

The core idea of our paper is to analyze bank trading around material corporate events, as trading can be particularly profitable when firms release new information (Cohen et al. (2008)). Corporate debt contracts include clauses that require borrowers to inform their lenders, on a regular basis and about material changes to the business. The question is then whether this potentially private information from the borrowers makes it to banks' trading desks. Such information flows cannot be directly observed. Instead, we combine several large micro-level data sets provided by different supervisory agencies to uncover informed trading. We use the German credit register from Deutsche Bundesbank to determine lending relationships. Next, we build a comprehensive database of corporate events for German firms. We merge these data sets with trade-by-trade data that banks must report to the German market supervisor (BaFin). Our data set contains all individual trades by all financial institutions with a German banking license that are executed on any domestic or foreign exchange or in the OTC markets. In total, we analyze around 168 million trades (with a volume of €3.5tn) around 39,994 corporate events. To the best of our knowledge, our analysis is the first time that credit-register information is combined with trade-by-trade data to investigate bank trading patterns.

One challenge for the analysis is that banks may specialize in dealing with certain industries, business models or firms. Such specialization, and the expertise that comes with it, could manifest in profitable trading, even without any direct information flow from the lending side to the trading desk. To overcome this challenges, our analysis differentiates between events that are widely anticipated (e.g., earnings announcements scheduled in advance) and those that are unscheduled and harder to anticipate (e.g., profit warnings, M&A). For the latter, it is less likely that bank expertise explains trading ahead of the event. To further tighten identification, we exploit time-series variation in lending relationships. Expertise should be longer-lived and hence still be present when the lending relationship has ended and the source of private information is gone. In addition, we analyze events that involve both a bank client and another firm. We then study bank trading in the other firm that is not a client but involved in the event and hence the bank could have obtained private information via its borrower.

To be clear, insider trading is illegal in Germany, as it is in most countries (Bhattacharya and Daouk (2002)). The European Union's Market Abuse Regulation (MAR) prohibits the use of insider information for trading activities.[2] However, there are important exceptions when trading in the presence of inside information is allowed. These exceptions give rise to a grey zone. For instance, market making activities are exempted and banks have discretion in declaring trades as proprietary trading versus market making.[3]. Furthermore, banks are allowed to trade when some part of the organization (e.g., lending) has inside information as long as banks' organizational structures (i.e., ethical walls) ensure that traders are not in possession of this information. Thus, the effectiveness of banks' organizational structures is an important regulatory question.

Our results suggest that banks' trading in their borrowers stocks is informed. 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 follow Griffin et al. (2012) and focus on the direction of trade, or trade net position, relative to the event news. As the news and the return of a given event are the same for all banks, the number of shares bought or sold ahead of the event determines the profit at the time of the event. Our specifications include fixed effects for each corporate event and banks' industry specialization. We find that relationship banks purchase more shares than non-relationship banks prior to events with positive news (i.e., positive market-adjusted returns). We also find negative net positions for relationship banks ahead of events with negative returns,

[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] For this reason, we combine both categories and differentiate them from bank trades on behalf of clients. That said, our results are not driven by this choice and hold if we exclude trades declared as market making from the analysis. On average, trades classified as prop trading (market making) account for about 63% (2%) of all trades and for 54% (16%) of all trading volume.

although the results tend to be weaker. The latter is perhaps not surprising as selling to benefit from negative news requires banks to own shares prior to the event or to short-sell, which comes with institutional constraints. The differential strength of the results is also consistent with the literature for insider purchases by corporate executives (e.g., Ke et al. (2003), Lakonishok and Lee (2001)).

Our results become more pronounced when we focus on unscheduled events related to firms' earnings, such as pre-announcements, earnings guidance, or special dividend events. We find that relationship banks build up significant net positions prior to unscheduled positive and negative events (0.20bp and -0.07bp of all shares outstanding, respectively). This finding is striking because, if anything, it should be harder to build positions in the "right" direction ahead of these events. The effects are even stronger when we restrict the analysis to unscheduled events with larger market-adjusted returns (above 2%). Mapping out trading around these unscheduled events confirms that relationship banks start building up their net positions beforehand and then reverse them in the weeks after the events.

Using all unscheduled events with market-adjusted returns above 2% for which relationship banks build up larger positions ahead of time (>0.5bp), relationship banks earn an average trading profit of €3,932 per event. Although this number is eight times larger than the average event profit of non-relationship banks, it is quite small. However, evaluating the magnitude of the estimated effects is not straightforward because there are many trades and not all are likely informed (see also Cohen et al. (2012)). Moreover, we winsorize banks' positions to ensure that our results do not reflect a few extreme cases but describe systematic trading patterns. If we evaluate trades by relationship banks in the aggregate and without winsorizing, we find that relationship trading contributes 14% of banks' total event-trading profits, even though relationship bank-event combinations account for only 1% of all bank-event combinations.[4]

To gauge the role of expertise versus private information from lending relationships, we

[4]This result is not driven by a few outliers. Relationship trading also contributes 14% of the event-trading profits when we winsorize profits at the top and bottom percentile before aggregating them.

analyze how often relationship banks trade in the "right" direction around an event, as compared to non-relationship banks. If positive and negative news (or abnormal returns) for corporate events are equally distributed and banks trade around events without any expertise or private information, there is a 25% chance that a bank buys prior to a positive news event and sells right after it (and vice versa for negative events). We find that, without conditioning on relationships, banks in our sample exhibit such a trade pattern for 25.7% of the events (in which they trade around an event). Thus, on average, bank trading around corporate events is only marginally better than chance. For relationship banks, however, this probability increases by 6.2pp for unscheduled events with absolute returns above 2% and further increases to 8.3pp when we restrict the analysis to net positions above 0.5bp.

Next, we conduct four sets of tests that shed light on the mechanism for our findings and at the same time rule out bank specialization as an explanation for our results. First, we introduce bank×firm fixed effects because bank expertise could be firm- (or client-) specific. Building up bank expertise for a client takes time and does not disappear immediately when the lending relationship ends. Thus, if bank specialization is the source of a bank's superior information, profitable trading should not coincide exactly with the duration of the lending relationship. We find, however, that adding bank×firm fixed effects hardly attenuates the results for relationship banks, which implies that banks have profitable positions around corporate events *only* when they concurrently have lending relationships. Even more tellingly, relationship banks' trading during "non-relationship periods" and even after a relationship ended does not look different from the trading of non-relationship banks.

Second, we test whether the trading results for relationship banks are more pronounced in situations, in which banks likely receive new information from their borrowers. For instance, banks obtain detailed information when granting a new loan. We find that relationship banks build up larger net positions prior to unscheduled events of borrowers that have been granted a new loan in the previous quarter. In a similar vein, we analyze M&A events. Firms are likely to discuss impending M&A transactions with their relationship banks (e.g., to secure funding).[5] We find a higher likelihood of "suspicious" trading, defined as trading in the "right" direction around the M&A event, in particular, when the relationship bank's client is a seller or a target as well as when the transaction ends up being cancelled. Thus, for both new loans and M&A transactions, it seems that information originating from banks' clients finds its way within the bank to the trading desk.

Third, we identify corporate events (e.g., legal disputes or mergers) that involve two firms, a borrower and an unrelated third party, with whom the bank has no lending relationship. We then analyze bank trading in the *unrelated* firm around the joint corporate event. We find that the probability of suspicious trades around the joint event increases by roughly 20pp. However, relationship banks do not exhibit such suspicious trade patterns around other events of the same unrelated firms when these event do not also involve their borrowers, suggesting that banks have no special expertise in these unrelated firms generally.

Fourth, we explore one potential channel through which private information could travel within banks. Effective risk management in universal banks requires information on all bank exposures, whether they are from lending or trading. The risk management function is therefore centralized, which creates the potential for information flows. Even if risk management does not directly share information, it sets (or adjusts) limits for bank activities on both sides of the wall, which could passively transmit information. For instance, the risk management knows when the trading desk has a large exposure (e.g., short position) and the lending side receives information about an impending corporate event with news in the "opposite" direction. Exploiting this idea, we determine banks' trading exposures ahead of major events and find that relationship banks are more likely to unwind an existing short (long) position before unscheduled positive (negative) news events. Thus, an intriguing insight that emerges from our analysis is that, aside from direct information flows, organizational structures that collect information centrally could play a role in banks' informed trading patterns.

In our last set of analyses, we study banks' trading strategies when executing informed

[5] M&A deals often involve conversations with the lending side of the bank. Literature reviews by Bhattacharya (2014) and Augustin and Subrahmanyam (2020) also point to concerns about informed trading prior to M&A transactions.

trades. If the documented trading behavior skirts or even violates the rules, we expect relationship banks to shroud their informed trading to avoid supervisory scrutiny. In particular, very large news events or very large trades are expected to hit the supervisory radar.[6] Consistent with this argument, we find that the informed trading results vanish for events with absolute returns greater 10%, which surely would attract supervisory attention. Moreover, we find that relationship banks build up profitable positions around corporate events using many small trades rather than a few large ones. We continue to see this pattern when we include bank×firm fixed effects, which implies that banks change their trading strategy for a given stock *once* they become (or cease to be) the relationship bank. Related to the shrouding of informed trades, we study intra-day transaction prices to see if other market participants understand that banks have superior information. Consistent with price protection, we find that relationship banks obtain worse prices for borrower stocks in the OTC market, where the identities of the trading parties are known. Relationship banks in turn respond by building up their suspicious positions mostly on exchanges.

Our study contributes to several strands of 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 arise when banks engage in commercial and investment banking. 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 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 bans proprietary trading by U.S. banks.

Against this backdrop, we provide evidence from a universal banking system that still

[6] DeMarzo et al. (1998) argue that supervisors maximize investor welfare by focusing on large price changes and large trading volumes. In fact, the absolute return for almost all prosecuted insider trading cases that BaFin discloses in its annual reports between 2012 and 2017 lies above 10%.

allows proprietary trading and relies on organizational structures to address conflicts of interest. Germany provides a powerful setting to study private information flows from lending because German firms traditionally maintain strong ties with their main lenders or *Hausbanken* (Allen and Gale (1995)). Our informed trading results question the effectiveness of banks' organizational structures (or walls) in managing conflicts arising from private lending information. In addition, they point out that centralized structures created to mitigate bank risks could be a source of "wall-crossing" and hence pose challenges for universal banks.

Second, we contribute to the literature studying the trading activities based on private information. Massa and Rehman (2008) and Bodnaruk et al. (2009) present evidence that mutual funds trade more profitably in firms that borrow from affiliated banks, suggesting informed trading when mutual funds and banks belong to the same financial conglomerate. Jegadeesh and Tang (2010) provide evidence of profitable trading prior to takeovers by target advisors. 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.[7] In contrast, Griffin et al. (2012) find little evidence of connected trading ahead of takeovers or earnings announcements when analyzing client trading and market making of investment banks that previously served as advisors in corporate transactions. Griffin et al. (2012) argue that their findings based on trade-level data cast doubt on prior evidence that uses less granular trading data.

