Know Your Customer: Informed Trading by Banks

Finance Working Paper N° 876/2023
July 2026

Rainer F. H. Haselmann
Goethe University and CEPR

Christian Leuz
University of Chicago, NBER, CEPR, CFS, Leibniz Institute SAFE, CESifo Research Network and ECGI

Sebastian Schreiber
Goethe University

ECGI Working Paper Series in Finance

Know Your Customer: Informed Trading by Banks

Working Paper N° 876/2023
July 2026

Rainer F. H. Haselmann
Christian Leuz
Sebastian Schreiber

Abstract

We analyze the con?ict of interest that arises when universal banks engage in proprietary trading of borrower stocks, which 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 ?ndings reveal that lending relationships inform banks' prop trading. To separate bank expertise and private information from lending as explanations, we study prop trading around corporate events. We show that banks execute purchases (sales) in borrower stocks in the weeks before positive (negative) news events, even when these events are unscheduled and surprising to the market. We link this trading pattern to situations when banks possess private borrower information, and rule out that it is explained by specialized expertise. We also ?nd evidence consistent with information ?ows through banks' centralized risk management, that banks alter trading patterns once they acquire private information, consistent with shrouding of informed trading, and that OTC counter-parties price-protect against relationship banks. Our evidence highlights the di?culty of avoiding con?icts in universal banking.

JEL Classification: G21, G14, G28

Rainer F. H. Haselmann
Goethe University and CEPR
Professor of Finance, Accounting and Taxation
Goethe University
e-mail: haselmann@econ.uni-frankfurt.de

Christian Leuz
University of Chicago, NBER, CEPR, CFS, Leibniz
Institute SAFE, CESifo Research Network and ECGI
Charles F. Pohl Distinguished Service Professor of Accounting and Finance
University of Chicago
e-mail: cleuz@chicagobooth.edu

Sebastian Schreiber
Goethe University
Researcher
e-mail: schreiber@safe.uni-frankfurt.de

GOETHE UNIVERSITÄT FRANKFURT AM MAIN

FOUNDATIONS OF LAW AND FINANCE

LawFin Working Paper No. 22

Conflicts of Interest in Banks: Evidence from Proprietary Trading

Rainer Haselmann | Christian Leuz | Sebastian Schreiber

Deutsche Forschungsgemeinschaft - DFG Project FOR 2774
Center for Advanced Studies on the Foundations of Law and Finance | House of Finance | Goethe University
Theodor-W.-Adorno-Platz 3 | 60629 Frankfurt am Main | Germany www.lawfin.uni-frankfurt.de

Conflicts of Interest in Banks: Evidence from Proprietary Trading*

Rainer Haselmann† Christian Leuz‡ Sebastian Schreiber§

July 2026

Abstract

We analyze the conflict of interest that arises when universal banks engage in proprietary trading of borrower stocks, which 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' prop trading. To separate bank expertise and private information from lending as explanations, we study prop trading around corporate events. We show that banks execute purchases (sales) in borrower stocks in the weeks before positive (negative) news events, even when these events are unscheduled and surprising to the market. We link this trading pattern to situations when banks 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, that banks alter trading patterns once they acquire private information, consistent with shrouding of informed trading, and that OTC counter-parties price-protect against relationship banks. Our evidence highlights the difficulty of avoiding conflicts in universal banking.

JEL Classification: G21, G14, G28

*We would like to thank Patrick Augustin, Brad Badertscher (discussant), Ray Ball, Utpal Bhattacharya (discussant), Elena Carletti, Yakshup Chopra (discussant), Hans Degryse, Luca Enriques, Nicola Gennaioli, Anil Kashyap, Marcin Kacperczyk, Victoria Ivashina, Andreas Neuhierl, Allison Nicoletti (discussant), Raghu Rajan, Stefano Rossi (discussant), Antoinette Schoar, Andrei Shleifer, Dan Taylor, Tobias Troeger, Gunseli Tumer-Alkan (discussant), Joseph Weber, Michael Weber, Kathleen Weiss Hanley (discussant), Regina Wittenberg-Moerman, and Luigi Zingales as well as workshop participants at the FIRS 2026, AFA 2025, Bocconi University, EAA 2025, EFA 2024, the 2023 NBER Big Data and Securities Markets Conference, the 2022 Swiss Winter Conference on Financial Intermediation, the 2022 FARS Conference, the Bocconi Summer Accounting Symposium, University of Chicago, University of Colorado Boulder, ECB Research Seminar, ECB Banking Supervision Seminar, Goethe University Frankfurt, Imperial College, LMU Munich, London Business School, University of Mannheim, University of Miami, MIT, Monash University, Office of Financial Research, UTS Sydney, and Vienna University of Economics and Business for their helpful comments. We are also grateful for insightful conversations with BaFin, Deutsche Bundesbank, ECB, Deutsche Börse as well as with traders, loan officers and risk managers at several banks. We gratefully acknowledge the excellent research assistance by Carol Seregni. The paper also benefited from a fellow visit of Leuz at the Center for Advanced Studies Foundations of Law and Finance, funded by the German Research Foundation (DFG) – Project FOR 2774. We acknowledge financial support from the Federal Ministry for Economic Affairs and Climate Action via the Gaia-X funding competition EuroDaT project. The project was conducted under Bundesbank research project number 2016/0116.

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

‡*Corresponding Author.* University of Chicago Booth School of Business, CEPR 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, 1997), Puri (1994)). Over time, the concerns waned and Glass-Steagall was repealed 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. banks with deposit insurance. 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 prevent private information flows.

Despite the prominent debates, we have little evidence on the effectiveness of ethical walls, banks' internal information flows, and banks' proprietary trading in general. One reason is that proprietary trading data are rarely available. In this paper, we exploit comprehensive supervisory data on banks' proprietary trading at the transaction level to shed light on the flow of private information from lending to trading, the resulting conflict of interest for proprietary trading as well as the effectiveness of organizational structures.

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., 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, de-

[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.

spite the creation of ethical walls to prevent this. Aside from direct communication, one potential channel for transmission is universal banks' risk management, for which prudential regulation stipulates that it centralizes information and *sits above the wall*.

The difficulty for any study in this space 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. 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 specialized 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 expertise and informed trading. For one, our analysis differentiates between widely anticipated or scheduled events (e.g., earnings announcements) and unscheduled events that are

[2]We establish this differential in (untabulated) within-bank regressions with market-return adjustment similar to Cohen et al. (2008). This analysis is only an initial gauge. We later present superior analyses.

