Conflicts of Interest in Universal Banks*

Rainer Haselmann† Christian Leuz‡ Sebastian Schreiber§

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Abstract

We analyze the conflict of interest that arises when universal banks engage in proprietary trading of borrower stocks. This conflict has been a prominent concern in the regulatory debates for a long time. We combine trade-by-trade supervisory data with credit registry information in Germany. Our findings reveal that lending relationships inform banks' proprietary trading. To separate bank expertise and trading based on private information from lending relationships, we study bank prop trading around corporate events. We show that banks execute net purchases (sales) in borrower stocks weeks before positive (negative) news events, even when these events are unscheduled and surprising to the rest of the market. We link this trading pattern to situations when banks should possess private borrower information and rule out that it is explained by specialized expertise. We also find evidence consistent with information flows through banks' centralized risk management as well as that banks' alter their trading patterns once they acquire private information, consistent with shrouding of informed trading. Our evidence highlights the importance of conflicts in universal banking.

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

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

§Goethe University and CAS LawFin; schreiber@econ.uni-frankfurt.de.

1 Introduction

The Glass-Steagall Act of 1933, which separated commercial and investment banking in the U.S., was largely motivated by concerns about conflicts of interest that arise when banks engage in both activities. A central concern was that universal banks have privileged access to confidential information in their borrowers that they could use when selling securities to investors or when trading on their own account. However, evidence in several influential studies questioned whether these concerns were a sufficient rationale for separating commercial and investment banking (e.g., Kroszner and Rajan (1994), Puri (1994), Kroszner and Rajan (1997)). Over time, the concerns waned and the U.S. repealed Glass-Steagall in 1999. The 2008 financial crisis led to renewed calls to separate commercial and investment banking. This time the debate centered on banks' speculative trading activities and resulted in the Volcker Rule, which bans proprietary trading by U.S. (commercial or universal) banks. In Europe, the report by Liikanen et al. (2012) proposed a similar ban, but the EU chose instead to require banks to have organizational structures (e.g., ethical walls) to mitigate conflicts of interest arising from combined investment and commercial banking.

We have little evidence on conflicts of interest in banks' proprietary trading, the effectiveness of ethical walls in addressing these conflicts, and banks' internal information flows. One reason is that banks' proprietary trading data are rarely available. In this paper, we exploit comprehensive supervisory data on universal banks' proprietary trading at the transaction level, which allows us to shed light on within-bank information flows from lending to trading, the resulting conflicts of interest as well as the effectiveness of organizational structures that are supposed to prevent such information flows.

It is well known that borrowers provide banks with private information in the lending process and for credit monitoring.[1] Such information is critical to banks' ability to screen, monitor, and form relationships with borrowers, and hence for credit provision (e.g.,

[1]For instance, corporate debt contracts include clauses requiring borrowers to inform their lenders about material changes to the business. Firms also approach banks for funding commitments ahead of major corporate transactions (e.g., M&A), essentially sharing private information.

Bernanke (1983), Diamond (1984), Petersen and Rajan (1994)). The key question for us is whether such private borrower information makes its way to the bank's trading desk, despite the creation of ethical walls to prevent this. Aside from direct communication, one potential channel for leakage are organizational units that centralize information. A prime example is risk management, which *sits above the wall* for prudential reasons.

The difficulty for any study is that banks' internal information flows cannot be observed directly. However, privately informed trading should exhibit different trading patterns and ultimately result in higher trading profits. Thus, we combine two large micro-level data sets from different supervisory agencies to uncover informed trading. We use the German credit register from the central bank to determine lending relationships and trade-by-trade data from the German financial market supervisor (BaFin). The latter data set contains all trades by all financial institutions with a German banking license executed on any domestic or foreign exchange or in the OTC markets. To the best of our knowledge, our analysis is the first time that credit-registry information is combined with comprehensive trade-by-trade data to investigate banks' proprietary trading.

As a first pass, we construct a relationship and a non-relationship portfolio for each bank (Cohen et al. (2008)). The relationship portfolio is formed by proprietary trading in stocks for which a bank is either the respective firm's largest lender or provides at least 25% of the firm's loans. We find that the relationship portfolio significantly outperforms the non-relationship portfolio by about 4.5 to 6.1% annually, suggesting that proprietary trading is substantially more profitable when banks trade in borrower stocks.[2] An obvious challenge to attributing this differential to informed trading is that banks may specialize in certain industries, business models or firms. Such specialization or expertise could manifest in profitable trading, even without any information flow from the lending side.

To overcome this challenge, we analyze information flows around corporate events. Analyzing bank trading ahead of material events allows us to construct tests that separate

[2]We establish this return differential in simple (untabulated) within-bank regressions with market return adjustment. We use this analysis only as a first gauge and present superior analyses later in the paper.

expertise and informed trading. For one, our analysis differentiates between widely anticipated or scheduled events (e.g., earnings announcements) and unscheduled events that are harder to anticipate even with expertise (e.g., profit warnings, M&A transactions). In addition, we exploit time-series variation in lending relationships, which allows us to perform analyses within bank-firm pairs to further tighten identification.

Insider trading is illegal in Germany, as it is in most countries (Bhattacharya and Daouk (2002)). The EU's Market Abuse Regulation (MAR) prohibits using insider information for trading activities.[3] However, there are exceptions when trading in the presence of inside information is permitted (see Section 2). These exceptions give rise to a grey zone and add to the difficulty of enforcing insider trading rules. Moreover, 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 they have organizational structures (i.e., ethical walls) that ensure traders are not in possession of this information. Hence, the effectiveness of banks' organizational structures is an important regulatory question. The Act further stipulates that, for prudential reasons, governance and supervisory activities (e.g., risk management) must be organized centrally, which creates a potential pathway for information to flow. Thus, as our paper highlights, for universal banks, there is a fundamental conflict between regulation to address conflicts of interest and prudential regulation to ensure financial stability.

We analyze around 168 million trades (with a volume of €3.5tn) around 39,994 corporate events. Our results indicate that banks' trading in their borrowers' stocks is informed. We first examine banks' proprietary trading two weeks prior to a corporate event. We follow Griffin et al. (2012) and focus on banks' net purchases 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 an event determines a bank's event profit. Our base model includes fixed effects for each event and bank-industry. Thus, we compare trades across banks within the same firm event as well as trades *within the same bank* in borrower

[3]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 security price if revealed. The definition of an insider is at least as broad in concept as it is under U.S. insider trading rules (Ventoruzzo (2015)).

stocks and stocks of the same industry for which the bank has no lending relationship. Using all events, we find that banks purchase significantly more shares prior to corporate events with positive news (market-adjusted) when they have a lending relationship.

Importantly, our results are much stronger for unscheduled events, such as pre-announcements, earnings guidance, or special dividend events. We find that banks engage in significantly larger net purchases (sales) before unscheduled positive (negative) news events (0.20bp and -0.07bp of shares outstanding, respectively) when they have a lending relationship. 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 material events, which we define as having absolute market-adjusted returns above 2%. The return to these events suggests that they are indeed surprising to market participants and hence difficult to anticipate, but apparently not to banks when they trade borrower stocks. Mapping out trading around these unscheduled events shows that banks start building up their positions four or five weeks before the event and then reverse them in the weeks after. Similarly, we analyze M&A events because firms are likely to discuss impending M&A transactions with their relationship banks (e.g., to secure funding).[4] We find larger net purchases by banks with lending relationships ahead of M&A events, particularly when the bank client is a seller or a target in the transaction.

To assess economic significance, we examine the direction of trade, which is not prone to outliers. We first show that banks trade much more frequently in the direction of the event news, when they are the relationship bank for the firm.[5] Suppose positive and negative news events are equally likely and banks trade around events by flipping a coin, i.e., without expertise or private information, implying 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 all events is 25.7%. Thus, on average, bank trading

[4]See also the literature reviews by Bhattacharya (2014) and Augustin and Subrahmanyam (2020) pointing to concerns about informed trading prior to M&A transactions.

[5]Trading more frequently in alignment with the event return generates an incremental return of 0.73pp per event when the bank has a relationship. This incremental return is sizable considering that the average (median) return for material unscheduled events is 6.5% (4.6%).

around corporate events is only marginally better than chance, illustrating how difficult it is for prop-trading banks to predict even the direction of the (market-adjusted) return of corporate events. However, when banks have lending relationships, this probability increases by 6.2pp for *unscheduled* events with absolute returns above 2%, which is remarkable, considering that the return magnitude implies that these events were major news to the market. This evidence suggests that private information flows from lending are economically material.

Naturally, incremental purchases (or sales) in short windows around specific events capture only a fraction of banks' prop trading profits. We therefore compute trading profits in the way banks manage their trading desks internally, namely, by marking trading positions to market on a daily basis and accumulating the profits. This approach provides a comprehensive assessment of proprietary trading profits. Comparing the profitability of trades in borrower stocks versus in stocks of other firms within the same bank, we find an incremental trading profit of roughly €400,000 per quarter and relationship. This profit increases to €800,000 when we estimate it with bank×firm fixed effects, which essentially isolates relationship periods for a bank-firm pair. Considering that relationship banks serve on average 11 firms in a given quarter, these results confirm that within-bank information flows are economically significant and raise questions about the effectiveness of banks' organizational structures. Moreover, we find that, without lending relationships, prop trading is on average *not* profitable, yet profits exhibit considerable volatility. Five percent of bank-quarter losses exceed €-0.63bn, which for the Top-5 banks is on average more than 2% of book equity or Tier 1 capital. These results underscore the concerns about banks' speculative trading activities, which were at the heart of the regulatory debate after the Financial Crisis and gave rise to the Volcker Rule (U.S. Government Accountability Office, 2011).