We add to this literature by studying information flows within banks and providing evidence on informed trading based on trade-by-trade data. 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, inferring it from market-level outcomes such as return

[7]Consistent with work for the U.S., Bittner et al. (2021) recently provide evidence of information transmission among German banks in syndicated loan networks around M&A events.

patterns or price discovery in CDS, secondary loan or stock markets as well as syndicate participation (e.g., Acharya and Johnson (2007), Bushman et al. (2010), Carrizosa and Ryan (2017), Kang (2021)). More direct evidence on trading is typically available only for non-bank, institutional participants in loan syndicates, as they provide holdings data in quarterly 13F filings. We in turn combine credit registry data with trade-level supervisory data to study banks' proprietary trading and are able to identify instances when banks make informed trades in borrowers stocks as well as provide evidence on the mechanism, including a potential indirect pathway for the information flows via banks' risk management.

Finally, we contribute to a recent literature on data-driven advances in financial regulation and supervision (Spatt (2020)). For example, Blattner et al. (2021) characterize optimal financial regulation when lending decisions are made by complex algorithms. Davis et al. (2022) create machine learning models that regulators can use to forecast credit risk. Anand et al. (2021) use comprehensive regulatory data from FINRA to identify brokers who offer lower execution quality for their customers. We contribute to this literature by showing how combining big supervisory data sets can uncover suspicious trading patterns, even with conventional empirical methods. This approach has the potential to improve supervisory practices. In fact, the Consolidated Audit Trail, which was initiated by the SEC and became fully implemented in December 2021, constitutes a data set that allows for the application of such methods.[8]

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

[8]The Consolidated Audit Trail enables regulators to track all order and trading activity throughout the U.S. markets for listed equities and options (https://www.catnmsplan.com/).

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, 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.[9]

Following the rejection of the Liikanen recommendations, Germany unilaterally proposed a law governing banks' trading activities, the so-called Bank Separation Act. This proposal was implemented in Article 2 of the German Banking Act and became effective on July 1, 2015, although banks were given until July 1, 2016 to comply with the law. The Bank Separation Act restricts specific proprietary trading activities by banks whose trading activities exceed a set threshold defined in terms of trading volume but does so by imposing organizational structure.[10] 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

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

[10]A bank exceeds this threshold if its trading activities in 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.

bank can continue to engage in proprietary trading as long as this activity is organized via a separate subsidiary of the bank.[11] Furthermore, the 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 is rather limited when it comes to restricting proprietary trading (e.g., Tröger (2016), Schaffelhuber and Kunschke (2015)). Consistent with these arguments, Table IA.1 shows that our sample banks' proprietary trading volume in 2016 and 2017 is only slightly lower than before the reform in 2015, and still *higher* than in 2012 and 2013.[12]

Germany like most countries imposes legal restrictions on insider trading. As Germany is a member of the EU, the EU's rule book for financial markets applies. 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, MAR lists situations, in which trading in the presence of inside information within a financial institution is not considered illegal. Trading is permitted if a 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

[11] 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 parent company would.

[12] Our relationship trading results presented below are present both before and after the reform.

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.

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

3 Data and Descriptive Statistics

3.1 Bank Trading and Lending Data

We use two proprietary data sets for this study: one on bank trading from the German Federal Financial Supervisory Authority (BaFin) and one on corporate lending from the German Central Bank (Deutsche Bundesbank). As they stem from different supervisory agencies, these data have previously not been linked and used for supervisory purposes.

The Securities Transactions Database is 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 German subsidiaries of foreign banks, to report all its trades to BaFin. Importantly, banks have to report trades irrespective of venue, so not only trades on German exchanges, but also on international exchanges or in the OTC market. The requirement applies to all desks within a bank (proprietary trading, market making, treasury, asset management, etc.). Furthermore, the data set comprises trades in different securities such as equities, bonds, options and other derivatives.

We have data from 2012 to 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 an indicator for OTC trades as well as a buy or sell indicator. Importantly, the data set 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 required to indicate 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.[13] By doing so, we do not rely on banks' discretionary classifications of trades as market making or proprietary trading. We then aggregate trades by bank and day across all venues. We treat each bank with a separate BaFin identifier as a stand-alone entity in terms of trading.[14]

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 equities, as they account for the vast majority of the trading volume on a given day. Most sample firms do not have traded bonds or options. However, when they exist, options could be important for banks' risk management or hedging. We therefore include options in our sensitivity analyses.[15]

[13]Consistent with our coding, Duffie (2012) argues that market making is inherently a form of proprietary trading and hence difficult for regulators to differentiate. We re-run our analyses excluding trades classified as market making and obtain very similar results. See Section 6 and Table IA.6 for more details.

[14]Our sample includes three cases 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, the results remain unchanged.

[15]See Table IA.6. Another reason to consider option trades is evidence that they are used for informed trading prior to takeovers (Augustin et al. (2019)).

Our second proprietary data set is the German credit register maintained by Deutsche Bundesbank. It 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. All banks with a German banking license (including German subsidiaries of foreign 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).[16] 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 data sets, 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

Public databases on corporate events differ in 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 data set 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 39,994 corporate events. For each event, we compute the market-adjusted daily return by subtracting the DAX index return on a given day[17]. Table 1, Panel A, provides frequency and return information for the different event categories. Most events (11,484) fall into the earnings and financial reporting category. There are 6,808 management guidance events, 3,168 dividend events, 6,303 M&A events.

[16] 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.

[17] We drop events where the [-1;+1]-return is exactly zero, as in this case a stock was not traded. Keeping these events does not alter our results.

The remaining categories contribute 12,231 corporate events. Bankruptcy events are rare. 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-announcements, other financial reporting events have relatively small returns. We distinguish between management guidance (e.g., earnings or sales forecasts) that is provided at the EA, jointly with past earnings and other news, and stand-alone management guidance events provided 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 by or sues another firm. Operating events comprise a large number and broad set of firm news, including product announcements, capacity expansions, strategic alliances, many of which are of lesser importance, resulting in smaller returns.

An important distinction for our analysis is whether events are scheduled in advance and therefore known to market participants ahead of time. For instance, we expect sophisticated investors to collect information, perform analyses and trade ahead of known corporate events. We thus distinguish between scheduled events (e.g., conference calls, earnings announcements) and unscheduled events. We define "unscheduled earnings-related events" (UEs) as pre-announcements, stand-alone management forecasts and unscheduled dividend events. The latter are announcements of special dividends, stock dividends or dividend decreases. We do not treat dividend increases as unscheduled because some firms maintain schedules that increase their dividends steadily.

The group of unscheduled earnings-related events plays a key role in our analysis. First, it is less clear for these events that market participants (can) expect information to be released that day. Put differently, it should be more difficult to anticipate unscheduled events and build positions ahead of them in a consistent fashion. In this sense, successful trading around unscheduled events is more likely to be indicative of private information. Second, and consistent with the argument that these events come as a surprise and release material information to investors, they exhibit large stock market reactions (Table 1, Panel A). Third, we have a large number of unscheduled events, which allows us to construct powerful tests. Fourth, event overlap is more limited for unscheduled events. On days when firms hold conference calls or announce their earnings, they usually discuss many matters, including guidance for the next year, strategy, operational issues or new products. 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 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 we have banks' securities trading. We identify these firms by ISIN, keeping only ISINs that start with 'DE', as other ISINs are not mapped by the Bundesbank to the credit register. We exclude financial or bank stocks, identified by Bundesbank industry codes starting with 64, 65, 66 and 84 (except for 64G, which comprises non-bank financial service companies) because 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.[18] The resulting sample comprises 618 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 for the median firm it is only about €100m. 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 per firm is highly skewed. Smaller firms have considerably fewer events, likely reflecting fewer reporting requirements (e.g., no quarterly reporting), fewer newsworthy events, and news database coverage skewed towards larger firms.

For banks to enter the sample, they have to trade at least once per month in one of the 618 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 47 German and foreign banks with a German banking license.[19] 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.[20] 28 of the 47 banks are assigned as relationship bank to at least one firm. It is possible (but not common) that a corporate borrower has more than one relationship bank. Seven banks make (smaller) loans to sample firms but are never coded as a relationship bank

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

[19] We obtain similar results when using alternative sample definitions: (i) the 47 banks with the largest equity trading volume over the sample period, rather than the 47 with at least one trade per month; (ii) all 249 banks that trade at least once per year; and (iii) all banks that serve at least once as relationship bank to a borrower.

[20] 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.

according to our definition.[21] Twelve banks do not make loans to sample firms, i.e., they trade only and are therefore also in the control group. The 28 relationship banks comprise all large German universal banks as well as several smaller banks. As shown in IA.2, the five largest universal banks contribute the majority of the lending relationships (83%).

Panel C of Table 1 provides descriptive information on banks' lending relationships and proprietary trading. 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. However, both of these averages are highly skewed. The median bank has a loan exposure of €43m and is the relationship bank for one corporate borrower. The same is true for the trading activities; the majority of the Euro trading volume stems 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 €49m. The average sample bank engages in 2,361 prop trades across 50 sample stocks per day, with an average trade size of €41,881. Focusing on the two weeks prior to corporate events, banks engage in prop trading in 19% 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 data set at the bank-event level. 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. Following Griffin et al. (2012), we accumulate trades to determine the net trading position for each of the 47 sample banks over the two weeks prior to the 39,994 corporate events. Thus, including zeros when banks do not trade ahead of an event, the resulting data set has 1,879,718 observations, i.e., 47 (banks) $\times$ 39,994 (events). Specifically, the net position is 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. 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 a particular event. By coding the relationship variable for the quarter prior to an event, we ensure that

[21] Coding all banks that provide loans as relationship banks does not materially alter our findings.

a bank already has a lending relationship by the time of the event to make it conceivable that the bank is in possession of private information from the lending relationship.

Panel D of Table 1 provides summary statistics for this bank-event data set. When a bank is coded as a relationship bank, its loan share is on average about 39%. Net Positions characterize banks' proprietary trading ahead of corporate events, which differs considerably across events and banks. On average, net positions are small and the median is zero because not all banks prop trade before every event. In fact, recall that only 19% of the events exhibit any prop trading by a bank in the two-week, pre-event window. We further note that the distribution of net positions exhibits extremely large observations on either end, reflecting a few out-sized trading positions. We therefore winsorize net positions at the 1st and the 99th percentiles 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) net position, which essentially represent the first (third) quartile of the distribution. The median negative (positive) net position conditional on trading is -0.24bp (0.27bp) of all shares outstanding. These median net positions translate into €-positions of about -€0.08m (€0.11m). Multiplying banks' net positions with the respective event return yields their trading profits from the positions. Profits (or losses) are generally small but again highly skewed in both directions.

Finally, we compute a binary indicator for how often banks trade in the "right" direction ahead of the event, meaning 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 for trading in the right direction should be 50%. Panel E of Table 1 shows that the probability of non-relationship banks' trading in the right direction over all corporate events is 50%. This number indicates that it is difficult for the average bank's trading desk to predict the direction of the return ahead of corporate events. For relationship banks, this number increases to 51.32%. Importantly, the increase in the probability of trading in the direction of the event return could indicate skill or expertise, due to research and financial analysis as well as the possession of private information. We also compute the probability for unscheduled corporate events, for which the event return is presumably even harder to predict, given the events themselves are not announced in advance. As shown in Panel E, however, the likelihood of trading in the right direction further increases for these events and relationship banks. This observation provides first suggestive evidence that relationship banks' trading desks are in possession of valuable information ahead of these events.

