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Is Proprietary Trading Detrimental to Retail Investors?

FALKO FECHT, ANDREAS HACKETHAL, and YIGITCAN KARABULUT*

ABSTRACT

We study the conflict of interest that arises when a universal bank conducts proprietary trading alongside its retail banking services. Our data set contains the stock holdings of every German bank and those of their corresponding retail clients. We investigate (i) whether banks sell stocks from their proprietary portfolios to their retail customers, (ii) whether those stocks subsequently underperform, and (iii) whether retail customers of banks engaging in proprietary trading earn lower portfolio returns than their peers. We present affirmative evidence for all three questions and conclude that proprietary trading can, in fact, be detrimental to retail investors.

INCREASING LIFE EXPECTANCY AND DEMOGRAPHIC changes have forced households in many developed countries to substantially extend their own provisions for retirement financing. These changes imply that households must become more actively involved in managing their personal finances. However, given their limited financial literacy (Lusardi and Mitchell (2007), van Rooij, Lusardi, and Alessie (2011)), retail investors often depend on professional financial advice when making investment decisions.[1]

*Falko Fecht is at the Department of Finance, Frankfurt School of Finance and Management. Andreas Hackethal is at Goethe University Frankfurt. Yigitcan Karabulut is at Rotterdam School of Management, Erasmus University, and CEPR. The usual disclaimer applies. We are indebted to Kenneth Singleton (the Editor), an anonymous Associate Editor, and two anonymous referees for their helpful suggestions and comments. We would like to thank Arnoud Boot; Joerg Breitung; Martin Brown; Dell'Arricia Giovanni; Degryse Hans; Egemen Genc; Reint Gropp; Luigi Guiso; Michalis Haliassos; Harry Huizinga; Roman Inderst; Stephan Jank; Janet Mitchell; Morkoetter Stefan; Madureira Leonarda; Jonathan Reuter; Jean-Charles Rochet; Klaus Schaeck; and Gregory Udell; as well as seminar participants at the 2011 NBER Summer Institute on Household Finance, the European Conference on Household Finance, the Banking Models and Banking Structure Conference at Banque de France, the 4 Swiss Winter Conference on Financial Intermediation, the Household Heterogeneity and Household Finance Conference at the Federal Reserve Bank of Cleveland, the 47 Annual Conference on Bank Structure and Competition at the Federal Reserve Bank of Chicago, the 12 Symposium on Finance, Banking and Insurance at KIT, the 2011 Annual Meeting of the German Finance Association, the 2011 Annual Meeting of the German Economic Association, Deutsche Bundesbank, Frankfurt School of Finance and Management, University of Leipzig, University of Kiel, Tilburg University, and Bangor Business School for their helpful comments and suggestions. The authors declare that they have no relevant or material financial interests that relate to the research described in this paper.

[1] Recent survey evidence suggests that the use of financial advice is pervasive. For instance, a survey conducted in the European Union shows that 80% of respondents report seeking professional

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Banks—particularly universal banks—should be well suited to provide such guidance to their retail customers. Playing a key role in many financial markets, banks dispose of and process information that is crucial to the provision of relevant financial advice that supports retail investors in their investment decisions. For example, compared with retail investors, banks are likely to have superior stock-selection and market-timing abilities, as they have more and better resources (e.g., technology, human capital) to collect and process information than do individual investors. Furthermore, banks can collect and process information at lower cost because they can exploit economies of scale in portfolio management and information acquisition. In addition, banks can obtain superior information about firms through their close lending and other direct business relationships (Acharya and Johnson (2007), Ivashina and Sun (2011)), thus, economies of scope should exist, particularly between banks' proprietary trading and portfolio management units and their retail banking services.

However, financial advice provided to retail investors resembles a "credence good": because of their limited financial literacy, households typically cannot assess the quality of financial products or services neither ex ante nor ex post. Several potential agency problems, such as misselling, can thus arise between banks and their retail customers.[2] Given their diverse lines of business, such as proprietary trading and retail banking, under the same roof, these agency problems might be particularly severe for universal banks. For example, when actively trading on their own account, to avoid a price impact, banks may face incentives to direct their retail customers to those stocks that they sell from their portfolios, which may not necessarily suit the needs of their customers. Thus, a question arises as to whether retail customers benefit from their banks' greater ability to provide guidance based on market knowledge from proprietary trading, or whether banks face incentives to exploit their uninformed retail customers, as banks trade stocks on their own account.[3]

To address this question, we study a unique data set provided by Deutsche Bundesbank that comprises the individual stock investments of each German bank and those of its retail customers. Using a series of panel regressions, we first examine the relationship between the stock investments of banks and those of their retail customers at the individual security level and find that when a bank sells a given stock from its proprietary trading portfolio, its retail customers tend to buy the same stock in that period. The direction of stock

advice before purchasing investment products (Chater, Huck, and Inderst (2010)). In a U.S. survey, Hung et al. (2008) document that 73% of all investors consider financial advice when making investment decisions.

[2] Misselling is generally understood as the practice of misdirecting customers to buy a product that does not suit their specific needs (Inderst and Ottaviani (2009)). This practice also includes selling customers financial instruments with an inferior risk-return profile.

[3] Recent studies that address this issue, such as Hackethal, Haliassos, and Jappelli (2012), Karabulut (2013), and Foerster et al. (2017), find evidence that the involvement of bank advisors negatively affects individual portfolio performance, despite having some benefits. However, these studies use data from only one advisory firm.

flows between bank and customer portfolios is negative only when banks sell stocks, not when they buy stocks. Further tests confirm that this finding is not a mere artifact of banks' market-making activities or retail investors' herding behavior and show that it is robust to using alternative empirical specifications, variable definitions, sampling restrictions, and econometric methods.

To strengthen the causal interpretation of our results, we exploit a reasonably exogenous shock that affected the stock investments of a subset of the sample banks over a certain period: Banks that obtained state assistance from the German Special Fund for Financial Market Stabilization were required to shut down most or all own-account trading and/or to substantially reduce their risky asset holdings during the assistance period. We exploit this exogenous sales pressure to isolate the causal link between bank and customer portfolios and obtain qualitatively and quantitatively similar results. We further explore the potential motives underlying this effect and provide several pieces of empirical evidence suggesting that banks do so to avoid a price impact. For example, the tendency of banks to sell stocks to their retail customers is significantly stronger for illiquid stocks (as measured by a higher Amihud ratio) in periods when financial markets are relatively more illiquid (i.e., after the collapse of Lehman Brothers in September 2008) and when the stock positions that banks liquidate are larger, all of which are associated with larger adverse price impacts.

We next analyze whether the observed behavior of banks has any negative implications for the portfolio performance of their retail customers. We find that retail customers experience trading losses from those transactions in which they purchase stocks that their banks sell from their proprietary trading portfolio and that these losses increase in the trading profits of the bank in the same stock. We further find that stocks sold by banks directly to their customers not only significantly underperform stocks that are held or purchased by banks but also underperform retail customers' other stock investments in their portfolios. These results suggest a potential conflict of interest between the proprietary trading activities of banks and their retail banking divisions. It is possible, however, that retail customers could still benefit from banks' greater ability to provide guidance, given banks' ability to draw on market knowledge from proprietary trading, which could compensate for the observed losses of retail customers. To address this possibility, we compare the stock portfolio performance of customers of banks with proprietary trading units with that of customers of banks without proprietary trading units. Using several performance indicators, we find that the stock portfolios of customers of banks with proprietary trading desks significantly underperform those of retail customers of banks without proprietary trading desks. Overall, our results reveal a potential conflict of interest arising from combining proprietary trading and retail banking under one roof, which seems to negatively affect the stock portfolio performance of retail investors.

These findings have important implications for the ongoing discussion about splitting up universal banks and separating their investment banking activity (in particular, proprietary trading) from their commercial and retail banking businesses. Proposals suggesting this separation have been advanced in the United States as a key part of the Dodd-Frank Act,[4] in the United Kingdom in the Vickers Report,[5] and in the European Union in the Liikanen Report.[6] Admittedly, the main aim of these regulatory initiatives is to prevent moral hazard problems. That is, to prohibit banks from using implicit and explicit guaranteed deposits and other bank liabilities to take excessive risks in their proprietary trading. Although our study does not directly contribute to the discussion of this moral hazard problem, our results suggest that such regulation might have the positive side effect of protecting retail investors.

From this perspective, our paper contributes to an important strand of the literature on conflicts of interest within financial institutions. This literature has focused largely on agency problems that may arise from the rampant sharing of information across different divisions of financial institutions.[7] For example, Massa and Rehman (2008) study possible information spillovers between the lending and asset management divisions of financial conglomerates and find that mutual funds that belong to bank families exploit their informational advantage (which they acquire through the lending relationships of their affiliated bank) by investing in the stocks of the borrowing firms. Similarly, Acharya and Johnson (2007) and Ivashina and Sun (2011) provide evidence of how banks use private information gained from lending activities when trading borrowing companies' credit derivatives or equities, respectively. Other studies of information sharing within financial institutions also document conflicts of interest among different divisions of banks, such as between analysts and investment banking divisions (e.g., Michaely and Womack (1999), Ljungvist et al. (2007), Agrawal and Chen (2008), Kadan et al. (2009), Haushalter and Lowry (2011)).

This literature is closely related to the debate on the benefits of universal banks, which culminated in the Gramm-Leach-Bliley Act in the United States in 1999. Puri (1996) shows that, in the pre-Glass-Steagall period, U.S. investors paid significantly more for IPOs underwritten by banks than for those underwritten by investment houses that could not establish credit relationships with firms.[8] Similarly, Ber, Yafeh, and Yosha (2001), show that for a sample of Israeli banks underpricing of initial public offerings (IPO) is reduced if the underwriting bank is also a major lender to the firm. This finding suggests that universal banks enhanced efficiency. However, Ber, Yafeh, and Yosha (2001) find that bank-managed investment funds pay too much for equities offered in IPOs that are underwritten by the bank in question. No paper has to date

[4] Dodd-Frank Wall Street Reform and Consumer Protection Act, enacted on July 21, 2010.

[5] Final Report of the United Kingdom's Independent Commission on Banking from 2011, chaired by John Vickers.

[6] Final Report of the High-level Expert Group on reforming the structure of the EU banking sector, chaired by Erkii Liikanen and initiated by EU Commissioner Michel Barnier.

[7] For a recent comprehensive survey of this literature, see, for example, Mehran and Stulz (2007).

[8] For a theoretical model illustrating the benefits of universal banks in this context, see Puri (1999). Kroszner and Rajan (1997) show that banks' organizational structures help to contain potential conflicts of interest and play a role in IPO underpricing.

investigated the link between the proprietary trading activities of banks and their retail banking divisions. Our paper is the first to document that combining proprietary trading and retail banking in universal banks might not be efficiency-enhancing because of potential conflicts of interest.

Finally, our work also relates to the growing literature on financial advice and household investment decisions (Bergstresser, Chalmers, and Tufano (2009), Hackethal, Haliassos, and Jappelli (2012), Karabulut (2013), Foerster et al. (2017)). We contribute to this literature by broadening the analysis to account for the larger organizations to which bank advisors are tied. Our results suggest that possible agency problems between advisors and their clients are not limited to the (monetary) incentives of advisors.

The remainder of the paper is organized as follows. Section I. introduces the data and provides summary statistics. Section II. presents results of tests that examine the interactions between stock investments of banks and those of their retail customer portfolios. In Section III., we first analyze the trading profits/losses that retail customers experience when purchasing stocks that their bank sells off. We then study how the stocks that are sold by banks to their retail customers perform relative to other stocks in the bank and customer portfolios. We also compare the stock portfolio performance of customers of banks that have proprietary trading units to the stock portfolio performance of retail customers of banks that do not have proprietary trading units. Section IV. concludes the paper.