Having established that informed trading is economically material, we conduct two sets of tests that all but rule out bank expertise as an explanation for our results and show that client relationships are the likely information source. First, we exploit that banks are likely to build up expertise prior to winning a client and that this expertise should not

disappear immediately after the lending relationship ends. Thus, if client-specific expertise drives our results, then we should see profits outside the relationship period, especially after relationships end. To the contrary, we do not find significant event-trading effects after the lending relationships end. Moreover, the total mark-to-market profits from relationships and the results for banks' event trading become more pronounced when we add bank×firm fixed effects, which essentially isolate relationship periods. Thus, banks trade profitably around corporate events when they concurrently have lending relationships, but lose their edge when the source of private information is gone.

Second, we identify corporate events (e.g., announcing legal disputes, joint ventures or M&A) that involve two firms, a borrower and a firm with whom the first firm's bank has no lending relationship (i.e., an *unrelated* third party). We analyze trading in the third party's stock around the joint corporate event. We find that borrowers' relationship banks are able to trade in the direction of the event return of joint events with about 20pp higher probability. However, the same banks do not exhibit such *skill* trading in the *same* unrelated firms around other events that do not involve their borrowers. This shows that these banks do not have general trading expertise in third party firms and instead indicates that borrowers are their source of private information, giving them an edge in joint events only.[6]

The evidence so far suggests that private borrower information finds its way to the trading desk, despite the presence of ethical walls and organizational structures to prevent such transmission. We therefore turn to the channels for such transmission. Private information could be passed on directly (e.g., in private conversations) but could also travel indirectly. We start by exploring an indirect channel that arises in universal banks from combining commercial and investment banking activities. For universal banks, effective risk management requires centralized information on and oversight of all significant bank activities and exposures, including lending and trading. In fact, the German Bank Separation Act explicitly stipulates a centralized risk management function for this reason. However, a centralized

[6]We also examine whether the effects are stronger when banks have recently obtained private information from their borrowers, e.g., after granting a new loan. Supporting this logic, we observe larger net purchases by banks before unscheduled events of borrowers to whom they issued a loan in the prior quarter.

unit that *sits above the wall* necessitates structures to prevent information flows and manage conflicts of interest.[7] Such a conflict arises for risk management, for instance, when the prop-trading desk has a large exposure to a borrower (say a short position), and the lending side receives information about an impending corporate event with valuation implications that go in the *opposite* direction. Even if risk management does not directly share information across units, it sets (or adjusts) limits for bank activities on both sides of the wall, which could indirectly transmit information. To explore this idea, we determine banks' trading exposures ahead of major events and find that banks are more likely to unwind an existing short (long) position before their borrowers have unscheduled, positive (negative) news events. Although these results do not rule out direct information flows, they raise the intriguing question of whether organizational structures that collect information centrally (perhaps even for prudential reasons) play a role in banks' informed trading patterns.

Finally, we gauge the extent to which information flows are deliberate or inadvertent. Doing so is obviously difficult, but studying trade execution patterns could provide clues. The idea is that, if trades are consistent with the rules, we would not expect banks to execute them differently simply because they involve stocks with lending relationships. Conversely, if banks use private information and thereby skirt or even violate the rules, we expect them 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 idea, we find that the informed trading results no longer exist 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* trade execution for a given stock *once* they enter (or end) the lending relationships. Thus, the change in banks' trading patterns coincides

[7] The same dilemma arises in complex U.S. financial institutions, which have centralized risk management overseeing broker-deal activities and lending operations (SEC, 2012).

[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%.

with their access to private information. We also study intra-day transaction prices to see if other market participants understand that banks have superior information. Consistent with price protection against adverse selection, we find that banks obtain worse prices when trading borrower (but not other) stocks in the OTC market, where their identity is known to market participants. We find that banks respond to this price protection by building suspicious positions in stocks with relationships more often on exchanges.

Our study contributes to an important literature and ongoing policy debate about conflicts of interest in universal banks. The existing literature has primarily concentrated on potential conflicts that arise when commercial banks provide loans and underwrite securities for the same firm. Several influential studies examining this conflict find little evidence for these concerns (e.g. Kroszner and Rajan (1994) and Puri (1994)). Instead, studies highlight the benefits of private information acquisition from lending, e.g., allowing a better certification of securities (see e.g. Puri (1996), Drucker and Puri (2005), Duarte-Silva (2010), and Neuhann and Saidi (2018)). Our paper examines a different conflict of interest that arises when universal banks possess private lending information and engage in prop trading. To shed light on this conflict, we study universal banks in Germany, which is a powerful setting because German firms traditionally maintain strong ties with their main lenders or *Hausbanken* (Allen and Gale (1995)). Moreover, Germany still allows proprietary trading but requires organizational structures to address the ensuing conflicts of interest. We show that, despite the existence of ethical walls, private lending information finds its way to the prop-trading desk. Our results raise questions about the effectiveness of banks' organizational structures in managing conflicts arising from access to private lending information, and as such point to a darker side of universal banking. In addition, our evidence exploring the channels of information transmission flags the bank's risk management as a potential source for the *wall-crossing* of private information, highlighting the inherent challenges of regulating universal banks for financial stability and proper market conduct.

We also 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 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 their findings based on trade-level data cast doubt on prior evidence using less granular trading data, typically constructed from holdings data in quarterly 13F filings. Based on 530 SEC investigations, Kacperczyk and Pagnotta (2024) document that insiders trade less aggressively and earlier when facing higher legal risk. Prior evidence that banks trade on borrower information tends to be indirect and inferred from market-level outcomes, such as return or price discovery patterns in CDS, secondary loan or stock markets, equity analyst forecasts or syndicate participation, (e.g., Acharya and Johnson (2007), Bushman et al. (2010), Carrizosa and Ryan (2017), Chen and Martin (2011), Kang (2021)). Our study adds to this literature by combining credit registry data with trade-level supervisory data, which allows us to provide more direct evidence on trading patterns, including shrouding of trades.

2 Institutional Setting

In this section, we first discuss the evolution of regulatory frameworks governing banks' proprietary trading. Thereafter, we describe the EU's legal rules for insider trading.

[9] Consistent with work for the U.S., Bittner et al. (2024) provide evidence of information transmission among German banks in syndicated loan networks around M&A events.

The conflict of interest that arises when universal banks obtain confidential information about their borrowers and, at the same time, trade securities of these borrowers in the capital markets has featured prominently in the regulatory debate. Concerns about this and related conflicts were central to the separation of commercial and investment banks in the U.S. under the 1933 Glass-Steagall Act (e.g., Kroszner and Rajan (1994)). In 1999, the latter was repealed by the Gramm–Leach–Bliley Act, but after the financial crisis of 2008, renewed concerns about prop trading led to the Volcker Rule in 2010, which again bans proprietary trading by financial institutions, but exempts market-making.[10]

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 and to strengthen financial stability. This expert group proposed, among other things, separating commercial and retail banking activities from certain investment banking activities (Liikanen et al. (2012)). Another recommendation was to ban 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 Group's recommendations were not implemented at the EU level, Germany took unilateral action enacting the Bank Separation Act, a law designed to shield deposit and credit operations from losses incurred through risky activities such as proprietary trading. The Act passed in August 2013, but banks had until July 1, 2016 to reorganize and 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

[10]One concern were large losses from prop trading by deposit-taking institutions. For instance, when analyzing the prop trading of the six largest U.S. banks from 2006 to 2010, U.S. Government Accountability Office (2011) finds banks had only modest gains from proprietary trading in non-crisis times, which were more than offset by large losses of almost $16bn during the financial crisis.

[11]For details on this proposal, see European Parliament (2014).

[12]The Act 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.

the thresholds are not prohibited from prop 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 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 prop trading volume in 2017, the first full year after the reform, is only slightly lower than in 2015 but still *higher* than in 2012 and 2013 before the Act passed.[14]

Germany, like most countries, has legal restrictions on insider trading. The relevant regulations are set by the EU and are broadly similar to those in the U.S.[15] Insider trading is regulated under the Market Abuse Directive 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

[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 overall funding costs in the same way a trading desk in the parent company would.

[14]Our informed trading results presented in Section 4 are present before and after the German Act.

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

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.

3 Data and Descriptive Statistics

3.1 Bank Trading and Lending Data

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

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 until 2017 when the WpHMV was replaced by EU regulation 600/2014 (Markets in Financial Instruments Regulation; MiFIR), requiring that banks report to the European Central Bank. For each transaction, we have the security traded, date, time, price, volume, currency, 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 focus on 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 in Table IA.7, but do not find evidence for them offsetting or attenuating the effects reported for equity trading. We do not find effects for corporate bond trading by banks, but this result is not surprising as bonds are typically very illiquid and rarely held in German banks' trading books.

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).[18] We aggregate all loans to a given firm at the level of the banking group to also capture lending relationships

[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.7 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] 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.

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.

3.2 Compilation of Corporate Events

Public databases on corporate events vary in their coverage, so we combine several sources (Capital IQ, Eikon, IBES, Factset, and Ravenpack) to compile a comprehensive set of events for our sample firms. The resulting data set comprises 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, resulting in 39,994 corporate events. For each event, we compute market-adjusted event returns by subtracting the DAX index return. As Figure IA.1 shows little evidence of leakage or price drifts, we use the [-1;+1] window to compute event returns. Yet, our results are comparable when using event returns computed over longer windows, e.g., [-7;+1].[19]

Table 1, Panel A, shows frequencies and returns across event categories. Most events (11,484) involve earnings or financial reporting, 6,808 relate to management guidance, 3,168 involve dividends, and 6,303 concern M&A. Such M&A events include consummated deals, announcements of intended deals, and rumors about potential transactions, explaining their high count. We flag when the firm is the target of an M&A transaction. Operating events (6,361) are frequent and comprise a broad range of firm news (e.g., product announcements, capacity expansions, strategic alliances) many are of lesser importance, resulting in smaller returns. Across all categories, most events exhibit (absolute) abnormal returns exceeding the firm-specific median over the sample period, indicating material news for investors.