4 Research Design

In this section, we describe our empirical strategy to assess whether relationship banks' trading in borrower stocks is informed. Banks are required under German law to obtain financial information prior to making a loan (KWG §18). Thereafter, banks regularly request information to monitor outstanding loans (Minnis and Sutherland (2017)). Moreover, corporate debt contracts commonly include clauses that require borrowers to inform their lenders at any point about material changes to their business. Thus, relationship banks obtain private information about their borrowers ahead of major corporate events. The question is whether this information makes its way to the trading desk and is used in proprietary trading. To answer this question, we center the analysis on corporate events when new and previously private information is revealed to the market and compare the trades of relationship banks in their borrowers ahead of these events with the trades of banks without lending relationships in the same stocks.

Importantly, there could be other reasons why banks have profitable trading positions ahead of specific corporate events. An important alternative explanation is that banks have expertise because they specialize both their lending and their trading in certain industries, business models or firms. This expertise could also explain why banks have lending relationships *and* trade more successfully ahead of corporate events. Below, we describe several empirical tests designed to rule out this alternative explanation.

4.1 Trading Net Positions around Corporate Events

Our main empirical model investigates whether relationship banks build larger and more profitable net trading positions for the same corporate event than non-relationship banks. We estimate the following specification:

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

where $NetPosition_{be}$ 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 of 2 for the net position 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. The panel for the base sample is balanced because banks that do not trade before the event have a net position of zero. However, for most of the analysis, we impose further restrictions on the sample (e.g., require a minimum absolute net position) to focus the analysis on banks that 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. 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 net position for relationship banks in the two weeks prior to positive-return events relative to the average net position of non-relationship banks. The latter estimates the same incremental net position for negative-return events.

The model includes a rich set of fixed effects. 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 or events) could explain differences in trading patterns before major corporate events. We cluster standard errors at the bank level.

4.2 Informed Trading vs. Bank Specialization

We design several empirical tests to distinguish between informed trading because of relationship information and bank expertise because of specialization. The main challenge is that within-bank information flows cannot be directly observed.

We begin by exploiting time-series variation in lending relationships. During our sample period banks start new lending relationships and end existing ones. Building up expertise takes time and does not disappear immediately when a lending relationship ends. However, once a lending relationship ends, firms stop reporting private information to their relationship banks. 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 not exactly coincide with the duration of the lending relationship and, in particular, should last for some time after the relationship. In contrast, private information from lending relationships is more closely tied to the duration of the relationship itself. To exploit this difference, we estimate the following specification:

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

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 net positions around positive-return corporate events of the *same* firm during times when the bank is a relationship lender with times when the bank is not a relationship lender.[22] The coefficient β_2 indicates whether relationship banks also trade profitably in their borrowers when they are not yet or no longer the main lender. We further refine this test and estimate a specification that includes $[After - Rel.Periods_{be}]$ instead of $[Non - Rel.Periods_{be}]$. This specification focuses on bank trading after the relationship has ended (but expertise should still be there). In addition, we estimate a model, in which we saturate the specification (2) with time-varying bank-firm fixed effects (i.e., bank $\times$ firm $\times$ year).

Our second test exploits that banks obtain new information from their borrowers when they grant new loans. German law requires that banks obtain financial information before granting a loan and the loan contracts typically stipulate the information items that borrowers have to furnish. We have reviewed a small sample of contracts by major German banks and confirm that the list includes both financial information as well as information about the business outlook and strategy. It is also common for lending officers to meet with their borrowers to discuss financial information and updates to the business. Such meetings are also likely to occur prior to granting new loans. Based on these institutional underpinnings, we separately analyze bank trading in the quarter after which a new loan has been granted.

Our third test focuses on specific events involving a third-party, for which information flows and expertise should be more separable. We analyze corporate events that involve

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

two firms (e.g., legal disputes or mergers). We then flag situations, in which a bank has a relationship with one of the firms but not with the other and analyze the relationship bank's trading in the unrelated firm around the joint corporate event as well as other events of this unrelated firm. The idea is that profitable trading in the unrelated firm is harder to explain with bank expertise and more likely to reflect information flows pertaining to the joint corporate event. For this test, we limit the sample to all bank trades around corporate events that involve two different sample firms. We identify such events by screening all event headlines for sample firm names. The majority of these cases are M&A events.[23] An example for such a third-party event is the following scenario: Firm F1 plans to take over Firm F2. Bank B has no link to Firm F1 but a relationship with Firm F2. As a relationship bank, B is likely informed about the impending M&A transaction by its borrower F2. We now examine Bank B's trading behavior in Firm F1 around the joint corporate event relative to all other banks that trade around this event. We then also analyze the trading patterns of Bank B around Firm F1's *other* corporate events not involving Firm F2. The latter serves as a benchmark indicating whether the bank has expertise in the third-party firm generally and allows us to compare trades in the same firm when information from its lending relationship with F2 could be relevant and when it is not.

5 Empirical Results

5.1 Relationship Banks' Trading around Corporate Events

We begin our analysis by investigating the trading behavior of relationship banks around corporate events of their clients, relative to other non-relationship banks. Table 2, Panel A, presents the results estimating our main specification (1). In Panel B, we examines the dynamics of these patterns over time.

As a starting point, we analyze all corporate events (see Section 3.2). We find that

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

relationship banks build up significantly larger net positions in the [-14,-1]-day window ahead of events with positive market-adjusted returns. The net positions of relationship banks are about 0.033bp larger than those of non-relationship banks (Panel A, Column 1). This effect remains roughly the same when we control for event-specific differences (Column 2) as well as differences in banks' industry specialization (Column 3).

Next, we restrict the analysis to corporate events that are not scheduled in advance and hence harder to predict by traders. Relatively speaking, an association for these unscheduled events is more likely to reflect informed trading than expertise. As discussed in Section 3.2, we focus unscheduled earnings-related (UE) events, comprising pre-announcements, management forecasts and unscheduled dividend events. In Column 4, we restrict the sample to UE events and find that the results become considerably stronger. The estimated incremental net position of relationship banks prior to positive return events increases substantially from 0.03bp to 0.20bp. Once we focus on UE events, we also find that relationship banks trade profitably around negative news events relative to non-relationship banks. For negative-return events, the incremental net position of relationship banks is equal to 0.07bp. The fact that the estimated effects are smaller in magnitude for negative news is consistent with previous evidence on trading by corporate insiders (Ke et al. (2003), Lakonishok and Lee (2001)). Moreover, to benefit from negative news, banks have to either own the stock prior to the event or need to short-sell it, which comes with additional institutional constraints.

We recognize that not all UE events reveal major news to the market. In fact, smaller event returns could reflect that some of the information has been anticipated by sophisticated investors and hence is already reflected in market prices. We therefore split UE events according to their absolute return to see if the results are more (or less) pronounced when UE events are more surprising or provide more news to the market. The findings in Panel A, Columns 5–6, provide little evidence that relationship banks trade differently when the absolute event return is small and below 2%. However, for UE events with absolute returns greater than 2%, the relationship trading effect is strong and increases substantially in magnitude for both positive and negative news events. Based on this evidence, we restrict the remaining tests to UE events with absolute abnormal returns of at least 2%. In doing so, we not only focus on events with relatively large information content, but also examine events that are a surprise to the market, which should aid the identification of privately informed trading.

In Panel B, we investigate the dynamics of relationship banks' trading strategies around UE events.[24] To do so, we compare the net positions of relationship and non-relationship banks for different two-week time windows. We find that relationship banks build up profitable positions shortly before positive UE events and reverse them in the month afterwards. However, as we zoom out, relationship banks trade comparably to non-relationship banks, i.e., they do not build up significantly different net positions during the [-42,-29] window or the [-28,-15] window prior to an event. In the [+1,+14] window and the [+15,+28] window after positive events, relationship banks have lower net positions than non-relationship banks. Interestingly, adding the coefficients for these two post-event windows almost exactly offsets the coefficient in the [-14,-1] window, suggesting that the position built up prior to the event is entirely reversed within one month after the event. Thereafter, in the [+29,+42] window, trading differences between relationship banks and non-relationship banks vanish. Panel B exhibits a similar pattern for negative news events, but it is again less pronounced. To graphically illustrate banks' trading patterns in absolute terms, we plot the cumulative mean net position around positive and negative UE events in Figure 1. For non-relationship banks, we do *not* observe trading *ahead* of positive or negative UE events. We observe small changes in the net positions after the events. Non-relationship banks appear to sell (buy) stocks of the respective company following a positive (negative) UE event. The trading patterns for relationship banks look considerably different. Here, we observe significant increases (decreases) of the net positions *prior* to a positive (negative) UE events, and reversals thereafter.

[24]Although Panel B focuses on UE events, we find comparable patterns for all corporate events, as shown in Table IA.4.

Having established that relationship banks trade differently around corporate events, we gauge the magnitude of these trading effects. Evaluating the profits from informed trades is not straightforward because not all trades by relationship banks prior to UE events are likely to be informed. The estimated coefficients in Table 2 therefore constitute an average over events for which the banks are informed and events for which they are not. In line with this reasoning, we observe that relationship (and non-relationship) banks do not trade before every UE event. In Table 3, we restrict the sample to bank-event observations for the absolute net positions is positive, which means that we include only banks that have traded prior to the event. As shown in Column 1, the coefficient of interest doubles in size with this restriction. In Column 2, we further narrow our sample to events for which banks built up substantial net positions prior to an event (i.e., net positions are larger than 0.5 bp). For these events, the net positions of relationship banks exceed the net positions of non-relationship banks on average by 1bp. We can translate the two-week net positions into incremental trading positions expressed in Euro. Columns 3 and 4 show that, in the two weeks prior to positive-return events, relationship banks build up on net positions that are on average about €160,000-€260,000 larger than those of non-relationship banks.

Next, we multiply banks' trading positions with the respective event return to estimate the additional profit that relationship banks generate per event. Columns 5 and 6 show that the incremental per-event profit is on average €2,700 and €3,900, respectively. Although these numbers seem quite small, banks' average profit for all UE events and observations included in the analysis in Column 6 (i.e., events with at least 2% return and net positions of at least 0.5bp) is only €523. Thus, when banks trade around corporate events of their borrowers, their profits are about eight times larger than the event profits of banks trading securities of unrelated firms. When aggregating profits over all events, the sample banks that account for 95% of all of our lending relationships make an average yearly event profit of about €2.3m with relationship trading.

When interpreting all these numbers it is important to keep in mind that we winsorize banks' positions in order to uncover systematic trading patterns, rather than to present results driven by a few extreme cases. When we instead focus on relationship banks' 1,000 most profitable positions (before winsorizing), the average event profit is about €0.5m. Similarly, we can aggregate (unwinsorized) event profits from relationship trades and compute their contribution to banks' total event-trading profits. Table IA.2 shows that relationship trades generate roughly 14% of banks' total event-trading profit, even though these trades account for only 1% of all bank-event combinations.[25]

There are two other ways to gauge the success of relationship banks' trading around corporate events. First, following Ivashina and Sun (2011), we use the trade direction interacted with the event return as a dependent variable. The relationship trading effect is then measured as an incremental event return. For net positions exceeding 0.5bp, we find that relationship banks earn an additional return of 0.91pp per event by more frequently building up net positions in the same direction as the abnormal event return (Column 8). Considering that the mean (median) absolute return for UE events with at least 2% abnormal returns is about 6.5% (4.6%), the incremental return from relationship trading is economically meaningful. Second, we assess the frequency with which banks trade in the "right" direction both before and after the event, meaning they buy during the two weeks prior to a positive event and sell during the two weeks afterwards (and vice versa for negative events). We refer to such cases as "suspicious trades." An advantage of this variable is not only that it is easy to interpret but also that it is already accounts for the direction of the news and hence allows us to jointly analyze positive and negative events. We find that, without conditioning on relationships, sample banks exhibit suspicious trades (or trades in the right direction) for 25.72% of the events (when they they trade around an event). This fraction can be viewed as a measure for the average (or aggregate) ability of banks to anticipate corporate events and the direction of their returns. The fact that this fraction is only 0.72pp larger than the 25% benchmark suggests that, on average, banks find it difficult to trade in the right direction.[26]

[25]This number is not driven by outliers. We also obtain a fraction of 14% attributable to relationship trading when winsorizing profits at the 1%/99% level before aggregating them.

