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 when banks are likely to possess private information about their borrowers and cannot be explained by specialized expertise in certain industries or firms. The results suggest that banks' lending relationships inform their trading and underscore the potential for conflicts of interest in universal banking - a prominent concern in the regulatory debate for a long time. Our analysis also illustrates how combining large data sets can enhance the supervision of markets and financial institutions.

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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 separating 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 their use of private client information in trading. One simple reason is that banks' 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 among other things 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 requiring borrowers to inform their lenders regularly about material changes to their business. The question is 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 from 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 executed on any domestic or foreign exchange or in the OTC markets. 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 these challenges, our analysis differentiates between widely anticipated or scheduled events (e.g., earnings announcements) and unscheduled events that are 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 still be present when the lending relationship has ended and the source of private information is gone. In addition, we identify events that involve a bank client and another firm, for which the bank could have obtained private information via its borrower, and then analyze trading in the *other* firm that is not a client but involved in the event.

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 using 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] According to the German Bank Separation Act, 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. Although the organizational requirements of the Bank Separation Act prohibit cross-subsidies between lending and trading entities within a universal bank, its governance and supervisory activities, such as risk management, must be organized centrally. Thus, the effectiveness of banks' organizational structures is an important regulatory question.

To motivate our findings, Figure 1 shows the performance of banks' relationship portfolio vs their non-relationship portfolio, with the relationship portfolio consisting of those stocks that banks are largest lender or a lender that accounts for at least 25% of the firm's loans. The figure suggests that the relationship portfolio outperforms the non-relationship portfolio significantly, with a differential of about 22pp after 4 years. This translates into a yearly profit on the relationship portfolio of about 6%, whereas the yearly profit on the non-relationship portfolio only amounts to about 1%. [4] Our results indicate that banks' trading in their borrowers' stocks is informed. We first examine whether relationship banks (defined as the largest lender or a lender that accounts for at least 25% of the firm's loans) trade more profitably than other non-relationship banks two weeks prior to a corporate event. In order

[2]The MAR (in §7) defines inside information as information that has not been made public, relates to a specific financial instrument, and would significantly impact the price of the security if revealed. The definition of an insider is at least as broad in concept as it is under U.S. insider trading rules. However, the latter have traditionally been enforced more stringently (Ventoruzzo (2015)).

[3]For this reason, we combine both categories and differentiate them from bank trades on behalf of clients. Our results are not driven by this design 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 54% (16%) of all trading volume. The remainder is classified as client trades.

[4]We find comparable numbers to those reported in this descriptive figure in a regression setting.

to do so, we follow Griffin et al. (2012) and focus on net trading positions or the direction of trade relative to the event news. As the news and return of a given event are the same for all banks, the number of shares bought or sold ahead of the event determines a bank's event profit. Our specifications include fixed effects for each corporate event and to control for 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 purchases for relationship banks ahead of negative news events, although the results tend to be weaker. The latter is 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.[5]

Our results become much more pronounced when we focus on unscheduled events, such as pre-announcements, earnings guidance, or special dividend events. We find that relationship banks carry out significantly larger net purchases before unscheduled, positive and negative news events (0.20bp and -0.07bp of 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 absolute returns (above 2% market-adjusted). Mapping out trading around these unscheduled events confirms that relationship banks start building up their positions before the event and then reverse them in the weeks after.

We winsorize net purchases to ensure that our results do not reflect a few extreme cases but describe systematic trading patterns.[6] Similarly, we focus on the direction of trade, which is not prone to outliers, and show that relationship banks trade more profitably by more frequently having net purchases in the same direction as the event news. Moreover, evaluating trades in aggregate, we find that "relationship trading" contributes 14% of banks' total event-trading profits, even though such events account for only 1% of all bank-event

[5] 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)).

[6] Without winsorizing, relationship banks exhibit roughly twice as many event profits exceeding one million € for a single event.

combinations. As the German banking market is fairly concentrated, as the U.S. and other markets, we check that our results are robust to excluding any of the largest 5 banks.

One way to gauge the role of expertise in trading is to compare how often all banks trade in the "right" direction around an event relative to random trading. Suppose positive and negative news (or abnormal returns) for corporate events are equally distributed and banks trade around events by flipping a coin, i.e., without expertise or private information. In this case, there is a 25% chance that a bank trades in the right direction before and after the event. We find that, for all banks in our sample, the likelihood of trading in the right direction around events is 25.7%. 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 increases to 8.3pp when we restrict the analysis to net purchases above 0.5bp, suggesting that the private information flow from lending is economically material.

Next, we conduct four sets of tests that shed light on the mechanism for our findings and simultaneously rule out bank expertise or specialization as an explanation for our results. First, we introduce bank×firm fixed effects because bank expertise could be 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 precisely 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 build profitable positions around corporate events *only* when they concurrently have lending relationships. Even more tellingly, relationship banks' trading during "non-relationship periods" and especially after a relationship ends does not look different from that of non-relationship banks.

Second, we test whether the results for relationship banks are more pronounced in situations where banks likely receive new information from their borrowers. For instance, banks obtain detailed information when granting a new loan. We find that relationship banks carry out larger net purchases prior to unscheduled events of borrowers who were 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).[7] We find a higher likelihood of "suspicious" trading, defined as trading in the "right" direction around the M&A event, particularly when the relationship bank's client is a seller or a target and when the transaction is canceled. Thus, for new loans and M&A transactions, it seems that client information finds its way within the bank to the trading desk.

Third, we identify corporate events (e.g., legal disputes or joint ventures) 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 trading in the right direction is about 20pp higher for relationship banks. However, relationship banks do not exhibit such suspicious trade patterns around other events of the same unrelated firms that do not involve their borrowers, suggesting that banks do not have general trading expertise in these unrelated firms.

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 from lending or trading. Therefore, the risk management function is centralized, which in turn 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, risk management knows when the trading desk has a large exposure (e.g., a 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 from our

[7] 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.

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 trades. If the documented trading behavior skirts or even violates the rules, we expect banks to shroud their informed trading to avoid supervisory scrutiny. In particular, very large news events or trades are expected to hit the supervisory radar.[8] Consistent with this argument, we find that the informed trading results vanish for events with absolute returns greater than 10%, which surely would attract supervisory attention. Moreover, we find that relationship banks build profitable positions around corporate events using many small trades, rather than a few large ones. We continue to see this pattern with bank×firm fixed effects, which implies that banks change their trading strategy for a given stock *once* they enter (or end) the relationship. We also 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. Related to shrouding of trades, relationship banks respond by building their suspicious positions more often 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. They resulted in the imposition of the Volcker

[8] DeMarzo et al. (1998) argue that supervisors maximize investor welfare by focusing on significant 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%.

Rule, which bans proprietary trading by U.S. banks.

Against this backdrop, we provide evidence from a universal banking system that still allows proprietary trading and relies on organizational structures to address conflicts of interest. Germany provides a powerful setting to study these issues because German firms traditionally maintain strong ties with their main lenders or *Hausbanken* (Allen and Gale (1995)). Our informed trading results raise questions about the effectiveness of banks' organizational structures (or walls) in managing conflicts arising from private lending information. In addition, these results point out that centralized structures created to mitigate bank risks could be a source of "wall-crossing," highlighting that financial stability rules can pose challenges for market conduct regulation.

Second, we contribute to the literature on 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 within 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, pension funds) that participate in loan syndication 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 amendments when they are loan syndicate participants.[9] 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 using 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

[9] 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.

(Minnis and Sutherland (2017)). However, evidence that banks trade profitably on this information tends to be indirect, in that it is inferred from market-level outcomes, such as return or price discovery patterns 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)). The reason is that trading data can typically be constructed only for non-bank institutional participants in loan syndicates using holdings data in quarterly 13F filings. We, in turn, combine credit registry data with trade-level supervisory data to study banks' proprietary trading and can 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 complex algorithms make lending decisions. 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 to clients. 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.[10]

2 Institutional Setting

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

The potential conflict of interest that arises when universal banks obtain confidential information about their borrowers and, at the same time, trade securities of these borrowers

[10] The Consolidated Audit Trail, initiated by the SEC and fully implemented in December 2021, constitutes a data set that allows for the application of such methods, as it enables regulators to track all order and trading activity in U.S. markets for listed equities and options (https://www.catnmsplan.com/).

in the capital markets has featured prominently in the regulatory debate. Concerns about this and related conflicts were central in separating 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 the EU. However, as in the U.S., banks' security trading activities were heavily debated in Europe after the financial crisis of 2008. Consequently, EU Internal Markets Commissioner Michel Barnier set up an expert group (known as the "Liikanen Group") to develop structural reforms of the EU banking system to strengthen financial stability. The recommendations of this expert group, the so-called Liikanen report, proposed, among other things, separating commercial and retail banking activities from certain investment banking activities (Liikanen et al. (2012)). Another key element of this proposal was a ban on proprietary trading and market-making for universal banks. The EU tried to institute this ban, but the proposal failed due to widely diverging positions across EU member states on this matter.[11]

As the Liikanen recommendations were not implemented at the EU level, Germany unilaterally proposed a law governing banks' trading activities, the so-called Bank Separation Act. This proposal passed and became effective on July 1, 2015, although banks had until July 1, 2016 to comply with the new law. The German Bank Separation Act imposes organizational requirements on banks in case their prop trading exceeds certain thresholds.[12] Banks above the thresholds are not prohibited from trading but have to direct these activities to a legally, organizationally, and financially separate subsidiary.[13] Nevertheless, banks' governance and supervisory activities, such as risk management, must be organized at a central

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

[12] The law applies if a bank's trading activities in a given year exceed €100bn or sum to more than 20% of its total assets and amount to at least €90bn in the preceding three years.