Next, we divide 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

[19] We drop events where the [-1;+1]-return is precisely zero, indicating no trading activity. Retaining these events does not change 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 given at the EA and stand-alone guidance offered separately; the latter is less common than guidance given at the EA.

An important distinction for our analysis is whether events are announced in advance. We expect sophisticated investors to collect and analyze information before announced corporate events. We thus distinguish between scheduled events (e.g., conference calls) and unscheduled ones. We define *unscheduled earnings-related events* (UE) as pre-announcements, stand-alone management forecasts, and unscheduled dividend events. The latter are announcements of special dividends, stock dividends, and dividend decreases. We treat dividend increases as scheduled, as many firms follow a known pattern of dividend hikes.

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 little leakage ahead of the events. The same is true for M&A events, which we analyze as a separate event category.

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.[20] We drop firms for which we do not have any corporate events.[21] 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.[22] 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.[23] It is therefore possible (but not common)

[20] 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).

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

[22] 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.

[23] 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 *both* adjacent ones. These large fluctuations indicate a firm maintains a current account at the bank but not necessarily a longer-term loan. 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 variable in Table IA.2. Even when we consider no threshold, so any lender counts as relationship bank, the results are still significant, albeit lower in magnitude. However, without a threshold, we often pick

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. 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 majority (83%) of the relationships. 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 bank.

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 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 accumulate trades to determine the net purchases (sales if negative) for each of the 47

up current accounts, which firms maintain at several banks, rather than their relationship lenders. Thus, as we increase the percentage threshold for the relationship definition, the results become stronger.

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). Net purchases are defined as $\frac{buys-sells}{shares\ outstanding} \times 10,000$. They are scaled by the respective firm's shares outstanding and expressed in basis points (bp) to make them 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 lending relationship.

Panel D of Table 1 provides summary statistics for this bank-event data set. The loan share of relationship banks 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 the firm's market capitalization. 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 some very large observations on either end (which is why we winsorized net purchases at the p1 and the p99). We 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 before an event exceed the size of the banks' holdings in the prior month. For a quarter of cases, banks carried out net purchases ahead of the event without having any holdings of the stock in the previous month.

4 Research Design

This section describes our main 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, 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 prop 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 that are 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 the shares outstanding. The base sample is a balanced panel because banks that do not trade before an event have net purchases of zero. However, for many analyses, we impose further sample restrictions, 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 (or *Hausbank* 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 banks' trading patterns of borrower stocks 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 by relationship banks in borrower stocks in the two weeks before negative-return events. The latter estimates the same incremental net purchases for positive-return events.

The model includes a fixed effect 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 also 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. Thus, the model compares net purchases *within bank* of borrower stocks and stocks without lending relationship. The expansion by industry accounts for potential expertise differences across banks (e.g., their ability to forecast earnings or events) that could stem from prop trading desks and research teams specializing in specific industries. We cluster standard errors at the bank level.

4.2 Informed Trading vs. Bank Expertise

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

We begin by exploiting time-series variation in lending relationships. In our sample, banks initiate new relationships and terminate existing ones. Building expertise takes time and does not disappear immediately when a relationship ends. However, firms stop reporting private information once the lending relationship ends. Hence, if bank specialization is the source of a bank's superior trading in a particular stock, such expertise should not precisely coincide with the duration of the lending relationship and, in particular, should outlast the active lending period. In contrast, private information flows exist only during the relationship itself. To exploit this difference, we estimate the following specification:

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

We include relationship-specific (bank×firm) fixed effects as indicated by γ_{bf}. Thus, our main coefficient of interest β_1 compares net purchases *within a given bank* around positive-return corporate events of the *same* firm for periods when the bank is a relationship lender with times when it is not.[24] To allow for an explicit comparison of coefficients, we introduce $[Non - Rel.Periods_{be}]$, which is an indicator variable equal to one for periods when the bank is not yet or no longer the relationship lender (and zero otherwise). The coefficient β_2 estimates whether banks can trade profitably in borrower stocks outside the relationship periods, which would indicate expertise. We further refine this test and replace the indicator with $[After - Rel.Periods_{be}]$. With this specification, we can compare the same bank's trading behavior during and after the relationship period, when expertise should still be there, but the firm no longer provides information to its lender.

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 busi-

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

ness 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. We exploit these institutional features and analyze bank trading prior to UE events in the quarter after a new loan has been granted, relative to the same bank's trading in other quarters. We also perform these tests within bank-firm pair to further tighten identification.

Our third test to separate bank expertise and informed trading focuses on corporate events that involve two firms (e.g., mergers, joint ventures or legal disputes).[25] Among such joint events, we select cases where a bank serves as *Hausbank* for one of the firms but has no relationship with the other firm. We then analyze the bank's trading in the *unrelated* firm (*third party*) around the joint event and around all other events of this firm. The idea is that successful trading around third-party events is harder to explain with bank expertise, especially if it is confined to joint events for which the bank likely has private information from its borrower.[26] To fix ideas, consider the following scenario: Firm F1 plans to take over Firm F2. Bank B is the *Hausbank* for F1 but has no relationship with F2. As *Hausbank*, B is likely informed about the impending M&A transaction involving its borrower F1, e.g., because B arranges financing. We examine the success of B's trading in the unrelated firm (F2) around the joint event, relative to the success of all other banks that trade around this event, but also relative to B's success in trading around *other* corporate events for F2 that do not involve F1. That is, we compare trades in the same third party for the same bank around events with and without private information. The latter serves as a benchmark indicating whether B has general expertise when prop trading F2's stock.

[25]We screen all event headlines for sample firm names and identify events that involve two different sample firms. M&A events account for about 75% of these cases. Firms forming a strategic alliance account for another 15%. The remainder is from miscellaneous event categories, including legal disputes.

[26]The idea of this test is related to the notion of shadow trading, where insiders exploit non-public information about their own firms by trading in other companies whose stock prices are indirectly affected. Notably, this activity is classified as privately informed trading, or insider trading (Enriques et al. (2025)).

5 Main Analysis

5.1 Relationship Banks' Trading around Corporate Events

Table 2, Panel A, presents the results of our main analysis, which analyzes banks' prop trading ahead of corporate events. We first estimate specification (1) over all corporate events. We find that, when banks have lending relationships, they engage in significantly larger net purchases of borrower stocks in the 14-day window ahead of events with positive market-adjusted returns. This finding holds when we estimate it within a given event comparing purchases by relationship and non-relationship banks of the same stock (Column 2) and within a given bank comparing its purchases of borrower stocks and non-borrower stocks in the same industry (Column 3).

Next, we restrict the analysis to corporate events that are not scheduled in advance and hence harder to predict. An association for these unscheduled events is more likely to reflect informed trading than bank 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 borrower stocks by relationship banks prior to positive-return events increases substantially from 0.03bp to 0.20bp. Now, we also see significantly larger net sales by relationship banks ahead of negative-return UE events of their borrowers. 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 less pronounced for negative news.

Not all unscheduled events are necessarily a surprise to the market; some of them or their news can be at least partially anticipated by sophisticated investors. If so, we expect event returns to be smaller. We therefore split UE events by their absolute return to analyze events with bigger and smaller surprises separately. The findings in Columns 5 and 6 show a stark difference. Net purchases (or sales) of stocks with relationships are not significant when the

absolute event return is small and below 2%. But for UE events with an absolute return greater than 2%, which are bigger news to the market, the relationship trading effect increases substantially in magnitude for both positive and negative news events. This difference in the results across Columns 5 and 6 already points in the direction of informed trading. Based on this evidence, we restrict the remaining tests to UE events with absolute abnormal returns of at least 2%. In doing so, we focus on events with relatively large information content that surprise the market, which should aid the identification of privately informed trading.[27]

In Panel B, we investigate the dynamics of banks' relationship trading around UE events.[28] To do so, we compare *within a given bank* net purchases of relationship stocks to net purchases of non-relationship stocks over different two-week time windows around a particular UE event. We find that, when banks have relationships, they build profitable positions shortly before positive UE events and reverse them in the month afterward. However, as we move further away from the event, banks trade comparably whether they have relationships or not, i.e., we do not find significant differences 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, banks engage in significantly more net sales of relationship stocks. Interestingly, the coefficients for these two post-event windows almost exactly offset the coefficient in the [-14,-1] window, suggesting that positions built prior to an event are essentially reversed within one month after the event. After that, trading differences become insignificant again. The dynamics of negative UE events are similar but less pronounced.

To graphically illustrate banks' trading patterns over time, we plot the cumulative mean net purchases around positive and negative UE events in Figure 1. The trading patterns around UE events look very different depending on whether a bank has a lending relationship for the stock or not. Without relationships, banks engage only in small net purchases or sales around UE events, consistent with the notion that anticipating UE events (or their

[27] We acknowledge that the choice of 2% is ad hoc, but it is not central to our results. The findings are similar without a cutoff or using other cutoffs such as 1% or 3%. The results tend to become more pronounced when the analysis focuses on material news events, which is telling. See also Table 9.

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

returns) is difficult. With relationships, we observe substantial net purchases *prior* to a positive (negative) UE event and subsequent reversals.

Prior work documents informed trading by capital market participants ahead of M&A announcements (e.g., Augustin et al. (2019)). M&A events are difficult to anticipate, just as UE events. Thus, they present another opportunity to analyze whether prop trading differs for stocks with and without lending relationships. We find strong evidence of trading by banks in stocks with relationships prior to positive-return M&A events. As shown in Table IA.5, the coefficient on all M&A events is significant, estimating incremental net purchases of about 0.16bp (Column 1). The magnitude of this effect further increases when we analyze events for which the borrower is central to the M&A event, i.e., a target (Column 3) or a seller (Column 5).[29] These findings closely align with our results for UE events, indicating that prop trading ahead of events is more pronounced when banks are likely in the possession of private information from their borrowers, in this case M&A-related information.[30]

5.2 Assessing the Economic Magnitude of Event Trading

It is difficult to assess banks' profits from informed trading for a number of reasons. For one, banks are unlikely to be privately informed about each and every borrower event in our analysis. Thus, the estimated event profit would be an average over events for which the bank is informed and those for which the bank had no private information. Moreover, for identification, our main analysis focuses on net purchases in a narrow window before unscheduled events. Event returns on the entire position in the borrower stock would not be captured. The same holds for potential gains from holding relationship stocks over longer periods as well as rents from private information unrelated to specific corporate events. Recognizing these challenges, we later measure and analyze banks' entire proprietary trading profits (see Section 5.4). Here, we use two simple approaches to gauge whether banks' event

[29] Consistent with our results in Section 5.3, these results are robust and strengthen when we include bank×firm fixed effects (Columns 2, 4 and 6).