[26]If trading were random, and considering that abnormal event returns are roughly centered around zero,

In contrast, relationship banks exhibit an incremental probability of suspicious trading of 6.19pp and 8.25pp, respectively (Columns 9-10). This increase is massive and implies that relationship banks systematically trade more often in the right direction (and hence more profitably) than non-relationship banks.

5.2 Information Flows vs. Bank Specialization

The results up to this point are consistent with the interpretation that banks use information they obtain from their lending relationships to earn higher profits when prop trading. However, banks may specialize in certain industries, business models or firms. Such specialization, and the expertise that comes with it, could manifest in lending relationships and profitable trading, even without any direct information flow from the lending side to the trading desk. In this subsection, we present three sets of tests that are intended to differentiate between the two potential explanations for banks' profitable trading: lending relationships and bank specialization. We consider this the main empirical challenge of the paper.

First, 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. In contrast, information flows take place when the relationship exists and debt contracts require borrowers to inform their relationship banks. By introducing bank × firm fixed effects, our coefficient of interest is estimated comparing trading net positions around corporate events during times when a bank is a relationship lender with times when the same bank is not yet or no longer a relationship lender for the *same* firm. In Table 4, Column 1, we find a strong relationship trading effect around positive effects even with bank-firm fixed effects, i.e., when banks have a lending relationship compared to when the same bank does not have a lending relationship with the

we expect to see (suspicious) trades in the right direction both before and after an event with 25% probability, i.e., 50% before an event times 50% after an event.

same firm. In Column 2, we illustrate this comparison by adding an interaction between the positive event return indicator and an indicator variable that takes the value of one for the "non-relationship periods," and zero otherwise. The coefficient for this interaction is small and statistically insignificant, suggesting that banks have abnormal net positions only concurrently with the relationship. In Column 3, we refine this analysis and create an interaction for the quarters after a lending relationship has been ended, for which any expertise should continue to exist (for at least a while). Again, we obtain a small and statistically insignificant coefficient. The results in Columns 1-3 suggest that banks' profitable net positions ahead of corporate events coincide exactly with their lending relationship, during which they presumably obtain information from their borrowers. To further tighten the analysis, we saturate the model with bank × firm × year fixed effects, which controls for any unobserved time-variant, bank-firm specific trading patterns. Even for this specification, the coefficient of interest remains significant and even increases in magnitude (Column 4).[27]

Second, we home in on information flows and separately estimate the relationship effect for situations in which banks obtain more or new information about the borrower. As discussed before, firms need to provide their relationship bank with detailed information before a new loan is granted.[28] In addition, banks are likely to have stronger information needs and hence more frequent exchanges with their borrowers when the loan is larger and more important to the bank. We explore this idea in Table 5 and find that the relationship trading effect is stronger the larger the loan share of the relationship bank is (Columns 1 and 2). Next, we analyze if the relationship trading effect differs for quarters after which the bank has granted a new loan. We code the bank as granting a new loan if the banks' loan amount to the borrower increases by at least 33% (following Behn et al. (2016)) and

[27]Importantly, these results are robust to alternative specifications of the relationship variable. In particular, they hold when we (i) define only the largest lender (instead of also banks with loan share of at least 25%) as relationship bank; (ii) eliminate observations for which a bank's loan share fluctuates between 20% and 30% (as such variation in the relationship variable could stem from mere oscillation around the 25% threshold); (iii) consider only those loan initiations (terminations) for which a bank did not lend at all in the quarter before (after) the event.

[28]In untabulated regressions, we investigate trading by the seven banks with loan exposures, but for which the relationship dummy is not equal to one. These banks do not trade differently around UE events compared to banks without any loan exposures. This result further validates our relationship bank classification.

€2m from one quarter to the next. Even with this relatively modest threshold, we find that relationship banks build up larger net positions prior to positive UE events, not just relative to non-relationship banks, but also relative to relationship banks that did not grant a new loan last quarter (Column 3). The estimated effect more than triples in Column 4 when analyzing larger new loans (i.e., the loan amount increases by at least 33% and at least €50m). We also obtain similar results if we define new loans as a relative increase in the loan share by at least 33% and an absolute increase by 10pp, and when introducing bank×firm fixed effects.

Third, we design a test that intends to separate bank expertise and information flow. Towards this end, we examine corporate events that involve two firms (e.g., legal disputes or mergers) for which one is a borrower and the other an (unrelated) third party (see Section 4.2). The idea is that for such events there is likely information flow between the relationship lender and the borrower, but the bank is less likely to have expertise in the unrelated third party. We analyze the relationship bank's trading in the unrelated firm around the joint corporate event and, separately, around all other events of this unrelated firm. We provide results for these third-party tests in Table 6. We employ the binary *Suspicious Trade* indicator because we have relatively few of these third-party events and this variable allows us to combine positive and negative news events as well as avoids that a few large net positions unduly influence the results. As it is possible that other (relationship) banks trade in third-party events or other events of unrelated firms, we control for these lending relationships with an indicator.[29] We find that the probability of seeing a suspicious trade pattern in unrelated firms increases by about 19.88pp when we focus on third-party events for which the bank could have obtained information from its borrower (Column 1). This effect becomes even more pronounced when excluding third-party events that overlap with other ones for the same firm on the same day. When we examine whether relationship banks trade suspiciously in other events for the unrelated firms, we find no evidence that banks generally

[29]As expected, the estimated coefficients on the RB indicator in Columns 5-6 are comparable to those estimated in Columns 9-10 in Table 3.

trade profitably in these stocks, e.g., due to other reasons. The results shown in Columns 3-6 (and Columns 5-6 for UE events) are statistically and economically insignificant.

In sum, the three sets of tests presented in this subsection link the observed trading patterns for relationship banks to situations, in which information flows are likely and hence relationship banks are expected to possess private information. Thus, the results largely rule out that the patterns arise due to bank specialization.

5.3 Risk Management as a Potential Pathway

The previous findings imply that information obtained from banks' borrowers finds its way to the trading desk. As the information flows cannot be observed, we do not know how the information travels within banks. One possibility is of course direct private communication. In this subsection, we explore another potential transmission channel within universal banks. The organizational structures in universal banks are designed to limit information flows between loan officers and traders (via ethical walls). However, it is possible that information travels more passively via centralized organizational units. For instance, the risk management of a universal bank collects information centrally and is simultaneously in the possession of information about loan exposures as well as trading positions, creating the potential for information flows across ethical walls. Such information flows could occur inadvertently if risk management sends "signals," for instance, by setting and adjusting trading limits or by approving or denying certain trading positions, using all the information the risk management function has. We present two tests to explore the role of risk management.

The first test exploits heterogeneity in the amount of information that risk management has to collect about a given borrower to determine its regulatory capital. German banks can choose between two approaches to determine the required regulatory capital for a given borrower and one of the approaches requires more detailed information about the borrower. The second test exploits banks' existing trading book exposures when an unscheduled event occurs. The idea is that the bank's risk management is more likely to intervene or adjust trading limits in response to negative (positive) borrower information when the trading desk has a long (short) position in the borrower's stock.

For the first test, we code each bank according to the approach it uses to determine capital charges for credit risk. We consider the approach as a proxy for how much information the risk management function has to collect for the borrower to determine these charges. Since Basel II, banks can opt to use their own ratings models to evaluate credit risk (internal ratings-based or IRB approach) rather than the standardized approach (SA) of Basel I (Behn et al., 2016). The IRB approach itself can be subdivided into foundation IRB (FIRB) and advanced IRB (AIRB). Under FIRB, the bank internally estimates the probability of default (PD) of a borrower only. Under AIRB, it also estimates the exposure at default (EAD), the loss given default (LGD) and the expected loan maturity. Thus, the latter approach requires more information about a borrower. We create an indicator variable *Relationship AIRB* (*Relationship FIRB*) that is equal to one when a relationship bank uses AIRB (FIRB), and zero otherwise.[30] In Table 7, we report results showing that relationship banks are more likely to trade in the right direction ahead of UE event when they use the AIRB approach instead of the FIRB approach. Column 1 indicates that relationship banks using the AIRB approach build up net positions prior to positive events that are 0.44bp larger than those of control banks. For relationship banks using FIRB, the effect is insignificant and amounts to only 0.04bp. We find similar effects for other dependent variables in Columns 2-4. We acknowledge that this test is essentially cross-sectional and that banks with different approaches can differ in other respects. We therefore present a second test that exploits within-bank variation in their securities positions in particular stocks prior to particular events.

In our second test, we determine whether a bank holds a long, short or no position in a firm's stock prior to building up a net position ahead of a corporate event. The relevant data are obtained from Deutsche Bundesbank's Security Holdings Statistics, which reports banks'

[30] In 5% of the cases, the regulatory approach chosen by a bank is neither AIRB nor FIRB; they are assigned to the control group. This group comprises cases for which the regulatory approach is the standardized approach (SA), the IRB approach for retail business or the bank's approach is not indicated.

security positions at the end of each month.[31] Around 16% of all nonzero bank-firm-month exposures are negative, indicating a short position at the end of the month. The analyses in Table 8 compare the trading behavior of relationship banks around UE events depending on whether the bank has an existing long or short position, or no position. Column 1 focuses on positive UE events with >2% abnormal returns. We find that relationship banks build larger net positions ahead of these positive events when they currently are short in a stock, which amounts to (at least partly) closing the short position. We do not observe this behavior for relationship banks when they already have a long position. Column 3 presents the results for negative UE events. Now, we see the reverse pattern, i.e., relationship banks build negative net positions or reduce their long positions, relative to non-relationship banks. In Columns 2 and 4, we impose the requirement that the short (long) position must be below (above) the median of all short (long) positions. This restriction does not alter our previous findings. Thus, the results are overall consistent with a risk management channel and more generally the idea that organizational structures that collect information centrally to mitigate bank risks could play a role in the information transmission. They also highlight that the earlier evidence does not necessarily imply that loan officers communicate directly with traders.

5.4 Flying under the Supervisory Radar

If the documented trading behavior indeed skirts or even violates the insider trading rules, we expect relationship banks to shroud their informed trading to avoid supervisory scrutiny. We therefore ask if there is evidence that banks avoid the attention of the supervisor when they trade in their borrowers. In this subsection we provide several tests to answer this question.

According to DeMarzo et al. (1998), supervisors maximize investor welfare by focusing on large price changes and large trading volumes. Consistent with this logic, almost all

[31] This database has the important feature that it distinguishes between banking book holdings and trading book holdings. As the former are long-term positions that cannot be adjusted quickly, we consider only the latter. The banking book and trading book distinction exists in the database since 2014. We thus set the variables *Short* and *Long* to zero for events in 2012 and 2013.

prosecuted insider trading cases that BaFin discloses in its annual reports between 2012 and 2017 pertain to instances for which the absolute return lies above 10%. Thus, if banks want to fly below the supervisor when they trade on superior information obtained from their borrowers, they could avoid corporate events that result in very large positive or negative returns. Similarly, large trades are more likely to attract the attention of the supervisor compared to small trades. For this reason, we expect relationship banks to build up net positions in their borrowers with many small trades rather then a few large trades.