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

level. 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. 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, in our sample, proprietary trading volume in 2016 and 2017 is only slightly lower than before the reform in 2015 but still *higher* than in 2012 and 2013.[14]

Germany, like most countries, has legal restrictions on insider trading. The relevant regulations are set by the EU and broadly similar to those in the U.S.[15] Insider trading is regulated under the Market Abuse Directive (MAD) and the Market Abuse Regulation (MAR). MAR Art. 7 defines inside information as information that has not been made public and that would significantly affect the price of a security, if revealed. Once such information emerges inside a firm with publicly traded securities, trading on this information is forbidden (MAR Art. 14). Furthermore, firms must disclose inside information that affects them directly as soon as possible (MAR Art. 17).

In Art. 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 (or "ethical walls") to ensure that its traders do not have access to inside information that is present in the bank. Further, financial institutions may conduct security transactions in the normal course of market-making even in the presence of inside information. Finally, banks can discharge obligations incurred before the inside information was obtained and can also proceed with facilitating a takeover after they gain access to inside information. These exceptions give rise to a grey zone for bank trading and the use of information from banks' lending activities.

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

[15] However, the U.S. has regulated insider trading for considerably longer than the EU. The SEC has a much longer enforcement record (e.g., Bhattacharya and Daouk (2002)), whereas the effectiveness of EU enforcement has been questioned (Ventoruzzo (2015)).

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 license (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 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, exchange code or an indicator for OTC trades, and 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 book, we combine these two trade types under proprietary trading.[16] By doing so, we do not rely on banks' discretionary trade classifications as market-making or proprietary trading. We aggregate all 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.[17]

All trades are expressed in euros (EUR). Trades in foreign currency are converted into EUR using daily exchange rates. We mostly analyze 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, options could be important for banks' risk management or hedging when they exist. We, therefore, include options in our sensitivity analyses, but do not find any evidence for them offsetting or even amplifying the effects reported for equity[18]

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) must 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).[19] We aggregate all loans to a given firm 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.

[16]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 similar results. See Section 6 and Table IA.8 for more details.

[17]Our sample includes three cases for which banks belonging to the same banking group have separate BaFin identifiers for part of the sample period. The results remain unchanged when we manually aggregate these cases and net trades by banking group.

[18]See Table IA.8. Another reason to consider option trades is evidence that they are used for informed trading prior to takeovers (Augustin et al. (2019)).

[19]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; in that sense, they work against us.

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[20]. 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, and 6,303 M&A events. M&A events cover not only days when deals are consummated but also announcements of intended or future deals and rumors about potential transactions, which is why the category contains many events. We separately flag when the focal firm is the target of a M&A transaction or takeover. The remaining categories are board and executive, capital structure and financing, operating, legal and bankruptcy events. They contribute 12,231 corporate events. Operating events are quite frequent (6,361) and comprise a broad set of firm news, including product announcements, capacity expansions, strategic alliances, but many are of lesser importance, resulting in smaller returns. In all categories, the majority of the events exhibit (absolute) abnormal returns exceeding the firm-specific median of daily market-adjusted returns over the sample period, indicating that most events in our database constitute material news for investors.

Next, we subdivide earnings events into earnings announcements (EAs), pre-announcements (prior to the regular EA), and other financial reporting events (e.g., reports of monthly revenues for a specific segment or country). Among the earnings events, pre-announcements

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

have the largest returns and the highest fraction of event returns exceeding the median daily abnormal return (Table 1, Panel A), as firms usually pre-announce their earnings only if they have material news for investors (Skinner (1994)). Compared to EAs and pre-announcements, the other financial reporting events have relatively small returns. We distinguish between management guidance (e.g., earnings or sales forecasts) 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.

An important distinction for our analysis is whether events are scheduled or announced in advance. We expect sophisticated investors to collect information, perform analyses and trade ahead of announced 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 treat dividend increases as scheduled events because some firms maintain schedules that increase their dividends steadily.

Unscheduled earnings-related events have several attractive features for our analysis. First, it is not clear that market participants (can) anticipate information to be released that day. This makes it more difficult to build positions ahead of unscheduled events consistently. Thus, successful trading around unscheduled events is more indicative of private information. Moreover, unscheduled events rarely overlap with other events on the same day. 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, define successful trading, and attribute the news to particular event categories. Consistent with the argument that unscheduled earnings-related events come as a surprise to investors, Figure IA.1 shows sharp reactions and no drift in returns ahead of the events. The same is true for M&A events, which we also analyze separately. These finding suggest little information leakage to the market in general.

3.3 Sample and Description of Bank Prop Trading

To construct the sample, we identify all non-financial firms that are based and listed in Germany between 2012 and 2017, which is the period for which we have bank trading data.[21] We drop firms for which we do not have any corporate events.[22] The resulting sample comprises 618 firms and constitutes the vast majority of publicly traded German stocks.

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), less news coverage or fewer newsworthy events.

To enter the sample, banks must 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 banks with trading desks that frequently engage in prop trading, reducing heterogeneity across banks. The sample comprises 47 German and foreign banks with a German banking license.[23] We define a lender as a relationship bank (in German called "Hausbank") if it is either a firm's largest lender or accounts for at least 25% of the firm's loan share in the quarter prior to the respective firm having an event.[24] It is therefore possible (but not

[21]We identify these firms by ISIN. Financial firms are identified by Bundesbank industry codes starting with 64, 65, 66, and 84 (except for 64G, which comprises non-bank financial service companies).

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

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

[24]We do not code a bank as relationship bank for a given firm if i) the bank's lending volume is below €2m or ii) the lending volume in one quarter is at least 50% larger than in the two adjacent ones. These large fluctuations indicate the firm likely maintains a current account at the bank but not necessarily a longer-term loan relationship. The first restriction prevents variation in the relationship variable arising because the outstanding loan balance fluctuates around the reporting threshold (€1.5m until 2015 and €1m after 2015). The two restrictions do not alter our results. We further report our baseline results with alternative definitions of the relationship regressor in Table IA.2. Even with a loan threshold of above 0%, i.e. when considering any lender a relationship lender, the results go in the right direction, only in lower magnitude.

common) that a corporate borrower has more than one relationship bank. In our sample, 28 out of 47 banks are assigned to at least one firm as relationship bank. Seven banks make (smaller) loans to sample firms but are never coded as a relationship bank according to our definition and twelve banks do not make loans to sample firms, i.e., they trade only and are therefore always in the control group.[25] The 28 relationship banks comprise all large German universal banks as well as several smaller banks.

As in the U.S. and many other countries, the German banking market has a few very large banks (World Bank, 2023). The top-5 banks account for the vast majority (83%) of the relationships (Table IA.3). Therefore, relationship trading is quite concentrated in our sample. However, no single bank accounts for more than a quarter of the relationship trading, and our results are robust to excluding any of the largest 5 banks.

Panel C of Table 1 provides descriptive information on banks' lending relationships and proprietary trading based on average per-firm long position over the entire period. Sample banks have, on average, a quarterly loan exposure of about €1.1bn against all sample firms and serve as relationship bank to 16 sample firms. However, both of these averages are highly skewed. The median bank has only one corporate borrower and a loan exposure of €43m. The same is true for trading activities; most EUR 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.

We construct the data set at the bank-event level to analyze banks' prop trading around corporate events. As the respective event return is the same for all bank-event pairs, we focus on the number of shares banks trade ahead of the events. Following Griffin et al. (2012), we

As many bank x firm observations comprise tiny amounts referring to e.g. current accounts, this minimum threshold adds much noise. Each of the higher thresholds reported in the table leads to results comparable or stronger to our baselines.

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

accumulate trades to determine the net trading position for each of the 47 sample banks two weeks before the 39,994 corporate events. 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, net purchases 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 (bp) 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 before an event, we ensure that a bank already has a lending relationship by the time of the event and hence it is conceivable that the bank possesses private information from this 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%. Conditional on trading ahead of an event, the median positive (negative) value of net purchases amounts to 0.27bp (-0.24bp) of all outstanding shares. Thus, banks' net purchases are sizeable but small relative to firms' market capitalizations. The unsigned median value of net purchases is zero as only 19% of the events exhibit prop trading by a bank in the two weeks prior to an event. Furthermore, the distribution of net purchases exhibits very large observations on either end (which is why we winsorized net purchases at the p1 and the p99). We can also compare the size of banks' net purchases carried out in the two weeks prior to an event relative to their holdings of the same firm in the previous month. We find that in about one third of the cases, the net purchases carried out before an event exceed the size of the banks' holdings in the prior month. Moreover, we observe that, in a quarter of the cases, banks that carried out net purchases ahead of the event did not have any holdings of the stock in the previous month.

4 Research Design

This section describes our empirical strategy to assess whether relationship banks' trading in borrower stocks is informed. Banks are required under German law to obtain financial information before making a loan (KWG §18). After that, banks regularly request information to monitor outstanding loans (Minnis and Sutherland (2017)). Moreover, corporate debt contracts commonly include clauses requiring borrowers to inform their lenders about material changes to their business. Thus, relationship banks obtain private information about their borrowers before 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 information is revealed to the market.

Importantly, there could be other reasons why banks have profitable trading positions ahead of specific corporate events. An alternative explanation is that banks have expertise because they specialize their lending and trading in specific 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 Net Purchases around Corporate Events

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

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

where $NetPurchases_{be}$ 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 net purchases means that a bank carried out net purchases 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 an event have net purchases of zero. However, for many analyses, we impose further restrictions on the sample, requiring that banks have traded before an event, carried out certain minimum net purchases or that the event has a certain minimum *absolute* abnormal return.