[30] Consistent with our results, recent evidence by Bittner et al. (2024) further suggests that German banks exchange information about M&A events within their syndicated loan networks.

trading documented in the previous section is economically meaningful.

First, we construct two simple binary variables. One that indicates whether a bank's net purchases (or sales) in the two weeks before an UE event were in the *right* direction, i.e., consistent with the event news. The second indicates whether a bank traded in the right direction in the two weeks before *and* then trades in the opposite direction after an UE event, essentially unwinding its prior trades. We refer to such cases as *suspicious trades*. These binary variables have two advantages. They allow us to jointly analyze positive and negative events and they are not prone to outliers or skewness in banks' net purchases. Moreover, they allow us to gauge how pervasive successful event trading is using random trading without skill as a benchmark. 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 (as defined above) would occur with 25% probability by chance.

Table 3, Column (1) suggest that the probability of trading in the right direction increases by 9.2pp when banks have a lending relationship with the stock. Relative to a baseline probability for random trading of 50%, this effect is economically large. When looking at the (relative) frequency of suspicious trades, we find that the probability increases by 6.19pp when banks trade in relationship stocks (Table 3, Column (2)). Furthermore, the mean of the variable *Suspicious Trade* for non-relationship observations indicates that the probability of suspicous (or successful) trades around major UE events is only 25.82% if banks do not have a relationship. This small increase relative to the random trading baseline probability of 25% indicates that banks generally find it difficult to trade in the right direction around major UE events and that average bank expertise for these events is limited. Viewed from this angle, the increase of the probability for relationship trades is massive.[31]

Second, we follow Ivashina and Sun (2011) and interact the trade direction with the event

[31] As another way to gauge the success of banks' event trading when they have relationships, we aggregate profits from all relationship trades (without truncation) and compute their contribution to banks' total event-trading profits. We find that, although relationship trades represent only 1.6% of all bank-event combinations, they contribute roughly 14% of banks' total event-trading profit.

return. With this construct as dependent variable, we can estimate the incremental event return generated by relationship trading. We find that relationship trades earn banks an additional return of 0.73pp per event, essentially by trading more frequently in the same direction as the event return (Table 3, Column 3). This return increment is sizeable in comparison to the event return earned without relationships and relative to the mean (median) absolute return of UE events with at least 2% abnormal returns, which is about 6.5% (4.6%).

5.3 Information from Relationships vs. Bank Expertise

The results up to this point are consistent with the interpretation that, despite the existence of ethical walls, banks use information from their lending relationships when prop trading. However, banks may specialize in certain industries, business models, or firms. Such specialization and the resulting expertise could manifest in profitable prop trading, even without any information flow from the lending side to the trading desk. In this subsection, we present three sets of tests that intend to differentiate between the two potential explanations.

First, we exploit changes in lending relationships by estimating specification (2). Bank expertise takes time to build and does not immediately disappear when a relationship ends. Thus, successful trading based on expertise should not exactly coincide with the duration of the lending relationship. In contrast, the bank obtains private information from lending only while the relationship exists and debt contracts require borrowers to inform their relationship banks. As discussed in Section 4.2, we introduce bank×firm fixed effects so that our coefficient of interest is estimated within bank-firm pair and compares net purchases around corporate events during times when the bank is a relationship lender of the firm with times when the same bank is not yet or no longer a relationship lender for the *same* firm. In Table 4, Column 1, we find a strong relationship trading effect around positive UE events even with bank×firm fixed effects. In Column 2, we estimate separate coefficients for relationship and *non-relationship* periods ahead of positive UE events. The latter coefficient is small and statistically insignificant, indicating that banks engage in abnormal net purchases

only when they have a relationship and hence have access to private information from the borrower. In Column 3, we refine this analysis and estimate a separate coefficient for banks' event trading ahead of positive UE events in periods *after* a lending relationship has ended but the bank should still have expertise, 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 obtain information from their borrowers.[32] To further tighten the analysis, we saturate the model with bank×firm×year fixed effects, which controls for unobserved variation in bank-firm specific trading patterns over time. Even with these controls, the coefficient of interest remains significant and increases in magnitude (Column 4).

Second, we home in on lending information flows and estimate whether the results are stronger when banks are likely to obtain more or new information from their borrowers. For instance, banks are likely to have more substantial information needs and hence more frequent exchanges with their borrowers when their loan exposures are (relatively) large. Moreover, firms need to provide their relationship bank with detailed information before a new loan is granted.[33] We explore these ideas in Table 5 and find that the estimated relationship trading effect increases in magnitude as the relationship bank's exposure or relative loan share becomes larger (Columns 1 and 2). We also find that the relationship trading ahead of UE events is more pronounced when a bank has recently granted a new loan. We code a relationship bank as granting a new loan if the loan amount to the borrower increases by at least 33% relative to the previous quarter (following Behn et al. (2016)) *and* its increase exceeds €2m, €50m or 10pp, respectively. In all three specifications, we find incrementally larger net purchases prior to positive UE events when relationship banks

[32]These results are robust to alternative definitions for the relationship variable. In particular, they hold when we (i) apply different relationship cutoffs (similar to Table IA.2); (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 of the loan share around the 25% coding threshold); (iii) consider only those loan initiations (terminations) for which a bank did not lend at all in the quarter before (after) the event.

[33]In untabulated regressions, we analyze trading by the seven sample banks, which have loan exposures but are not classified as relationship (or Haus) banks. We find that these banks do not trade differently around UE events compared to banks without loan exposures, which further validates our relationship classification.

recently granted new loans (Columns 3-5). The same holds for negative UE events but is not tabulated. Lastly, we introduce bank×firm fixed effects to compare the trading behavior in quarters after a new loan is granted to other quarters within the same bank *and* borrower and show that the effect is three times larger after new loans (Column 6).

Our third and last test pitches the two explanations against each other. As explained in Section 4.2, we analyze corporate events that involve two firms (e.g., legal disputes, joint ventures, or mergers), one of which is a borrower and the other is an unrelated firm with which the bank has no relationship (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 firm. The idea of the test is that there is likely information flow between the borrower's relationship lender and the borrower for such joint events, but not for other events of the third party. Thus, the information flow explanation suggests that banks can trade successfully trade ahead of joint events but not prior to other events. If the explanation is bank expertise, then this expertise should show up ahead of all events. We provide results for the third-party test in Table 6. 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* banks could have relationships with the third party and hence may also trade ahead of its events, we control for these lending relationships with a separate indicator.[34] We find that the probability of *a suspicious trade* (as defined earlier) increases by about 19.88pp when we focus on joint events for which the bank could have obtained information from its borrower (Column 1). This effect becomes even more pronounced (Column 2) when we focus on isolated joint events (that do not overlap with other events for the same firm on the same day). When we now examine whether the same banks trade successfully in *other* events of the third party, we find no evidence that they can; the results in Columns 3-4 (and in Columns 5-6 for UE events) are statistically and economically insignificant.

[34]As one would expect, the coefficients for this indicator (not reported) are comparable to those for relationships in Table 3. We obtain similar results in Columns 1 and 2 when we use bank×firm fixed effects.

5.4 Mark-to-Market Profits from Proprietary Trading

Having established that banks' lending relationships are a source of informed trading, we come back to the question of economic magnitude and analyze banks' profits from relationship trading and more generally prop trading as a whole. We compute these profits in the same way banks manage their trading desks internally, i.e., by marking individual trading positions to market on a daily basis and then aggregating these profits.[35] This approach should capture all prop trading profits from banks' relationships, including but not limited to profits around specific corporate events. For the regression analysis, we aggregate daily profits by bank and firm over a quarter. Thus, data are at the bank-firm-quarter level, which allows us to compare the profitability within bank across stocks with and without lending relationships. Table 7 presents this analysis of quarterly profits from prop trading. In Column (1), we find an incremental profit of roughly €400,000 per quarter and relationship, using bank fixed effects. Next, we include bank×industry fixed effects (Columns 2) to account for banks' industry expertise and additionally firm fixed effects (Column 3). The results are similar and profits slightly increase. In Column (4), we introduce bank×firm fixed effects to exploit changes in relationships (see Section 4.2). As this analysis is quite demanding, the statistical significance is lower, but the estimated magnitude of quarterly trading profits per relationship doubles to approximately €800,000. Considering that relationship banks in our sample serve on average 11 firms in a given quarter, the incremental trading profits per bank and quarter are clearly economically significant. Moreover, profits of this magnitude raise questions about the effectiveness of banks' organizational structures in addressing conflicts of interest in universal banks.

The estimates for the constant in Table 7 further reveal that banks' average quarterly profit from trading stocks *without* relationships is close to zero or even negative, with values

[35] To compute mark-to-market profits, we need to start with banks' pre-existing holdings in the trading book. The Securities Holdings Statistics (SHS) at the Bundesbank provide such data, separately for the banking and trading book, but only starting in 2014. Thus, our analysis covers 2014 to 2017. We do not winsorize daily profits to accurately capture banks' earnings. Starting our construction of daily profits without prior holdings and using the full sample period (2012 to 2017) provides a similar picture but with smaller magnitudes, presumably because we are missing some holding returns early in the sample period.

ranging from -€51,000 to -€63,000. Thus, on average, banks' prop trading is not profitable. Yet, banks' quarterly prop trading profits are very volatile, which is noteworthy from a financial stability perspective. Across all bank-quarters, even the Top-5 banks do not make money. Their average quarterly profit is only €-25m, but their worst quarter losses (i.e., p5) exceed €-0.63bn. These losses amount to roughly -2.1% of Tier 1 capital or -2.4% of book equity. Our finding of low prop trading profits combined with high volatility is consistent with calculations by the U.S. Government Accountability Office (2011) for six large U.S. banks after the 2008 financial crisis. Together, they clearly highlight the role of prop trading in the risk-taking by banks with deposit guarantees, a central concern in the regulatory debate that led to the ban of prop trading (see Section 2).