We first analyze the frequency of trades by relationship and non-relationship banks around corporate events and report the results in Table 9. We find that, after controlling for the size of the net position, suspicious trades by relationship banks exhibit a larger number of trades to build up the position (Column 1). Columns 2-4 show that the likelihood that relationship banks build up a suspicious trade position with an above-median number of trades is 10pp to 13pp higher than for non-relationship banks. We note that this behavior could also reduce price impact, which we explore in the next subsection.

Next, we explore heterogeneous effects in relationship trading depending on the absolute abnormal event return. Table 10 reports results for events with absolute returns below 2%, between 2-6%, 6-10% and above 10%, respectively. As shown before, relationship banks do not exhibit abnormal net positions for UE events with small returns (Column 1). We find higher net positions for relationship banks for event returns in the next two bins (Columns 2 and 3) but not for events with absolute returns above 10% (Column 4). The latter finding is consistent with the notion that relationship banks avoid trading around corporate events that likely have very large returns and hence receive attention from the supervisor.

5.5 Price Protection in OTC Trades against Relationship Banks

A final question is whether other market participants understand that relationship banks engage in informed trading. If so, we expect market participants to price protect when they know that relationship banks are on the other side of the trade. However, this is only feasible for OTC trades, for which the trading parties know their identities. For exchange trades, the counterparties are not known. As our data set indicates whether a trade was executed in the OTC market or on an exchange, we can use this logic and test for price protection against relationship banks in OTC trades (relative to exchange trades).

We start with all (intra-day) trades by relationship banks but keep only one trade per bank, firm and second to avoid double counting of what are essentially the same trades in an auction.[32] We define a benchmark price for each transaction by a relationship bank. This benchmark is computed as the price in a prior transaction for the same stock not involving a relationship bank. We determine this benchmark price separately for OTC and exchange trades. As we have a rich trade-by-trade dataset, the median time span between the focal relationship bank transaction and the benchmark transaction is only 12 seconds.

Table 11 reports the price protection results. In Columns 1 and 2, we use the €-difference between transaction price and benchmark price as dependent variable. We find that when relationship banks buy (sell) in the OTC markets, they pay (get) about €0.0106 (€0.0087) more (less) than the benchmark price, relative to when they trade on an exchange. As the average (median) sample €-difference in absolute terms is €0.0295 (€0.0100), the magnitude of the estimated effects is economically large.[33] Columns 3 and 4 translate the €-numbers into percentages of the transaction price and document that when relationship banks buy (sell) OTC, they pay (get) about 0.0190% (0.0165%) more (less) than the benchmark price, relative to when they trade on an exchange. These results suggest that other market participants are aware that relationship banks trade with superior information and are, therefore, price protecting.

In light of the documented price protection, we expect that relationship banks rather trade on exchanges where they cannot be identified as the counter party. We document in Appendix Table IA.7 that relationship banks are more likely to build up net positions ahead

[32]This restriction removes many trades that stem from opening or closing auctions, for which many trades are carried out at the same price (see e.g., https://www.xetra.com/xetra-en/trading/trading-models/auctionschedule).

[33]As with the net position variable in our main analysis, the €-difference is centered around 0. Thus, it is better to rather use its absolute value to gauge magnitudes.

of UE events with significant absolute returns on exchanges rather than OTC. These results are remarkably consistent with the price protection results, suggesting that relationship banks are aware that they receive less favorable prices or concerned with shrouding their suspicious trades.

6 Further Results and Robustness Tests

Our analysis either used all corporate events (Table 2) or UE events. Other work documents suspicious trading patterns around M&A events (e.g., Augustin et al. (2019)). We therefore provide separate results for relationship trading around M&A related events in Table 12. We find strong evidence for relationship trading prior to positive-return M&A events. The coefficient on all M&A events is about 0.16bps and highly significant (Column 1). The magnitude of this effect increases when considering events for which a firm is a target (Column 3) or a seller (Column 5) and are robust to including Bank x Firm Fixed Effects (Columns 2, 4 and 6). These findings are in line with our previous results as relationship banks are very likely to have access to M&A related information via their loan monitoring. They are also broadly consistent with recent evidence in Bittner et al. (2021) suggesting that German banks share information in their syndicated loan networks around M&A events.

We provide two further robustness tests. First, we transform our data set from the bank×event level to the bank×event×time level. Doing so allows us to benchmark a bank's trading behavior right before an event to that of the same bank over a longer time period prior to the same event. In this analysis, we can introduce bank×event fixed effects, which essentially conditions on banks' trading positions in the given stock prior to the 14-day pre-event period. The results, presented in Table IA.5 are very similar to those in the main analysis. We still find that relationship banks build up positive (negative) net positions in the two weeks prior to positive (negative) unscheduled earnings-related events and then reverse these positions in the following month. Figure 2 visualizes these results.

Second, we analyze option trading as well as banks' trading on behalf of their clients.

A priori, the role options can play is ambiguous: From a risk management perspective, options could be used to hedge or offset equity trading positions and hence it is possible that our equity trading results no longer exist when we account for option trades. On the other hand, a growing literature finds evidence for suspicious positions being built up prior to M&A events, as options allow traders to build up large positions more easily and more cheaply (Lowry et al. (2019), Augustin et al. (2019)). However, in contrast to the US, options exist for less than 20% of our sample stocks and are rather infrequently traded. Thus, we likely have less power to detect suspicious option trades. Consistent with this conjecture, the results are statistically insignificant, but if anything the evidence points in the same direction; relationship banks' option trades ahead of major events are also more profitable (Table IA.6 in Columns 1-2). In Column 3, we combine the net equity position with the net option position (to allow for hedging). The results remain statistically and economically significant, suggesting that options trades are not used to offset equity positions. In Columns 4-6, we analyze banks' equity trades on behalf of their clients. We have no clear prediction for this analysis. It is possible that relationship banks pass on potential information to their clients. They could also use the private information to the disadvantage of their clients (Fecht et al., 2018). Our results do not show any client effects. In Columns 7 and 8, we solely analyze trades classified as market making, which could also be client-initiated. We again do not find any effects showing that our main results are driven by banks' proprietary trading.

7 Conclusion

This paper provides novel evidence that banks engage in profitable proprietary trading ahead of corporate events when they are a firm's main lender. Using extensive micro-level data, we find that relationship banks build up positive (negative) trading positions in the two weeks before events with positive (negative) news, even when these events are unscheduled, and unwind positions shortly after the event. This trading pattern is more pronounced in situations when banks are likely to possess private information about their borrowers, and cannot be explained by banks specializing their lending and trading in certain industries, firms or business models. Our results suggest that banks' lending relationships inform their trading.

These findings underscore the potential for conflicts of interest in universal banking, which have been a prominent concern in the regulatory debate for a long time. They suggest that banks benefit from their privileged access to information beyond their lending business. In light of these results, banks' opposition to the Volcker rule or the proposed Liikanen reform is understandable.

Interestingly, and consistent with the main trading results, we find evidence suggesting that other market participants are aware of the information advantages of relationship banks as well as evidence consistent with the notion that relationship banks shroud their trades to fly below the supervisory radar and to avoid price protection by other market participants.

Finally, our analysis points to one potential pathway for information flows within universal banks, despite the existence of ethical walls to prevent trading with inside information. We find that, aside from direct communication, banks' centralized risk management could be a potential channel through which private information travels within banks. Following the Global Financial Crisis, organizational structures that collect information centrally within banks (i.e., risk management) has been strengthened globally. It is intriguing that precisely these organizational structures could play an important role in explaining banks' informed trading patterns.