The indicator variable $Relationship_{be}$ is equal to one if bank b is a relationship bank (as defined above) 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).

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. Taking advantage of negative information is typically harder for traders because it 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 purchases for relationship banks in the two weeks before negative-return events relative to the average net purchases of non-relationship banks. The latter estimates the same incremental net purchases for positive-return events.

The model includes a rich set of fixed effects. We include fixed effects for each corporate event, γ_e, to control for the event return and any event-specific characteristics, such as differences in the extent to which all market participants can anticipate an event and its return. We add bank × 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. The latter accounts for expertise differences across banks (e.g., their ability to forecast earnings or events) that could come from banks' prop trading desks and research teams specializing in specific industries. 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 expertise takes time and does not disappear immediately when a lending relationship ends. However, firms stop reporting private information to their relationship banks once a lending relationship ends. Thus, if bank specialization is the (joint) source of a bank's superior trading in a particular stock (and its loan to the firm), such bank expertise should not precisely 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 existence of the relationship itself. To exploit this difference, we estimate the following specification:

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

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 net purchases around positive-return corporate events of the *same* firm when the bank is a relationship lender with times when the bank is not a relationship lender.[26] 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 (when expertise should still be there). In addition, we estimate a model

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

in which we add time-varying bank-firm fixed effects, i.e., bank $\times$ firm $\times$ year, to absorb bank or borrower specific shocks.

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 loan contracts typically stipulate certain information items that borrowers have to furnish. We have reviewed a small sample of contracts by major German banks and confirm that they require financial information and 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. Exploiting these institutional features, we separately analyze bank trading in the quarter after which a new loan has been granted.

Our third test focuses on corporate events that involve two firms (e.g., legal disputes, joint ventures, or mergers), for which information flows and expertise should be more separable. We identify situations in which a bank has a relationship with one of the firms but not with the other, which we call a third party. We then analyze the relationship bank's trading in the *unrelated* firm around the joint corporate event and 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.[27] An example for such a third-party event is the following scenario: Firm F1 plans to take over Firm F2. Bank B has no relationship with Firm F1 but is the relationship bank for Firm F2. As a relationship bank, B is likely informed about the impending M&A transaction by its borrower F2. We examine B's trading behavior in the unrelated firm (F1) around the joint corporate event relative to all other banks that trade around this event. We also analyze the trading patterns of B

[27] 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.

around *other* corporate events of F1 that do not involve F2. The latter serves as a benchmark indicating whether B more generally has expertise in trading F1. In essence, we compare trades in the same firm for the same bank around events when information from its lending relationship with another firm is likely relevant and when it is not.

5 Empirical Results

5.1 Relationship Banks' Trading around Corporate Events

Table 2, Panel A, presents the results estimating specification (1). We first analyze all corporate events (Columns 1-3). We find that relationship banks carry out significantly larger net purchases in the [-14,-1]-day window ahead of events with positive market-adjusted returns. Net purchases of relationship banks are about 0.033bp larger than those of non-relationship banks (Column 1). This effect remains roughly the same when we control for event-specific differences (Column 2) and 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. An association for these unscheduled events is more likely to reflect informed trading than expertise. As discussed in Section 3.2, we focus on unscheduled earnings-related (UE) events, comprising pre-announcements, management forecasts, and unscheduled dividend events. In Column 4, we find that the results for UE events are considerably stronger. The estimated incremental net purchases 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 purchases of relationship banks are equal to 0.07bp. As discussed earlier, we expect that the effects are smaller in magnitude for negative news.

Some unscheduled events might not be a major surprise to the market or be anticipated by sophisticated investors. In this case, we expect event returns to be smaller. We therefore split UE events by their absolute return to analyze whether the results are more (or less) pronounced when UE events are more surprising or reveal more news to the market. The findings across Columns 5–6 show a stark difference. Net purchases of relationship banks are not statistically different when the absolute event return is small and below 2%. But for UE events with an absolute return 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 surprise 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.[28] To do so, we compare the net purchases of relationship and non-relationship banks for different two-week time windows. We find that relationship banks build profitable positions shortly before positive UE events and reverse them in the month afterward. However, as we zoom out, relationship banks trade comparably to non-relationship banks, i.e., they do not carry out significantly different net purchases 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 carry out net sales relative to 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 prior to the event is entirely reversed within one month after the event. After that, in the [+29,+42] window, trading differences between relationship banks and non-relationship banks vanish. Panel B exhibits a similar but less pronounced pattern for negative news events. To graphically illustrate banks' trading patterns over time, we plot the cumulative mean net purchases around positive and negative UE events in Figure 2. The trading patterns look very differ-

[28] Although Panel B focuses on UE events, we find comparable patterns for all corporate events, as shown in Table IA.5.

ent for relationship and non-relationship banks. For non-relationship banks, we only observe relatively small changes in the net purchases ahead and after UE events. The trading patterns for relationship banks look considerably different. We observe substantial increases (decreases) of net purchases *prior* to a positive (negative) UE event and subsequent reversals. Our analysis encompassed all corporate events (Table 2) and specifically focused on UE events. Notably, previous research has highlighted suspicious trading patterns surrounding M&A events (e.g., Augustin et al. (2019)). In response to this, we present our findings on relationship trading around M&A-related events in Table IA.6. Significant evidence emerges for relationship trading preceding positive-return M&A events. The coefficient for all M&A events stands at approximately 0.16 bps and exhibits high significance (Column 1). Notably, this effect intensifies when examining events where a firm is a target (Column 3) or a seller (Column 5). Importantly, these results remain robust even with the inclusion of Bank x Firm Fixed Effects (Columns 2, 4, and 6). These outcomes align with our prior findings, indicating that relationship banks, likely through loan monitoring, possess access to M&A-related information.[29]

5.2 Discussion of the Economic Magnitude

It is difficult to derive meaningful magnitudes of banks' profits from relationship trading from our previous analysis for the following reasons. Since we focused on incremental profits around unscheduled events, profits from earlier purchases or on the entire position in the stock of relationship firms are excluded. Moreover, previous analysis captures only short-term profits (essentially the event return) rather than the potential gains from holding relationship stocks over longer periods and rents from soft private information unrelated to specific corporate events. Further, banks are unlikely to be privately informed about each and every event that we include in our analysis. Thus, the estimated event profit is an average over events for which the bank was informed and those for which the bank had no

[29] Furthermore, our results are consistent with recent research by Bittner et al. (2021), which suggests that German banks exchange information within their syndicated loan networks concerning M&A events.

private information (and hence on average earns zero profits). In this sense, focusing on the average profit is misleading.

First, we construct a simple indicator of whether a bank traded in the right direction in the two weeks before an UE event. Table 3, Column (1) suggest that relationship banks' incremental probability of trading in the right direction amounts to 9.23pp. Given that the estimate on the constant suggests that non-relationship banks' probability of trading in the right direction amounts to 49.43% (which suggests that they trade worse better than when randomly buying or selling), the increment for relationship banks is economically sizeable.[30]

We refine this measure by constructing an indicator of whether a bank traded in the right direction in the two weeks before *and* after an UE event. We refer to such cases as "suspicious trades." The advantage of this variable is that it allows us to jointly analyze positive and negative events. Moreover, it is not prone to outliers or skewness in banks' net purchases and should give us a sense for how pervasive successful trading by relationship banks is. Suppose banks traded randomly around corporate events by flipping a coin. Conditional on trading before and after the event, and considering that abnormal event returns are roughly centered around zero, suspicious trades would occur with 25% probability by chance. In contrast, when we compare the (relative) frequency of suspicious trades across relationship and non-relationship banks, we find that relationship banks exhibit an incremental probability of suspicious trading of 6.19pp (Table 3, Column (2)), whereas the probability for such suspicious trading for non-relationship banks only amounts to 25.66%. Thus, the increase for relationship banks is massive and implies that they systematically trade more often in the right direction than non-relationship banks.

Next, we follow Ivashina and Sun (2011) and interact the trade direction with the event return as a dependent variable to estimate the incremental event return generated by relationship trading. We find that relationship banks earn an additional return of 0.73pp per event by more frequently carrying out net purchases in the same direction as the abnormal event return (Table 3, Column 3). This return increment is sizeable both in comparison

[30] The same holds when considering all corporate events in our sample, as shown in Table IA.4.

to the return earned by non-relationship banks (-0.1%, estimated by the constant in the regressions) and in comparison to the mean (median) absolute return for UE events with at least 2% abnormal returns, which is about 6.5% (4.6%).

We further aggregate (unwinsorized) event profits from relationship trades and assess their contribution to banks' total event-trading profits. Despite representing only 1% of all bank-event combinations, relationship trades contribute approximately 14% to banks' total event-trading profit.[31] Table IA.3 further illustrates that this fraction remains similar for both the top 5 banks and the remaining banks.

Finally, we calculated banks' prop trading profits in the same way banks manage their trading desks internally, i.e., marking their trading positions to market on a daily basis. This approach captures banks' prop trading profits in a comprehensive fashion, rather than just the short-term profits around specific events, yet it allows us to compare (within bank) the profitability of trades in stocks of borrowers versus stocks of other firms. Table 4 presents results for all relationship trades and not just the incremental profits around corporate events. To do so, we construct a bank x firm x quarter level dataset by calculating daily mark-to-market profits per bank, considering both trades executed on that day and pre-existing stock holdings.[32] Notably, no winsorization is applied to accurately capture banks' earnings.