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] Thus, private information that a bank obtains from a lending relationship cannot be used in prop trading. However, the mere existence of this information within the bank does not prevent it from trading the borrower stock. According to MAR §9, 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. Moreover, bank prudential regulation (see Section 2) stipulates that governance and supervisory activities (e.g., risk management) must be organized centrally, pooling information within the bank, e.g., to set limits for different bank units. This creates a potential pathway for information to flow indirectly. Thus, 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 stocks and stocks of the same industry for which the bank has no lending relationship. Using

[3] In §7, MAR defines inside information as information that has not been made public, relates to a specific financial instrument, and would significantly impact its price if revealed. In principle, the restriction of insider trading in the EU is at least as broad as it is under U.S. insider trading rules (Ventoruzzo (2015)).

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 as much as four 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 around corporate events is only marginally better than chance, illustrating how difficult it is

[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%).

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 prop 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, on average and without lending relationships, prop trading is *not* profitable, yet profits exhibit considerable volatility. In the worst quarters, losses from prop trading exceed €-0.58bn, which even for Top-5 banks amounts to more than 3% of their 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 additional tests that all but rule out bank expertise as an explanation for our results. First, we exploit that banks need to build up expertise prior to winning a client and that this expertise should not disappear immediately after the lending relationship ends. Thus, the client expertise explanation predicts that banks trade successfully ahead of events not only when a relationship is active, but also before and especially after the relationship ends. In contrast, we do not find significant event-trading effects outside the period, not even after lending ends. Interpreting this pattern as evidence of expertise would require that trading expertise forms right after a loan is granted and then disappears as soon as the relationship ends, which seems implausible. Moreover, both the total mark-to-market profits from relationships and the results for trading around corporate events become more pronounced when we add bank×firm fixed effects, which home in on the relationship period. Thus, consistent with the information flow explanation, banks trade profitably 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 with about 20pp higher probability for joint events. 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 their borrowers are the source of private information, giving them an edge in joint events only.[6]

The evidence so far implies 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 in universal banks because they combine 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. As noted earlier, German and EU bank regulation explicitly requires a centralized risk management

[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. We observe significantly larger net purchases by banks before unscheduled events of borrowers to whom they issued a loan in the prior quarter.

function for this reason. However, this unit faces a dilemma: It *sits above the wall* to pool information across all units to assess risks and exposures, yet cannot share information with the units that need to adjust their activities accordingly.[7] Such a dilemma arises, 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 the specifics of the event across units, it has to set (or adjust) limits for bank activities on both sides of the wall, which in turn could indirectly transmit (economically valuable) 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 could also reflect direct information flows, they raise the intriguing question of whether organizational structures that collect information centrally 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. Even more tellingly, 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

[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%.

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 with their access to private information. We also study intra-day transaction prices to see if other market participants understand that banks trade with superior information. Consistent with others protecting 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, and that banks respond to this price protection by building suspicious positions in stocks with relationships more often on exchanges.[9] Even when quantitatively small, such evidence matters, as adverse selection directly implicates fairness concerns and market efficiency—both essential to well-functioning markets.

Our study contributes to an important literature and ongoing policy debate about conflicts of interest in banks. The existing literature has primarily focused 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. It arises when 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 question the effectiveness of these organizational structures in managing conflicts, which are the central instrument to manage conflicts in banking (and also broker-dealers). Moreover, our evidence

[9]See Kacperczyk and Pagnotta (2024) for related evidence from SEC insider trading investigations on how insiders respond to potential detection and legal risk.

points to risk management as another potential source for *wall-crossing* of private information. This evidence uncovers a regulatory challenge inherent to universal banks, which has not been recognized, stemming from the mandate to integrate risk management across lending and trading for financial stability reasons. In doing so, our findings highlight a structural tension between prudential regulation and market conduct (or insider trading) regulation.

We also contribute to the literature on trading based on private information. Massa and Rehman (2008) and Bodnaruk et al. (2009) present evidence that mutual funds trade profitably in firms borrowing from affiliated banks, suggesting informed trading within financial conglomerates. Jegadeesh and Tang (2010) document profitable trading by target advisors before takeovers. Ivashina and Sun (2011) find return outperformance for institutional investors participating in loan syndications around major loan amendments. Massoud et al. (2011) show that hedge funds short-sell companies prior to loan origination or amendments when funds are syndicate participants.[10] However, 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 serving as advisors in corporate transactions. They argue their findings using trade-level data cast doubt on evidence using less granular trading data, typically based on quarterly 13-F holdings. Other evidence that banks trade on borrower information is less direct and inferred from market-level outcomes, such as return or price discovery patterns in CDS, secondary loan or stock markets, 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 and trade-level supervisory data, which allows us to provide direct evidence on prop trading patterns. Our analysis also sheds light on how banks execute and shroud informed trades through trade frequency, event selection and venue choice and on how counter-parties respond to informed trades. These questions are difficult to study without trade-level data, adding to studies focusing on whether informed trading occurs.

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

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.

The conflict of interest that arises when universal banks obtain confidential information from 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 led to the Volcker Rule in 2010, which bans proprietary trading by financial institutions, but exempts market-making.[11]

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' 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 diverging positions on this matter across EU member states.[12]

As the Liikanen Group's recommendations were not implemented at the EU level, Germany took unilateral action enacting the Bank Separation Act (BSA), a law designed to shield deposit and credit operations from losses incurred through risky activities such as

[11]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 prop trading in non-crisis times, which were more than offset by large losses of almost $16bn during the financial crisis.

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

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 BSA imposes organizational requirements on banks in case the volume of prop trading exceeds certain thresholds.[13] Banks above the thresholds are not prohibited from prop trading but have to direct these activities to a legally, organizationally, and financially separate subsidiary.[14] However, 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 BSA 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.[15]

The requirement of a centralized, bank-wide risk management is not unique to the German BSA; it is also mandated under the MaRisk framework (AT 4.1), which implements the Basel III principles in Germany. MaRisk explicitly stipulates that risk management must be conducted across the entire institution. One implication is that borrower ratings (i.e., probability-of-default estimates) produced by the credit desk are taken into account when risk management sets bank-wide exposure limits and risk metrics, which subsequently also govern the bank's trading activities. Thus, it is possible that, through the limit-setting process and risk oversight, borrower information indirectly travels to the trading desk. Put differently, bank prudential regulation institutionalizes an internal channel through which non-public information may be transmitted, intentionally or inadvertently, to areas of the bank that should not receive such information.

[13] 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.

[14] 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.

[15] Moreover, our evidence of informed trading (in Section 4) is similar before and after the BSA.

Germany, like most countries, has legal restrictions on insider trading. The relevant regulations are set by the EU under the Market Abuse Directive and the Market Abuse Regulation (MAR).[16] MAR §7 defines inside information as information that has not been made public and that, if revealed, would significantly affect the price of a security. MAR §14 stipulates that trading on such information is forbidden. However, the mere existence of this information within the bank does not prohibit its trading of the borrower stock. MAR §9 states that trading by the bank (i.e., the legal person) is permitted as long as it has adequate and effective internal arrangements and procedures that ensure its traders (i.e., the natural persons) do not have access to this inside information. Thus, private information that a bank obtains from a lending relationship cannot be used in prop trading and the central instrument to prevent such use are *ethical walls*. A key question is therefore the effectiveness of these internal arrangements in universal banks with a centralized risk management.