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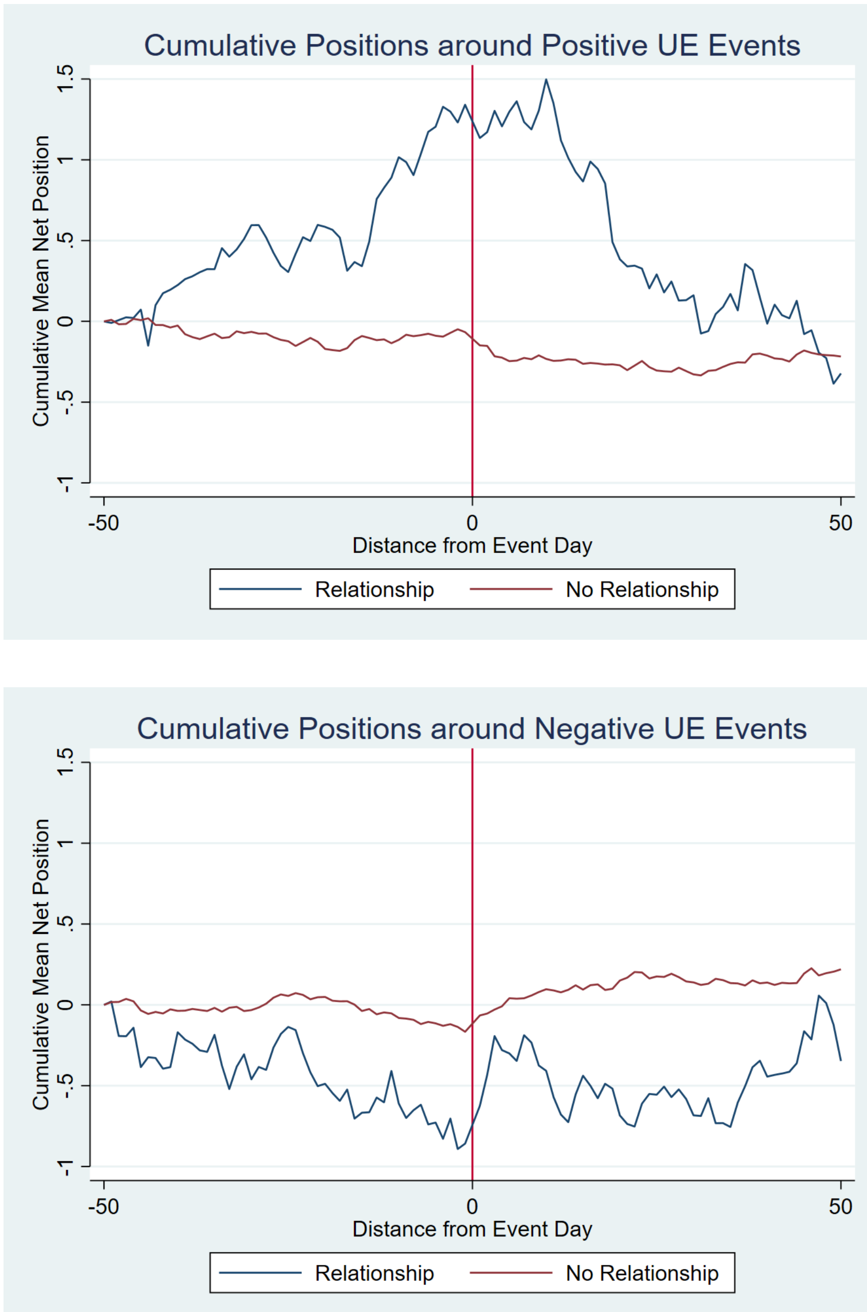
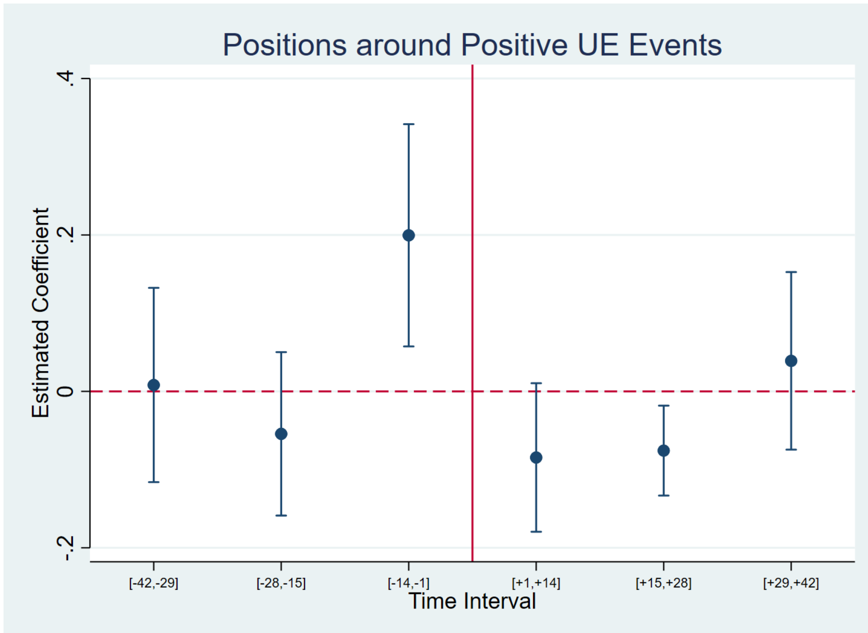
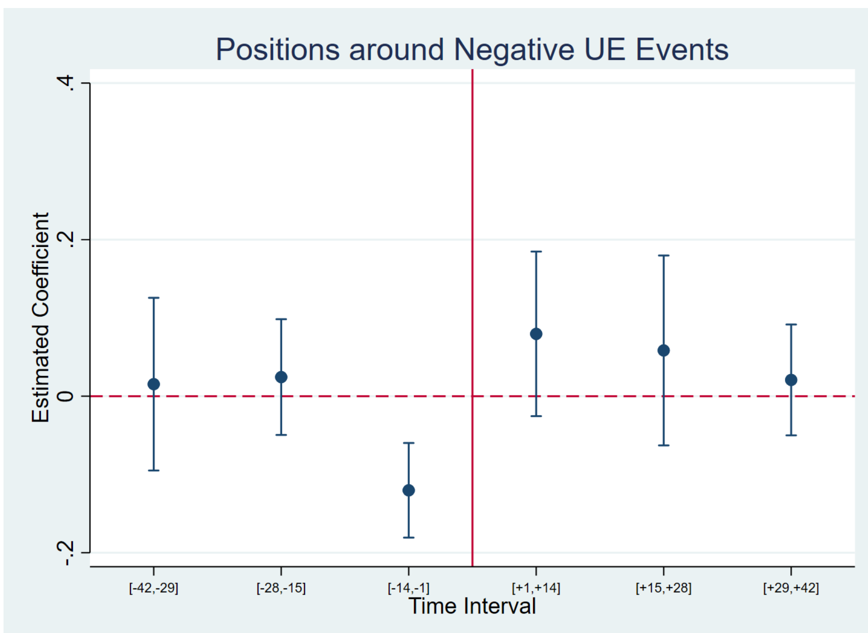
Figure 1: Banks' Cumulative Trading Positions around UE Events



The above figures visualize trading dynamics by relationship banks vs. non-relationship banks around unscheduled earnings-related (UE) events. We first demean all net positions at the bank level and then take the average of these net positions per day separately for relationship and non-relationship observations. The blue and red line plot the cumulative value of these net positions over the [-50,+50] day window for relationship and non-relationship banks, respectively. The vertical line marks the event day.

Figure 2: Relationship Trading - Mapping Out Estimates over Time





The above figures plot abnormal net positions of relationship banks relative to non-relationship banks in different two-week time windows around the event day, relative to the [-84,-43] window (omitted). The sample is restricted to unscheduled earnings-related (UE) events with large absolute returns (>2%). The vertical bands for each coefficient represent 95% confidence intervals, using standard errors adjusted for bank-level clustering. The red vertical line indicates the event day. We report underlying regressions Table IA.5.

Table 1: Descriptive Statistics

Panel A: Corporate Events

Event Category	N	Return Distribution		Relevance Score
		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	3,168	-0.0155	0.0233	62
Unscheduled dividend events	605	-0.0316	0.0226	72
M&A	6,303	-0.0114	0.0181	57
Firm is target	1,749	-0.0123	0.0296	64
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.)	618	2,220	1.02	25.45	93.16	508.58	50,369
Number of shares outst. (m.)	618	63.46	0.05	3.99	9.73	31.81	1,069
Firm is in Prime Standard	618	0.39	0	0	0	1	1
Number of events per firm	618	64.72	1	11	40	92	485
Number of UE-events per firm	618	6.42	0	1	4	10	26

Panel C: Banks - Lending Relationships and Proprietary Trading

	N	Mean	Median	SD
Average loan exposure to sample firms (€m.)	47	1,127	43	2,415
Number of firms for which a bank is Relationship Bank	47	16.21	1	37.87
Number of different sample stocks traded per day	47	50.00	15.07	83.21
Number of prop trades in sample stock per day	47	2,361	149	7,451
Trading volume in sample stocks per day (€m.)	47	49.37	3.41	138.57
Average trade size (€)	47	41,881	23,033	93,012
Average long position (€m.)	33	5.24	0.12	11.61
Average short position (€m.)	28	-4.20	-0.12	18.44
Fraction of events with trading in [-14,-1] window	47	0.19	0.08	0.23

Panel D: Descriptives Statistics at the Trade-Level

	N	Mean	p1	p25	p50	p75	p99
Relationship bank	1,879,718	0.0157	0	0	0	0	1
Loan share if rel. bank	29,575	0.39	0.11	0.23	0.31	0.48	1
Net Position [-14,-1] in bp cond. on trading	355,402	0.0591	-20.15	-0.24	0.00	0.27	25.25
Position [-14,-1] in €m cond. on trading	355,402	1.11	-26.77	-0.08	0.00	0.11	37.61
Profit [-14,-1] in € cond. on trading	355,402	4,511	-379,437	-1,157	0.01	1,206	425,580

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

		P(Correct)
	Expected Prob	50.00%
All events	Non-rel banks	50.00%
	Rel banks	51.32%
UE events	Non-rel banks	50.14%
	Rel banks	53.77%

Panel A provides the frequency of corporate events by event category as well as statistics for the returns of these events. Earnings announcements refer to regular quarterly/half-yearly/yearly earnings reports. Pre-announcements occur when firms announce key financial 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. The *Relevance Score* of an event is computed as the fraction of events in the respective category that exceed firms' above-median *absolute* daily stock returns. To illustrate, if the median absolute daily return of a firm from 2012-2017 is 0.5% and 60% of the firm's EAs have an absolute return greater than 0.5%, the Relevance Score 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 B provides descriptive statistics for the 618 non-financial sample firms (or borrowers) in which sample banks trade. Panel C provides descriptive statistics for the sample banks, their lending relationships and proprietary trading. Panel D provides descriptive statistics for our main dataset, which is at the bank-event level. It consists of 1,879,718 (= 47 banks x 39,994 events) observations. Panel E shows the probability that banks trade in the "right" direction prior to an event, i.e., build up a positive position in the two weeks prior to an event with positive return and vice versa, conditional on trading. We show separate statistics for relationship and non-relationship banks as well as all events vs. unscheduled earnings-related (UE) events. More details on the variable definitions are provided in the Variable Appendix.

Table 2: Relationship Trading

Panel A: Equity Trading Net Positions by Relationship Banks around Corporate Events

Dependent variable:	Net Position [-14,-1]					
	(1)	(2)	(3)	(4)	(5)	(6)
Relationship	0.0278	0.0251	0.0042	-0.0707***	-0.0345	-0.0961**
	(1.00)	(0.86)	(0.25)	(-3.56)	(-0.47)	(-2.05)
Relationship x Pos	0.0331***	0.0343***	0.0318***	0.1982***	0.0326	0.3069***
	(3.51)	(3.53)	(3.23)	(3.77)	(0.27)	(3.55)
Event FE	no	yes	yes	yes	yes	yes
Bank x SIC FE	no	no	yes	yes	yes	yes
Events	All	All	All	UE	UE	UE
Event Return	-	-	-	-	<2%	>2%
Observations	1,439,610	1,439,610	1,439,610	186,308	76,046	110,027
Adj.R^2	0.0001	0.0035	0.0049	0.0054	0.0126	0.0045

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

Dependent variable:	Net Position					
	[-42,-29]	[-28,-15]	[-14,-1]	[+1,+14]	[+15,+28]	[+29,+42]
Relationship	0.0413	0.0222	-0.0961**	0.0700	0.0582	0.0048
	(0.72)	(0.53)	(-2.05)	(1.06)	(0.80)	(0.21)
Relationship x Pos	-0.0111	-0.0722	0.3069***	-0.1837**	-0.1376**	0.0076
	(-0.11)	(-1.03)	(3.55)	(-2.50)	(-2.32)	(0.22)
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	110,027	110,027	110,027	110,027	110,027	110,027

Panel A examines whether relationship banks build up larger net positions 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 with large absolute returns (¿2%) in two-week time windows before and after the events. We estimate and report a separate regression with net positions computed over the respective time window indicated. Variable definitions are provided in the Variable Appendix. We include event fixed effects and bank × 3-digit industry code fixed effects. t-statistics based on 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:	Net Position		€-Position		€-Profit		Return x Direction		Suspicious Trade	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Relationship	-0.1856*	-0.1922	-15,120	44,206	2,720***	3,932***	0.0073***	0.0091***	0.0619***	0.0825***
	(-1.81)	(-1.39)	(-0.33)	(0.56)	(6.58)	(3.93)	(3.64)	(3.43)	(3.15)	(3.61)
Relationship x Pos	0.6202***	0.9169***	158,419***	259,511*						
	(5.22)	(7.09)	(2.76)	(1.83)						
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. Net Position	>0	>0.5bp	>0	>0.5bp	>0	>0.5bp	>0	>0.5bp	>0	>0.5bp
Observations	15,740	7,208	15,740	7,208	15,740	7,208	15,740	7,208	13,300	4,379

This table presents results for alternative dependent variables and estimates for relationship banks' trading profits. The sample is restricted to unscheduled earnings-related events with large absolute returns (>2%). We then further restrict the analysis to non-zero net positions and absolute net positions exceeding 0.5bp, respectively. That is, we present results for two alternative samples for each dependent variable. *Suspicious Trade* is an indicator variable equal to 1 if a bank builds up a positive net position in the two weeks before a positive event and a negative net position in the two weeks after a positive event (and vice versa for negative events). Given this coding of the suspicious trade indicator, we can estimate the relationship trading effect for positive and negative news events in one coefficient. The coding requires that banks trade in the two weeks before and after the respective event. Variable definitions are provided in the Variable Appendix. We include event fixed effects and bank × 3-digit industry fixed effects. T-statistics based on 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: Relationship Trading vs. Bank Specialization