6 Channel Exploration, Trading Patterns and Price Protection

The preceding findings suggest that private borrower information makes its way to banks' trading desks despite ethical walls and organizational structures intended to prevent such information flows. In Section 6.1, we explore one potential indirect channel, the centralized risk management in universal banks. In Section 6.2, we study trade execution patterns to shed light on the extent to which banks shroud their informed trades. Section 6.3 investigates price protection by other market participants in response to banks' informed trading.

6.1 Risk Management as a Potential Pathway

Information about a borrower could be conveyed directly, e.g., through private conversations between loan officers and traders within the same institution. Banks also hold staff meetings that are attended by people on the "public" and the "private side", in which information could be exchanged directly (SEC (2012)). To prevent direct flows of private information, banks create organizational rules and structures (i.e., ethical walls). In addition, private

information could be transmitted indirectly through centralized functions that sit above the wall for governance and oversight reasons. For instance, bank risk management collects information centrally and possesses information about loan exposures and trading positions. Such structures are necessary in universal banking, as effective risk management in such institutions requires centralized oversight of all risk exposures. Recognizing this, the German Bank Separation Act explicitly mandates a centralized risk management function, noting that such a unit must implement strict controls to prevent information flows and mitigate the conflicts of interest that inherently arise from the universal banking. But even if risk management does not explicitly share information between units, it approves, sets or adjusts limits on activities on both sides of the wall based on all its information and hence may indirectly transmit information.

Of course, we cannot observe information flows within a bank. But we can explore the role of risk management with an empirical test that focuses on situations that pose a conflict of interest for the bank and its risk management. Imagine a situation in which a bank's prop-trading desk has a significant exposure to a borrower, say a short position, and the lending division learns about an impending major corporate event that likely will move the borrower's valuation in the opposite direction. In this situation, risk management might curtail the trader's limit for the respective stock, forcing the trader to reduce or close the short position. We do not have data on limits but we can construct tests that examine bank trading in such situations, again comparing within bank across relationship and non-relationship stocks.

To determine whether banks have short or long positions before a corporate event, we accumulate purchases and sales by each bank for each stock starting in 2012 on a daily basis. We then take the bank's net position at the end of the month prior to an event for the respective stock to code the binary indicator variables $Short$ and $Long$. Creating interactions with these variables, we can analyze whether bank trading behaves differently in the two weeks ahead of positive or negative UE events, depending on whether they have had a long,

short or no position in the respective borrower stock.[36] Based on this coding, around 16% of all nonzero bank-firm-month exposures are negative, indicating a short position at the end of the month. Table 8 presents results analyzing prop-trading behavior in borrower stocks ahead of major unscheduled events depending on whether a bank's prior position. Column 1 focuses on positive UE events above 2% abnormal returns. We find that banks engage in (significantly larger) net purchases in borrower stocks ahead of these events when they have a short position, thus reducing or closing the short position ahead of the positive news. We also observe purchases of relationship stocks prior to positive UE events when banks already have a long position in the borrower. This is essentially our earlier main result. The results in Column 2 are similar and, if anything, slightly stronger when we require the prior short positions to be above the median short position over the sample period. Column 3 presents the results for negative UE events above 2% abnormal returns. Here, we see the reverse pattern. Banks engage in sales in relationship stocks when they have a long position, thereby reducing or closing their long exposures ahead of negative news events. The interaction with *Short* is negative but not significant, indicating that relationship trading ahead of negative events focuses on reducing positive exposures, rather than shorting. Again, the results are similar (Column 4) when the long position is above the sample median for long positions.

These findings do not prove that private information travels via the risk management function, but the documented combination of holding and trading patterns is what we would expect to see if risk management were to influence positions and prop trading with limits set based on information from the lending side. As such, the results pose an intriguing question: Could centralized organizational structures, which are created for prudential oversight and financial stability, play a role in the transmission of private information transmission? At a minimum, they highlight a fundamental conundrum in universal banking.

[36] As noted earlier, the Deutsche Bundesbank's SHS database, which reports banks' security positions in the trading book at the end of each month, starts only in 2014. If we use this database to code the variables *Short* and *Long* from 2014 onward, the results are similar.

6.2 Flying under the Supervisory Radar

Next, we gauge the extent to which information flows are deliberate or inadvertent. Assessing this is inherently challenging, but studying trade execution patterns could provide clues. The idea is that, if prop trades adhere to the rules, we would not expect banks' trading patterns to systematically differ for stocks with and without lending relationships. Conversely, if banks use private information and thereby skirt or even violate the rules, we expect them to shroud their informed trading to avoid supervisory scrutiny.

Naturally, very large news events or very substantial trades are more likely to hit the supervisory radar.[37] Consistent with this logic, almost all prosecuted insider trading cases that 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 supervisory radar when they trade on superior information obtained from their borrowers, they should avoid corporate events that they expect to generate very large positive or negative returns. Similarly, large trades are more likely to attract the supervisor's attention than small trades. Thus, if banks act deliberately and want to shroud their informed trades, we expect them to build their trading positions in relationship stocks ahead of corporate events with many small trades rather than a few large ones. We explore both ideas empirically.

We first explore heterogeneous effects in relationship trading depending on the absolute abnormal event return. Table 9 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 significant abnormal net purchases in their borrowers' stocks for UE events with small returns (Column 1). We find higher net purchases for relationship banks in their borrowers' stocks 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 suggests that relationship banks avoid trading in their borrowers' stocks around corporate events that likely have substantial returns and hence receive attention from the supervisor.

[37] According to DeMarzo et al. (1998), supervisors maximize investor welfare by focusing on events with significant price changes and large trading volumes.

Next, we analyze trade frequency and trade size. The model includes bank×industry as well as event fixed effects. Thus, we compare trades within the same bank when it trades in relationship and non-relationship stocks in the same industry around corporate events as well as within event when banks with and without lending relationships trade the same stock. Table 10 reports the results. We find that, controlling for the overall size of the net purchases ahead of the respective event, banks execute suspicious trades around corporate events with a larger number of trades (Column 1). Column 2 shows that the likelihood that relationship banks build their suspicious trade positions in their borrower stocks with an above-median number of trades is 10pp to 13pp higher than for non-relationship banks. The results are similar requiring trade frequency to be above the 75th percentile (Column 3). In Column 4, we include bank×firm fixed effects and hence conduct the analysis within bank-firm pair, exploiting relationship changes. We still find the same result (Column 4). This finding implies that banks adjust their trade execution patterns for a given stock after entering (or ending) a lending relationship. This shift in trading behavior aligns with the timing of banks' access to private information. Such behavior may also reduce the price impact of informed trades, potentially explaining the absence of pre-event drift in returns observed in Figure IA.1. We come back to the issue of price impact in the following subsection.

6.3 Price Protection in OTC Trades against Relationship Banks

A final question is whether other market participants understand that banks engage in informed trading in their borrowers' stocks. If so, we expect market participants to price protect against adverse selection when they know that relationship banks are on the other side of the trade (see e.g., Kacperczyk and Pagnotta (2024)). However, it is only for OTC trades that the trading parties know their identities. For exchange trades, counter parties 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 trades in OTC trades.

We start with all (intra-day) trades by relationship banks in their borrowers' stocks and 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 trade by a bank in a borrower stock. This benchmark price stems from a prior transaction by a non-relationship bank trading in the same stock. Thus, we essentially match two transactions that are close in time and compare the prices. As we have rich trade-by-trade data, the median time between the focal transaction by the relationship bank and the benchmark transaction is only 12 seconds. We determine this benchmark price separately for OTC and exchange trades and introduce an indicator for OTC trades to test whether relationship banks face price protection in borrower stocks in the OTC market relative to the exchanges. We control for the size of the relationship trade, as larger trades could have more price impact (i.e., worse prices).

Table 11 reports the price protection results. Columns 1 and 2 use the €-difference between the focal transaction price and the respective benchmark price as dependent variable. We find that when banks buy (sell) borrower stocks in the OTC markets (rather than on an exchange), they pay (get) about €0.0106 (€0.0087) more (less) than other banks trading the same stock at the same time. As the average (median) sample €-difference in absolute terms is €0.0295 (€0.0100), the magnitude of the estimated effects is economically large.[39] In Columns 3 and 4, we first divide the €-price difference by the average bid-ask spread for the respective stock on the respective day, so that we can estimate price protection relative to the bid-ask spread. We find that relationship banks pay approximately 20-24% of the stock's bid-ask spread when they trade in borrower stocks in the OTC market. These results indicate significant price protection and suggest that other market participants are aware that relationship banks trade with superior information.

In light of the documented price protection, we expect that relationship banks prefer to

[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, we use the absolute value to gauge magnitudes.

trade borrower stocks on exchanges where counter parties are not known. Besides, trading on exchanges reduces the risk that counter parties report suspicious trading to the supervisor. We document in Appendix Table IA.8 that banks are more likely to execute net purchases in their borrowers' stocks ahead of large positive UE events on exchanges rather than the OTC market.[40] This finding is remarkably consistent with the price protection results and suggest that banks are aware that they receive less favorable prices when they have relationships and are hence concerned with shrouding their suspicious trades. These findings are in line with studies on strategic trading by informed investors (e.g., Garriott and Riordan (2024)).