3 Data and Descriptive Statistics

3.1 Bank Trading and Lending Data

We use two proprietary data sets: one on bank securities trading[17] 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

[16] The EU's approach to insider trading is conceptually broader than the U.S. approach, which is based on fiduciary duty (Ventoruzzo (2015)). However, the U.S. has regulated insider trading for much longer than the EU and has historically been quite aggressive in its enforcement (e.g., Bhattacharya and Daouk (2002)).

[17] See Cagala et al. (2021); doi: 10.12757/Bbk.MiFID2008-2017.02

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.[18] 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.[19]

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

[18] 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.

[19] 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.

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).[20] We aggregate all loans to a given firm at the level of the banking group to also capture lending relationships by bank subsidiaries. Given the proprietary nature of the data sets, the credit register data and the securities transactions data are merged by Deutsche Bundesbank.

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].[21]

[20] 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.

[21] We drop events where the [-1;+1]-return is precisely zero, indicating no trading activity. Retaining these events does not change our results.

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 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 significant reactions with little leakage ahead of these 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.[22] We drop firms for which we do not have any corporate events.[23] 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

[22]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).

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

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

[24] 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.

[25] 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 100% 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 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.

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 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) × 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 bank (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 research design. Banks are required under German law to obtain financial information before making a loan (KWG §18). Thereafter, 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 on a regular basis. The key question is whether this information makes its way to the trading desk and is used in prop trading. However, such information flows cannot be directly observed. Thus, we center the analysis on corporate events when new information about the borrowers is revealed to the market and analyze trading ahead of and around these events.

Importantly, however, banks could specialize their lending and trading in specific industries, business models, or firms. This specialization could result in expertise, which in turn could explain why banks with lending relationships generate superior trading performance in borrower stocks (even without private information flows). The key identification challenge is therefore to distinguish between information flows and bank expertise. For this reason, much of our analysis focuses on trading ahead of specific corporate events that are unscheduled and hence difficult to predict or anticipate even with expertise. In addition, we design several tests that all but rule out bank expertise as an explanation for the results.

4.1 Net Purchases around Corporate Events

Our main empirical model investigates whether banks build larger and more profitable net trading positions ahead of events for stocks of firms, with which they have lending relationships. 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 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 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 Deutsche Bundesbank's 3-digit industry classification to account for any time-invariant bank- and industry-specific trading patterns.[26] Thus, the model compares net purchases of stocks with and without lending relationships *within a bank*, rather than simply across banks. The expansion of the bank fixed effect by industry accounts for potential bank expertise (e.g., the ability to forecast earnings or events) when prop trading desks and research teams specialize in specific industries. We cluster standard errors at the bank level.[27]

4.2 Information Flows vs. Bank Expertise

In addition to analyzing unscheduled events within bank-industry to minimize the role of expertise, we design three tests that zero in on information flows from lending relationships. In our first test, bank expertise and private information flows predict different trading patterns. The core idea is that building expertise arises from specialization and takes time. Moreover, it should not disappear immediately when a relationship ends, but decay slowly. In contrast, private information flows are tied to the lending relationship. In particular, firms stop reporting private information once the lending relationship ends. Thus, the information flow explanation implies that superior trading performance coincides with the lending relationship, whereas the bank expertise explanation predicts some superior trading in a borrower stock outside the lending relationship and, in particular, afterwards.

Thus, we exploit time-series variation in lending relationships, i.e., that banks initiate new relationships and terminate existing ones. We estimate the following specification:

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

[26]Although the classification is formally defined at the 3-digit level (Destatis (2008)), in our sample, third-digit variation is relatively limited, resulting in 62 distinct industries.

[27]Our inferences are robust to two-way clustering by bank and firm.

To separate relationship and non-relationship period trading by a bank in the same firm, we include bank×firm fixed effects. 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.[28] 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 bank (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 introduce the indicator $[After-Rel.Periods_{be}]$. In 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 private 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 as well as information about the business outlook and strategy. It is also common for lending officers to meet with their borrowers to discuss financial information and updates to the business. Such meetings likely occur prior to granting new loans. We exploit these institutional features and analyze 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. The idea of the test is to analyze whether banks trade more successfully ahead of borrower events when the lending desk recently received private information. We also perform these tests within bank-firm pair to tighten identification.

Our third test to separate bank expertise and information flows focuses on corporate events that involve two firms (e.g., mergers, joint ventures or legal disputes).[29] Among such

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

[29] 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

joint events, we select cases where a bank serves as relationship bank 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.[30] To fix ideas, consider the following scenario: Firm F1 plans to take over Firm F2. Bank B is the relationship bank for F1 but has no relationship with F2. As relationship bank, 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.

5 Main Analysis

5.1 Relationship Banks' Trading around Corporate Events

Table 2, Panel A, presents the results analyzing 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).

another 15%. The remainder is from miscellaneous event categories, including legal disputes.

[30]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)).

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; sophisticated investors might be able to at least partially anticipate them. 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 (below 2%). But for UE events with absolute returns above 2%, which are bigger news to the market, the relationship coefficients are significant and much larger in magnitude for both positive and negative events. This difference in the results across columns already points towards informed trading because an expertise explanation would predict weaker, not stronger, results for events that are hard to anticipate and surprising. Based on this evidence, we restrict the remaining tests to UE events with absolute abnormal returns above 2%, which is roughly the median abnormal return of UE events. 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.[31]

[31]The choice of 2% (or median) as cutoff is ad hoc, but it is close to the median firm's tandard deviation of daily returns. The precise cutoff is not central to our results; they are similar without a cutoff or using others, such as 1% or 3%. The results tend to be more pronounced when we focus on material news events, which in itself is telling. See also Table 9.

In Panel B, we investigate the dynamics of banks' relationship trading around UE events.[32] 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 returns) is difficult. With relationships, we observe substantial net purchases *prior* to a positive (negative) UE event and subsequent reversals.

Prior work finds evidence consistent with informed trading by capital market participants ahead of M&A announcements (e.g., Augustin et al. (2019)). M&A transactions are difficult to anticipate, just as UE events. Thus, they present another opportunity to analyze whether prop trading in stocks with M&A events differs depending on whether banks have lending relationships. We find strong evidence of purchases by banks with relationships prior to 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 prior to positive M&A events and

[32] Although Panel B focuses on UE events, we find similar patterns for all events. See Table IA.4.

-0.08bp prior to negative M&A events (Column 1). The magnitude of this effect further increases when we analyze events for which the borrower is a target (Column 3) or a seller (Column 5).[33] 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.[34]

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 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

[33] 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).

[34] 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.

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.[35]

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

[35] 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.