I. Data and Variable Definitions

Proprietary trading is generally defined as the purchase or sale of financial instruments on a firm's own account with the intention of earning trading profits. In our analysis, we focus on banks' proprietary trading activities in single stocks. In addition to proprietary trading in its narrow form of making (short-term) profits, banks can also hold stock inventories when they act as market-makers. In addition to these stock positions that appear in banks' trading books, banks might also hold strategic stock investments in client firms in their banking books.

The original data set employed in this study provides security-by-security information on the portfolios of each German bank and those of its retail customers for the period from December 2005 to September 2009. This information is collected by the Deutsche Bundesbank from all monetary financial institutions at the end of each quarter to compile the "Security Deposits Statistics."[9] As defined by the Bundesbank, retail customers in our sample comprise all clients of a bank's mass retail, private banking, and wealth management businesses, excluding any institutional clients. The security holdings of banks in our data

[9] Prior to December 2005, monetary financial institutions in Germany were only required to report on an annual basis their own portfolio holdings, but not those of their customers. Our sample period, therefore, begins in December 2005.

set comprise security positions from proprietary trading, market-making, and strategic investments.

We use changes in end-of-quarter holdings to measure the net sales/purchases of a stock by a bank and its customers.[10] Since, by definition, strategic investments in a bank's banking book cannot frequently change, the observed net transactions reflect, in essence, changes in a bank's trading book. An obvious disadvantage of our data is that they do not contain information on individual transactions and the counterparties to banks' trades. Thus, a key challenge for our analysis is to econometrically infer the counterparties, particularly whether a bank traded with its retail customers, and control for other transaction motives such as market-making using auxiliary data. A further obstacle in this regard is the low frequency of our data, as it only allows us to derive a bank's net trade in a stock over one quarter and relate it to the net quarterly trades of the bank's customers.

Turning to a description of our main data set, as of December 2005, a total of 2,037 monetary financial institutions in Germany (e.g., commercial banks, investment banks, real-estate credit institutions) were required to report their portfolio holdings to the Bundesbank. Although our original data set covers the entire universe of monetary financial institutions in Germany, many small (regional) banks, particularly the Sparkassen and Volksbanken, have very limited stock holdings in their proprietary portfolios. Therefore, we consider the banks in the top 10$^{\text{th}}$ percentile according to the time-series average of the quarterly stock portfolio value. As we are interested in the possible interdependence between the stock investment decisions of banks and those of their retail customers, we also exclude from our sample those banks that have no retail banking unit, which leaves us with 102 banks in the final sample. Finally, we consider only the long positions of banks in listed stocks.[11] We complement these data with daily information from Thomson Reuters Datastream on the price, return index, free-float market capitalization, trading volume, market-to-book ratio, and industry classification for each stock in the sample for the entire observation period. The final sample comprises 8,203 different stocks and 133,177 bank-stock observations, representing nearly 63% of the stock investments made by all monetary financial institutions in Germany during the observation period.

Table I contrasts the portfolio sizes and portfolio shares of different asset classes for the sample banks with the average portfolio shares of all monetary financial institutions in Germany. First, we observe that sample banks have, on average, significantly higher proprietary portfolio volumes than the German average (8.24 billion euros vs. 1.61 billion euros), which is not surprising given

[10] The original data set provides security-by-security information for different asset classes, such as bonds, equities, and mutual funds. We restrict our attention to single stocks as they are more information-sensitive than bonds or mutual funds. Therefore, possible information asymmetries are more crucial in the case of stocks, which may give rise to potential conflicts of interest between banks and their retail customers.

[11] In the Internet Appendix available in the online version of this article, we provide a detailed description of the procedure that we use to construct the estimation sample for our analysis.

Table I

Portfolio Composition: Banks in the Final Sample versus All Banks in Germany

This table provides summary statistics for the portfolio compositions of banks in the final sample and those of all banks in Germany. Panel A describes portfolio shares of each asset class in the portfolios of sample banks and those of all banks in Germany. For comparison, Panel B presents the euro values of each asset class in the bank portfolios. The summary statistics are (1) the number of bank-quarter observations in each group, (2) the sample average of the portfolio share (value) of a given asset, and (3) the sample standard deviation of the portfolio share (value) of a given asset in each group. For variable definitions, see Table XIII. The data come from the Deutsche Bundesbank and cover the period from December 2005 to September 2009.

	All Banks			Banks in the Final Sample		
	No of Obs	Mean	*SD*	No of Obs	Mean	*SD*
Panel A: Portfolio Shares						
Portfolio size (in euro)	30,581	1.61e + 09	1.17e + 11	1,600	8.24e + 09	1.92e + 10
Short-term bonds share	30,581	0.0192	0.058	1,600	0.027	0.061
Long-term bonds share	30,581	0.790	0.235	1,600	0.714	0.198
Listed equities share	30,581	0.01	0.053	1,600	0.058	0.135
Nonlisted share	30,581	0.0133	0.085	1,600	0.003	0.010
Other equities share	30,581	0.001	0.01	1,600	0.0011	0.007
Mutual funds share	30,581	0.166	0.220	1,600	0.197	0.181
Panel B: Euro Values						
Short-term bonds	30,581	3.91e + 07	9.37e + 08	1,600	4.01e + 08	2.02e + 09
Long-term bonds	30,581	7.70e + 08	4.84e + 09	1,600	6.63e + 09	1.58e + 10
Listed equities	30,581	3.94e + 07	6.72e + 08	1,600	4.81e + 08	2.26e + 09
Nonlisted equities	30,581	3,508,774	7.05e + 07	1,600	5.34e + 07	2.98e + 08
Other equities	30,581	6.69e + 08	1.17e + 11	1,600	3,547,663	2.12e + 07
Mutual funds	30,581	9.29e + 07	5.37e + 08	1,600	6.71e + 08	1.60e + 09

that we consider those banks with the largest (stock) portfolios in our sample. Similarly, the share of stocks in the propriety portfolios of the sample banks is approximately six times larger than that of the average monetary financial institution (5.8% vs. 1%).[12] In Panel B of Table I, we also report the euro values of the banks' holdings in different asset classes.

Table II presents descriptive statistics for the stock investments of the sample banks and their retail customers along with the characteristics of the stocks in the final sample. The average holding of a bank in a given stock ($Holdings^B$) is 2.51 million euros, whereas this figure is 2.20 million euros in the aggregated customer portfolios of the average bank ($Holdings^C$). The mean stock portfolio of a bank is valued at 481 million euros, while the mean aggregated customer portfolio is 833 million euros. As shown in the table, 48% of banks' stock holdings in our sample display a positive average return in a given quarter (*Dummy*

[12] Our final sample captures the major parts of the German banking sector, as there are banks from all three main banking groups in Germany, namely, private banks, savings banks, and cooperative banks.

Table II
Descriptive Statistics for the Final Sample

This table provides summary statistics for the dependent variables and control variables employed in the analysis. The summary statistics are (1) the number of observations for each variable, (2) the sample mean, (3) the sample standard deviation, (4) the 25^{th} percentile of the distribution, (5) the sample median, and (6) the 75^{th} percentile of the distribution for each variable. The summary statistics are computed across bank-stock observations and over time. Note that we winsorize all stock controls by setting the extreme values that fall above (below) the 99^{th} (first) percentile to the corresponding upper (lower) boundary of the sample. For variable definitions, see Table XIII. The data come from the Deutsche Bundesbank and cover the period from December 2005 to September 2009.

	No of Obs	Mean	*SD*	25% percentile	Median	75% percentile
$Holdings^B$	133,177	2,513,902	2.10e + 07	4,879.33	91,609.56	543,380
$Holdings^C$	133,177	2,202,146	1.82e + 07	0	10,465.51	309,195.9
$\Delta Share^B$	133,177	0.542	3.785	−0.0175	0.003	0.289
$\Delta Share^C$	133,177	0.361	2.407	−0.0005	0	0.01
Dummy Gain	133,177	0.483	0.499	0	0	1
Return Volatility	133,177	0.033	0.029	0.0162	0.024	0.037
FFMC	133,177	1.19e + 10	2.56e + 10	3.17e + 08	2.10e + 09	1.02e + 10
Trading Volume(/100)	133,177	56.144	142.091	0.295	7.058	41.922
MtBV	133,177	2.396	2.754	1.08	1.771	2.903

Gain). When we examine the sectoral decompositions of the stocks, which we tabulate in the Internet Appendix, we observe that industrials represent the largest share of stocks (17.6% of the sample stocks), followed by financials with a share of 17.5%.

The main variables of interest in our analysis are changes in the normalized stock holdings of banks and their retail customers, which capture how banks and their customers actively change their holdings in a given stock in a given quarter. Specifically, we first calculate the percentage of company shares held by banks and their customers in a given quarter:

$$Share^B_{ijt} = \frac{Holdings^B_{ijt}}{FFMC_{it}} \quad \text{and} \quad Share^C_{ijt} = \frac{Holdings^C_{ijt}}{FFMC_{it}},$$

where $Holdings^B_{ijt}$ ($Holdings^C_{ijt}$) refers to the euro value of the holdings of bank j (its private customers) in a given stock i, and $FFMC_{it}$ denotes the free-float market capitalization of stock i in a given quarter t.[13]

[13] We normalize the euro values of stock holdings by the free-float market capitalization for three reasons. First, doing so eliminates possible stock valuation effects that could otherwise generate a spurious positive correlation between the holdings of banks and those of their retail customers. Second, our measure accounts for stock splits and other such developments. Finally, our measure also helps account for possible differences in market impact (e.g., the price impact of a sell trade in a small and illiquid stock vs. a large and liquid stock). In additional analysis, tabulated in the Internet Appendix, we also use changes in the share of stocks normalized by the portfolios of banks and retail customers and find similar results.

Table III

Stock Investments of Banks and Their Retail Customers: Univariate Analysis

This table presents Pearson correlation coefficients for changes in the normalized stock holdings (i.e., $Holdings^B/FFMC$) of a bank and those of its retail customers in a given quarter. Column (1) reports the unconditional correlation between $\Delta Share^C_{ijt}$ and $\Delta Share^B_{ijt}$. Column (2) is restricted to the sell trades of banks, and column (3) considers only the buy trades of banks. The corresponding p-values of the pairwise correlations are reported in parentheses. The data come from the Deutsche Bundesbank and cover the period from December 2005 to September 2009.

	Full Sample $\Delta Share^C_{ijt}$ (1)	*Sell Trades* $\Delta Share^C_{ijt}$ (2)	*Buy Trades* $\Delta Share^C_{ijt}$ (3)
$\Delta Share^B_{ijt}$	0.105	−0.05	0.106
	(0.000)	(0.000)	(0.000)
No of Obs	133,177	53,200	79,642

We then compute changes in the normalized stock holdings of banks and their customers:

$$\Delta Share^B_{ijt} = \frac{Holdings^B_{ijt}}{FFMC_{it}} - \frac{Holdings^B_{ijt-1}}{FFMC_{it-1}} \quad \text{and}$$

$$\Delta Share^C_{ijt} = \frac{Holdings^C_{ijt}}{FFMC_{it}} - \frac{Holdings^C_{ijt-1}}{FFMC_{it-1}}.$$

We convert both of these measures to basis points by multiplying by 10,000. Furthermore, to ensure that our results are not driven by outliers, we trim the data at the 2.5% level. As indicated in Table II, the average quarterly change in the normalized stock holdings of banks ($\Delta Share^B_{ijt}$) and of their retail customers ($\Delta Share^C_{ijt}$) is 0.54 and 0.36 basis points, respectively.