7 Discussion and Conclusion

This paper provides novel evidence on the conflicts of interest inherent in universal banking, which have been a longstanding concern in regulatory discussions. By combining supervisory trade-level data with credit registry information, we demonstrate that banks' proprietary trading desks trade more successfully and profitably in stocks with which the bank has major lending relationships, suggesting that the trading desks use private borrower information obtained on the lending side. We show that banks build up positions in borrowers' stocks in the weeks leading up to corporate events in the direction of the event news and unwind these positions shortly after. This pattern is especially pronounced for unscheduled events, which are harder to anticipate without private information. Importantly, we show that these trading behaviors cannot be attributed to bank prop trading expertise or specialization in certain industries, firms, or business models. Our findings raise serious questions about the effectiveness of organizational safeguards such as ethical walls, which are designed to prevent internal information flows. Moreover, our findings reveal that, in the absence of lending relationships, prop trading profits are on average close to zero, yet highly volatile, underscoring the financial stability concerns about prop trading activities by banks with

[40] We do not find this ahead of large negative UE events, but note that our findings for negative events are generally less pronounced.

deposit guarantees.

On the mechanism for the documented information flows, we present two novel pieces of evidence. First, our study points to a potential indirect channel in addition to direct communication between a bank's lending and trading units. The bank's risk management is centralized and sits above the ethical walls for financial stability reasons, as bank regulation requires it to oversee exposures across all bank activities. This position could lead to (inadvertent) information flows, for instance, when the risk management adjusts limits or exposures in response to borrower-specific developments. We present evidence consistent with this channel being at play. Importantly, this finding underscores a regulatory tension that is inherent in universal banking: the very organizational structures that strengthen financial stability may undermine market conduct rules by creating pathways for sensitive information to reach trading desks.

Second, we find that banks appear to shroud their informed trades, consistent with a desire to minimize price impact and regulatory detection. For instance, we find that banks tend to build suspicious positions in borrower stocks using smaller and more frequent trades. Interestingly, trade frequency changes within a bank-firm pair with access to borrower information. Banks also avoid trading in borrower stocks ahead of events with very large market-adjusted returns, which are more likely to attract supervisory scrutiny. These pieces of evidence suggest deliberate actions.

Finally, we show that banks obtain worse prices when they trade borrower stocks in the OTC markets, where the identities of the counter parties are known. This evidence suggests that other market participants are aware of the use of private information from lending relationships and hence they price protect accordingly. In response, banks appear to favor exchanges, where trade is anonymous, when they trade borrower stocks.

Taken together, our results provide compelling evidence that banks' prop trading is informed by banks' lending activities. This evidence calls for a reassessment of extant organizational safeguards within universal banks. Our findings also help explain banks' resistance

to regulatory reforms such as the Volcker Rule or the changes proposed by the Liikanen Group in response to the Financial Crisis.

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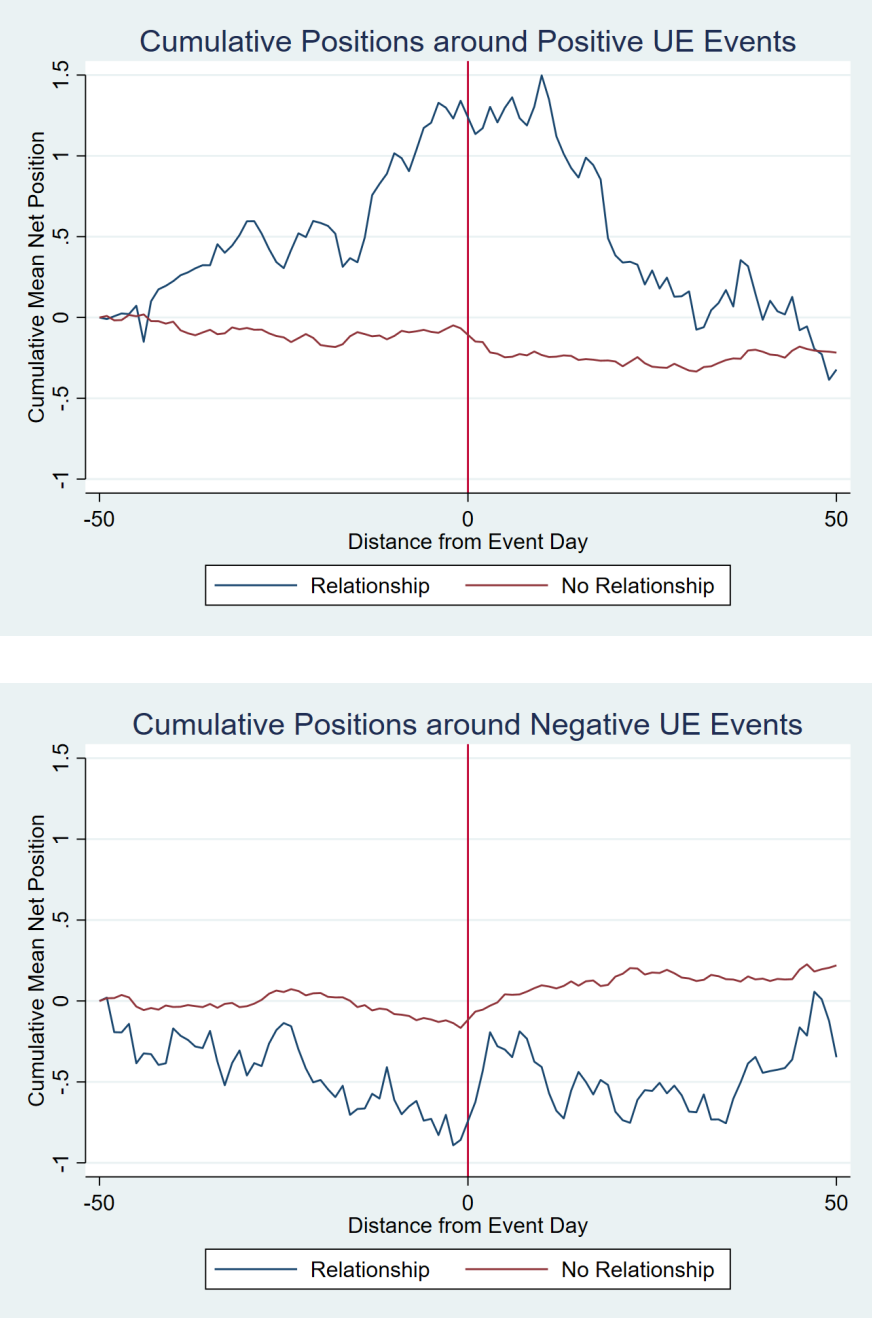
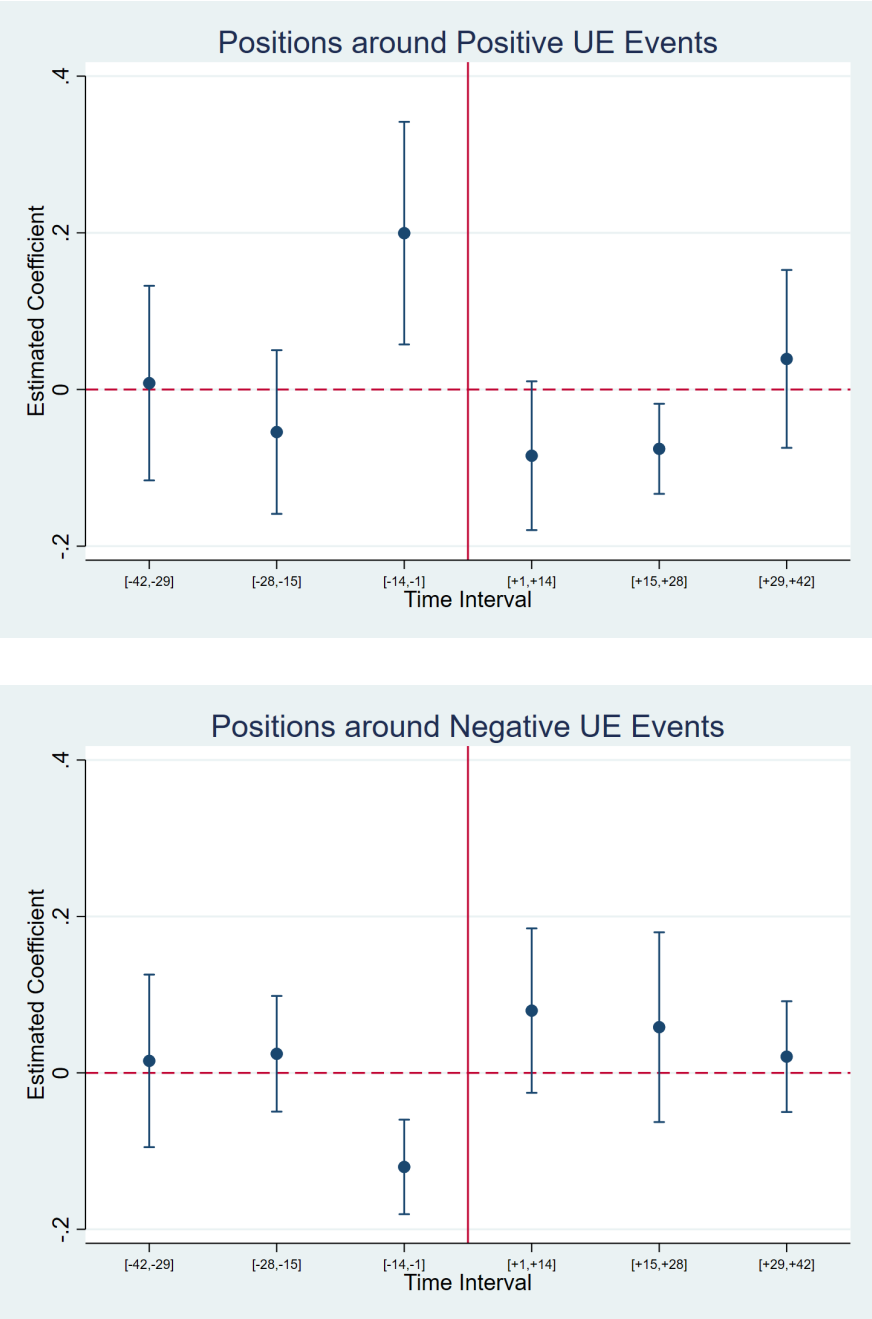
Figure 1: Banks' Net Purchases around UE Events



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 2: 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.6.