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, universal banks use information from their lending relationships when prop trading. For instance, it is difficult to explain with expertise why banks trade *more* successfully ahead of borrower events when these events are difficult to anticipate versus when they are scheduled.[36] If it is expertise, we should see the opposite. In this subsection, we present results from three additional tests. As discussed in Section 4.2, they zero in on information flows and intend to all but rule out bank expertise as an explanation.

First, we exploit changes in lending relationships and 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 bank of the firm with times when the same bank is not yet or no longer has a relationship with 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. Still, we obtain a small and statistically insignificant coefficient. We find the same result for negative UE events (not tabulated for brevity). The results in Columns 1-3 imply that banks' profitable net purchases ahead of corporate events coincide exactly with their lending relationship, during which they private obtain information from their borrowers.[37] The

[36]Illustrating this point, when we compare the results for UE events with an absolute return above 2% (Table 2, Panel A, Column 6) with the results for scheduled earnings announcements of the same return magnitude, we find that the coefficients for the former are much larger.

[37]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.

expertise explanation would not predict such sharp results. Bank expertise takes time to build and does not immediately decay. Thus, successful trading based on expertise should not exactly coincide with the duration of the lending relationship. To further tighten the analysis, we saturate the model with bank×firm×year fixed effects, which allows for time-series variation within a bank-firm relationship. 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.[38] 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 trading of borrower stocks 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 recently granted new loans (Columns 3-5). We find analogous results for negative UE events but do not tabulate the coefficents due to space constraints. 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 find 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

[38] In untabulated regressions, we analyze trading by the seven sample banks, which have loan exposures but are not classified as relationship 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.

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 bank 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, it 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.[39] 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). However, when we examine whether the same banks trade successfully in *other* events of the third party, we find no evidence that they can, i.e., the results in Columns 3-4 (and in Columns 5-6 for UE events) are statistically and economically insignificant, which is inconsistent with expertise.

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

[39] 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.

trading positions to market on a daily basis and then aggregating these profits.[40] We do not winsorize daily profits. 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 isolate profits over the relationship period in a bank-firm pair (see Section 4.2). As this analysis is quite demanding with quarterly data, 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. In fact, we argue that profits of this magnitude raise questions about the effectiveness of organizational structures designed to address conflicts of interest in universal banks.

The estimates for the constant in the regression further reveal that banks' average quarterly profit from trading stocks *without* relationships is close to zero or even negative, with values ranging from -€66,000 to -€80,000 (Table 7). Thus, on average, banks' prop trading is *not* profitable, which makes the profits from relationship trades economically even more significant. At the same time, quarterly prop trading profits are highly volatile, which is

[40] 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 and not for all sample banks (see Blaschke et al. (2020); doi: 10.12757/Bbk.SHSBaseplus.05122006). Thus, our analysis covers 2014 to 2017 for the 33 sample banks that report to the SHS. If we construct daily profits without information on prior holdings, we can use the full sample period (2012–2017) and include all sample banks, not only those reporting to the SHS. The results show a similar pattern, although with smaller magnitudes, likely because we do not capture all returns on prior holdings.

noteworthy from a financial stability perspective. Across all bank-quarters, even the Top 5 banks do not earn positive profits on average. The worst quarterly losses exceed €0.58bn (using the 1st percentile), an amount that corresponds to more than 3% of the Top 5 banks' Tier 1 capital or book equity. Our finding that prop trading is on average not profitable, combined with the high volatility is consistent with the calculations by U.S. Government Accountability Office (2011) for six large U.S. banks after the 2008 financial crisis. Taken together, these results underscore the role of prop trading in the risk-taking behavior of banks with deposit insurance—an issue that was central to the regulatory debate leading to the prohibition of proprietary trading in the U.S. (see Section 2).

6 Channels, Trading Patterns and Price Protection

Our findings show that significant private borrower information makes its way to banks' trading desks, despite the existence ethical walls 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 how banks execute their informed trades and the extent to which they shroud them. Section 6.3 investigates price protection by other market participants to shed light on adverse selection and efficiency implications.

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, universal banks are required to create internal structures and rules. 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, banking regulation (e.g., Basel III rules or MaRisk in Germany) 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 has to approve, set or adjust limits on activities on both sides of the wall based on all its information, which in turn could 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 in which risk management might have to intervene. Imagine a situation in which a bank's prop-trading desk has a significant exposure, say a short position, in a stock that is also a borrower and the lending division learns about an impending major event that will likely move the borrower's valuation in the opposite direction. In this situation, risk management might curtail the trader's limit for the respective stock or flag 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 a short or a long position prior to a corporate event, we use the monthly Security Holdings Statistics (SHS), which provides end-of-month holdings for each stock in trading book, as a starting point and use the securities trading data backwards to infer the bank's net position in the borrower's stock 15 days before the event and then again analyze trading over the [-14,-1] window. We create indicators for long, short, or no position in the borrower's stock and interact them with the *Relationship* dummy to analyze whether relationship banks' proprietary trading differs in the two weeks ahead of positive and negative unscheduled earnings events, depending on their prior net position.[41]

[41] As noted earlier, not all sample banks report to the SHS database. Hence, 14 banks without SHS

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 large net purchases in borrower stocks when they have a short position, essentially reducing or closing the short position ahead of positive news events. We also observe purchases of relationship stocks prior to positive UE events when banks already have a long position in the borrower and, to a lesser extent, when they have no prior position, consistent with our earlier results. In Column 2, we focus on larger (above-median) short positions and find that the results become, if anything, slightly stronger. Column 3 presents the results for negative UE events. Here, we see the reverse pattern. Banks engage in significant sales of relationship stocks when they have a prior long position, thereby reducing or closing their long exposures ahead of negative news events. Again, the results are more pronounced when focusing on larger exposures (Column 4). Consistent with the notion that prior exposures monitored by risk management matter, the coefficients for the interaction with *Long* are much larger than in Table 2 (Panel A, Column 6). The interactions with *Short* and *NoPrior* are not significant, indicating that relationship trading ahead of negative events focuses on reducing positive exposures, rather than shorting borrowers.

Of course, 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 prop trading with limits set based on information from the lending side. Moreover, centralized risk management is not the only channel through which private information could reach the trading desk, but our findings point to a plausible and institutionally important pathway. 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

reporting are excluded from this test. When we instead define *Short* and *Long* purely based on trades (which is less precise but allows us to include all sample banks), the results are broadly comparable.

information? At a minimum, they highlight a fundamental conundrum in universal banking.

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 trades to avoid supervisory scrutiny.

Naturally, very large news events or very substantial trades are more likely to hit the supervisory radar.[42] 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. Splitting up trades may also reduce price impact of informed trades. We analyze price impact in the following subsection.

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

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

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 ahead of corporate events that likely have substantial returns and hence will receive attention from the supervisor.