In Column (1), the findings indicate an incremental profit of €405,548 per quarter from relationship borrowers, controlling for banks' industry specifications via bank x SIC fixed effects. Introducing firm fixed effects in Column (2) maintains this result. In Column (3), additional bank x firm fixed effects are incorporated, revealing a slightly lower statistical significance but a substantial increase in economic magnitude to approximately €800,000. Considering that the average sample bank is a relationship bank to 5 firms (10 firms) in the average quarter, the coefficient from Column (2) translates into a total incremental profit of about €400k*5=€2m (€4m) per bank-quarter.

[31] This percentage remains consistent when accounting for outliers, as demonstrated by winsorizing profits at the 1%/99% level before aggregation.

[32] Security holdings data is sourced from the Securities Holdings Statistics (SHS), available in high quality from 2014 onwards, thus restricting the sample window for this analysis to 2014-2017.

Column (4) provides an alternative event-independent specification, assessing profits through portfolio returns comparable to Cohen et al. (2008). Each bank's stock holdings are allocated to a relationship portfolio and a non-relationship portfolio at the quarter's start. Weighted %-returns are then calculated for each portfolio until the quarter's end. With bank x quarter fixed effects, the estimated coefficient indicates a quarterly incremental return from relationship trading of approximately 3pp, equivalent to around 12pp per year. In sum, these new results illustrate that banks' trading in relationship stocks is very profitable.

5.3 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, as noted earlier, 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 to shed light on the mechanism and to differentiate between the two potential explanations for banks' profitable trading: lending relationships and bank specialization.

First, we exploit changes in lending relationships by estimating specification (2). Suppose bank specialization is the (joint) source of a bank's superior trading in a particular stock (and its loan to the firm). In that case, such trading should be long-lasting and not exactly coincide with the duration of the lending relationship. In contrast, information flows occur when the relationship exists and debt contracts require borrowers to inform their relationship banks. By introducing bank $\times$ firm fixed effects, our coefficient of interest is estimated comparing net purchases 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 5, 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 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 purchases 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 purchases ahead of corporate events coincide exactly with their lending relationship, during which they presumably obtain information from their borrowers.[33] To further tighten the analysis, we saturate the model with bank $\times$ firm $\times$ year fixed effects, which controls for 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).

Second, we home in on information flows and separately estimate the relationship effect for situations where banks obtain more or new information about the borrower. Firms need to provide their relationship bank with detailed information before a new loan is granted.[34] In addition, banks are likely to have more substantial information needs and hence more frequent exchanges with their borrowers when the loan is larger. We explore this idea in Table 6 and find that the relationship trading effect is higher in magnitude 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 bank's loan amount to the borrower increases by at least

[33] 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.

[34] 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 than banks without loan exposures. This result further validates our relationship bank classification.

33% (following Behn et al. (2016)) and €2m from one quarter to the next. Even with this relatively modest threshold, we find that relationship banks carry out larger net purchases prior to positive UE events, relative to non-relationship banks and 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 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 there is likely information flow between the relationship lender and the borrower for such events. However, 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 7. We employ the binary *Suspicious Trade* indicator because we have relatively few third-party events, which allows us to combine positive and negative news events and avoids that a few large net purchases unduly influence the results. As other (relationship) banks may also trade in third-party or other events of unrelated firms, we control for these lending relationships with an indicator.[35] 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 events for the same firm on the same day. When we examine whether relationship banks trade successfully in *other* events of unrelated firms, we find no evidence that they can; the results in Columns 3-6 (and Columns 5-6 for UE events) are statistically

[35]As expected, the estimated coefficients on the RB indicator in Columns 5-6 are comparable to those estimated in Columns 3-4 in Table 3.

and economically insignificant.

In sum, the three sets of tests presented in this subsection support the interpretation that trading is informed by lending relationships and largely rule out that the patterns arise due to bank specialization.

5.4 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 need to know how the information travels within banks. One possibility is a 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, information may travels more passively via centralized organizational units. For instance, the risk management of a universal bank collects information centrally and simultaneously possesses information about loan exposures and trading positions, creating the potential for information flow across ethical walls. Such information flows could occur inadvertently if risk management sends "signals," for instance, by setting and adjusting trading limits or 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 risk management collects 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 requires more detailed information about the borrower. The second test exploits banks' existing trading book exposures when an unscheduled event occurs. 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 its approach 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 rating 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 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.[36] In Table 8, 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 carry out net purchases 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 net purchases across 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 before carrying out net purchases ahead of a corporate event. The relevant data are obtained from Deutsche Bundesbank's Security Holdings Statistics, which reports banks' security positions at the end of each month.[37] Around 16% of all nonzero bank-firm-month

[36] 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.

[37] 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 has existed in the database since 2014. We thus set the variables *Short* and *Long* to zero for events in 2012 and 2013.

exposures are negative, indicating a short position at the end of the month. The analyses in Table 9 compare the trading behavior of relationship banks around UE events depending on whether the bank has a long, short, or no position. Column 1 focuses on positive UE events with >2% abnormal returns. We find that relationship banks carry out larger net purchases 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 carry out negative net purchases or reduce their long positions relative to non-relationship banks. In Columns 2 and 4, we require 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 information transmission. They also highlight that the earlier evidence does not necessarily imply that loan officers communicate directly with traders.

5.5 Flying under the Supervisory Radar

If the documented trading behavior violates insider trading rules, we expect relationship banks to shroud their informed trading to avoid supervisory scrutiny. Therefore, we ask if there is evidence that banks avoid the supervisor's attention 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 significant price changes and large trading volumes. Consistent with this logic, almost all prosecuted insider trading cases BaFin discloses in its annual reports between 2012 and 2017 pertain to instances where 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 substantial positive or negative returns. Similarly, large trades are more likely to attract the supervisor's attention than small trades. For this reason, we expect relationship banks to carry out net purchases in their borrowers' stocks with many small trades rather than 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 10. We find that, after controlling for the size of net purchases, 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. This behavior could also reduce price impact, which we explore in the following subsection.

Next, we explore heterogeneous effects in relationship trading depending on the absolute abnormal event return. Table 11 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 purchases for UE events with small returns (Column 1). We find higher net purchases 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 substantial returns and hence receive attention from the supervisor.

5.6 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.[38] 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 between the focal relationship bank transaction and the benchmark transaction is only 12 seconds.

Table 12 reports the price protection results.Columns 1 and 2 use the €-difference between the transaction price and benchmark price as dependent variables. 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.[39] Columns 3 and 4 translate the €-numbers into fractions of the average bid-ask spread for the respective instrument on the respective day and document that when relationship banks buy OTC, they pay an incremental 23.81% of the bid-ask spread or, when selling OTC, get about 20.49% less of the bid-ask-spread, relative to when they trade on an exchange. These results suggest that other market participants know that relationship banks trade with superior information and are, therefore, price protecting.

In light of the documented price protection, we expect that relationship banks instead trade on exchanges where they cannot be identified as the counter party.[40] We document in Appendix Table IA.9 that relationship banks are more likely to carry out net purchases ahead 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 are concerned with shrouding their

[38]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).

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

[40]Resorting to exchanges also eliminates the risk of OTC counter-parties reporting the bank to the supervisor in case of suspicious trading.

suspicious trades.

6 Discussion and Conclusion

This paper provides novel evidence that banks engage in proprietary trading ahead of corporate events that is informed by their lending relationships. Using extensive micro-level data, we find that relationship banks build 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 particularly pronounced in situations when banks are likely to possess private information about their borrowers. It cannot be explained by banks specializing their lending and trading in specific industries, firms, or business models. Our results question the effectiveness of banks' organizational arrangements (or ethical walls).

Our analysis also uncovers a novel potential pathway for information flows within universal banks. Aside from direct communication, banks' centralized risk management could be a channel through which private lending information travels within banks. Following the Global Financial Crisis, organizational structures that collect information centrally within banks (i.e., risk management) have been strengthened globally. Intriguingly, these organizational structures could play a role in explaining banks' informed trading patterns. Our findings illustrate that rules for financial stability and market conduct could be in conflict. In universal banking, centralized risk management is essential to ensure the financial stability of such banks. However, with centralized risk management in place, information flows from the lending activities to the trading desk could passively occur even if organizational structures prevent direct information exchange or communication.

Finally, we provide evidence suggesting relationship banks shroud their informed trading to avoid supervisory scrutiny, by building their positions with many small trades and by avoiding events with very large returns. However, relationship banks obtain a less favorable prices in the OTC market as compared to exchange trades. This evidence suggests that other market participants are aware of the information advantages of relationship banks and price protect when the counter party is known. Relationship banks respond to this price protection by favoring exchanges when they trade their borrowers' stocks.

Overall, our 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.