Table 1: Descriptive Statistics

Panel A: Corporate Events and Event Returns

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$\times$39,994 events) observations. All variables are defined in the Variable Appendix.

Table 2: Relationship Trading Around Corporate Events

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×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×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×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×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 banks purchase (sell) more stocks of firms for which they serve as relationship bank prior to positive (negative) corporate events. To avoid double-counting event trading, we limit 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 specific two-week time windows before and after the events. We estimate a separate regression for each specific window as indicated in the respective column. 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 (1)	Suspicious Trade (2)	Return×Direction (3)
Relationship	0.0923***	0.0619***	0.0073***
	(4.15)	(3.15)	(3.64)
Event FE	yes	yes	yes
Bank×SIC FE	yes	yes	yes
Abs. Event Return	>2%	>2%	>2%
Observations	15,740	13,300	15,740
Mean Dep. Var. for Non-Rel.	0.4966	0.2582	-0.0008

This table gauges the success of banks' event trading in borrower stocks. We restrict the sample to unscheduled earnings-related events with large absolute returns (>2%). Dependent variables are defined only 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 the respective stock in the two weeks before and after the respective event for the construction of *Suspicious Trade*. The dependent variable *Return* × *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). The last row reports the mean value of each dependent variable for observations without a lending relationship (*Relationship* = 0), which essentially provides a benchmark for the relationship effect. 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: Relationship Trading vs. Bank Expertise

Dependent variable:	Net Purchases [-14,-1]			
	(1)	(2)	(3)	(4)
Relationship×Pos	0.2728***	0.2712***	0.2733***	0.5353***
	(3.26)	(3.30)	(3.26)	(3.04)
Non-Rel. Periods×Pos		-0.0653		
		(-0.55)		
After-Rel. Periods×Pos			0.0300	
			(0.24)	
Event FE	yes	yes	yes	yes
Bank×Firm FE	yes	yes	yes	-
Bank×Firm×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 to 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 ends a relationship bank for the respective firm. Coefficients for negative events are included in the specifications but are not tabulated. 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 5: Information Flows: Bank Monitoring and New Loans

Dependent variable:	Net Purchases [-14,-1]					
	(1)	(2)	(3)	(4)	(5)	(6)
RB Loan Share×Pos	0.5646***	0.5629***				
	(4.05)	(3.53)				
Relationship NL×Pos			0.4435**	1.6499**	0.7578***	0.8471***
			(2.07)	(2.02)	(3.33)	(2.87)
Relationship NoNL×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×SIC FE	yes	-	yes	yes	yes	-
Bank×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 whether banks' pre-event trading in borrower stocks is more pronounced when they likely engage in more monitoring due to large loan share or have recently given a new loan. The sample is restricted to unscheduled earnings-related events with large absolute returns (>2%). In Columns (1) and (2), we use a relationship bank's loan share rather than a binary relationship indicator. *RB Loan Share* is defined relative to a firm's total loans (or borrowing). In Columns (3)-(6), we use a binary variable indicating that a relationship bank has granted a new loan in the previous quarter. 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 of the firm's total loan volume, respectively. We also include a separate coefficient for net purchases ahead of corporate events prior to which the bank did not grant a new loan. Coefficients for negative events are included in the specifications but are not tabulated. 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 6: Prop Trading in *Third-Party* Events

Dependent variable:	Suspicious Trade					
	(1)	(2)	(3)	(4)	(5)	(6)
RB trades in joint event	0.1988**	0.3063***				
	(2.66)	(2.97)				
RB trades in other third-party events			-0.0078	-0.0076	-0.0064	-0.0183
			(-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×SIC FE	yes	yes	yes	yes	yes	yes
Third-Party Events	Joint	Joint	All other	All other	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 around events of unrelated *third-party* firms that have a joint event with a borrower (as described in Section 4.2). We distinguish between trading around joint events, for which a relationship bank might posses private information from its borrower (*RB trades in joint event* in columns (1) and (2)) and trading around other events of the third party for which it is unlikely that a relationship bank has private information (*RB trades in other third-party events* in columns (3)-(6)). We use *Suspicious Trade* as dependent variable and construct indicator variables for third-party events. In columns (5) and (6), the sample is restricted to unscheduled earnings-related (UE) events of the third party. In columns (2), (4) and (6), we look at a cleaner set of events by excluding joint events that overlap with other corporate events in our sample on the same firm-day. *Control for other RBs* indicates that we include an indicator variable which equals one when the third-party's own relationship banks trade in the third-party 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 7: Profits from Prop Trading in Stocks with Relationships

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)
Constant	-50,739***	-50,964***	-51,754***	-62,751**
	(-2.78)	(-2.71)	(-2.72)	(-2.36)
Bank FE	yes	-	-	-
Bank×SIC FE	no	yes	yes	-
Firm FE	no	no	yes	-
Bank×Firm FE	no	no	no	yes
N	115,402	115,284	115,284	114,018

This table estimates incremental quarterly profits from prop trading in stocks for which a bank serves as relationship bank. The dependent variable is the *Quarterly Profit* earned in € per bank×firm×quarter. These profits are constructed by first calculating the daily mark-to-market profit per bank, firm and day, taking into account both the bank's daily trades and its existing holdings in the stock, and then aggregating by bank, firm and quarter. We start this construction with banks' initial holdings of the stock in the trading book, which we obtain from the Securities Holdings Statistics (SHS). Such data are available from 2014. Thus, the analysis covers the years 2014-2017. We cluster standard errors at the bank×year 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: Short vs. Long Positions before Events

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

This table examines relationship banks' trading ahead of event depending on their holdings (long, short, no position) prior to the event month. These positions are determined based on accumulating purchases and sales by a given bank in a given stock on a daily basis over the sample period from 2012 to 2017. The sample is restricted to unscheduled earnings-related events with large absolute returns (>2%). Columns (1) and (2) analyze positive UE events and Columns (3) and (4) analyze negative UE events. *Short* (*Long*) is a binary indicator variable set to one if a bank holds a short (long) position in the borrower firm's stock at the end of the month preceding the respective corporate event. In Columns (2) and (4), we restrict the coding of long and short positions to those that are below (above) the median short (long) position (computed over the sample period). Main effects for *Short* and *Long* positions in non-relationship stocks are included in all specifications, but their coefficients are not reported. 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: Supervisory Radar: Event Return Magnitude

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×Pos	0.0326	0.3414***	0.4023***	0.0256
	(0.27)	(2.94)	(2.93)	(0.23)
Event FE	yes	yes	yes	yes
Bank×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 whether banks purchase (sell) more stocks of firms for which they serve as relationship bank prior to positive (negative) corporate events, conditional on the magnitude of the event return. We estimate separate regressions for different event return bins (*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 10: Supervisory Radar: Trade Frequency Patterns

Dependent variable:	Suspicious Trade			
	(1)	(2)	(3)	(4)
Relationship×ln(Trades)	0.0275***			
	(2.83)			
Relationship×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×SIC FE	yes	yes	yes	-
Bank×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 trade frequency patterns for *Suspicious Trades* around corporate events (as defined in Table 3). The sample is restricted to unscheduled earnings-related events with large absolute returns (>2%). We use a binary indicator for trades in stocks for which the bank has a lending relationship. *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 for the number of trades (i.e., above the sample median in Columns (2) and (4) and above the p75 in Column (3)). In Column (5), we use bank×firm fixed effects to estimate changes in trade execution patterns within bank-firm pair. We control for the magnitude of the respective net purchases in the 14-day window before the event as well as its interaction with the relationship indicator, which is also included 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.

Table 11: Price Protection Against Informed Trading in the OTC Markets

Dependent variable:	Price Difference (€)		Price Diff. (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 ln(Trade Size)	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 face price protection in the OTC markets (when counter parties are known) relative to the exchanges (where trading is anonymous). The sample consists of all trades that banks carry out in relationship stocks, keeping one trade per bank, stock and second. For each of these transactions, we determine a benchmark price, defined as the price of the last prior transaction in the same stock that does not involve a relationship bank. In Columns (1) and (2), the dependent variable *Price Difference (€)* is the €-difference between the respective focal transaction price and its benchmark price. In Columns (3) and (4), we scale the price difference by the average bid-ask spread of the stock on the same day. Columns (1) and (3) analyzes buys and Columns (2) and (4) examines sells. *OTC* is a binary indicator variable for trades executed in the OTC markets. We control for the (natural log) size of the respective transaction in EUR 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 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 trades in joint event (Indicator)	Equals 1 for trades of a relationship bank in an unrelated *third-party* firm, which experiences a joint corporate event with the bank's borrower (e.g., joint venture, M&A).
RB trades in other third-party events (Indicator)	Equals 1 for trades of a relationship bank (B) in other events of the unrelated third-party firm, which are not connected to or joint with the bank's borrower).
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.

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. 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)	$\frac{shares\ purchased - shares\ sold}{shares\ outstanding} \times 10,000$ 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 when net purchases prior to an event are executed with more trades than the median or alternatively the p75 of the pre-event net purchases in the sample.
OTC (Indicator)	Equals 1 for OTC trades and equals 0 for trades on exchanges.
Price Difference (€)	*Transaction Price - Benchmark Price* using the price of the closest prior transaction by a non-relationship bank in the same stock 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 the closest prior transaction by a non-relationship banks in the same stock as benchmark. Computed separately for OTC and exchange trades and winsorized at p1 and p99.
Ln(Trade Size) (€)	Natural log size of the absolute value of a trade.
ExchgIntens (%)	Measures the intensity with which the bank executed the net purchases prior to an event on exchanges (relative to the OTC market). For instance, if the net purchases prior to a particular event 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.