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 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. Tellingly, this shift in behavior aligns with the timing of banks' access to private information, suggesting shrouding of informed trades.

6.3 Price Protection in OTC Trades against Relationship Banks

A final question is whether 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, only for OTC trades, 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.[43] 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 span 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 trading on 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 €0.0099 (€0.0092) 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.[44] 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 22-23% 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.

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

[44]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.

In light of the documented price protection, we expect that relationship banks prefer to 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.[45] 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 conflict of interest that arises when banks make corporate loans and trade in the borrower's equity. This and similar conflicts are inherent in universal banking and 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, consistent with private information flows from the lending side. We show that banks build up positions in borrower stocks in the weeks leading up to corporate events in the direction of the event news and unwind these positions shortly after. This pattern becomes more pronounced for unscheduled corporate events, which are harder to anticipate, pointing to private information flows. We further tighten the design to rule out that these trading behaviors reflect prop trading expertise or bank 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 intended to prevent internal information flows and play an important role, not just in universal banks but also

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

in broker-dealers. Moreover, our findings reveal that, in the absence of lending relationships, banks' prop trading profits are on average close to zero, yet highly volatile, underscoring the financial stability concerns about prop trading activities by banks with deposit guarantees.

On the channels for the documented information flows, we present two novel pieces of evidence. First, our study points to a potential indirect channel, besides 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 (e.g., Basel III) 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, banks appear to shroud their informed trades, consistent with a desire to avoid regulatory detection. For instance, we find that banks tend to build suspicious positions in borrower stocks using smaller and more frequent trades. Tellingly, we show that trade frequency changes within a bank-firm pair when the access to borrower information changes, i.e., the relationship starts or ends. 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 market, 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. This evidence showing adverse selection in public markets is important as it highlights that banks' informed trading can have efficiency implications and raise fairness concerns.

Taken together, our evidence calls for a reassessment of the inherent conflicts of interest in universal banks and the role of ethical walls as the central organizational safeguard. 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.

References

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

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

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

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

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

Bernanke, B. (1983). Nonmonetary effects of the financial crisis in the propagation of the Great Depression. *The American Economic Review*, 73(3):257–276.

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

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

Bittner, C., Fecht, F., Pala, M., and Saidi, F. (2024). Strategic communication among banks. *Available at SSRN 3990924*.

Blaschke, J., Sachs, K., and Yalcin, E. (2020). Securities holdings statistics base plus, data report 2020-14 – metadata version 3-1.

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

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

Cagala, T., Gomolka, M., Krüger, M., and Sachs, K. (2021). Markets in financial instruments directive (mifid), data report 2021-13 – metadata id 1.0.

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

Chen, T. and Martin, X. (2011). Do bank-affiliated analysts benefit from lending relationships? *Journal of Accounting Research*, 49(3):633–675.

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

DeMarzo, P. M., Fishman, M. J., and Hagerty, K. M. (1998). The optimal enforcement of insider trading regulations. *Journal of Political Economy*, 106(3):602–632.

Destatis (2008). Klassifikation der Wirtschaftszweige, Ausgabe 2008.

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

Drucker, S. and Puri, M. (2005). On the benefits of concurrent lending and underwriting. *the Journal of Finance*, 60(6):2763–2799.

Duarte-Silva, T. (2010). The market for certification by external parties: Evidence from underwriting and banking relationships. *Journal of Financial Economics*, 98(3):568–582.

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

Enriques, L., Alex Lee, Y.-H., and Romano, A. (2025). The placebo effect of insider dealing regulation. *Oxford Journal of Legal Studies*, page gqaf019.

European Parliament (2014). Regulation of the European Parliament and the council on structural measures improving the resilience of EU credit institutions. Document 52014PC0044.

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

Garriott, C. and Riordan, R. (2024). The price impacts of informed investors. *Available at SSRN 4866008*.

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

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

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

Kacperczyk, M. and Pagnotta, E. S. (2024). Legal Risk and Insider Trading. *Journal of Finance*, 79(1):305–355.

Kang, J. K. (2021). Gone with the big data: Institutional lender demand for private information. *Harvard Business School Accounting & Management Unit Working Paper*, 22-053.

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

Kroszner, R. S. and Rajan, R. G. (1994). Is the Glass-Steagall Act justified? A study of the US experience with universal banking before 1933. *The American Economic Review*, 84(4):810–832.

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

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

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

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

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

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

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

Neuhann, D. and Saidi, F. (2018). Do universal banks finance riskier but more productive firms? *Journal of Financial Economics*, 128(1):66–85.

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

Puri, M. (1994). The long-term default performance of bank underwritten security issues. *Journal of banking & finance*, 18(2):397–418.

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

Schaffelhuber, K. and Kunschke, D. (2015). Das sogenannte Trennbankengesetz. In *Banken-rating*, pages 387–403. Springer.

SEC (2012). Report on Examinations of Information Barriers: Broker-Dealer Practices under Section 15(g) of the Securities Exchange Act of 1934. *Staff Summary Report.*

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

Tröger, T. (2016). Strukturreform im Finanzsektor–Das Trennbankengesetz als untauglicher Versuch der Verwirklichung von Nachhaltigkeitszielen im Aufsichtsrecht. *Nachhaltigkeit im Bankensektor. Konzepte, Rechtsfragen, Kulturwandel*, pages 139–61.

U.S. Government Accountability Office (2011). Proprietary Trading - Regulators Will Need More Comprehensive Information to Fully Monitor Compliance with New Restrictions When Implemented. *Report to Congressional Committees.*

Ventoruzzo, M. (2015). Comparing insider trading in the United States and in the European Union: History and recent developments. *European Company and Financial Law Review*, 11(4):554–593.

World Bank (2023). 5-Bank Asset Concentration for the United States. *FRED, Federal Reserve Bank of St. Louis.*

Table 1: Descriptive Statistics

Panel A: Corporate Events and Event Returns

Event Category	N	Return Distribution p25	Return Distribution p75	Relevance Score
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×39,994 events) observations. All variables are defined in the Variable Appendix. Source: Deutsche Bundesbank, Research Data and Service Centre (FDSZ), Credit Register and MiFID transaction data (doi: 10.12757/Bbk.MiFID2008-2017.02), SHS-Base Plus (doi: 10.12757/Bbk.SHSBaseplus.05122006), 2012–2017, own calculations. See Section 3 for a complete description of all data sources.

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. Source: Deutsche Bundesbank, Research Data and Service Centre (FDSZ), Credit Register and MiFID transaction data (doi: 10.12757/Bbk.MiFID2008-2017.02), 2012–2017, own calculations. See Section 3 for a complete description of all data sources.

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. Source: Deutsche Bundesbank, Research Data and Service Centre (FDSZ), Credit Register and MiFID transaction data (doi: 10.12757/Bbk.MiFID2008-2017.02), 2012–2017, own calculations. See Section 3 for a complete description of all data sources.