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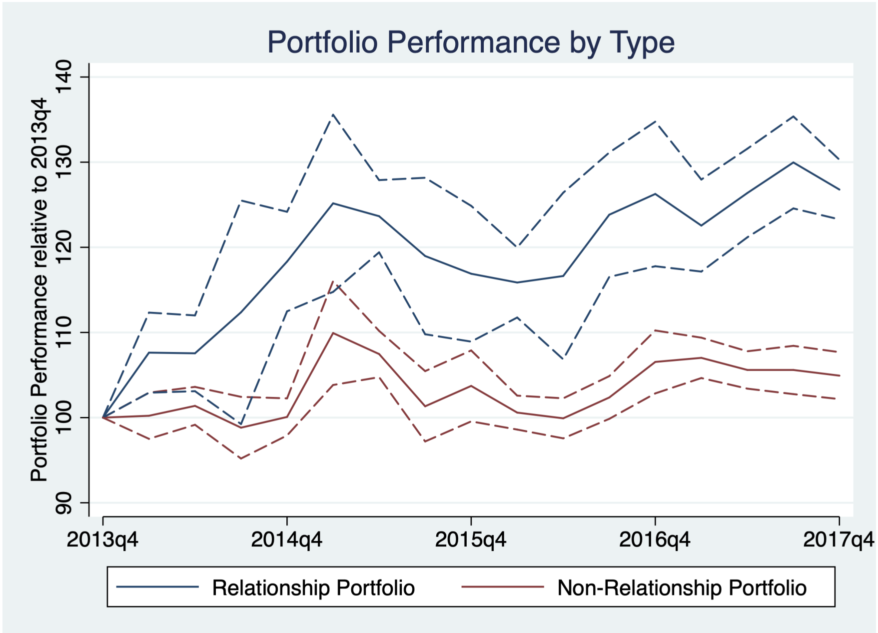
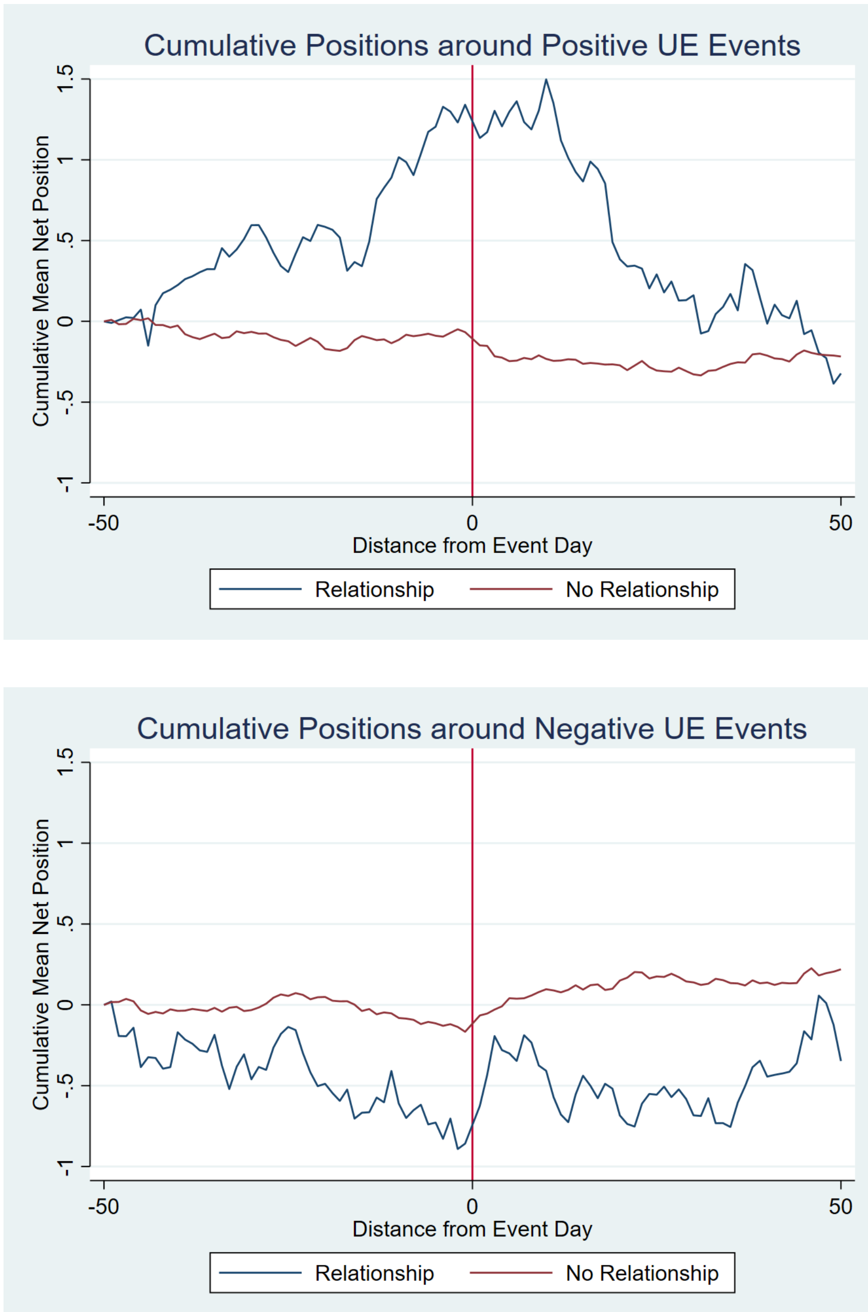
Figure 1: Portfolio Returns across Time



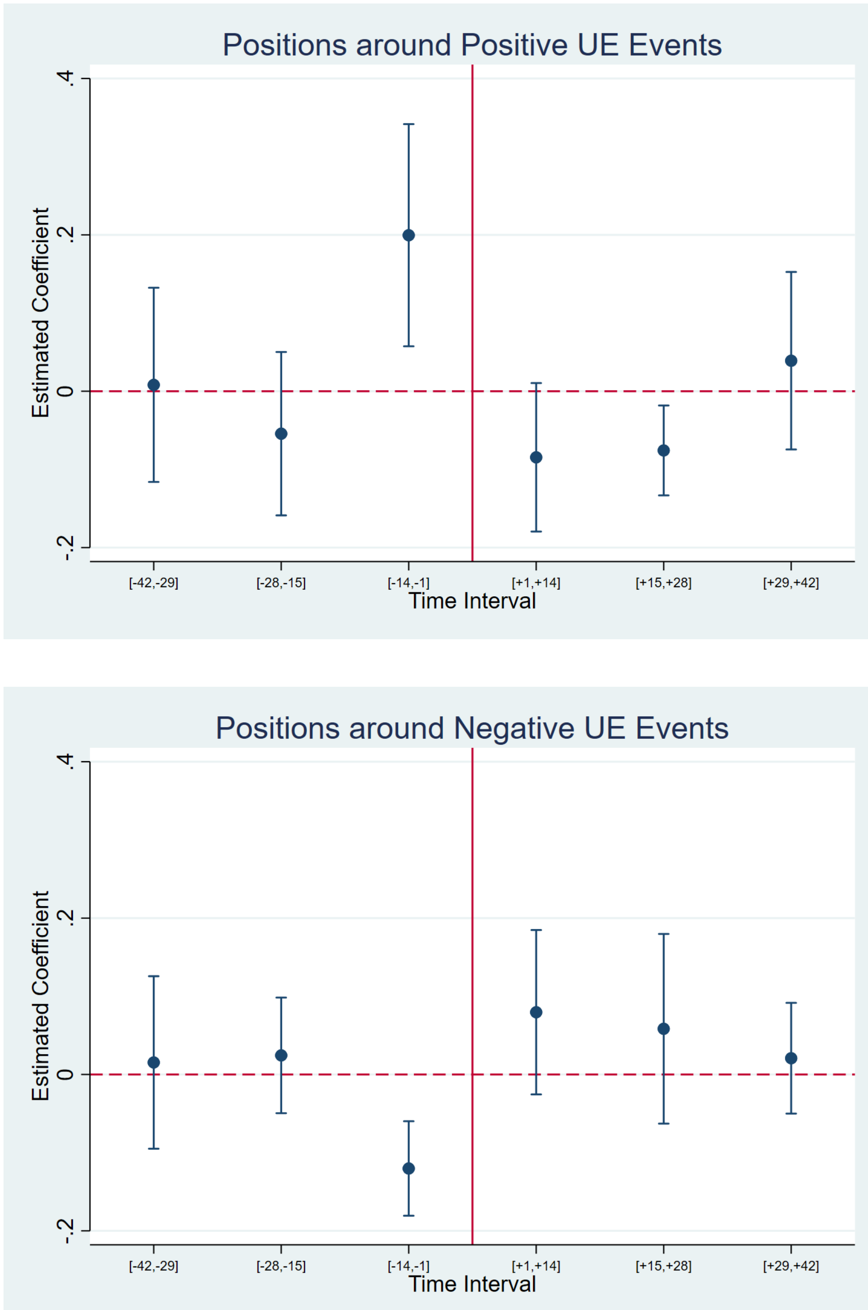
This figure shows the performance of banks' relationship portfolio vs their non-relationship portfolio over time, with the relationship portfolio consisting of those stocks that banks are largest lender or a lender that accounts for at least 25% of the firm's loans. The return on each portfolio is calculated by multiplying the security holdings at the beginning of each quarter with the respective returns (see e.g. Cohen et al. (2008)). As the portfolio holdings data is obtained from the Securities Holdings Statistics (SHS), which is only available from 2014 on, such that the sample window for this analysis is 2014-2017. We only keep bank x quarters where both a relationship and a non-relationship portfolio exists. Dashed lines represent 95% confidence intervals.

Figure 2: Banks' Net Purchases around UE Events



This figure visualizes banks' trading dynamics at unscheduled earnings-related (UE) events. We demean net purchases at the bank level and average the demeaned net purchases per day separately for relationship and non-relationship bank observations. The blue and red lines depict the cumulative value of these net purchases in basis points over the [-50,+50] day window for relationship and non-relationship banks, respectively. The vertical line marks the event day.