As a first step toward understanding the interaction between the stock investments of banks and those of their retail customers, we report the correlations between $\Delta Share^B_{ijt}$ and $\Delta Share^C_{ijt}$. As shown in column (1) of Table III, we find that, for the entire sample, the unconditional correlation is positive and statistically significant ($\rho = 0.105$; p-value <0.01). However, column (2) of Table III indicates that the sign of the correlation coefficient reverses when we consider only those stocks in which banks partially or fully sell off a position ($\rho = -0.05$; p-value <0.01), while for buy trades of banks we observe a significantly positive relationship ($\rho = 0.106$; p-value <0.01). In short, the univariate analysis suggests that there is an asymmetry in the equity flows between the bank and customer portfolios. In the next section, we conduct more formal tests to analyze this relationship in greater detail.

We conclude this section with a brief note on the possible heterogeneity in the financial sophistication levels of retail investors across banks. One could argue that financially literate individuals may anticipate the potential conflicts of interest emanating from proprietary trading activities. Hence, they may be less inclined to hold their stock portfolios at banks with proprietary trading desks.

Table IV
Comparison of Bank Customers by the Presence of a Proprietary Trading Unit

This table presents the mean and median years of schooling for customers of banks grouped by whether the bank has a proprietary trading desk. Information on educational attainment comes from an annual representative household panel survey conducted by a large German market research institute. See the Internet Appendix for further details about the household survey. The sample period covers the years between 2005 and 2011.

Years of Schooling	Banks without Proprietary Trading				Banks with Proprietary Trading				
	No of Obs	Mean	*SD*	Median	No of Obs	Mean	*SD*	Median	*t*-Test
Full sample (2005 to 2011)	1,564	13.205	3.018	11.00	2,976	13.210	3.021	11.00	−0.0541
2005	318	12.89	3.00	11.00	565	13.16	3.07	11.00	−1.2476
2006	264	13.44	3.06	11.00	487	13.42	3.07	11.00	0.0700
2007	219	13.32	3.06	11.00	339	13.14	3.01	11.00	0.6837
2008	176	13.39	3.04	11.00	339	13.14	2.99	11.00	0.8864
2009	176	13.24	3.06	11.00	328	13.22	3.02	11.00	0.0767
2010	181	12.78	2.84	11.00	367	13.04	2.94	11.00	−1.0025
2011	230	13.42	3.01	11.00	551	13.26	3.02	11.00	0.6664

As our sample only comprises banks with proprietary trading, such customer self-selection would imply that our estimates may represent an upper bound for both banks' ability to opportunistically sell stocks to their retail customers and the effect on the portfolio performance of those banks' retail investors.[14] To assess the severity of such selection bias, we use survey data on the general education levels of clients across banks operating in Germany.[15] These data from an annual representative household panel survey provided by a large German market research institute cover the years between 2005 and 2011, and contain more than 20,000 participating households in a given year. Table IV shows that both the mean and the median years of schooling for clients of banks with and without proprietary trading desks are not statistically different from one another. This is true for each year in our sample and for the full sample period. Hence, our results do not appear to be affected by potential customer self-selection.

II. Stock Flows between Banks and Their Retail Customers

A. Theoretical Background and Empirical Strategy

In this subsection, we first motivate our empirical analysis by the existing theoretical literature on informed trading and strategic trading by speculators. We then introduce our empirical model and discuss some estimation issues.

[14] For example, less sophisticated individuals make more severe investment mistakes and thus achieve lower investment performance irrespective of any conflicts of interest at their bank.

[15] As noted by van Rooij, Lusardi, and Alessie (2011), financial literacy increases substantially with general educational attainment. We provide detailed information about the survey in the Internet Appendix.

The incentives of banks are similar to those of other institutional investors when they trade stocks on their own account to maximize their trading profits: banks also intend to minimize both explicit and implicit transaction costs that substantially impact investment performance.[16] Following classical market microstructure reasoning (e.g., Kyle (1985), Easley and O'Hara (1987)), a bank's perceived private information will lead to an adverse price impact of a bank's orders and diminish its trading profits. If a bank disposes of private information about a stock's fundamentals, the bank will attempt to prevent others from inferring this information from its order flows and from front-running. For example, Madrigal (1996) formally shows that less informed traders can free-ride on the trades of better informed traders at the expense of the latter's trading profits.[17] In a recent paper, Agarwal et al. (2015) model and empirically show that regulatory disclosure of mutual fund trades does indeed diminish the performance of better informed funds. Even if banks do not possess any private information, but trade solely for liquidity reasons, they may still face the risk of being front-run by speculators and suffer from predatory trading, as modeled by Brunnermeier and Pedersen (2005) and Carlin, Lobo, and Viswanathan (2007). Taken together, prior literature suggests that banks may face strong incentives to sell stocks from their proprietary portfolios directly to their retail customers to conceal their trading intentions from the broader market and limit the potential price impact.[18]

An essential question that arises is: how can banks sell stocks directly to their retail customers? In contrast to most other institutional investors, banks can directly or indirectly influence the investment decisions of other market participants (particularly those of their retail customers), as information provision by banks is an essential dimension of their relationship with customers (Bolton, Freixas, and Shapiro (2007)). Specifically, in the absence of perfect "Chinese Walls," banks can steer their customers toward stocks that they intend to sell from their proprietary portfolios through at least three channels. First, banks can influence the investment decisions of their retail customers through analyst recommendations or their financial advisors.[19] In particular, studies of investor reactions to analyst recommendations and financial advice suggest that at least some investors are not wary of potential conflicts of interest underlying

[16] See, for instance, Keim and Madhavan (1998) for a survey of the relevance of different transaction costs for institutional investors. Chan and Lakonishok (1995) find that institutional buy trades have had a stronger and more persistent price impact, whereas Chiyachantana et al. (2004) report evidence that, since 2001, stock sales of institutional investors in the United States have had a significantly stronger price impact than buy trades.

[17] See also Frank et al. (2004) for empirical evidence from the mutual fund industry.

[18] We focus on both sell and buy trades of banks in the analysis of the interactions between the stock investments of banks and the stock investments of their retail customers. We acknowledge that it is unlikely that banks can buy stocks directly from their retail customers when they intend to buy securities, largely because of the short-sale constraints faced by retail investors.

[19] Typically, a bank's analyst recommendations serve as guidelines for the bank's financial advisors and wealth managers. When providing financial advice, bank-affiliated advisors can follow the recommendations of the bank's analysts, but they must provide justification when they deviate from those guidelines and make other recommendations.

professional advice, and individuals tend to overly trust analysts and exactly follow their recommendations (Malmendier and Shanthikumar (2007), Hong, Scheinkman, and Xiong (2008)). Second, if a bank offers discretionary portfolio management services to its clients, the bank's portfolios managers can buy stocks directly into managed individual client portfolios without explicit client consent. The final channel is relevant for banks with affiliated mutual funds, as motivated by the findings of previous literature on information sharing and interactions between the portfolio holdings of banks and their affiliated mutual funds (e.g., Massa and Rehman (2008), Golez and Marin (2015)). Note that the remuneration of client relationship and fund managers at (German) banks is based predominantly on the volume of assets under management rather than on portfolio performance (Deli (2002), Del Guercio, Genc, and Tran (2015)). Hence, they will be disciplined only if the flow of client funds is sufficiently performance sensitive, which is not necessarily the case.[20]

To evaluate whether banks direct their customers to those stocks that they seek to sell from their proprietary portfolios, we employ an interaction model. Our baseline model takes the following form:

$$\Delta Share^{C}_{ijt} = \beta_1 \cdot \Delta Share^{B}_{ijt} + \beta_2 \cdot Sell^{B}_{ijt} + \beta_3 \cdot \Delta Share^{B}_{ijt} \times Sell^{B}_{ijt} + \beta_4 \cdot Controls_{it-1} + \gamma_j + \gamma_t + \gamma_k + \epsilon_{ijt} \tag{1}$$

$$Sell^{B}_{ijt} = \begin{cases} 1 & \text{if } \Delta Share^{B}_{ijt} < 0, \\ 0 & \text{if otherwise.} \end{cases}$$

Here, $\Delta Share^{B}_{ijt}$ and $\Delta Share^{C}_{ijt}$ represent quarterly changes in the percentages of company i's shares held by bank j and its retail customers, respectively, $Sell^{B}_{ijt}$ is a dummy variable that takes a value of one if bank j reduces its holdings of stock i in quarter t and zero otherwise, and Controls$_{it-1}$ includes stock-specific characteristics such as performance, volatility, market-to-book ratio, and trading volume, which are measured in quarter $t-1$. All standard errors are clustered at the bank level to broadly account for any correlations that can impact banks and their retail customers (e.g., deleveraging), and all regressions control for fixed effects for banks, γ_j, firm industries, γ_k, and quarters of observation, γ_t.[21]

The model given in equation (1) allows us to investigate the extent to which the investment decisions of a bank's retail customers regarding a given stock

[20] Glaser and Weber (2007), for instance, report survey-based evidence showing that German retail investors are not even aware of their actual portfolio performance. Furthermore, previous literature shows that, although investors flock to funds with stellar past performance, funds with poor recent performance do not experience large outflows, which leads to a convex flow-performance relationship (Sirri and Tufano (1998)).

[21] In robustness checks tabulated in the Internet Appendix, we also employ bank-time- or stock-time-level fixed effects and obtain similar results. Notably, our results are robust to accounting for any correlation in error terms at the stock or bank-stock level. When we account for the possible serial and cross-sectional correlation of error terms using Driscoll and Kraay (1998) standard errors, we obtain similar results.

are related to their bank's investment choices regarding that stock during the same quarter. By incorporating the interaction term, we are able to test for potential asymmetries between when a bank sells a stock and when it buys a stock, as indicated in the univariate analysis. If banks do indeed exhibit a tendency to direct their retail customers to those stocks that they sell from their proprietary portfolios, the coefficient on the interaction term should be negative and relatively large in magnitude compared to that of the stand-alone variable ($\beta_1 + \beta_3 < 0$). Furthermore, if price impact is the dominant motive, the negative relationship between the equity flows of the portfolios of banks and those of their retail customers should be more pronounced when the stocks that banks intend to sell are relatively illiquid or banks' sell trades are larger in size (as in Kyle (1985)).

We acknowledge that one can question the causal interpretation of the estimates from equation (1). For example, it is possible that banks, rather than selling stocks directly to their customers to limit the price impact, cater to investor demand by acting as counterparties for trades initiated by their retail clients. To alleviate concerns about the direction of causality, we exploit a regulatory intervention that required some banks to shut down most or all own-account trading over a certain period and thus exogenously triggered sell trades at a subset of the sample banks. We exploit this exogenous variation to isolate the causal effect of banks' sell trades in a given stock on their customers' investment decisions regarding that stock.

Finally, as noted in the classical market microstructure literature, order size is an endogenous decision of both informed and liquidity traders (see Kyle (1985), Easley and O'Hara (1987) and more recently, Vayanos (1999)). This implies that, other things being equal, if a bank intends to liquidate a larger stock position, it has incentives to split the order to limit the price impact, which leads to serial correlation in bank transactions.[22] This further suggests that a bank's incentives to mitigate price impact are stronger among those stocks for which the bank splits its orders, and hence, ceteris paribus, the bank might also be more inclined to sell those shares directly to its customers.[23] To check for this possibility, we use generalized method of moments (GMM) estimators for dynamic models of panel data developed by Arellano and Bover (1995), which allows us to model the banks' dynamic trading strategies and control for possible serial correlation in the equity flows.

B. Baseline Results

In Table V, we present results of the panel regressions as specified in equation (1). The unit of observation in these regressions is the bank-stock-quarter. In column (1), we show that the investment flows of banks in a given

[22] See Biais, Hillion, and Spatt (1995).