Dependent variable:	Net Position [-14,-1]			
	(1)	(2)	(3)	(4)
Relationship x Pos	0.2728***	0.2712***	0.2733***	0.5353***
	(3.26)	(3.30)	(3.26)	(3.04)
Non-Rel. Periods x Pos		-0.0653		
		(-0.55)		
After-Rel. Periods x Pos			0.0300	
			(0.24)	
Event FE	yes	yes	yes	yes
Bank x Firm FE	yes	yes	yes	-
Bank x Firm x Year FE	no	no	no	yes
Events	UE	UE	UE	UE
Abs. Event Return	>2%	>2%	>2%	>2%
Observations	106,408	106,408	106,408	75,435

This table exploits variation in banks' lending relationships to distinguish between informed trading due lending relationships vs. bank specialization. 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, for which the bank is a relationship bank of the respective firm at some point over the sample period. *After-Rel. Periods* is a binary indicator marking non-relationship periods of a bank-firm pair after the bank was a relationship bank for the respective firm. Other variable definitions are provided in the Variable Appendix. We include event fixed effects and bank × firm fixed effects in Columns (1)-(3). In Column (4), we add bank × firm × year fixed effects. The table focuses on the coefficients for positive events but the coefficients for negative events are included in the model. T-statistics based on 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: Information Flows, Bank Monitoring and New Loans

Dependent variable:	Net Position [-14,-1]					
	(1)	(2)	(3)	(4)	(5)	(6)
RB Loan Share x Pos	0.5646***	0.5629***				
	(4.05)	(3.53)				
Relationship NL x Pos			0.4435**	1.6499**	0.7578***	0.8471***
			(2.07)	(2.02)	(3.33)	(2.87)
Relationship NoNL x Pos			0.2876***	0.2817***	0.2851***	0.2433***
			(3.43)	(3.08)	(3.35)	(2.96)
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
Events	UE	UE	UE	UE	UE	UE
New Loan Threshold	-	-	33%, €2m	33%, €50m	33%, 10pp	33%, 10pp
Abs. Event Return	>2%	>2%	>2%	>2%	>2%	>2%
Observations	110,027	106,408	110,027	110,027	110,027	106,408
p-value of F-test	-	-	0.4444	0.0994*	0.0202**	0.0325**

This table examines relationship banks' trading as a function of loan share and after banks have 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 separately estimate coefficients for events that occur after a relationship bank has granted a new loan in the previous quarter. We define a new loan as an increase in the bank's loan exposure to the firm of at least 33%. Additionally, we require the new loan to exceed €2m, €50m or 10pp of the firm's total loan volume, respectively. Variable definitions are provided in the Variable Appendix. We include event fixed effects and bank $\times$ 3-digit industry fixed effects. In Column (6), we include bank $\times$ firm fixed effects. The table focuses on the coefficients for positive events but the coefficients for negative events are included in the model. The last row reports F-tests comparing the two separate coefficients (NL for new loan vs. NoNL for no new loan). T-statistics based on 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: Trading in "Third-Party" Events

Dependent variable:	Suspicious Trade					
	(1)	(2)	(3)	(4)	(5)	(6)
RB third party trades	0.1988**	0.3063***				
	(2.66)	(2.97)				
Other RB trades			-0.0078	-0.0076	-0.0064	-0.0183
(in unrel. firm)			(-0.59)	(-0.60)	(-0.23)	(-0.58)
Control for other RBs	yes	yes	yes	yes	yes	yes
Event FE	yes	yes	yes	yes	yes	yes
Bank x SIC FE	yes	yes	yes	yes	yes	yes
Events	Third Party	Third Party	All	All	UE	UE
Overlap excluded	no	yes	no	yes	no	yes
Abs. Event Return	>2%	>2%	>2%	>2%	>2%	>2%
Observations	742	533	75,166	50,275	13,288	6,492

This table provides results examining relationship banks' trading around "third-party" and other events in the "unrelated" firms (as described in Section 4.2). In Columns (1) and (2), the sample comprises all bank trades around the third-party events involving sample firms. In Columns (3) and (4), the sample consists of all bank trades around the other events of the unrelated firm identified in the third-party events. In Columns (5) and (6), that sample is further restricted to UE events. In Columns (2), (4) and (6), we exclude events that overlap with other, non-third party corporate events (i.e. events that occur on the same firm-day). Bank trades in the respective samples are coded as suspicious or not and the resulting *Suspicious Trade* indicator is used as a dependent variable. As it is possible that other (relationship) banks trade in third-party events or other events of unrelated firms, we control for these lending relationships with an indicator. Variable definitions are provided in the Variable Appendix. We include event fixed effects and bank $\times$ 3-digit industry code fixed effects. t-statistics based on 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: Role of Risk Management: Internal Risk Ratings

Dependent variable:	Net Position	€-Position	€-Return	Return x Dir.
	(1)	(2)	(3)	(4)
Relationship AIRB	-0.1075	-11,516	1,576***	0.0040***
	(-1.65)	(-0.70)	(6.22)	(6.84)
Relationship FIRB	-0.0251	16,146	214	0.0019
	(-0.51)	(1.24)	(0.62)	(1.42)
Relationship AIRB x Pos	0.4364***	127,452***		
	(8.38)	(3.30)		
Relationship FIRB x Pos	0.0421	-285		
	(0.84)	(-0.01)		
Event FE	yes	yes	yes	yes
Bank x SIC FE	yes	yes	yes	yes
Events	UE	UE	UE	UE
Abs. Event Return	>2%	>2%	>2%	>2%
Observations	110,027	110,027	110,027	110,027

This table examines relationship banks' trading depending on whether a bank employs the "foundation internal-ratings based" approach (FIRB) or the "advanced internal-ratings based" approach (AIRB) to determine a borrower's regulatory capital requirements. We create separate indicators for relationship banks with AIRB and relationship banks with FIRB. The sample is restricted to unscheduled earnings-related events with large absolute returns (>2%). Variable definitions are provided in the Variable Appendix. We include event fixed effects and bank × 3-digit industry fixed effects. T-statistics based on 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: Role of Risk Management: Short vs. Long Positions before Events

Dependent variable:	Net Position [-14,-1]			
	(1)	(2)	(3)	(4)
Relationship x Short	0.4092***	0.5014***	0.2124	0.2303
	(4.37)	(3.13)	(1.59)	(1.43)
Relationship x Long	-0.0450	0.0218	-0.3848**	-0.3009**
	(-0.26)	(0.11)	(-2.34)	(-2.17)
Relationship	0.2247**	0.1974**	0.0075	-0.0554
	(2.12)	(2.61)	(0.08)	(-1.48)
Event FE	yes	yes	yes	yes
Bank x SIC FE	yes	yes	yes	yes
Events	Pos UE	Pos UE	Neg UE	Neg UE
Abs. Event Return	>2%	>2%	>2%	>2%
Only Above-Median	no	yes	no	yes
Observations	56,964	56,964	52,687	52,687

This table examines relationship banks' trading depending on their prior trading positions (long, short, no position) prior to the event month. The sample is restricted to unscheduled earnings-related events with large absolute returns (>2%). *Short* (*Long*) is a binary variable set to one if a bank holds a short (long) position in the firm's equity at the end of the month preceding the respective corporate event. In Columns (2) and (4), we consider only short (long) positions that are below (above) the median short (long) position. Variable definitions are provided in the Variable Appendix. We include event fixed effects and bank × 3-digit industry fixed effects. T-statistics based on 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: Supervisory Radar: Trade Frequency

Dependent variable:	Suspicious Trade			
	(1)	(2)	(3)	(4)
Relationship x ln(Trades)	0.0275***			
	(2.83)			
Relationship x Many Trades		0.1007***	0.1293***	0.1238***
		(2.83)	(2.77)	(2.75)
Control for Net Position 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
Trade-Dummy Threshold	-	P50	P75	P50
Events	UE	UE	UE	UE
Abs. Event Return	>2%	>2%	>2%	>2%
Observations	13,300	13,300	13,300	12,657

This table examines whether relationship banks build up their positions using many small trades (rather than 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. *Many Trades* is an indicator set to one if the number of trades over the [-14,-1] window exceeds a predefined threshold for the number of trades. We control for the size of the respective net position that the bank builds up, interacted with the relationship indicator. Variable definitions are provided in the Variable Appendix. We include event fixed effects and bank × 3-digit industry fixed effects. In Column (4) we include bank × firm fixed effects. T-statistics based on 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: Supervisory Radar: Event Return

Dependent variable:	Net Position [-14,-1]			
	(1)	(2)	(3)	(4)
Relationship	-0.0345	-0.1454***	-0.1511	0.0886
	(-0.47)	(-3.35)	(-1.09)	(0.49)
Relationship x Pos	0.0326	0.3414***	0.4023***	0.0256
	(0.27)	(2.94)	(2.93)	(0.23)
Event FE	yes	yes	yes	yes
Bank x SIC FE	yes	yes	yes	yes
Events	UE	UE	UE	UE
Abs. Event Return	<2%	2-6%	6-10%	>10%
Observations	76,046	71,769	21,150	15,745

This table examines relationship banks' trading around UE events for different event return categories (in absolute terms). Variable definitions are provided in the Variable Appendix. We include event fixed effects and bank $\times$ 3-digit industry fixed effects. T-statistics based on 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: Price Protection in the OTC Markets

Dependent variable:	Price Difference (€)		Price Difference (%)	
	(1)	(2)	(3)	(4)
OTC	0.0106***	-0.0087***	0.0190***	-0.0165***
	(9.47)	(-8.40)	(7.76)	(-7.16)
Control for log trade volume	yes	yes	yes	yes
Trade Direction	buy	sell	buy	sell
Observations	5,623,962	5,589,207	5,623,962	5,589,207

This table examines whether trades by relationship banks face price protection in the OTC markets relative to the exchanges (where trading is anonymous). The data set comprises all trades by relationship banks, keeping one trade per bank, firm and second. For each of these transactions, we determine a benchmark price, which is the price of the last prior transaction that does not involve a relationship bank. The *Price Difference* is the difference between the relationship bank's transaction price and the benchmark price. Columns (1) and (3) are buys and Columns (2) and (4) are sells. We control for the (log) Euro volume of the transaction in all specifications. Variable definitions are provided in the Variable Appendix. T-statistics based on 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 12: Relationship Trading Around M&A Events

Dependent variable:	Net Position [-14,-1]					
	All M&A		M&A Target		M&A Seller	
	(1)	(2)	(3)	(4)	(5)	(6)
Relationship x Pos	0.1564***	0.2343**	0.2324**	0.3016**	0.6269***	0.7927***
	(2.97)	(2.31)	(2.22)	(2.44)	(2.95)	(3.21)
Event FE	yes	yes	yes	yes	yes	yes
Bank x SIC FE	yes	-	yes	-	yes	-
Bank x Firm FE	no	yes	no	yes	no	yes
Overlap excluded	yes	yes	yes	yes	yes	yes
Abs. Event Return	>2%	>2%	>2%	>2%	>2%	>2%
Observations	88,924	83,190	35,720	29,798	11,703	9,118

This table provides results for all M&A events as well as M&A events for which the firm is either a target or the seller. For each event category, we consider only events that do not overlap with other non-M&A event. Variable definitions are provided in the Variable Appendix. We include event fixed effects and bank × 3-digit industry fixed effects or, alternatively, bank × firm fixed effects. The table focuses on the coefficients for positive events but the coefficients for negative events are included in the model. T-statistics based on 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.