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. Source: Deutsche Bundesbank, Research Data and Service Centre (FDSZ), Credit Register and MiFID transaction data (doi: 10.12757/Bbk.MiFID2008-2017.02), 2012–2017, own calculations. See Section 3 for a complete description of all data sources.

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. Source: Deutsche Bundesbank, Research Data and Service Centre (FDSZ), Credit Register and MiFID transaction data (doi: 10.12757/Bbk.MiFID2008-2017.02), 2012–2017, own calculations. See Section 3 for a complete description of all data sources.

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. Source: Deutsche Bundesbank, Research Data and Service Centre (FDSZ), Credit Register and MiFID transaction data (doi: 10.12757/Bbk.MiFID2008-2017.02), 2012–2017, own calculations. See Section 3 for a complete description of all data sources.

Table 7: Profits from Prop Trading in Stocks with Relationships

Dependent variable:	Quarterly Profit			
	(1)	(2)	(3)	(4)
Relationship	401,577**	407,387**	437,835**	808,557
	(2.43)	(2.12)	(2.20)	(1.65)
Constant	-66,211***	-66,471***	-67,569***	-80,423**
	(-3.12)	(-3.04)	(-3.06)	(-2.59)
Bank FE	yes	-	-	-
Bank×SIC FE	no	yes	yes	-
Firm FE	no	no	yes	-
Bank×Firm FE	no	no	no	yes
N	97,950	97,875	97,875	96,997

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. Further, only 33 out of 47 sample banks report to the SHS and are included in this analysis. 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. Source: Deutsche Bundesbank, Research Data and Service Centre (FDSZ), Credit Register, MiFID transaction data (doi: 10.12757/Bbk.MiFID2008-2017.02), SHS-Base Plus (doi: 10.12757/Bbk.SHSBaseplus.05122006), 2014–2017, own calculations. See Section 3 for a complete description of all data sources.

Table 8: Role of Risk Management: Short vs. Long Positions before Events

Dependent variable:	Net Purchases [-14,-1]			
	(1)	(2)	(3)	(4)
Relationship×Short	0.8082***	1.0121***	0.1696	0.1380
	(3.00)	(2.99)	(1.06)	(1.20)
Relationship×Long	0.1597***	0.2908***	-0.2523***	-0.3382***
	(2.80)	(3.68)	(-4.25)	(-2.97)
Relationship×No Prior	0.0398*	0.0533	-0.0307	-0.0329
	(1.85)	(1.57)	(-0.99)	(-1.03)
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	39,996	39,996	36,993	36,993

This table examines how relationship banks trade ahead of corporate events, conditional on their prior holdings before the [-14,-1] event window. Holdings are classified 15 days before the respective corporate event with binary indicators as *Long*, *Short*, or *No Prior* position. We determine these positions starting from the end-of-month position based on the Security Holdings Statistics (SHS) and adjusting the position backwards to day 15 prior to the event using cumulative net trades. The sample is restricted to banks reporting to the SHS. We analyze 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. 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 across all positions over the sample period). Main effects for *Short*, *Long* and *No Prior* 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. Source: Deutsche Bundesbank, Research Data and Service Centre (FDSZ), Credit Register, MiFID transaction data (doi: 10.12757/Bbk.MiFID2008-2017.02), SHS-Base Plus (doi: 10.12757/Bbk.SHSBaseplus.05122006), 2012–2017, own calculations. See Section 3 for a complete description of all data sources.

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. Source: Deutsche Bundesbank, Research Data and Service Centre (FDSZ), Credit Register and MiFID transaction data (doi: 10.12757/Bbk.MiFID2008-2017.02), 2012–2017, own calculations. See Section 3 for a complete description of all data sources.

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. Source: Deutsche Bundesbank, Research Data and Service Centre (FDSZ), Credit Register and MiFID transaction data (doi: 10.12757/Bbk.MiFID2008-2017.02), 2012–2017, own calculations. See Section 3 for a complete description of all data sources.

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	0.0099***	-0.0092***	0.2277***	-0.2163***
	(8.86)	(-9.01)	(10.06)	(-10.28)
Control for ln(Trade Size)	yes	yes	yes	yes
Trade Direction	buy	sell	buy	sell
Observations	5,624,799	5,587,341	5,621,330	5,583,832

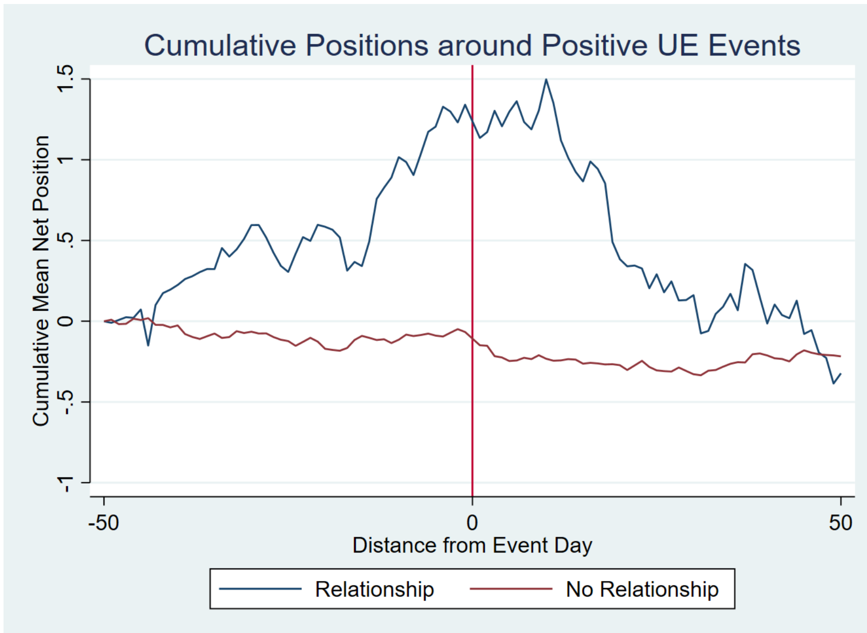
This table examines whether trades by relationship banks face price protection in the OTC markets (when counter parties are known) relative to the exchanges (where trading is anonymous). The sample consists of all trades that banks carry out in relationship stocks, keeping one trade per bank, stock and 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. Source: Deutsche Bundesbank, Research Data and Service Centre (FDSZ), Credit Register and MiFID transaction data (doi: 10.12757/Bbk.MiFID2008-2017.02), 2012–2017, own calculations. See Section 3 for a complete description of all data sources.