[23] Note, however, the possibility of a substitutive relationship between these two means of mitigating price impact: if order splits do little to mitigate the price impact, a bank will prefer to sell more shares to its retail customers.

Table V

Stock Investments of Banks and Their Retail Customers: Baseline Analysis

This table reports coefficient estimates from the baseline regressions. In column (1), we estimate the baseline regression. In column (2), we include in the model an additional control variable that measures the aggregate investment decisions of retail investors in a specific stock. In column (3), we remove those stock observations for which banks serve as market-makers. In column (4), we include as a control variable the lagged normalized holdings of a given stock in the portfolios of bank customers. In column (5), we include the lagged dependent variable in the estimation model. In columns (1) to (4), we estimate pooled panel regressions with bank, time, and industry fixed effects using ordinary least squares, while in column (5) we use generalized method of moments (GMM) estimators for dynamic models of panel data developed by Arellano and Bover (1995), controlling for bank-stock fixed effects. t-statistics, reported in parentheses, are calculated by correcting the standard errors by clustering at the bank level. For variable definitions, see Table XIII. ***, **, and * denote significance at the 0.001, 0.01, and 0.05 level, respectively. The data come from the Deutsche Bundesbank and Thomson Reuters Datastream and cover the period from December 2005 to September 2009.

	Regressand: $\Delta Share^{C}_{ijt}$				
	(1)	(2)	(3)	(4)	(5)
$\Delta Share^{B}_{ijt}$ (β_1)	0.058**	0.055**	0.058**	0.057**	0.0227***
	(3.29)	(3.17)	(3.09)	(3.33)	(5.28)
$Sell^{B}_{ijt}$ (β_2)	−0.415***	−0.379***	−0.400***	−0.414***	−0.123***
	(−6.11)	(−5.96)	(−6.23)	(−6.12)	(−11.88)
$\Delta Share^{B}_{ijt} \cdot Sell^{B}_{ijt}$ (β_3)	−0.076**	−0.062**	−0.066*	−0.067**	−0.038***
	(−2.66)	(−2.37)	(−2.55)	(−2.66)	(−5.50)
$Dummy\ Gain_{it-1}$	−0.106***	−0.055***	−0.100***	−0.102***	−0.028*
	(−4.72)	(−2.77)	(−4.79)	(−4.56)	(−2.55)
$Return\ Volatility_{it-1}$	2.334	2.596	2.314	2.315	1.178***
	(1.69)	(1.94)	(1.70)	(1.71)	(5.34)
$MtBV_{it-1}$	−0.011**	−0.008*	−0.010*	−0.008**	−0.0044*
	(−2.94)	(−2.40)	(−2.60)	(−2.64)	(−2.28)

(Continued)

Table V—*Continued*

	Regressand: $\Delta Share^{C}_{ijt}$				
	(1)	(2)	(3)	(4)	(5)
$Trading\ Volume_{it-1}/100$	−0.001***	−0.001***	−0.001***	−0.0006***	−0.002***
	(−5.60)	(−4.94)	(−5.47)	(−5.36)	(−8.57)
$\Delta Share^{others}_{it}$	–	0.035***	–	–	–
	–	(3.88)	–	–	–
$Share^{C}_{ijt-1}$	–	–	–	34.056***	–
	–	–	–	(7.60)	–
$\Delta Share^{C}_{ijt-1}$	–	–	–	–	−0.0192
	–	–	–	–	(−1.36)
					–
Constant	0.593***	0.320***	0.551***	0.574***	0.0896***
	(8.27)	(3.57)	(8.15)	(8.09)	(4.27)
Bank fixed effects	Yes	Yes	Yes	Yes	No
Time fixed effects	Yes	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	Yes	No
Bank-stock fixed effects	No	No	No	No	Yes
Clustering	Bank level	Bank level	Bank level	Bank level	Bank level
R^2	0.054	0.071	0.055	0.068	–
No of Obs	133,177	133,177	131,491	133,177	95,575
Hansen test (p-value)	–	–	–	–	0.422
Serial Correlation test (p-value)	–	–	–	–	0.308

stock are positively related to those of their retail customers when banks buy a stock. This is reflected by the significantly positive β_1 coefficient reported in the first row.[24] For the sell trades of banks, however, this relationship is significantly negative ($\beta_1 + \beta_3 < 0$), which suggests that when a bank sells a stock from its portfolio, its retail customers tend to buy that stock in the same quarter. This finding confirms the asymmetry in equity flows revealed in the univariate tests and further supports the notion that banks tend to direct their retail clients to those stocks that they sell from their proprietary portfolios. Regarding the control variables, we find that retail investors tend to sell those stocks that displayed a positive average return in the previous quarter, while we find no significant effect of past realized volatility. Finally, the retail investors in our sample tend to sell stocks with higher market-to-book ratios and when their liquidity, as measured by turnover rate, is high.

A potentially confounding factor when analyzing the investment decisions of individual investors in a given stock is that these decisions can be driven in part by the investment choices of their peers. Individuals might engage in herding behavior simply because they suspect that others have superior information (Banerjee (1992)), or they might attempt to ride a bubble.[25] What might appear to be herding behavior could also result from investors responding jointly to investment recommendations from the same professionals or similar individuals (Scharfstein and Stein (1990), Graham (1999)). In any case, the large-scale, possibly sentiment-driven demand of retail investors for particular stocks might drive some banks with those stocks in their portfolios to sell those—possibly overpriced—stocks to their customers. Thus, according to this argument, our results could be an artifact of increased retail investor demand for particular stocks. To rule out this potential channel, we construct a variable that measures the aggregate investment decisions of retail investors for a specific stock. To do so, we first aggregate the changes in the normalized stock holdings of all retail investors in stock i and quarter t. We then deduct the changes in stock i for retail customers of bank j:

$$\Delta Share_{ijt}^{others} = \sum_{k \neq j}^{J} \Delta Share_{ikt}^{B}.$$

Column (2) in Table V shows that the herding measure enters the model with a significant positive sign, which suggests that retail customers of a bank tend to buy (sell) those stocks that customers of other banks buy (sell) in the same period. However, we still find that, for banks' sell trades, there is a significant

[24] We note that the positive association between $\Delta Share_{ijt}^{B}$ and $\Delta Share_{ijt}^{C}$ may be due to the time variation in the free-float market capitalization of a given stock. However, this relationship may also indicate that banks front-run their retail customers, that banks and their customers trade on similar information, or even that banks share some of their information with their retail customers.

[25] As noted by De Long et al. (1990), the sentiment-driven demand of individual investors can be correlated if they follow similar signals from the market, such as the forecasts of Wall Street gurus or past price and volume patterns.

negative relationship between the investment flows of a bank in a given stock and those of its customers. Hence, it appears that our results are not driven by investor herding behavior.

A powerful alternative interpretation of our results is that banks, rather than pushing stocks on their customers, cater to investor demand by acting as market-makers or counterparties for trades initiated by their retail clients. In particular, banks may sell to their customers those stocks that the customers demand, and they buy those stocks that their customers sell from their portfolios. Under this hypothesis, without assuming any causality, there would be a negative relationship between the stock investments of banks and those of their customers when retail investors buy or sell stocks. However, as shown in the analysis thus far, we find a negative relationship only for sell trades, while the effect is significantly positive for banks' buy trades,[26] which suggests that banks do not simply act as counterparties for all of their retail customers' trades. To further confirm that our results are not driven by the market-making activity of banks, we complement our sample with auxiliary data from Deutsche Börse that indicate at the bank-stock level whether a bank serves as market-maker. We then rerun our analysis after excluding those stocks for which the sample banks act as explicit market-makers. According to data from Deutsche Börse, banks in our sample serve as "designated sponsors" for 307 stocks during the sample period.[27] As presented in column (3) of Table V, excluding those stocks from the sample does not alter our main findings. In an additional analysis, we include as a control variable in our model the lagged normalized holdings of a given stock in the portfolios of bank customers, to account for the fact that retail customers may be less likely to increase their holdings of a stock if they already hold a substantial amount of the stock (Haushalter and Lowry (2011)). Prior studies also show that individual investors tend to overweight particular stocks in their portfolios for various reasons such as local or industry bias. Accordingly, banks may accommodate their retail customers' demand for those stocks by directly selling them those stocks from their own trading portfolios, which could account for our empirical results. Column (4) in Table V reports the estimation results, which show that our main findings are robust to controlling for this potential channel. Overall, these additional tests suggest that our key finding is not a mere artifact of banks acting as market-makers or counterparties for trades initiated by their retail customers.

Our analysis thus far has focused on the relationship between bank and customer portfolios over a given period, implicitly assuming that banks and their retail customers make investment choices within the same period. Given our data are available at a quarterly frequency, this assumption is likely to hold.

[26] We also more formally analyze the effects of banks' buy trades in a given stock on the investment decisions of their retail customers in that stock. The results, reported in the Internet Appendix, confirm the findings of the univariate analysis that banks' buy trades are positively related to the investment flows of their retail customers in a given stock.

[27] The vast majority of these stocks have German origins, although there are also a small number of stocks from other countries, such as Austria, the United Kingdom, the Netherlands, or the United States, for which the banks in our sample act as market-makers.

However, as we discussed previously, banks may also follow a dynamic portfolio strategy, especially when sales are larger, and hence they may spread their trades over several periods. This would lead to serial correlation in changes in a bank's end-of-quarter holdings of a given stock. To address this possibility, we next use dynamic panel techniques, controlling for unobserved heterogeneity at the bank-stock level. While the former allow us to account for possible serial correlation in equity flows, the latter enables us to control for heterogeneity in the type of relationship between a bank-firm pair. We rely on the GMM estimators for dynamic panel data models developed by Arellano and Bover (1995). As presented in column (5) of Table V, we still observe that retail customers tend to buy those stocks that their banks sell from the banks' own trading portfolios.[28] This result also provides indirect evidence that banks steer their customers toward those stocks that they intend to sell from their proprietary portfolios to avoid a potential price impact.

B.1. Pinning Down Causality: Rescue Interventions of 2008 and Forced Sales

In the tests above, we find evidence of a strong, negative relationship between the stock investment flows of banks and those of their retail customers when banks sell stocks from their proprietary portfolios. While these findings are consistent with the view that when intending to partly liquidate a stock position, banks sell those stocks to their retail customers, these results do not allow us to identify such a causal relationship. In this section, we use an exogenous event that forced some banks to sell stocks from their proprietary portfolios to isolate the causal effect of banks' sales of stocks from their own portfolios on their retail customers' decisions regarding whether to invest in those stocks.

Following the worsening of the global financial crisis in 2008, the German Parliament passed the Financial Market Stabilization Act and, as part of it, established the German Special Fund for Financial Market Stabilization (SoFFin) in late October of that year. SoFFin was mandated to help eligible German financial institutions overcome potential liquidity shortages by providing guarantees on certain debt instruments and overcome solvency problems by the outright provision of bank equity and asset swaps.[29] To limit the exposure of German taxpayers' money and comply with European Commission regulations on state aid, SoFFin assistance was tied to a series of regulatory measures imposed on beneficiary financial institutions that were intended to curb risk-taking by these institutions while preventing the assistance grants from conferring undue competitive advantages.[30] Relevant to our analysis is a distinct policy measure imposed on all banks that came under the scheme. Specifically,

[28] For further details on the dynamic panel estimation, please see the Internet Appendix.

[29] The total volume of SoFFin was 480 billion euros, of which a maximum of 168 billion euros were used for guarantees on the debt instruments of nine financial institutions in 2009, a maximum of 28.4 billion euros were used to recapitalize four banks in 2010, and a maximum of 5.9 billion euros were used for a risk transfer from one bank in 2009.