Figure 3: Relationship Trading - Mapping Out Estimates over Time



This figure depicts the abnormal net purchases of relationship banks by estimating separate coefficients in eq. (1) for different two-week time windows around the event day, relative to the [-84,-43] window (omitted category). The sample is restricted to unscheduled earnings-related (UE) events with large absolute returns (>2%). The top (bottom) panel contains the coefficients for positive (negative) UE events. The vertical bands for each coefficient represent 95% confidence intervals with standard errors clustered at the bank level. The vertical line marks the event day. We report the regressions in Table IA.7.

Table 1: Descriptive Statistics

Panel A: Corporate Events and Relevance

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: Lending Relationships of and Proprietary Trading by Banks

	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 Stocks 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: Trades at the Bank-Event 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 Purchases [-14,-1] conditional on Trading	355,402	0.0591	-20.15	-0.24	0.00	0.27	25.25

Panel A provides the frequency of corporate events by event category and 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. A stand-alone forecast comprises management guidance which 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 calculated 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 (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 at the bank-event level. This sample consists of 1,879,718 (47 banks x 39,994 events) observations. All variables are defined in the Variable Appendix.

Table 2: Relationship Trading

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

Dependent variable:	Net Purchases [-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
Abs. 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 Purchases					
	[-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 change their net purchases prior to positive events (interaction) and negative events (baseline) of borrowers. We avoid double-counting by limiting the sample to one event per firm-day when analysing "All" events. UE events are unscheduled earnings-related events and refer to pre-announcements, stand-alone forecasts and unscheduled dividend events. Panel B maps out bank trading around UE 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 purchases computed over the respective time window indicated. All variables are defined in the Variable Appendix. We cluster standard errors at the bank level and report t-statistics in parentheses. Superscripts *, ** and *** indicate statistical significance at the 10%, 5% and 1%-level (two-tailed), respectively.

Table 3: "Suspicious Trades" and Event Trading Returns

Dependent variable:	Right Direction	Suspicious Trade	Return x Direction
	(1)	(2)	(3)
Constant	0.4943***	0.2566***	-0.0010***
	(422.72)	(229.65)	(-9.02)
Relationship	0.0923***	0.0619***	0.0073***
	(4.15)	(3.15)	(3.64)
Event FE	yes	yes	yes
Bank x SIC FE	yes	yes	yes
Abs. Event Return	>2%	>2%	>2%
Observations	15,740	13,300	15,740

This table presents results for alternative dependent variables. We restrict the sample to unscheduled earnings-related events with large absolute returns (>2%). Any of the dependent variables further is only defined for non-zero net purchases. *Right Direction* is an indicator variable that equals 1 when a bank carries out positive net purchases in the two weeks before a positive event (and vice versa for negative events) *Suspicious Trade* is an indicator variable that equals 1 when a bank carries out positive net purchases in the two weeks before a positive event and negative net purchases in the two weeks after a positive event (and vice versa for negative events). We require that banks trade in the two weeks before and after the respective event for the construction of *Suspicious Trade*. The dependent variable *Return* $\times$ *Direction* is constructed by multiplying the market-adjusted event return with the relationship bank's trade direction, i.e. the variable *Right Direction* from Column (1). All variables are defined in the Variable Appendix. We cluster standard errors at the bank level and report t-statistics in parentheses. Superscripts *, ** and *** indicate statistical significance at the 10%, 5% and 1%-level (two-tailed), respectively.

Table 4: Event-Independent Profits

Dependent variable:	Quarterly Profit			
	(1)	(2)	(3)	(4)
Relationship	399,714**	405,548**	431,012**	800,810*
	(2.43)	(2.12)	(2.19)	(1.65)
Bank FE	yes	-	-	-
Bank x SIC FE	no	yes	yes	-
Firm FE	no	no	yes	-
Bank x Firm FE	no	no	no	yes
N	115,402	115,284	115,284	114,018

This table examines the incremental trading profit in € earned by relationship banks. *Quarterly Profit* is the total profit earned per bank x firm x quarter. The dataset is constructed by first calculating the daily mark-to-market profit per bank and day, taking into account both the day's trades and existing stock holdings. The latter data is obtained from the Securities Holdings Statistics (SHS), which, as described in greater detail below, is only available from 2014 on, such that the sample window for this analysis is 2014-2017. We cluster standard errors at the bank x year level and report t-statistics in parentheses. Superscripts *, ** and *** indicate statistical significance at the 10%, 5% and 1%-level (two-tailed), respectively.

Table 5: Relationship Trading vs. Bank Specialization

Dependent variable:	Net Purchases [-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. Coefficients for negative events are included in the specifications but are untabulated. All variables are defined in the Variable Appendix. We cluster standard errors at the bank level and report t-statistics in parentheses. Superscripts *, ** and *** indicate statistical significance at the 10%, 5% and 1%-level (two-tailed), respectively.

Table 6: Information Flows, Bank Monitoring and New Loans

Dependent variable:	Net Purchases [-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 either a function of loan share (columns (1) and (2)) or when banks recently (i.e., in the previous quarter) granted a new loan (columns (3)-(6)). The sample is restricted to unscheduled earnings-related events with large absolute returns (>2%). *RB Loan Share* of a relationship bank is defined as the lending by this bank relative to a firm's total lending. For the construction of *Relationship NL* 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 (depending on the estimated specification) of the firm's total loan volume, respectively. Coefficients for negative events are included in the specifications but are untabulated. All variables are defined in the Variable Appendix. We cluster standard errors at the bank level and report t-statistics in parentheses. The F-tests compare the estimates of the two depicted interactions. Superscripts *, ** and *** indicate statistical significance at the 10%, 5% and 1%-level (two-tailed), respectively.

Table 7: Trading in Events of "Third-Party" Firms

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 examines relationship banks' trading (with *Suspicious Trade* as dependent variable) in events of unrelated "third-party" firms (as described in Section 4.2). We distinguish between scenarios in which a relationship bank might posses private information about a third-party firm's event (*RB third party trades* in columns (1) and (2)) and scenarios in which it is unlikely that a relationship bank posses private information about a third-party firm's event (*Other RB trades* in columns (3)-(6)). We construct the indicator variable *RB third party trades* to equal one when a third-party firm (F1) experiences a joint corporate event with a firm (F2) to which the bank (B) is the relationship bank. In columns (5) and (6), the sample is restricted to unscheduled earnings-related 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). 'Control for other RBs' indicates that we include an indicator variable which equals 1 when other relationship banks trade in third-party events or other events of unrelated firms. All variables are defined in the Variable Appendix. We cluster standard errors at the bank level and report t-statistics in parentheses. Superscripts *, ** and *** indicate statistical significance at the 10%, 5% and 1%-level (two-tailed), respectively.

Table 8: Role of Risk Management: Internal Risk Ratings

Dependent variable:	Net Purchases	Return x Direction	Suspicious Trade
	(1)	(2)	(3)
Relationship AIRB	-0.1075	0.0040***	0.0718***
	(-1.65)	(6.84)	(3.92)
Relationship FIRB	-0.0251	0.0019	0.0178
	(-0.51)	(1.42)	(0.78)
Relationship AIRB x Pos	0.4364***		
	(8.38)		
Relationship FIRB x Pos	0.0421		
	(0.84)		
Event FE	yes	yes	yes
Bank x SIC FE	yes	yes	yes
Events	UE	UE	UE
Abs. Event Return	>2%	>2%	>2%
Observations	110,027	110,027	13,300

This table examines relationship banks' trading (with either *Net Purchases*, *Return* $\times$ *Direction*, or *Suspicious Trade* as dependent variable) as a function of 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. The sample is restricted to unscheduled earnings-related events with large absolute returns (>2%). All variables are defined in the Variable Appendix. We cluster standard errors at the bank level and report t-statistics in parentheses. Superscripts *, ** and *** indicate statistical significance at the 10%, 5% and 1%-level (two-tailed), respectively.

Table 9: Role of Risk Management: Short vs. Long Positions before Events

Dependent variable:	Net Purchases [-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 as a function of their 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%). Columns (1) and (2) consider positive UE and columns (3) and (4) consider negative UE. *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 respectively consider short (long) positions that are below (above) the median short (long) position throughout the sample. All variables are defined in the Variable Appendix. We cluster standard errors at the bank level and report t-statistics in parentheses. Superscripts *, ** and *** indicate statistical significance at the 10%, 5% and 1%-level (two-tailed), respectively.

Table 10: 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 Purchases 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
'Many Trades' 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 relationship banks' trading (with *Suspicious Trade* as dependent variable) as a function of whether a bank carries out its net purchases 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 executes in the stock of a firm in the [-14,-1] window. *Many Trades* is an indicator set to one if the number of trades during the [-14,-1] window exceeds a predefined threshold (above median in columns (2) and (4), above p75 in column (3)) for the number of trades. We control for the size of the respective net purchases that the bank builds up, interacted with the relationship indicator. All variables are defined in the Variable Appendix. We cluster standard errors at the bank level and report t-statistics in parentheses. Superscripts *, ** and *** indicate statistical significance at the 10%, 5% and 1%-level (two-tailed), respectively.

Table 11: Supervisory Radar: Event Return

Dependent variable:	Net Purchases [-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 conditional on event returns (i.e., bins of *Abs. Event Return*). The sample is restricted to unscheduled earnings-related events. All variables are defined in the Variable Appendix. We cluster standard errors at the bank level and report t-statistics in parentheses. Superscripts *, ** and *** indicate statistical significance at the 10%, 5% and 1%-level (two-tailed), respectively.