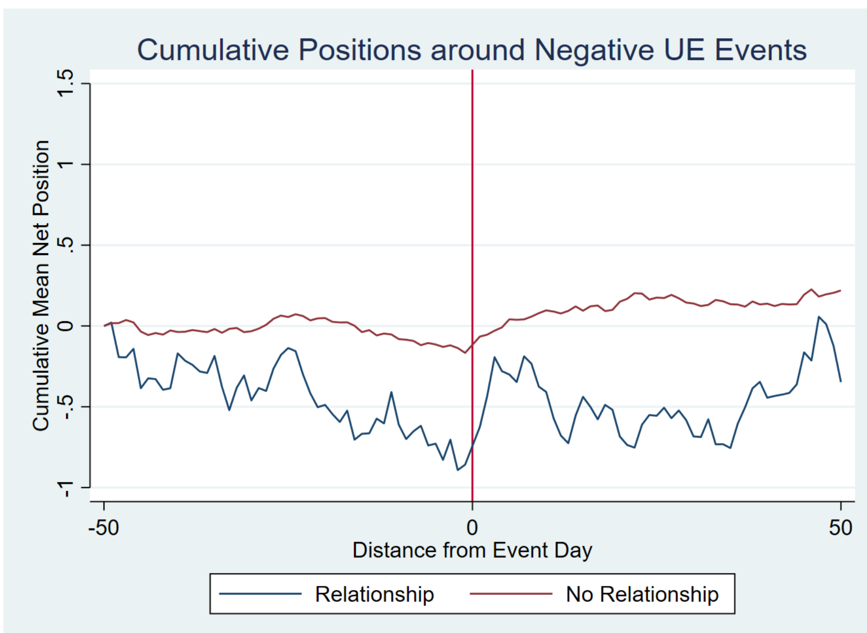
Variable Appendix

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.

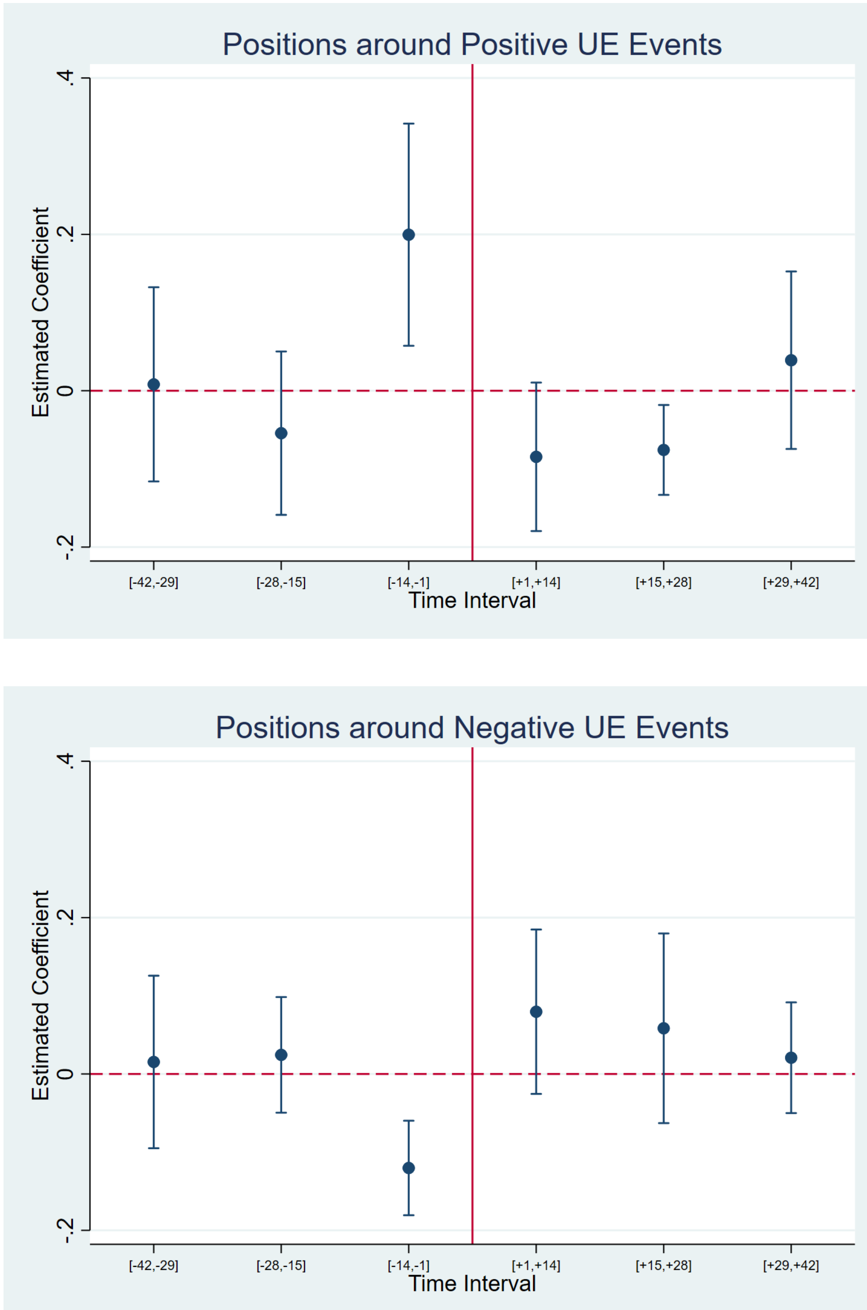
Figure 1: Banks' Net Purchases around UE Events





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. Source: Deutsche Bundesbank, Research Data and Service Centre (FDSZ), Credit Register and MiFID transaction data (doi: 10.12757/Bbk.MiFID2008-2017.02), 2012–2017, own calculations. See Section 3 for a complete description of all data sources.

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. Source: Deutsche Bundesbank, Research Data and Service Centre (FDSZ), Credit Register and MiFID transaction data (doi: 10.12757/Bbk.MiFID2008-2017.02), 2012–2017, own calculations. See Section 3 for a complete description of all data sources.

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*) is a binary indicator variable set to one if a bank holds a short (long) position in the borrower firm's stock 15 days before the respective corporate event, i.e right before we cumulate trades in the [-14,-1] window. To derive daily positions, we take end-of-month holdings from the Security Holdings Database (SHS) as reference points. For days between SHS reporting dates, we work backwards from the next SHS observation by adjusting the reported position with the net trades between the target date and that SHS date.

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 Banks: Evidence from Proprietary Trading

List of Tables in the Internet Appendix

List of Figures in the Internet Appendix

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. Source: Deutsche Bundesbank, Research Data and Service Centre (FDSZ), MiFID transaction data (doi: 10.12757/Bbk.MiFID2008-2017.02), 2012–2017, own calculations. See Section 3 for a complete description of all data sources.