[30] In a letter to the European Commission (EC) on October 27, 2008, the German government acknowledged that the SoFFin scheme is in the nature of state aid but simultaneously appealed

beneficiary banks had to shut down most or all own-account trading and/or substantially reduce their holdings of risky assets during the assistance period.[31] We treat this obligation, imposed by SoFFin on the beneficiary banks in our sample on very short notice, as a negative exogenous shock to banks' stock holdings in their proprietary portfolios. We find that on average the sample beneficiary banks reduce their stock portfolios by 46.1%, or by 2.82 billion euros in the treatment period.

We exploit this exogenous variation to examine the causal effect of banks' stock sales on the investment decisions of their retail customers. To do so, we first construct the indicator variable $Forced\ Sales^B_{jt}$ to identify those banks that received state aid through SoFFin and thus were required to substantially reduce the volume of risky assets in their trading books at the beginning of the assistance period. We then interact this indicator variable with changes in banks' normalized stock holdings to examine the causal impact of banks' forced stock sales on the investment decisions of their retail customers regarding those stocks. The model takes the following form:

$$\begin{aligned}\Delta Share^C_{ijt} = b_1 \cdot \Delta Share^B_{ijt} + b_2 \cdot Forced\ Sales^B_{jt} + b_3 \cdot \Delta Share^B_{ijt} \\ \times Forced\ Sales^B_{jt} + b_4 \cdot Controls_{it-1} + \gamma_j + \gamma_t + \gamma_k + e_{ijt}. \qquad (2)\end{aligned}$$

Similar to the baseline model, we include bank, firm industry, and quarter-of-observation fixed effects. We also account for time-varying stock characteristics and correct the standard errors by clustering at the bank level. The regression results are presented in column (1) of Table VI. For banks that were forced into sell trades by the regulation, we again find that the investment flows of banks in a given stock have a significant negative effect on those of their retail customers, as represented by the sum of the coefficients b_1 and b_3. This suggests that when (beneficiary) banks are exogenously required to liquidate/reduce their stock portfolios, to a large extent their retail customers buy those stocks that the banks sell from their proprietary portfolios, which confirms the causal interpretation of our findings from the previous section. It is important to note that the implied magnitudes in Table VI are also comparable to those of the baseline regressions presented in Table V. Because the government intervention and guarantees coincided with the onset of the global financial crisis, one might wonder whether the negative relationship between rescued banks' forced sales and their customers' stock purchases merely reflects the fact that, during the crisis, all banks used any channels available to deleverage and sell off their stock holdings. To address this possibility, we next include the interaction between the financial crisis indicator and changes in banks' normalized stock holdings and rerun our analysis. As reported in column (2) of Table VI, accounting for a generally different relationship between banks' stock investment flows and those of their retail customers during the financial

to Article 87(3) (b) of the EC Treaty, which allows such aid as a remedy for a serious disturbance in the economy of a member state.

[31] For details, see http://ec.europa.eu/competition/.

Table VI

Stock Investments of Banks and Their Retail Customers: Rescue Interventions of 2008 and Forced Sales

This table reports coefficient estimates from the regression specification shown in (2). In column (1), $ForcedSales^{B}_{jt}$ is an indicator variable that identifies those banks that received state aid and SoFFin guarantees during our observation period and thus were required to substantially reduce the volume of risky assets in their trading books at the beginning of the assistance period. In column (2), we also account for the adverse effects of the financial crisis period by introducing the indicator variable $Crisis_t$, which takes a value of one for the sample period following 2008Q3, and zero otherwise. t-statistics, reported in parentheses, are calculated by correcting the standard errors by clustering at the bank level. For variable definitions, see Table XIII. ***, **, and * denote significance at the 0.001, 0.01, and 0.05 level, respectively. The data come from the Deutsche Bundesbank and Thomson Reuters Datastream and cover the period from December 2005 to September 2009.

	Regressand: $\Delta Share^{C}_{ijt}$	
	(1)	(2)
$\Delta Share^{B}_{ijt}$ (b_1)	0.0615***	0.0627***
	(4.70)	(4.34)
$Forced\ Sales^{B}_{jt}$ (b_2)	−0.299**	−0.299**
	(2.69)	(2.69)
$\Delta Share^{B}_{ijt} \cdot Forced\ Sales^{B}_{jt}$ (b_3)	−0.0784***	−0.0752***
	(−5.58)	(−4.55)
$Dummy\ Gain_{it-1}$	−0.096***	−0.096***
	(4.30)	(4.30)
$Return\ Volatility_{it-1}$	2.515	2.519
	(1.83)	(1.37)
$MtBV_{it-1}$	−0.010**	−0.010**
	(−3.07)	(−3.06)
$Trading\ Volume_{it-1}/100$	−0.001***	−0.001***
	(−5.69)	(−5.69)
$Crisis_t$	–	−0.117
	–	(−1.15)
$\Delta Share^{B}_{ijt} \cdot Crisis_t$	–	−0.004
	–	(−0.31)
Constant	0.0465***	0.464***
	(5.99)	(6.06)
Bank fixed effects	Yes	Yes
Time fixed effects	Yes	Yes
Industry fixed effects	Yes	Yes
Clustering	Bank level	Bank level
R^2	0.048	0.0481
No of Obs	133,177	133,177

crisis does not affect our key results, although there is a slight decline in the magnitudes of the estimated coefficients.

In summary, the tests presented in this section provide further support for the view that banks tend to push some of the stocks that they sell from their proprietary trading portfolio to their retail customers.

B.2. Additional Robustness and Sensitivity Analysis

In this section, we perform several additional tests to ensure the robustness of our findings. We present these results in Table VII. First, we verify our results using a different definition of our main variables, that is, changes in the share of stocks normalized by the portfolios of banks and retail customers (in lieu of the free-float market capitalization of the respective stocks). The results, tabulated in column (1), are consistent with those of our baseline regression.

Next, we exclude financial stocks from the sample to alleviate concerns that (i) banks might have an information advantage over individual investors when trading stocks of firms that are involved in the same industry and (ii) our results might be driven by banks trading in their own stocks or in stocks of related firms. As reported in column (2), excluding financial stocks from the sample does not affect our results, despite the slight decline in the magnitudes of the estimated coefficients.

Third, in column (3) of Table VII, we expand our sample to include all banks with proprietary trading units that have a quarterly average stock portfolio value of more than 5 million euros. Using this threshold increases the number of sample banks from 102 to 120. The regression results show that our findings are robust to increasing the number of banks in our sample. Including those banks with relatively smaller stock portfolios increases our sample size only marginally, from 133,177 to 135,929 observations, suggesting that our working sample largely captures banks' proprietary trading in Germany.

In column (4) of Table VII, we only consider those stock observations for which banks hold less than 3% of the free-float market capitalization. By law, investors are obliged to disclose transactions if they hold a block exceeding 3% of a firm's free-float market capitalization. After excluding large stock positions from the sample, we continue to observe a similar pattern as in the baseline sample, with the implied magnitudes in column (4) slightly larger than those of the baseline regressions presented in Table V, which is in line with our theoretical arguments.[32]

We next restrict our sample to those stock observations for which both sample banks and their retail customers simultaneously have positive holdings in their respective portfolios, which results in a subsample of 85,415 bank-stock observations. The regression results, reported in column (5), show that, for sell trades, the negative relationship between the investment flows of banks and those of their retail customers remains significant and is even larger in magnitude for this subsample.

Finally, in columns (6) and (7), we, respectively, include stock-time and bank-time fixed effects in our baseline model. The inclusion of stock-time fixed effects enables us to account for any unobserved time-varying changes in stock characteristics that might affect the demand of banks and the demand of their customers for a particular stock in different ways. Including bank-time fixed

[32] If a bank is obliged to disclose its trades in any case, its incentives to conceal trades by selling to its customers are dampened. Thus, we would also expect to find stronger effects if we confined our sample to trades in stocks in which the respective bank holds less than the threshold.

Table VII

Stock Investments of Banks and Their Retail Customers: Additional Robustness and Sensitivity Checks

This table reports regression results for various robustness checks. In column (1), we use changes in the share of stocks scaled by the portfolio values of banks and retail customers. In column (2), we remove financial stocks from the sample. In column (3), we expand our sample to include all banks with proprietary trading units that have a quarterly average stock portfolio value of more than 5 million euros. In column (4), we only consider those stock observations for which banks hold less than 3% of the free-float market capitalization. In column (5), we consider only those stock observations in which both sample banks and their retail customers have positive holdings in their respective portfolios. For variable definitions, see Table XIII. In columns (1) to (5), we estimate pooled panel regressions with bank, time, and industry fixed effects using ordinary least squares; in columns (6) and (7), we include stock-time and bank-time fixed effects in our baseline model, respectively. t-statistics, reported in parentheses, are calculated by correcting the standard errors by clustering at the bank level. ***, **, and * denote significance at the 0.001, 0.01, and 0.05 level, respectively. The data come from the Deutsche Bundesbank and Thomson Reuters Datastream and cover the period from December 2005 to September 2009.

	Regressand: $\Delta Share^C_{ijt}$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\Delta Share^B_{ijt}$	0.0375***	0.0556**	0.0593**	0.0592**	0.1603***	0.0573**	0.0616**
	(9.47)	(3.25)	(3.31)	(3.28)	(5.08)	(3.19)	(3.23)
$Sell^B_{ijt}$	−0.3820***	−0.4422***	−0.4115***	−0.4137***	−1.1147***	−0.404***	−0.421***
	(−5.22)	(−6.03)	(−6.21)	(−6.08)	(−9.51)	(−6.01)	−0.075
$\Delta Share^B_{ijt} \cdot Sell^B_{ijt}$	−0.0400***	−0.0769*	−0.0759**	−0.0775**	−0.1928***	−0.072*	(−1.97)
	(−5.22)	(−2.48)	(−2.67)	(−2.66)	(−4.14)	(−6.01)	–
$Dummy\ Gain_{it-1}$	0.3923***	−0.1020***	−0.1044**	−0.1035***	−0.225***	−0.104***	–
	(5.25)	(−4.15)	(−4.76)	(−4.62)	(−5.50)	(−4.64)	–
$Return\ Volatility_{it-1}$	−1.3907**	1.7996	2.350	2.358	2.038***	2.477	–
	(−3.15)	(1.43)	(1.73)	(1.70)	(3.54)	(1.75)	–

(Continued)

Table VII—*Continued*

	Regressand: $\Delta Share^{C}_{ijt}$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$MtBV_{it-1}$	−0.0085***	−0.0131***	−0.011**	−0.0105**	−0.032***	−0.010**	–
	(−3.42)	(−3.47)	(−2.96)	(−2.93)	(−3.67)	(−2.76)	–
$Trading\ Volume_{it-1}/100$	−0.0002	−0.0008***	−0.0006***	−0.0007***	−0.0017***	−0.0007***	–
	(−0.75)	(−5.92)	(−5.60)	(−5.58)	(−6.35)	(−5.64)	–
Constant	0.6462***	0.6573***	0.589***	0.5889***	0.872***	0.497***	0.0461***
	(5.39)	(7.99)	(8.48)	(8.18)	(3.78)	(11.29)	(6.09)
Bank fixed effects	Yes	Yes	Yes	Yes	Yes	No	No
Time fixed effects	Yes	Yes	Yes	Yes	Yes	No	No
Industry fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	No
Bank-time fixed effects	No	No	No	No	No	Yes	No
Stock-time fixed effects	No	No	No	No	No	No	Yes
Clustering	Bank level	Bank level	Bank level	Bank level	Bank level	Bank level	Bank level
R^2	0.112	0.055	0.055	0.055	0.058	0.074	0.395
No of Obs	139,864	107,472	135,929	132,813	85,415	133,177	133,177

effects would capture any unobserved changes in bank characteristics that might, for instance, induce a bank to deleverage and sell large parts of its portfolio in a certain quarter. We find qualitatively similar results as in the baseline regressions after the inclusion of these additional fixed effects.