Table 12: Price Protection in the OTC Markets

Dependent variable:	Price Difference (€)		Price Dif. (rel. to Spread)	
	(1)	(2)	(3)	(4)
OTC	0.0106***	-0.0087***	0.2381***	-0.2049***
	(9.47)	(-8.40)	(10.69)	(-9.75)
Control for Log Trade Volume	yes	yes	yes	yes
Trade Direction	buy	sell	buy	sell
Observations	5,623,962	5,589,207	5,620,490	5,585,696

This table examines whether trades by relationship banks are subject to price protection in the OTC markets relative to the exchanges (where trading is anonymous). The sample consists of 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 dependent variable *Price Difference (€)* is the €-difference between the relationship bank's transaction price and the benchmark price. This difference is express as fraction of the average bid-ask spread per instrument x day in Columns (3) and (4). Columns (1) and (3) are buys and columns (2) and (4) are sells. *OTC* is an indicator variable that equals 1 when a trade is executed OTC. We control for the (log) Euro volume of a transaction in all specifications. All variables are defined in the Variable Appendix. We cluster standard errors at the bank level and report t-statistics in parentheses. Superscripts *, ** and *** indicate statistical significance at the 10%, 5% and 1%-level (two-tailed), respectively.

Variable Appendix

Panel A: Relationship Bank 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 *Relationship Bank* for at least one event between 2012 and 2017.
Relationship (Indicator)	Equals 1 if a bank is the largest lender of the firm or has a loan share of at least 25% (of the firm's total borrowing) 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)	Equals 1 for the non-relationship periods of a bank-firm pair when the bank is a relationship bank for the respective firm at any point over our sample period.
After-Rel. Periods (Indicator)	Equals 1 for non-relationship periods of a bank-firm pair, after the bank relationship ends for the respective firm.
RB Third Party Trades (Indicator)	Equals 1 for trades of a relationship bank (B) in an unrelated "third-party" firm (F1) which is connected to the bank's client firm (F2), when F1 and F2 experience a joint corporate event.
Other RB Trades (Indicator)	Equals 1 for trades of a relationship bank (B) in other events of the unrelated firm (F1), which are not connected to F2 (i.e., they are not joint corporate events for F1 and the bank client F2).
Relationship NL and *Relationship No NL* (Indicators)	Rel. NL (Rel. No NL) equals 1 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 the bank's lending to the respective firm by at least 33% and more than €2m (in other specifications: €50m or 10pp) from one quarter to the next.
Relationship FIRB and *Relationship AIRB* (Indicators)	Relationship FIRB (Relationship AIRB) equals 1 when a relationship bank employs the foundation (advanced) internal ratings-based approach for a borrower in a certain quarter. Under FIRB the bank internally estimates only the probability of default (PD), whereas 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 (#)	Count of how many different sample stocks each bank prop trades per day on average. We compute the average for each bank over all trading days in our sample.
Number of Prop Trades in Sample Stocks per Day (#)	Average number of prop trades a bank carries out in the sample stocks per day. We compute the average for each bank over all trading days in our sample.
Trading Volume in Sample Stocks per Day(€m.)	Average daily prop trading volume in sample stocks. We compute the average for each bank over all trading days in our sample.
Average Trade Size (€)	Average bank-level prop trade size. We compute the average for each bank over all trading days in our sample.
Average Long Position and *Average Short Position* (€m.)	Average long (short) position across all sample firms and all months per bank; calculated using the Security Holdings Statistics Database (for which we cannot match all sample banks). We use only holdings in the trading book because bank book holdings are not related to trading purposes. Data are limited to years after 2013.
Fraction of Events with Trading in [-14,-1] Window (Fraction)	Fraction of corporate events for which a bank prop traded the respective stock in the two weeks prior to the respective event.
Net Purchases (basis points)	$\frac{\textit{shares purchased} - \textit{shares sold}}{\textit{shares outstanding}} \times 10,000$ over the two weeks prior to an event. In some analyses, net purchases is computed for alternative windows (as indicated). We winsorize positions at p1 and p99, unless indicated otherwise.
Right Direction (Indicator)	Equals 1 if a bank carries out positive net purchases in the two weeks before a positive-return event (vice versa for negative-return events). We require that a bank trades in the two weeks before the event (irrespective of direction).
Suspicious Trade (Indicator)	Equals 1 if a bank carries out positive net purchases in the two weeks before a positive event and negative net purchases in the two weeks after the positive event (which indicates selling). The reverse applies for negative events. We require that a bank trades in the two weeks before and after the event (irrespective of direction).
Return × Direction (#)	Constructed by multiplying the market-adjusted event return with the trade direction (−1,0,+1 for negative, zero and positive net purchases, respectively). Captures the incremental return that a relationship bank earns around a corporate event by trading in the same direction as the event return (Ivashina and Sun (2011)).
Short and *Long* (Indicators)	Short (Long) equals 1 if a bank holds a short (long) position in the event firm's equity at the end of the month preceding the event; calculated using the Security Holdings Statistics Database. We use only holdings in the trading book because bank book holdings are not related to trading purposes. Data are limited to years after 2013.

Panel B: Trade Variables (Continued)

Variable Name	**Definition**
ln(Trades) (#)	The natural log of the number of trades a bank executes in the stock of a firm in the [-14,-1] window of an event.
Many Trades (Indicator)	Equals 1 for net purchases that are built up with more trades than the median or p75 net purchases.
OTC (Indicator)	Equals 1 for OTC trades and equals 0 for trades on exchanges.
Price Difference (€)	*Transaction Price - Benchmark Price* using the price of a previous transaction between non-relationship banks as benchmark. Computed separately for OTC and exchange trades and winsorized at p1 and p99.
Price Difference (relative to Spread)	$\frac{Transaction\ Price\ -\ Benchmark\ Price}{Transaction\ Price}$ using the price of a previous transaction between non-relationship banks as benchmark. Computed separately for OTC and exchange trades and winsorized at p1 and p99.
P(Trade) (Indicator)	Equal 1 if a bank prop traded the stock of a firm in the two weeks prior to a corporate event.
ExchgIntens (%)	Measures the exchange intensity of each net purchases observation. For instance, if net purchases consisted of two trades, one OTC trade with volume 5 and one exchange trade with volume 20, *ExchgIntens* would equal 20/(20+5)=80% (independent of whether the trades are buys or sells).
MostlyExchg (Indicator)	Equal 1 for net purchases with above-median *ExchgIntens*.

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)	Equals 1 if the firm is in the Prime Standard, 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 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)	Equals 1 for events with market-adjusted returns larger than zero.

Internet Appendix to accompany

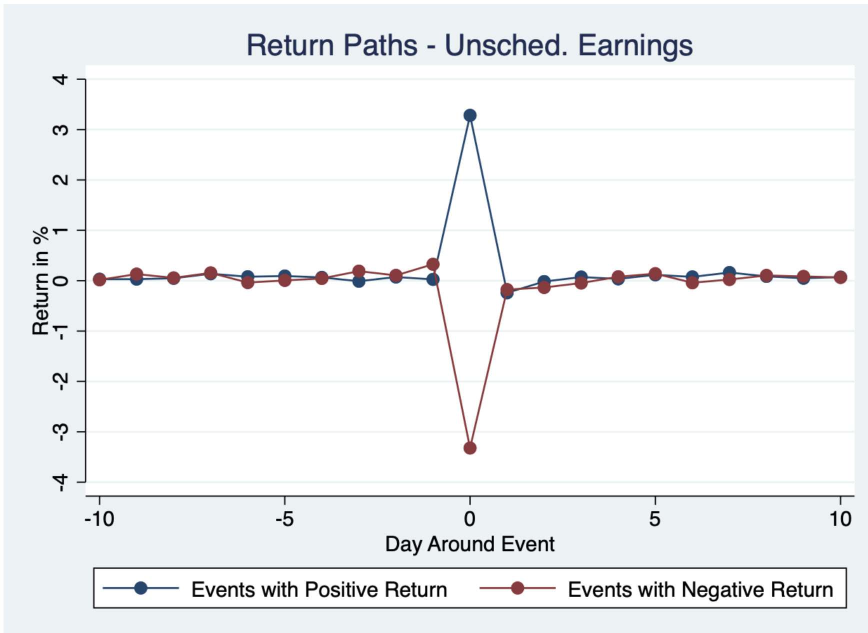
Know Your Customer: Informed Trading by Banks

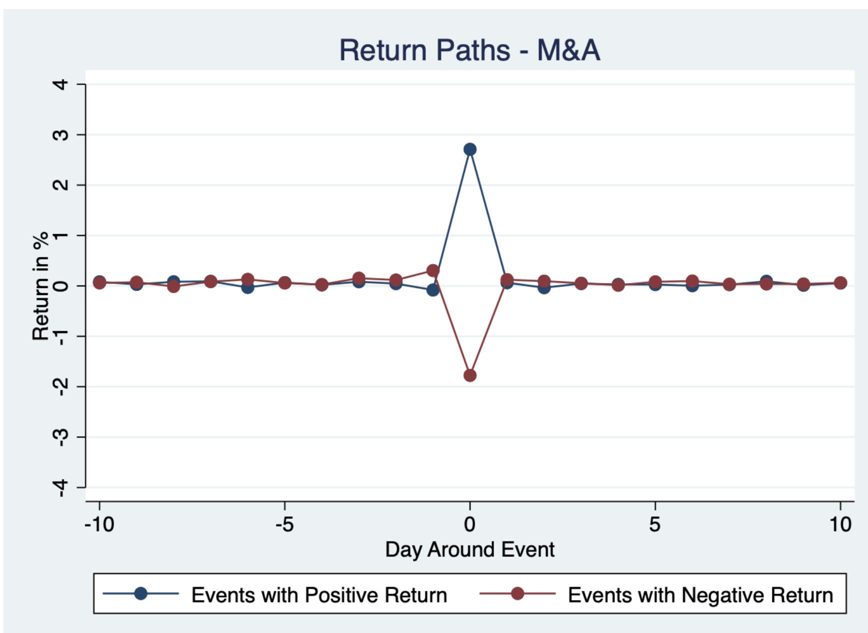
(for online publication)

List of Figures in the Internet Appendix

List of Tables in the Internet Appendix

Figure IA.1: Return Paths Around Selected Event Categories





This figure visualizes return paths around UE events in the upper and around M&A events in the lower panel. We measure the (abnormal) return as the difference between the %-change in stock price relative to the previous day and the return of the German DAX index. Returns are averaged across all events per event category and day around event. We depict separate lines for events with positive returns and negative returns (both measured at the event date).