Table IA.2: Variations of the Relationship Definition

Dependent variable:	Net Purchases [-14,-1]					
	(1)	(2)	(3)	(4)	(5)	(6)
Relationship	-0.0961**	-0.0947	-0.1341***	-0.0178	-0.0558	-0.3043***
	(-2.05)	(-1.41)	(-3.97)	(-0.68)	(-1.46)	(-3.36)
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. 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. Source: Deutsche Bundesbank, Research Data and Service Centre (FDSZ), Credit Register and MiFID transaction data (doi: 10.12757/Bbk.MiFID2008-2017.02), 2012–2017, own calculations. See Section 3 for a complete description of all data sources.

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. Source: Deutsche Bundesbank, Research Data and Service Centre (FDSZ), Credit Register and MiFID transaction data (doi: 10.12757/Bbk.MiFID2008-2017.02), 2012–2017, own calculations. See Section 3 for a complete description of all data sources.

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. Source: Deutsche Bundesbank, Research Data and Service Centre (FDSZ), Credit Register and MiFID transaction data (doi: 10.12757/Bbk.MiFID2008-2017.02), 2012–2017, own calculations. See Section 3 for a complete description of all data sources.

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	-0.0779*	-0.1298*	-0.1981**	-0.2285	-0.2487	-0.6559**
	(-1.94)	(-1.68)	(-2.10)	(-1.34)	(-1.27)	(-2.13)
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%). 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. Source: Deutsche Bundesbank, Research Data and Service Centre (FDSZ), Credit Register and MiFID transaction data (doi: 10.12757/Bbk.MiFID2008-2017.02), 2012–2017, own calculations. See Section 3 for a complete description of all data sources.

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. Source: Deutsche Bundesbank, Research Data and Service Centre (FDSZ), Credit Register and MiFID transaction data (doi: 10.12757/Bbk.MiFID2008-2017.02), 2012–2017, own calculations. See Section 3 for a complete description of all data sources.

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	0.0005	-0.0859**	-0.0653	0.0109	-0.0367
	(0.22)	(-2.07)	(-1.42)	(0.20)	(-1.45)
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). Although we usually combine proprietary trading and market making, column (5) shows results using only trades coded as market making. 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. Source: Deutsche Bundesbank, Research Data and Service Centre (FDSZ), Credit Register and MiFID transaction data (doi: 10.12757/Bbk.MiFID2008-2017.02), 2012–2017, own calculations. See Section 3 for a complete description of all data sources.

In this test, we analyze options trading and banks' trading on behalf of their clients. We include option trades whose underlying is in our stock sample. We convert option contracts into share equivalents using the contract multiplier and then compute positions and imbalances in the same way as for equities. We do not have a prior how banks trade their borrowers' stock options in case they possess 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 rather suggest that clients trade in the same direction as the relationship bank, yet the estimates are small and statistically insignificant. 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.[46]

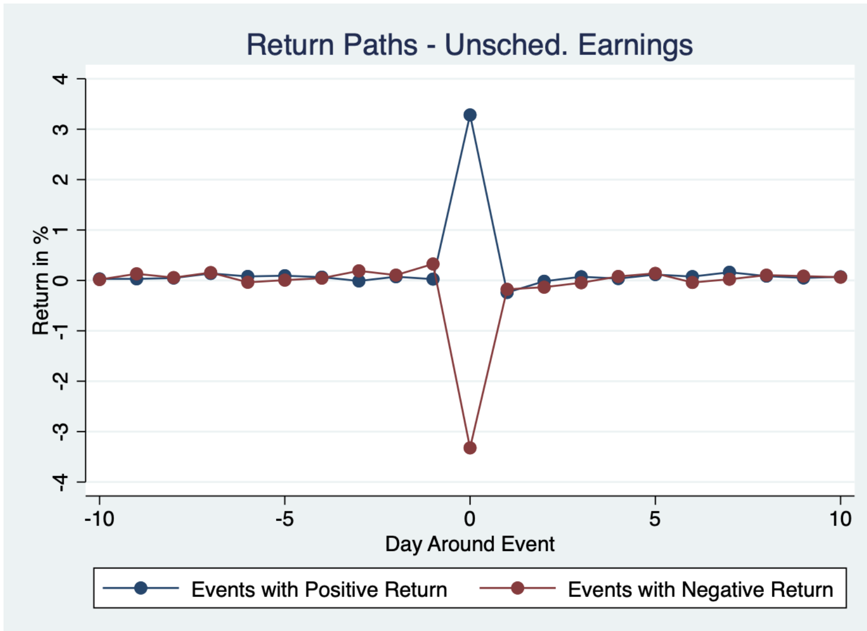
[46] A potential explanation for this finding is that, at least on the largest German exchange, market-making is primarily done via automatic algorithmic trading.

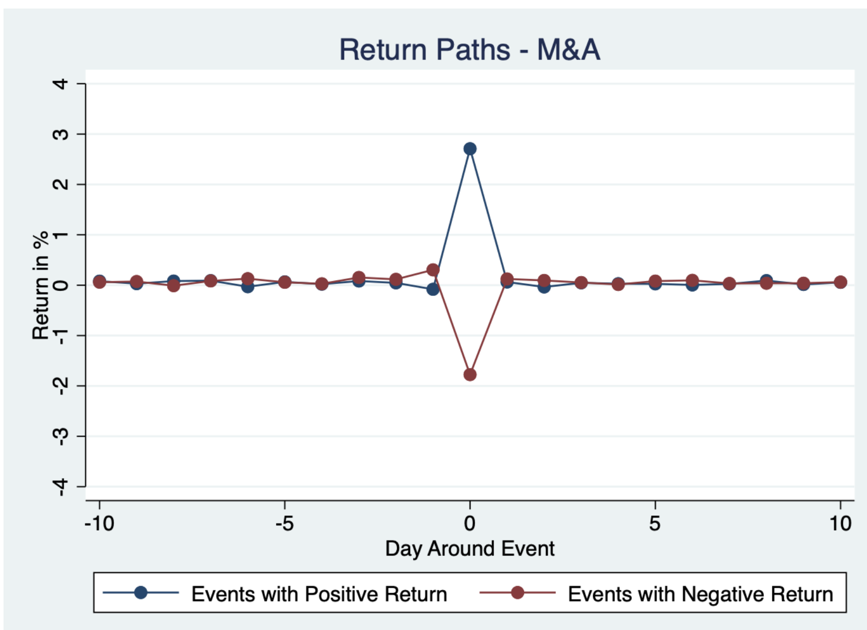
Table IA.8: Do Banks Prefer Trading on Exchanges for Relationship Trades?

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. Source: Deutsche Bundesbank, Research Data and Service Centre (FDSZ), Credit Register and MiFID transaction data (doi: 10.12757/Bbk.MiFID2008-2017.02), 2012–2017, own calculations. See Section 3 for a complete description of all data sources.

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).

About ECGI

ECGI is an international non-profit membership organisation that provides a platform for debate and dialogue among academics, policymakers, and business leaders, with a focus on major corporate governance, ESG, and stewardship issues.

The views expressed in this working paper are those of the authors, not those of the ECGI or its members.