C. Channels for the Stock Flows between Banks and Their Retail Customers

An essential question that arises is how banks sell stocks to their retail customers. We argue that, in the absence of perfect "Chinese Walls," banks' portfolio management units are a natural candidate for such a channel.[33] When retail clients mandate their bank to manage their portfolios (e.g., as in private wealth management), they may not be fully aware of their investments in particular stocks. Thus, a bank's portfolio managers can buy on behalf of their customers those stocks that the bank's proprietary trading desks intend to sell from their own trading books. Whether portfolio managers do so, being fully aware of the potential conflicts of interest, or whether they simply follow, for instance, a "hot stock tip" from a colleague is beyond the scope of this paper.

Using our data set, we can evaluate the extent to which the portfolio management divisions of banks play a role in this process. To do so, we hand-collect additional information on whether a bank in our sample has an active portfolio management unit. We then split the sample in two and run the baseline regressions for these two subsamples separately. Columns (1) and (2) of Table VIII report the estimation results for banks with a portfolio management unit and those without such a unit, respectively. For both subsamples, we find a negative relationship between the stock investment flows of banks and those of their customers when banks sell stocks from their own portfolios. However, the effect is statistically significant only among those banks that have portfolio management divisions (column (1)). In column (3), we verify our results using a three-way interaction on the full sample. Overall, the combination of portfolio management and proprietary trading appears to provide banks with an opportunity to sell stocks from their proprietary trading portfolios to their retail customers.

D. Motives for Stock Flows between Banks and Retail Customers

We next turn to the question of what motivates banks to sell stocks to their retail customers rather than to investors in financial markets. As discussed above, we conjecture that the key motive for banks is likely to avoid a price impact if they are trading on private information or for liquidity reasons. To address this question, we first focus on the cross-section of stocks held by banks and their retail customers. In particular, we focus on illiquidity at the stock level as measured by the Amihud ratio (Amihud (2002)), as price impact is

[33] Note that we use the term "portfolio management" in referring to discretionary portfolio management services offered by banks to their individual clients for the sake of brevity.

Table VIII

Stock Investments of Banks and Their Retail Customers: Role of Portfolio Management

This table reports coefficient estimates for the analysis in which we estimate the baseline regressions for subsamples of banks divided according to whether they have an active portfolio management unit. In column (1), we estimate the baseline regression for banks that have an active portfolio management unit. In column (2), we estimate the baseline regression for banks that do not have an active portfolio management unit. In column (3), we estimate the baseline regression for the full sample using the three-way interaction between AM_{jt}, $\Delta Share^{B}_{ijt}$, and $Sell^{B}_{ijt}$. In specifications (1), (2), and (3), we estimate pooled panel regressions with bank, time, and industry fixed effects using ordinary least squares. t-statistics, reported in parentheses, are calculated by correcting the standard errors by clustering at the bank level. For variable definitions, see Table XIII. ***, **, and * denote significance at the 0.001, 0.01, and 0.05 level, respectively. The data come from the Deutsche Bundesbank and Thomson Reuters Datastream and cover the period from December 2005 to September 2009.

	Regressand: $\Delta Share^{C}_{ijt}$		
	Banks with AM (1)	Banks without AM (2)	Full Sample (3)
$\Delta Share^{B}_{ijt}$	0.0624*	0.046***	0.045***
	(2.68)	(3.60)	(0.011)
$Sell^{B}_{ijt}$	−0.442***	−0.370**	−0.357**
	(−5.28)	(−3.18)	(−2.94)
$\Delta Share^{B}_{ijt} \cdot Sell^{B}_{ijt}$	−0.092*	−0.01	−0.038*
	(−2.41)	(−0.73)	(−2.62)
$Dummy\ Gain_{it-1}$	−0.113**	−0.079**	−0.105***
	(−3.59)	(−3.44)	(−4.74)
$Return\ Volatility_{it-1}$	4.639	0.918	2.356
	(1.79)	(0.77)	(1.72)
$MtBV_{it-1}$	−0.010*	−0.011	−0.011**
	(−2.12)	(−1.83)	(−2.84)
$Trading\ Volume_{it-1}/100$	−0.001***	−0.0004***	−0.0001***
	(−5.40)	(−2.83)	(−5.69)
$AM_{jt} \cdot \Delta Share^{B}_{ijt}$	–	–	0.0173
	–	–	(0.65)
$AM_{jt} \cdot Sell^{B}_{ijt}$	–	–	−0.084
	–	–	(−0.57)
$AM_{jt} \cdot \Delta Share^{B}_{ijt} \cdot Sell^{B}_{ijt}$	–	–	−0.0848*
	–	–	(−2.04)
Constant	0.648***	0.397***	0.592***
	(6.51)	(4.34)	(8.30)
Bank fixed effects	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes
Clustering	Bank level	Bank level	Bank level
R^2	0.046	0.094	0.054
No of Obs	90,491	42,686	133,177

more pronounced among thinly traded stocks.[34] The Amihud ratio is defined as

$$Amihud_{it} = \frac{1}{D_{it}} \sum_{d=1}^{D_{it}} \frac{|Ret_{idt}|}{Vol_{idt}}, \tag{3}$$

where D_{it} is the number of trading days in quarter t for stock i, and Ret_{idt} and Vol_{idt} are stock i's return and trading volume, respectively, on day d in quarter t.

Since the Amihud ratio is a measure of illiquidity, we define those stocks with an Amihud ratio above the sample median in a given quarter as illiquid and assign them an indicator variable ($Illiquid1_{it}$). We then include in the estimation model the interaction between the indicator variable characterizing illiquid stocks, the dummy variable for banks' sell trades, and changes in banks' normalized stock holdings (i.e., $\Delta Share^{B}_{ijt} \times Sell^{B}_{ijt} \times Illiquid1_{it}$). Column (1) of Table IX presents the regression results. Consistent with the price impact motive, we find that banks' tendency to sell stocks from their proprietary trading portfolios to their customers is significantly stronger among relatively more illiquid stocks.

We next redefine illiquid stocks to ensure that our results are not driven by stock observations that are close to the median value. In particular, we sort stocks into terciles based on the Amihud ratio in each quarter, where the most liquid stocks are denoted Q1, the middle group is denoted by Q2, and the least liquid stocks are denoted by Q3, and we define those stocks in the bottom tercile as illiquid stocks. Using this conservative definition, we estimate an interaction model analogous to specification (1) for a subset of observations that contains only the most and least liquid stocks (Q1+Q3). In column (2) of Table IX, we again observe that banks appear to push stocks from their portfolios to their retail customers more when the stocks that they intend to sell are more illiquid.[35]

If price impact is the dominant motive, we should also observe a stronger negative relationship in equity flows when banks seek to liquidate a larger position in the outstanding shares of a given firm (Kyle (1985)). To test this conjecture, we rerun our analysis limiting attention to banks' relatively larger sell trades, which we define as those that fall into the percentile with the largest negative changes in banks' normalized stock holdings. The regression results,

[34] The Amihud ratio is generally viewed as a good approximation of the price impact of security trades. For a comprehensive comparison of different market liquidity measures, see, for example, Goyenko, Holden, and Trzcinka (2009), who also note that the Amihud ratio is a good indicator of the price impact of trades.

[35] In additional tests tabulated in the Internet Appendix, we rerun our analysis for subsamples of stocks by their degree of liquidity and find that the magnitude of the push effect is monotonically increasing in the illiquidity of the stocks, which is in line with the price impact motive. In further sensitivity checks, we eliminate penny stocks from the sample to ensure that our results are not driven by extremely illiquid stocks. In the Internet Appendix, we show that our results remain qualitatively similar.

Table IX

Stock Investments of Banks and Their Retail Customers: Price Impact Motive

This table reports coefficient estimates from regressions that test the price impact motive. In column (1), we include the three-way interaction term between the indicator variable characterizing illiquid stocks, the dummy variable for banks' sell trades, and changes in banks' normalized stock holdings. $Illiquid1_{it}$ takes the value of one if the Amihud ratio of stock i exceeds the sample median in quarter t. In column (2), we redefine illiquid stocks such that $Illiquid2_{it}$ takes the value of one if the Amihud ratio of stock i falls in the bottom tercile of stocks. In column (3), we restrict attention to relatively larger sell trades of banks, which we define as those that fall into the bottom first percentile of changes in banks' normalized stock holdings. In column (4), we again consider relatively larger sell trades of banks and account for bank-stock fixed effects. In specifications (1), (2), and (3), we estimate pooled panel regressions with bank, time, and industry fixed effects using ordinary least squares. In column (4), we estimate pooled panel regressions with bank-stock and time fixed effects using ordinary least squares. For variable definitions, see Table XIII. t-statistics, reported in parentheses, are calculated by correcting the standard errors by clustering at the bank level. ***, **, and * denote significance at the 0.001, 0.01, and 0.05 level, respectively. The data come from the Deutsche Bundesbank and Thomson Reuters Datastream and cover the period from December 2005 to September 2009.

	Regressand: $\Delta Share^C_{ijt}$			
	(1)	(2)	(3)	(4)
$\Delta Share^B_{ijt}$	0.010	0.006	0.0682***	0.0523***
	(1.49)	(0.63)	(4.31)	(3.87)
$Sell^B_{ijt}$	−0.166***	−0.1645***	−1.169**	−0.697
	(−4.52)	(−3.51)	(−3.09)	(−1.64)
$\Delta Share^B_{ijt} \cdot Sell^B_{ijt}$	0.006	0.0304*	−0.1542***	−0.0895*
	(0.58)	(2.00)	(−3.55)	(−2.36)
$Dummy\ Gain_{it-1}$	−0.113***	−0.124***	−0.0957***	−0.0608**
	(−4.70)	(−3.97)	(−4.28)	(−3.20)
$Return\ Volatility_{it-1}$	0.716	−0.385	2.455	2.495*
	(0.63)	(−0.38)	(1.79)	(2.03)
$MtBV_{it-1}$	−0.006	−0.005	−0.010**	−0.003
	(−1.94)	(−1.25)	(−2.96)	(−0.87)
$Trading\ Volume_{it-1}/100$	−0.00001	0.0001	−0.0007***	−0.000001
	(−0.14)	(0.74)	(−5.69)	(0.29)
$Illiquid1_{it}$	0.6794***	–	–	–
	(5.49)	–	–	–
$Illiquid1_{it} \cdot Sell^B_{ijt}$	−0.521***	–	–	–
	(−4.08)	–	–	–
$Illiquid1_{it} \cdot \Delta Share^B_{ijt}$	0.065***	–	–	–
	(5.83)	–	–	–
$Illiquid1_{it} \cdot \Delta Share^B_{ijt} \cdot Sell^B_{ijt}$	−0.1087***	–	–	–
	(−3.94)	–	–	–
$Illiquid2_{it}$	–	1.0598***	–	–
	–	(5.00)	–	–
$Illiquid2_{it} \cdot Sell^B_{ijt}$	–	−0.699***	–	–
	–	(−3.86)	–	–
$Illiquid2_{it} \cdot \Delta Share^B_{ijt}$	–	0.0754***	–	–
	–	(6.06)	–	–

(Continued)

Table IX—*Continued*

	Regressand: $\Delta Share^{C}_{ijt}$			
	(1)	(2)	(3)	(4)
$Illiquid2_{it} \cdot \Delta Share^{B}_{ijt} \cdot Sell^{B}_{ijt}$	–	−0.1401***	–	–
	–	(−4.16)	–	–
Constant	0.278***	0.214	0.452***	0.395***
	(3.57)	(1.70)	(6.07)	(6.06)
Bank fixed effects	Yes	Yes	Yes	No
Time fixed effects	Yes	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	No
Bank-stock fixed effects	No	No	No	Yes
Clustering	Bank level	Bank level	Bank level	Bank level
R^2	0.069	0.081	0.049	0.406
No of Obs	133,177	88,631	133,177	133,177

presented in column (3) of Table IX, imply that the negative relationship is indeed significantly more pronounced when banks' order size is larger, which is associated with a larger price impact. This remains true even when we account for unobserved bank-firm heterogeneity, as reported in column (4).[36] In sum, our results strongly support the view that banks appear to push stocks that they sell from their proprietary portfolios to their retail customers to avoid a price impact.