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 summarizes the total prop trading volume, number of trades and average trade size by sample banks in sample stocks per year. Trades are double-counted when two sample banks prop-trade with each other.

Table IA.2: Variations of the Relationship Definition

Dependent variable:	Net Purchases [-14,-1]					
	(1)	(2)	(3)	(4)	(5)	(6)
Relationship x Pos	0.3069***	0.2912***	0.3058***	0.0913*	0.1993***	0.4543**
	(3.55)	(3.33)	(3.33)	(1.99)	(2.81)	(2.05)
Rel Definition	LL or >=25%	LL	>=25%	>0%	>=15%	>=50%
Event FE	yes	yes	yes	yes	yes	yes
Bank x SIC FE	yes	yes	yes	yes	yes	yes
Events	UE	UE	UE	UE	UE	UE
Abs. Event Return	>2%	>2%	>2%	>2%	>2%	>2%
Observations	110,027	110,027	110,027	110,027	110,027	110,027

This table provides the results when changing the scope of what we consider a relationship bank. Column (1) is the baseline setting employed throughout the paper, where relationship is defined as a bank being either largest lender or having a loan share larger than 25%. In Column (2), we change this to largest lender only. In Columns (3)-(6), we change this to threshold only, where the threshold varies from ¿0% to ¿=50%. The sample is restricted to unscheduled earnings-related events with absolute abnormal return above 2%. All variables are defined in the Variable Appendix. We cluster standard errors at the bank level and report t-statistics in parentheses. Superscripts *, ** and *** indicate statistical significance at the 10%, 5% and 1%-level (two-tailed), respectively.

Table IA.3: 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 summarizes the number of relationships and the total event-trading profits, separately for the 5 banks with the most relationships and the remaining 42 sample banks. The number of relationships refers to the bank x event observations for which a bank is the relationship bank to a firm. 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 purchases a bank carried out in the two weeks prior to the event.

Table IA.4: 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. carrying out positive (negative) net purchases in the two weeks prior to an event with a positive (negative) return. We avoid double-counting by limiting the sample to one event per firm-day when analysing "All" events (columns (1) to (3)). UE events are unscheduled earnings-related events and refer to pre-announcements, stand-alone forecasts and unscheduled dividend events (columns (4) to (6)). All variables are defined in the Variable Appendix. We cluster standard errors at the bank level and report t-statistics in parentheses. Superscripts *, ** and *** indicate statistical significance at the 10%, 5% and 1%-level (two-tailed), respectively.

Table IA.5: Mapping out Bank Trading around Corporate Events

Dependent variable:	Net Purchases					
	[-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 purchases computed over the respective time window indicated. The specifications include 'All" events for which we avoid double-counting by limiting the sample to one event per firm-day. All variables are defined in the Variable Appendix. We cluster standard errors at the bank level and report t-statistics in parentheses. Superscripts *, ** and *** indicate statistical significance at the 10%, 5% and 1%-level (two-tailed), respectively.

Table IA.6: Relationship Trading Around M&A Events

Dependent variable:	Net Purchases [-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 examines relationship banks' trading conditional on M&A events. We distinguish between specifications which include all M&A events (columns (1) and (2)), M&A events in which the firm is the target (columns (3) and (4)), and M&A events in which the firm is the seller (columns (5) and (6)). We respectively consider M&A events that do not overlap with other non-M&A events. The sample is restricted to events with large absolute returns (>2%). Coefficients for negative events are included in the specifications but are untabulated. All variables are defined in the Variable Appendix. We cluster standard errors at the bank level and report t-statistics in parentheses. Superscripts *, ** and *** indicate statistical significance at the 10%, 5% and 1%-level (two-tailed), respectively.

Table IA.7: Panel Analysis at the Bank x Event x Time Level

Dependent variable:	Net Purchases			
	(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 Purchases	-	>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 preceding and subsequent to corporate events (i.e., from [-84,-71] to [+15,+28]). We distinguish between positive events (interaction) and negative events. Net Purchases are computed for each bank and event so that the analyses are at the Bank $\times$ Event $\times$ Time level. We separately estimate coefficients for the four windows which center around the event whereas the coefficients are estimated relative to the net purchases in the windows that span [-84,-29]. 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 purchases. In Column (4), we impose the prop trading condition in the [-84,-71] window. All variables are defined in the Variable Appendix. We include bank $\times$ event fixed effects in all specifications. We cluster standard errors at the bank level and report t-statistics in parentheses. Superscripts *, ** and *** indicate statistical significance at the 10%, 5% and 1%-level (two-tailed), respectively.

Panel Analysis at the Bank x Event x Time Level - Remarks

For this test, 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 more extended period prior to the same event. In this analysis, we can introduce bank×event fixed effects, which essentially conditions on banks' net purchases in the given stock before the 14-day pre-event period. The results, presented in Table IA.7 are very similar to those in the main analysis. We still find that relationship banks build up positive (negative) net purchases two weeks before positive (negative) unscheduled earnings-related events and then reverse these positions in the following month. Figure 3 visualizes these results.

Table IA.8: Options Trading and Client Trading

Dependent variable:	Net Purchases [-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
Events	UE	UE	UE	UE	UE	UE	UE	UE
Securities	Options	Options	Eq.+Opt. Netted	Equity	Equity	Equity	Equity	Equity
Trade Classification	PropMM	PropMM	PropMM	Clients	Clients	PropMM - Clients	MM	MM
Abs. Net Purchases	-	>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 and their equity trading on behalf of clients. The sample is restricted to unscheduled earnings-related events with large absolute returns (>2%). Column (1) conditions on net purchases for equity options. Column (2) further restricts the sample to observations of banks with non-zero net purchases. In column (3), we combine banks' net purchases in the stock and the options market when computing net purchases. Column (4) shows the results when using client trades to compute net purchases (instead of prop trades). Column (5) conditions the sample from column (4) on banks with non-zero net purchases. In column (6), we compute banks' prop trading net purchases relative to their client net purchases (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. Coefficients for negative events are included in the specifications but are untabulated. All variables are defined in the Variable Appendix. We cluster standard errors at the bank level and report t-statistics in parentheses. Superscripts *, ** and *** indicate statistical significance at the 10%, 5% and 1%-level (two-tailed), respectively

Options Trading and Client Trading - Remarks

In this test, we analyze option trading and banks' trading on behalf of their clients. We do not have a prior have banks trade their borrowers' stock options in case they poses superior information from their lending operations: From a risk management perspective, options could be used to hedge or offset equity trading positions. Hence, our equity trading results may 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 significant positions more quickly and cheaply (Lowry et al. (2019), Augustin et al. (2019)). However, compared to the US, options exist for less than 20% of our sample stocks and are relatively infrequently traded. Thus, we likely have less power to detect suspicious option trades. Consistent with this conjecture, the results are statistically insignificant. If anything, the evidence points in the same direction; relationship banks' option trades ahead of significant events are also more profitable (Table IA.8 in Columns 1-2). In Column 3, we combine net equity purchases with net option purchases (to allow for hedging). The results remain statistically and economically significant, suggesting that options trades are not used to offset equity purchases. A potential explanation is that the option market in Germany, in contrast to the equity market, is relatively centralized, making it harder to shroud trades by, e.g., splitting them across exchanges. In Columns 4-6, we analyze banks' equity trades on behalf of their clients. We have no precise prediction for this analysis. Relationship banks may 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 analyze only trades classified as market-making, which could also be client-initiated. We find that our main results are driven by banks' proprietary trading, rather than market-making.[41]

[41] A potential explanation for this finding is that, at least on the largest German exchange, market-making is primarily done via automatic algorithmic trading.

Table IA.9: Positions Built up with Exchange Trades vs OTC Trades

Dependent variable:	Net Purchases [-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 Purchases	>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 banks' trading as a function of whether profitable positions are built up mainly with exchange trades or OTC trades. *ExchgIntens* measures the exchange intensity of each net purchases observation. For instance, if net purchases consisted of two trades, one OTC trade with volume 5 and one exchange trade with volume 20, *ExchgIntens* would equal 20/(20+5)=80% (independent of whether the trades are buys or sells).The construction of *ExchgIntens* requires to condition on trade because 0-net purchases prohibit calculation of *ExchgIntens*. *MostlyExchg* is an indicator variable that equals one for net purchases with above-median *ExchgIntens*. Columns (1)-(3) (columns (4)-(6)) limit the sample events with positive (negative) abnormal returns. All variables are defined in the Variable Appendix. We cluster standard errors at the bank level and report t-statistics in parentheses. Superscripts *, ** and *** indicate statistical significance at the 10%, 5% and 1%-level (two-tailed), respectively