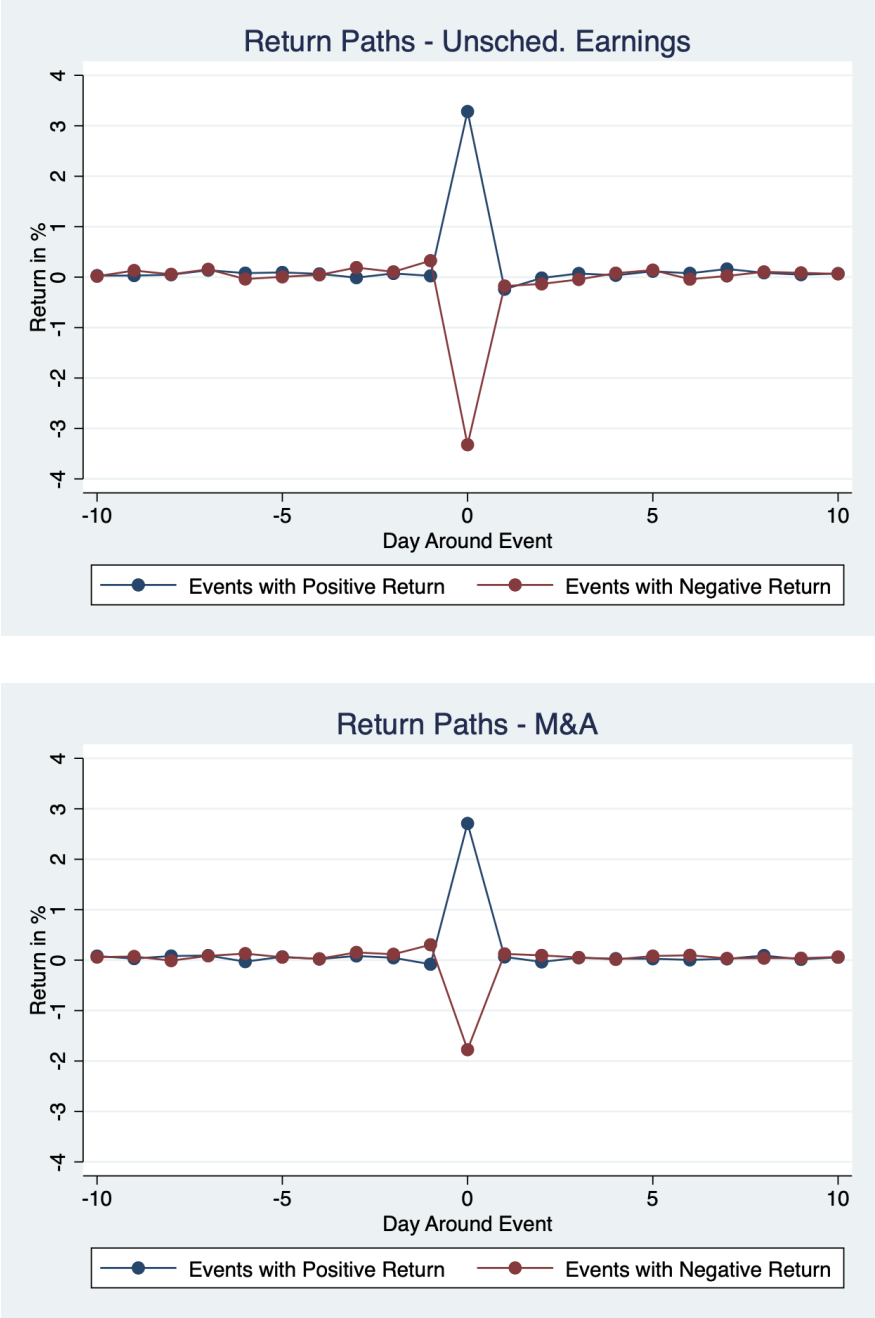
Internet Appendix

Conflicts of Interest in Universal Banks

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 Activity 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×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×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 how we define a relationship bank (or Hausbank). Column (1) is the baseline setting employed throughout the paper, for which a relationship is defined as a bank being either largest lender (LL) or having a loan share larger than 25%. In Column (2), we change this to largest lender only. In Columns (3)-(6), we change the definition to using a threshold only, and then we vary the threshold 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: Trading in the Right Direction before Corporate Events

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×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 the frequency with which banks trade in the right direction prior to an event of a borrower stock, i.e., execute positive (negative) net purchases in the two weeks prior to an event with a positive (negative) return. This specification allows us to simply introduce a relationship indicator (without an interaction for positive and negative events). We avoid double-counting by limiting the sample to one event per firm-day when analyzing *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.4: 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×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×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 in the header. The sample includes *all* types of corporate events, not just UE events, but avoids 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.5: Relationship Trading before 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×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×SIC FE	yes	-	yes	-	yes	-
Bank×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 trading in relationship stocks prior to 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 exclude M&A events that 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 not tabulated. 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: Panel Analysis at the Bank×Event×Time Level

Dependent variable:	Net Purchases			
	(1)	(2)	(3)	(4)
Relationship×[-28,-15]	0.0206	0.0243	0.0021	-0.0294
	(0.51)	(0.31)	(0.02)	(-0.41)
Relationship×[-14,-1]	-0.1241***	-0.2900***	-0.5065***	-0.1876**
	(3.85)	(-4.61)	(-4.07)	(-2.08)
Relationship×[+1,+14]	0.0758	0.0641	0.0649	0.0252
	(1.31)	(0.53)	(0.35)	(0.28)
Relationship×[+15,+28]	0.0546	0.0982	0.1988	0.1768
	(0.96)	(0.78)	(0.86)	(1.46)
Relationship×Pos×[-28,-15]	-0.0769	-0.1454	-0.1743	-0.1115
	(-0.93)	(-0.87)	(-0.72)	(-1.05)
Relationship×Pos×[-14,-1]	0.3216***	0.7056***	1.3224***	0.5733***
	(3.31)	(4.42)	(5.55)	(3.41)
Relationship×Pos×[+1,+14]	-0.1623**	-0.2431	-0.2804	-0.1571
	(-2.16)	(-1.50)	(-1.18)	(-0.97)
Relationship×Pos×[+15,+28]	-0.1324***	-0.3236***	-0.5522***	-0.3973***
	(-3.05)	(-3.90)	(-4.25)	(-4.27)
Bank×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 × Event × 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×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.

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.6 are very similar to those in the main analysis. We still find that banks build up positive (negative) net purchases in borrower stocks two weeks before positive (negative) unscheduled earnings-related events and then reverse these positions in the following month. Figure 2 visualizes these results.

Table IA.7: Options Trading and Client Trading

Dependent variable:	Net Purchases [-14,-1]				
	(1)	(2)	(3)	(4)	(5)
Relationship x Pos	0.0025	0.2759***	0.0400	0.2948**	0.0208
	(0.57)	(3.33)	(1.10)	(2.10)	(0.70)
Event FE	yes	yes	yes	yes	yes
Bank x SIC FE	yes	yes	yes	yes	yes
Events	UE	UE	UE	UE	UE
Securities	Options	Eq.+Opt. Netted	Equity	Equity	Equity
Trade Classification	PropMM	PropMM	Clients	PropMM - Clients	MM
Abs. Event Return	>2%	>2%	>2%	>2%	>2%
Observations	110,027	110,027	110,027	110,027	110,027

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. In column (2), we combine banks' net purchases in the stock and the options market when computing net purchases. Column (3) shows the results when using client trades to compute net purchases (instead of prop trades). In column (4), 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, column (5) shows 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.

In this test, we analyze options trading and banks' trading on behalf of their clients. We do not have a prior how 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, options could weaken our results for relationship trading of equities. However, a growing literature finds evidence for suspicious positions being built up prior to M&A events with options, as options allow traders to build up significant positions more quickly and cheaply (Lowry et al. (2019), Augustin et al. (2019)). Thus, options trading could also exacerbate the findings for equities. Unfortunately, options exist for less than 20% of our sample stocks and are relatively infrequently traded. Thus, we likely have less power to detect suspicious options trading. Consistent with this conjecture, the results are statistically insignificant. If anything, however, the evidence points in the same direction as our main results, that is, banks purchase options prior to major positive UE events (Table IA.7, Column 1). In Column 2, we combine net equity purchases with net option purchases (to allow for hedging). The results remain statistically and economically significant, suggesting that option trades are not used to offset equity purchases. In Columns 3-4, we analyze banks' equity trades on behalf of their clients. We again do not have strong priors 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 effects in trading for clients. In Column 5, we analyze only trades classified as market-making, which could also be client-initiated. We find that our main relationship trading results are driven by trades marked as 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.8: Do Banks Prefer Trading on Exchanges for Relationship Trades?

Dependent variable:	Net Purchases [-14,-1]					
	(1)	(2)	(3)	(4)	(5)	(6)
Relationship×ExchgIntens	0.6876**			0.3663		
	(2.17)			(1.15)		
Relationship×MostlyExchg		0.4117***	1.0298***		-0.0383	-0.3954
		(3.61)	(3.91)		(-0.12)	(-0.57)
Bank×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 UE	Pos UE	Pos UE	Neg UE	Neg UE	Neg UE
N	7,794	7,794	3,439	7,689	7,689	3,545

This table examines whether banks prefer to trade on exchanges when trading in borrower stocks before corporate events. *ExchgIntens* measures the extent to which the pre-event net purchases were executed on exchanges. For instance, if the pre-event net purchases consist 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 that the bank traded in the respective event. *MostlyExchg* is an indicator variable that equals one for net purchases with above-median *ExchgIntens*. Columns (1)-(3) analyze events with positive returns. Columns (4)-(6) examine events with negative 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