III. The Effect on Portfolio Performance of Retail Customers

A. *Trading Profits and Stock Performance*

The analysis thus far is silent on whether the observed behavior of banks has any negative implications for the portfolio performance of their retail customers. For instance, if banks trade stocks based on (private) information about firms' fundamentals, then the stocks that they sell from their proprietary portfolios are likely to perform poorly in subsequent periods.[37] Even if banks sell stocks solely for liquidity reasons, those trades can be perceived by other market

[36] Our sample period also covers the peak of the recent financial crisis, that is, the failure of Lehman Brothers (Ivashina and Scharfstein (2010)), and includes four quarters of the subsequent crisis. As noted by Brunnermeier (2009), the collapse of Lehman caused liquidity to evaporate in most financial markets, including stock markets. Thus, banks may have been more inclined to sell stocks directly to their retail customers in the period following Lehman's bankruptcy when the markets were relatively more illiquid, and hence the potential price impact was higher. In the Internet Appendix, we present separate regression results for pre-Lehman and post-Lehman periods. Again, we find supportive evidence for the price impact motive: retail customers tend to purchase more heavily those stocks that banks sell from their portfolios in the post-Lehman period.

[37] For example, Alexander, Cici, and Gibson (2007) show that valuation-motivated trades of institutional investors significantly outperform relevant benchmarks, which supports the notion that institutional investors possess superior stock selection skills.

participants as revealing negative information, which could have a detrimental price impact and harm the investment performance of retail customers.[38]

To analyze the implications of banks' behavior for their retail customers, we next turn to performance analyses of stocks that are sold by banks to their retail customers. We begin the analysis by examining trading profits/losses that retail customers incur when purchasing stocks that their bank sells off from its own portfolio. Specifically, we estimate the following regression specification:

$$Profit^C_{ijt} = b_1 \cdot Profit^B_{ijt} + b_2 \cdot Sell2C^B_{ijt} + b_3 \cdot Profit^B_{ijt} \times Sell2C^B_{ijt} + \gamma_j + \gamma_t + \epsilon_{ijt}, \quad (4)$$

where $Profit^B_{ijt}$ and $Profit^C_{ijt}$ represent the quarterly trading profits of bank j and its retail customers, respectively, for trades in stock i,[39] and $Sell2C^B_{ijt}$ is an indicator variable that takes the value of one if bank j sells stock i and its retail customers buy this stock in the same quarter. The regression results are presented in Table X. We find that the coefficient on $Sell2C^B_{ijt}$ is negative and statistically significant, which suggests that bank customers tend to incur losses from those transactions whenever they buy the stocks that their bank sells from its proprietary portfolio. Furthermore, we find that the interaction term ($Profit^B_{ijt} \times Sell2C^B_{ijt}$) has a significantly negative effect on the trading profits of retail customers. This suggests that, for stocks that the bank sells to its retail customers, the trading profits of the bank and its customers are negatively related. These findings are also robust to controlling for bank-time or bank-stock fixed effects, as presented in columns (2) and (3), respectively. We interpret these results as the first preliminary evidence for a detrimental effect of banks selling stocks from their proprietary portfolios directly to their retail customers.[40]

Next, we conduct a more formal analysis in which we compare the performance of stocks that are sold by banks to their customers (*Case Group*) to the performance of other stocks held or traded by the banks and their retail customers during the same period. It is important to note that we construct

[38] Gompers and Metrick (2001) and Plerou et al. (2006) show that the trades of institutional investors can influence the low-frequency movements of stock prices in relatively illiquid markets. Similarly, Holthausen, Leftwich, and Mayers (1990) provide evidence that institutional investor sales of larger positions have a lasting price effect, while Hendershott and Menkveld (2014) find that even in the absence of private information, the sell trades of banks have significant short-term price effects.

[39] Similar to the methodology in Hau (2001a, 2001b), we calculate quarterly marked-to-market profits as $Profit^B_{ijt} = (\Delta Q^B_{ijt} \times \Delta P_{it})$ and $Profit^C_{ijt} = (\Delta Q^C_{ijt} \times \Delta P_{it})$, respectively, where ΔQ^B_{ijt} and ΔQ^C_{ijt} represent the quarterly change in the number of shares of stock i in the portfolio of bank j and of its retail customers, while ΔP_{it} is the quarterly price change of stock i following the transaction between banks and their retail customers.

[40] We acknowledge that quarterly trading profits may be an imperfect measure, as we are only able to observe stock inventories of banks and their customers at a quarterly frequency. However, Hau (2001b) examines proprietary trading profits of domestic and foreign investors on a subset of German stocks at different frequencies and shows that the relative trading losses of foreign investors are most pronounced for low-frequency trading.

Table X

Stock Performance: Trading Profits and Losses of Retail Investors

This table reports coefficient estimates from the trading profit/loss regressions as shown in equation (4). $Profit^{B}_{ijt}$ and $Profit^{C}_{ijt}$ represent the quarterly trading profits of bank j and its retail customers for a given transaction in stock i, respectively. $Sell2C^{B}_{ijt}$ is an indicator variable that takes the value of 1 if bank j sells stock i and its retail customers buy this stock in quarter t, and zero otherwise. In column (1), we estimate pooled panel regressions with bank and time fixed effects using ordinary least squares. In column (2), we estimate pooled panel regressions with bank-time fixed effects using ordinary least squares. In column (3), we estimate pooled panel regressions with bank-stock fixed effects using ordinary least squares. For variable definitions, see Table XIII. t-statistics, reported in parentheses, are calculated by correcting the standard errors by clustering at the bank level. ***, **, and * denote significance at the 0.001, 0.01, and 0.05 level, respectively. The data come from the Deutsche Bundesbank and Thomson Reuters Datastream and cover the period from December 2005 to September 2009.

	Regressand: $Profit^{C}_{ijt}$		
	(1)	(2)	(3)
$Profit^{B}_{ijt}$	0.158***	0.154***	0.149***
	(5.99)	(6.00)	(5.34)
$Sell2C^{B}_{ijt}$	−13,145.81***	−12,548.81***	−6,273.26*
	(−4.24)	(−4.30)	(−1.82)
$Sell2C^{B}_{ijt} \cdot Profit^{B}_{ijt}$	−0.166***	−0.161***	−0.168***
	(−4.66)	(−4.67)	(−3.89)
Constant	55,570.76***	−3,284.94***	59,228.8***
	(4.86)	(−10.69)	(4.09)
Bank fixed effects	Yes	No	Yes
Bank-time fixed effects	No	Yes	No
Bank-stock fixed effects	No	No	Yes
Time fixed effects	Yes	No	No
Clustering	Bank level	Bank level	Bank level
R^2	0.11	0.156	0.313
No of Obs	132,269	132,269	132,269

various portfolios at the bank level.[41] The first control group (*Control Group I*) includes all stock holdings of a bank's retail customers other than those in the *Case Group*, which allows us to assess how these stocks perform compared to stocks that are presumably sold to retail customers by their banks. Next, *Control Group II* consists of stock purchases of retail investors excluding those that their respective banks simultaneously sell from their proprietary portfolios. The other three control groups focus on the performance of banks' stock investments, as we seek to assess whether the stocks that banks sell to their customers perform differently than their other investments. Specifically, *Control Group III* includes all stocks held by a bank other than those in

[41] As we define the stock portfolios at the same institution, we can account for bank-specific characteristics or other spurious correlations that would contaminate our results if we were to analyze performance at the stock level across different banks. In the Internet Appendix, we also present return comparisons at the stock level, which are pooled across banks and over time.

the *Case Group*, *Control Group IV* consists of banks' purchases as a measure of their stock-picking ability, and *Control Group V* includes stocks for which banks reduce their positions but their retail customers do not increase their holdings.[42]

When studying stock performance, we rely on a similar assumption as in Daniel et al. (1997) and first calculate, for each portfolio, the hypothetical monthly return that would result from holding the same portfolio share of stocks in each month within a quarter, as reported by the end of that quarter. We then calculate the equal-weighted return for each of these portfolios at the bank level:

$$EWR_{jt}^{G} = \frac{1}{N}\sum_{i}^{N} r_{it+1}^{excess} \quad \forall \quad i \in G_{j,t}, \tag{5}$$

where $G = 0$ indicates the case group for bank j in month t, and $G = \{1, ...5\}$ for the control portfolios. To account for stocks possibly having different weights in different stock portfolios, we also calculate the value-weighted portfolio returns, that is, VWR_{jt}^{G}, for each bank in each period:

$$VWR_{jt}^{G} = \sum_{i}^{N} w_{ijt}^{G} \cdot r_{it+1}^{excess} \quad \forall \quad i \in G_{j,t}, \tag{6}$$

where w_{ijt}^{G} is the weight of stock i in portfolio G of bank j in month t.

To account for stock-specific characteristics, we use excess stock returns (r_{it+1}^{excess}), which we compute using characteristics-based benchmarks. Specifically, using the full universe of stocks that sample banks and their retail investors hold in their portfolios (i.e., a total of 16,165 different securities), we construct passive benchmark portfolios based on a double sort of each firm's market equity value and market-to-book ratio. For each formation date, we first sort the sample stocks into quintiles based on each firm's end-of-June market value from the previous year. Next, we sort the stocks in each size quintile into further quintiles based on their market-to-book ratio, the end-of-December value from the previous year. This gives us a total of 25 benchmark portfolios in each year. The average monthly return for each benchmark portfolio aggregates over all the component stocks using value weighting in the portfolio. The excess return of a given stock is computed as its monthly return in excess of that of the benchmark portfolio to which the stock belongs.

Table XI presents the return comparisons of different stock portfolios at the bank level for both equal and value weightings. The analysis excludes those months in which a given portfolio contained no stock. We use the t-test (with unequal variances) and the Wilcoxon test to assess whether the mean and median returns of the stocks in the case and control groups are significantly different from one another at the bank level. First, we observe that

[42] When constructing the control groups, we restrict our attention to those stock observations for which the holdings of the banks or their retail customers exceed 100 euros.

Table XI

Stock Performance: Trading Profits and Losses of Retail Investors

This table presents monthly return comparisons of different stock portfolios for both equal and value weightings at the bank level. Note that the analysis excludes those months in which there was no stock in a given portfolio. We use the t-test (with unequal variances) and the Wilcoxon test to assess whether the mean and median returns of the stocks in the case and control groups are significantly different from one another at the bank level. The *Case Group* comprises stocks that are sold by banks to their retail customers. *Control Group I* includes all of the stock holdings of the retail customers of a bank other than those in the *Case Group*. *Control Group II* consists of the purchases of retail investors of a bank, excluding those stocks that their respective banks simultaneously sell from their proprietary portfolios. *Control Group III* includes all stocks held by a bank other than those stocks in the *Case Group*. *Control Group IV* comprises the purchases of banks. *Control Group V* comprises the sales of banks. To account for stock-specific characteristics, we use excess stock returns computed using characteristics-based benchmarks. Using the full universe of stocks that the sample banks and their retail investors hold in their portfolios (i.e., 16,165 different securities), we begin by constructing passive benchmark portfolios based on a double sort on each firm's market equity value and market-to-book ratio. On each formation date, we sort the sample stocks into quintiles based on each firm's end-of-June market value from the previous year. Next, we sort the stocks in each size quintile into further quintiles based on their market-to-book ratio, the end-of-December value from the previous year. This yields 25 benchmark portfolios in each year. To ensure that the performance comparisons are not driven by extreme return observations, we winsorize the monthly portfolio returns at the 1% level. The excess return of a given stock is computed as its monthly return in excess of that of the benchmark portfolio to which the stock belongs. The average monthly return for each benchmark portfolio aggregates over all the component stocks using value weighting in the portfolio. The data come from the Deutsche Bundesbank and Thomson Reuters Datastream and cover the period from December 2005 to September 2009.