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 share of the relationship bank. Calculated as 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.
After-Rel. Periods (Indicator)	Binary indicator marking non-relationship periods of a bank-firm pair, after the bank was relationship bank for the respective firm.
RB third party trades (Indicator)	Set equal to one for firm F2's relationship bank B prior to an event by firm F1 where firm F2 also is mentioned, i.e. where B might possess private information about F1 via F2.
Other RB trades (Indicator)	Set equal to one for firm F2's relationship bank B prior to an event by firm F1 where firm F2 is not involved, i.e., non-third party events.
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% and €2m (in other specifications: €50m, 10pp) from one quarter to the next.
Relationship FIRB and *Relationship AIRB* (Indicators)	Relationship FIRB (Relationship AIRB) is set equal to one when a relationship bank employs the foundation (advanced) internal ratings-based approach for a borrower in a certain quarter. Under FIRB the bank only internally estimates the probability of default (PD), while under AIRB it also estimates the exposure at default (EAD), the loss given default (LGD) and the loan's expected maturity.

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).
Average long position and *Average short position* (€m.)	*Average long (short) position* is the mean of all long (short) positions of a bank across sample firms and months. We only consider holdings in the trading book as banking book holdings are not related to trading purposes. As the Security Holdings Statistics Database uses a different identifier than the trading data, not all banks can be matched. The holdings data is available from 2014 on.
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.
Net Position (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 net positions for other time windows, securities or trading parties in some tests. Winsorized at 1%/99% unless indicated otherwise.
€-Position (€)	$(shares\ purchased\ -\ shares\ sold) \times share\ price$ cumulated over the two weeks prior to an event. Winsorized at 1%/99%.
€-Profit (€)	$(shares\ purchased\ -\ shares\ sold) \times share\ price \times$ *(market-adjusted event return)* cumulated over the two weeks prior to an event. Winsorized at 1%/99%.
Trade in Right Direction (Indicator)	Set equal to 1 if a bank builds up a positive net position 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 net position in the two weeks before a positive event and a negative net position 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 × Direction (Number)	Multiplying the market-adjusted event return and the trade direction (−1,0,+1 for a negative, zero and positive net position, respectively) estimates the incremental return that relationship banks earn around corporate events by trading more frequently in the direction of the event return (Ivashina and Sun (2011)).

Panel B: Trade Variables (Continued)

Variable Name	**Definition**
Short and *Long* (Indicators)	Short (Long) is a binary variable set to one if a bank holds a short (long) position in the event firm's equity at the end of the month preceding the event month. We only consider holdings in the trading book as banking book holdings are not related to trading purposes. As the database uses a different bank identifier than the trading data, not all banks can be matched. The holdings data is available from 2014 on.
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).
OTC (Indicator)	Set equal to one for OTC trades and equal to zero for trades on exchanges.
Price Difference (€)	*Transaction Price - Benchmark Price* using the price of the previous transaction (separately for OTC and exchange trades) between non-relationship banks as benchmark price. Winsorized at 1%/99%.
Price Difference (%)	$\frac{\textit{Transaction Price - Benchmark Price}}{\textit{Transaction Price}}$ using the price of the previous transaction (separately for OTC and exchange trades) between non-relationship banks as benchmark price. Winsorized at 1%/99%.
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.

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.

Internet Appendix to accompany

Know Your Customer: Informed Trading by Banks

(for online publication)

List of Tables in the Internet Appendix

Table IA.1: Prop Trading over Time

Year	Trading Volume (€bn)	# of Trades (m)	Average Trade Size (€)
2012	494	25	19,459
2013	511	28	18,437
2014	552	26	20,911
2015	788	33	23,553
2016	544	29	18,840
2017	636	26	24,431
Sum	3,525	168	20,982

This table shows the total prop trading volume, number of trades and average trade size by sample banks in sample stocks per year. Note that a trade is double-counted when two sample banks prop-trade with each other.

Table IA.2: Relationships and Trading Profits across Banks

Banks	# of Relationships	% of all Relationships	Total Event-Trading Profit (€m; unwinsorized)		
			All Events	Events where Rel. Bank	Rel / All
5 Banks with most Rel.	24,505	83%	595	86	15%
Rest	5,070	17%	318	42	13%
Sum	29,575	100%	913	128	14%

This table shows the number of relationships as well as the total event-trading profit, separately for the 5 banks with the most relationships and the remaining 42 sample banks. The number of relationships is the number of bank x event observations where a bank is considered relationship bank to a firm because it was either the largest lender to a firm or accounted for at least 25% loan volume in the quarter prior to the event. The total event-trading profit is calculated as the sum across all individual event profits, which are calculated as the event return multiplied with the net position a bank built up in the two weeks prior to the event.

Table IA.3: Probability of Trading in the Right Direction

Dependent variable:	Trade in Right Direction					
	(1)	(2)	(3)	(4)	(5)	(6)
Relationship	0.0131***	0.0131***	0.0073	0.0503**	0.0031	0.0923***
	(3.20)	(3.31)	(1.55)	(2.28)	(0.11)	(4.15)
Event FE	no	yes	yes	yes	yes	yes
Bank x SIC FE	no	no	yes	yes	yes	yes
Events	All	All	All	UE	UE	UE
Event Return	-	-	-	-	<2%	>2%
Observations	272,859	270,881	270,714	28,377	12,419	15,740

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 and refers to pre-announcements, stand-alone forecasts and unscheduled dividend events. Variable definitions are provided in the Variable Appendix. We include event fixed effects and bank $\times$ 3-digit industry code fixed effects. t-statistics based on 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 IA.4: Mapping out Bank Trading around Corporate Events

Dependent variable:	Net Position					
	[-42,-29]	[-28,-15]	[-14,-1]	[+1,+14]	[+15,+28]	[+29,+42]
Relationship	0.0303	0.0018	-0.0074	0.0857*	0.0307	-0.0132
	(1.20)	(0.15)	(-0.58)	(1.75)	(1.40)	(-0.70)
Relationship x Pos	-0.0164	-0.0074	0.0557***	-0.0954**	-0.0416**	0.0352
	(-1.00)	(-0.44)	(4.58)	(-2.08)	(-2.14)	(1.44)
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	635,205	635,205	635,205	635,205	635,205	635,205

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 net positions 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. Variable definitions are provided in the Variable Appendix. We include event fixed effects and bank $\times$ 3-digit industry code fixed effects. t-statistics based on 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 IA.5: Panel Analysis at the Bank x Event x Time Level

Dependent variable:	Net Position			
	(1)	(2)	(3)	(4)
Relationship x [-28,-15]	0.0206	0.0243	0.0021	-0.0294
	(0.51)	(0.31)	(0.02)	(-0.41)
Relationship x [-14,-1]	-0.1241***	-0.2900***	-0.5065***	-0.1876**
	(3.85)	(-4.61)	(-4.07)	(-2.08)
Relationship x [+1,+14]	0.0758	0.0641	0.0649	0.0252
	(1.31)	(0.53)	(0.35)	(0.28)
Relationship x [+15,+28]	0.0546	0.0982	0.1988	0.1768
	(0.96)	(0.78)	(0.86)	(1.46)
Relationship x Pos x [-28,-15]	-0.0769	-0.1454	-0.1743	-0.1115
	(-0.93)	(-0.87)	(-0.72)	(-1.05)
Relationship x Pos x [-14,-1]	0.3216***	0.7056***	1.3224***	0.5733***
	(3.31)	(4.42)	(5.55)	(3.41)
Relationship x Pos x [+1,+14]	-0.1623**	-0.2431	-0.2804	-0.1571
	(-2.16)	(-1.50)	(-1.18)	(-0.97)
Relationship x Pos x [+15,+28]	-0.1324***	-0.3236***	-0.5522***	-0.3973***
	(-3.05)	(-3.90)	(-4.25)	(-4.27)
Bank x Event FE	yes	yes	yes	yes
Events	UE	UE	UE	UE
Abs. Net Position	-	>0	>0.5	>0 in [-84,-70]
Abs. Event Return	>2%	>2%	>2%	>2%
Observations	881,344	121,286	56,475	121,504

This table presents results from panel regressions using eight two-week windows around corporate events (i.e., [-84,-71], [-70,-57],.., [+15,+28]). We compute a net position for each bank and event. 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 net positions 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 net positions. In Column (4), we impose the trading condition long before the event, i.e., in the [-84,-71] window. Variable definitions are provided in the Variable Appendix. We include bank × event fixed effects in all specifications. t-statistics based on 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 IA.6: Options Trading and Client Trading

Dependent variable:	Net Position [-14,-1]							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Relationship x Pos	0.0025	0.0936	0.2759***	0.0400	0.0011	0.2948**	0.0208	0.1411
	(0.57)	(0.64)	(3.33)	(1.10)	(0.02)	(2.10)	(0.70)	(0.92)
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. Net Position	-	>0	-	-	>0	-	-	>0
Abs. Event Return	>2%	>2%	>2%	>2%	>2%	>2%	>2%	>2%
Observations	110,027	169	110,027	110,027	36,594	110,027	110,027	14,294

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 net positions for equity options. Column (2) conditions on trading by restricting the sample to observations from banks with non-zero net positions. In Column (3), we combine banks' positions in the stock and the options market when computing net positions. Column (4) shows the results when using client trades to compute net positions (instead of prop trades). Column (5) again conditions on trading. In Column (6), we compute banks' prop trading net positions relative to their client net positions (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. Variable definitions are provided in the Variable Appendix. We include event fixed effects and bank $\times$ 3-digit industry code fixed effects. The table focuses on the coefficients for positive events but the coefficients for negative events are included in the model. t-statistics based on 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 IA.7: Positions Built up with Exchange Trades vs OTC Trades

Dependent variable:	Net Position [-14,-1]					
	(1)	(2)	(3)	(4)	(5)	(6)
Relationship x ExchgIntens	0.6876**			0.3663		
	(2.17)			(1.15)		
Relationship x MostlyExchg		0.4117***	1.0298***		-0.0383	-0.3954
		(3.61)	(3.91)		(-0.12)	(-0.57)
Bank x SIC FE	yes	yes	yes	yes	yes	yes
Event FE	yes	yes	yes	yes	yes	yes
Abs. Event Return	>2%	>2%	>2%	>2%	>2%	>2%
Abs. Net Position	>0	>0	>0.5	>0	>0	>0.5
Events	Pos	Pos	Pos	Neg	Neg	Neg
N	7,794	7,794	3,439	7,689	7,689	3,545

This table examines whether profitable positions are built up mainly with exchange trades vs OTC trades. *ExchgIntens* measures the Exchange Intensity of each net position. If e.g. a net position consists of two trades, one OTC trade with volume 5 and one exchange trade with volume 20, *ExchgIntens* would be equal to 20/(20+5)=80% (independent of whether the trades are buys or sells). *MostlyExchg* is a dummy that is equal to one for net positions with above-median *ExchgIntens*. Note that this test design makes it necessary to condition on trade, as for 0-net positions (containing no trades) *ExchgIntens* cannot be calculated. Columns (1)-(3) only consider events with positive abnormal return, Columns (4)-(6) only those with negative abnormal return. Variable definitions are provided in the Variable Appendix. We include event fixed effects and bank $\times$ 3-digit industry code fixed effects. t-statistics based on 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.

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