	Equal-Weighted Portfolios					*Value-Weighted Portfolios*				
	No of Obs	Mean	t-Test	Median	Wilcoxon	No of Obs	Mean	t-Test	Median	Wilcoxon
Case Group vs.		−0.0033		0.0011			−0.0005		−0.0002	
Control Group I	2,490	−0.0008	−2.152	0.0009	−0.411	2,490	0.006	−5.399	−0.0004	−5.995
Control Group II	2,490	0.0206	−19.996	0.0220	−22.058	2,490	0.023	−17.288	−0.0011	−18.168
Control Group III	2,459	0.0002	−2.809	0.0021	−2.561	2,459	0.0033	−2.752	−0.0002	−2.463
Control Group IV	2,388	0.0088	−9.245	0.0082	−10.165	2,388	0.0119	−8.708	−0.0005	−8.368
Control Group V	2,285	−0.0104	4.825	−0.0068	7.861	2,285	−0.0079	4.727	0.0002	6.396

the *Case Group* significantly underperforms *Control Groups III* and *IV*, which implies that stocks sold by banks to their retail customers tend to perform worse than banks' other stock holdings or their stock purchases. For example, the difference in benchmark-adjusted returns between the purchases of banks and stocks in the *Case Group* amounts to 1.21%, indicating that the portfolio rebalancing of banks appears to be information-driven. Interestingly, the *Case Group* does not significantly underperform *Control Group V*, which suggests that trades in the *Case Group* do not appear to be more informed than other sell trades of the banks. The performance differences of the stocks in the *Case Group* relative to banks' other stock holdings or their purchases can be attributed to their better stock-selection and market-timing abilities (Bollen (2001)). From that perspective, the observed underperformance does not necessarily imply that banks' behavior of selling stocks from their portfolios directly to their customers is detrimental to retail investors; rather, it would suggest that retail investors do not fully benefit from the potential stock-selection and market-timing abilities of their banks. To analyze the implications of banks' behavior for their retail customers, we next consider comparisons with the investments of retail investors. We observe that stocks in the *Case Group* significantly underperform all other stock holdings of the retail customers and their other stock purchases, that is, *Control Groups I* and *II*.

In further tests, reported in the Internet Appendix, we contrast both raw and risk-adjusted returns (as measured by the four-factor alpha) of stocks in the *Case Group* that we sort into terciles by their illiquidity. We find that both, stocks with medium and low liquidity significantly underperform the most liquid stocks, while there is no significant performance difference between stocks with medium and low liquidity. This additional result suggests that the underperformance of the stocks in the *Case Group* can be attributed to relatively more illiquid stocks, which is consistent with our findings in the previous section. Taken as a whole, these findings suggest that those stocks that banks sell from their proprietary portfolios to their retail customers (to avoid price impact) turn out to be underperformers, which negatively affects the investment performance of their retail customers.

B. Is Proprietary Trading Truly Detrimental to Retail Investors?

Our results thus far highlight a potential conflict of interest between the proprietary trading activities of banks and their retail banking divisions, a conflict that appears to negatively affect the stock performance of retail investors. This does not necessarily imply, however, that the net effect of being a retail customer of a bank with proprietary trading is negative—retail customers could still benefit from their banks' guidance, given banks' ability to draw on market knowledge from proprietary trading and these gains could compensate for retail investors' potential losses resulting from the effect identified in the previous section. To address this question, we next focus on differences in the stock portfolio performance of retail customers grouped in terms of whether their banks have proprietary trading divisions.

Table XII

Is Proprietary Trading Truly Detrimental to Retail Investors?

This table presents mean and median differences across the stock portfolios of retail customers of banks with proprietary trading divisions and the stock portfolios of customers of banks without proprietary trading units. We first calculate the monthly raw returns for each bank's customer portfolio that would be realized by holding the same portfolio share of stocks as reported by the end of the previous quarter in each month of the following quarter. We then compute equal-weighted monthly portfolio returns, which gives us 48 equal-weighted raw return observations for each bank's customer portfolio. Using the monthly returns, we calculate the monthly one-factor and four-factor alphas for each of these customer portfolios. The four-factor model includes the Fama and French (1993) factors and the Carhart (1997) momentum factor. We also use the time-series average of equal-weighted raw returns and excess stock returns computed using characteristics-based benchmarks. To ensure that the performance comparisons are not driven by extreme portfolio returns, we winsorize all performance measures at the 1% level. See the notes to Table XI for the definition of excess returns. The data come from the Deutsche Bundesbank and Thomson Reuters Datastream and cover the period from December 2005 to September 2009.

	No of Obs		Banks without Proprietary Trading	Banks with Proprietary Trading	t-Test/Wilcoxon Test
Raw Returns	687	Mean	−0.0088	−0.0105	7.590
	1,176	Median	−0.0100	−0.0109	8.945
One-Factor Alpha	687	Mean	−0.0091	−0.0106	7.423
	1,176	Median	−0.0101	−0.0109	8.687
Four-Factor Alpha	687	Mean	−0.0072	−0.0089	7.883
	1,176	Median	−0.0083	−0.0092	9.488
Excess Returns	687	Mean	0.0003	−0.00002	3.918
	1,176	Median	0.0001	−0.0001	3.517

In the following, we no longer restrict attention to the subsample of banks with the largest proprietary trading portfolios. Instead, we consider all banks for which we have information on the stock investments of their retail customers. In particular, we consider the 1,863 banks that report the stock holdings of their retail customers to the Bundesbank. Of these banks, 37% (687 banks) have no stock investments, while the remaining 63% (1,176 banks) have positive stock investments in their proprietary portfolios.[43]

We first calculate monthly raw returns for the stock portfolios of each bank's retail customers by holding the same portfolio share of stocks, as reported by the end of the previous quarter, in each month of the following quarter (Daniel et al. (1997)). This gives us 48 monthly return observations over the October 2005 to September 2009 period. We then compute abnormal returns for each customer portfolio using one- and four-factor models that include the Fama and French (1993) factors and the Carhart (1997) momentum factor.[44] As

[43] We now consider all stock holdings in retail customers' portfolios that have a value of at least 100 euros.

[44] The size portfolio return (SMB) is proxied by the difference in monthly returns on the small cap SDAX index and the large cap DAX 30 index. The book-to-market portfolio return (HML) is proxied by the return difference between the MSCI Germany Value Index and the MSCI Germany Growth Index. Finally, the momentum portfolio return (MOM) is the difference in monthly returns

Table XIII
Variable Definitions

Variable	Description
$Share^{C}_{ijt}$	Percentage of company shares i held by the retail customers of bank j in quarter t.
$Share^{B}_{ijt}$	Percentage of company shares i held by bank j in quarter t.
$Holdings^{B}_{ijt}$	Euro value of holdings of bank j in a given stock i in time t.
$Holdings^{C}_{ijt}$	Euro value of holdings of the retail customers of bank j in a given stock i in time t.
$FFMC_{it}$	Free-float market capitalization of stock i in quarter t.
$\Delta Share^{C}_{ijt}$	Changes in the normalized stock holdings of the retail customers of bank j in stock i in time t.
$\Delta Share^{B}_{ijt}$	Changes in the normalized stock holdings of bank j in stock i in time t.
$Sell^{B}_{ijt}$	A dummy variable equal to one if bank j sells stock i from its proprietary portfolio.
Buy^{B}_{ijt}	An indicator variable equal to one if bank j buys stock i in time t.
$Dummy\ Gain_{it-1}$	A dummy variable equal to one if stock i displayed positive average returns in the previous quarter, and zero otherwise.
$Return\ Volatility_{it-1}$	Standard deviation of the daily returns of stock i within quarter $t-1$.
$Trading\ Volume_{it-1}$	Quarterly average number of shares traded for stock i as measured in the previous quarter.
$MtBV_{it-1}$	Quarterly average of the market value of common equity divided by the balance sheet value of common equity in the company as measured in time $t-1$.
$\Delta Share^{others}_{it}$	Aggregate investment decisions of retail investors (other than bank j) in stock i at time t.
$Illiquid1_{it}$	An indicator variable that is equal to one if the Amihud ratio of stock i is above the median Amihud ratio across all stocks in quarter t, and zero otherwise.
$Illiquid2_{it}$	A dummy variable that is equal to one if the Amihud ratio of stock i is falls into the highest tercile based on the Amihud ratio across all stocks in quarter t, and zero otherwise.

additional performance measures, we also use the time-series average of equal-weighted raw returns and portfolio returns using excess stock returns, which are computed using the characteristics-based benchmarks that we introduced in the previous section. Finally, we sort the sample banks into two groups according to whether they have a proprietary trading division and compare the stock portfolio performance of their retail customers using the t-test and the Wilcoxon test.

Table XII presents the mean and median differences in stock portfolio performance for the retail customers of the sample banks, grouped in terms of whether they have proprietary trading divisions. Both the t-test and the Wilcoxon test indicate that the mean and median performance of the two groups differ significantly. In particular, the stock portfolio performance of retail customers of banks with proprietary trading significantly underperforms that of

between a group of stocks with recent above-average returns and another group of stocks with recent below-average returns from the CDAX index.

retail customers of banks without proprietary trading divisions. This result is robust to using different performance measures. For example, the difference in the four-factor alpha is 17 basis points, which corresponds to an annualized return spread of 2.04%. The economically and statistically significant differences in portfolio performance indicate that even if banks share their market knowledge with retail customers, the negative effect of pushing underperforming stocks from their proprietary trading portfolios onto their customers appears to offset those potential benefits. This finding leads us to conclude that the proprietary trading of banks is indeed detrimental to their retail customers.

IV. Conclusion

In this paper, we study the conflicts of interest between banks and their retail customers that can arise as a result of banks having proprietary trading and retail banking under one roof. To do so, we analyze the stock investments of banks and those of their retail customers on a security-by-security basis. Although we cannot directly observe the stock flows between bank portfolios and the portfolios of their retail customers, we provide strong evidence suggesting that banks tend to push some of the stocks that they sell from their proprietary trading portfolio onto their retail customers. We show that the observed pattern is not a mere artifact of banks' market-making activities and is not driven by herding behavior by retail investors. Using exogenously imposed sales pressure on some banks due to government intervention, we find evidence of a causal relationship between a bank's stock sales and the purchases of the same stock by that bank's retail customers.

When we analyze the possible motives underlying this pattern, we find that banks' tendency to sell stocks directly to their customers appears to be more pronounced when stocks are relatively illiquid and when the bank liquidates a relatively large position. These results suggest that price impact appears to be a major motive for banks to sell stocks to their customers rather than investors in the financial markets. In additional tests, we also show that those stocks that appear to flow from bank portfolios to the portfolios of their retail customers tend to be underperformers. Finally, we find that the stock portfolio performance of customers of banks with proprietary trading is significantly worse than that of customers of banks without a proprietary trading desk. This finding suggests that the costs that retail customers face because of this particular conflict of interest appear to outweigh any potential positive spillovers from the market knowledge that their banks acquire through proprietary trading.

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Supporting Information

Additional Supporting Information may be found in the online version of this article at the publisher's website:

Appendix S1: Internet Appendix.