MiFID II and the side effects of price unbundling for investment research

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Abstract

The Markets in Financial Instruments Directive (MiFID II) requires European financial initiations to unbundle sell-side research costs from commission fees beginning in January 2018. Using a unique data set, we answer three important empirical questions regarding the effectiveness and the potential downside effects of this regulation update: First, did the information content of sell-side research reports improve after the cost unbundling was enacted? Second, conditional on a higher informativeness of sell-side research, do investors react more strongly to recommendations? Third, did banks use the potentially stronger responsiveness of investors to steer their clients more opportunistically? We find that with the implementation of MiFID II, the information content of analysts' reports did indeed improve. In addition, we find that clients buy larger quantities of a stock if their *affiliated bank* issued a buy recommendation on that stock, possibly due to the improved quality, whereas retail clients don't react anymore to changes in the market consensus of analysts' opinions after MiFID II. However, we also find that banks use this strong responsiveness to more opportunistically steer their affiliated retail clients to buy into stocks that their own bank intends to sell. Hence, while the price unbundling improved the quality of sell-side research reports it comes with the downside of amplifying implicit conflict of interest.

Keywords: Financial institutions, Financial markets regulation, MiFID II/MiFiR, Conflicts of interest, Proprietary trading

JEL classifications: G11, G23, G24, G28

1 Introduction

The second *Markets in Financial Instruments Directive* (henceforth MiFID II) was implemented in January 2018 across Europe and requires financial institutions to unbundle the costs of provided sell-side research reports from commission fees. The key motivations behind this regulatory change are to contain the opportunistic use of analyst recommendations by banks[1] and to increase the transparency for investors. In this paper, we investigate a potential downside effect of this cost unbundling and show that it actually fostered the ability of banks to use their own analysts' recommendations to steer their affiliated (i.e. own) clients' accounts more opportunistically into stocks that the bank wants to sell.

Research on the real effects of the updated MiFID II regulation has so far been rather limited. In a recent paper, Guo and Mota (2019) study the effect of MiFID II on the quality of analyst reports and find that forecast accuracy improved after the cost unbundling. Lang, Pinto, and Sul (2021) find that analysts shrink firm coverage while they put more effort on their remaining coverage, implying that research quality might have been improved. In another study, Fang, Hope, Huang, and Moldovan (2020) show that market reactions to analyst recommendations after MiFID II became significantly larger while Zhao and Zhao (2020) build a theoretical model and predict that price unbundling ultimately decreases the cost on information, but also decreases the price efficiency.[2] In sum, the literature so far mainly argues that MiFID II has improved the research quality and led to stronger market reactions to sell-side research recommendations.

Our paper adds to this recent literature by investigating whether banks might abuse the increased sensitivity of their clients' investment decisions to analyst recommendation resulting from the cost unbundling. The underlying assumption is that investors' investment behaviour will be influenced by financial advisors using in-house analyst sell-side research information. The idea that banks might actually exploit an increased sensitivity to their sell-side research recommendations follows Fecht, Hackethal, and Karabulut (2018), who observe that banks systematically sell stocks from their proprietary portfolio to their retail clients that subsequently underperform, hypothesizing that the recommendations of affiliated analysts of banks might serve as a channel for banks to steer their retail clients' investment decisions. Indeed, earlier research indicated that

[1] Jackson, 2005 for example shows that banks use analyst recommendations to generate trading flows.

[2] An earlier work by Pope, Tamayo, and Wang (2019) show that the voluntary unbundling of sell-side analyst reports introduced in 2015 by the three largest Swedish asset management companies increased the market reactions (in terms of the stock absolute abnormal return) to analyst reports.

banks have a motivation to generate trades by issuing (positive) recommendations (see Jackson, 2005; Cowen, Groysberg, & Healy, 2006). Private investors also often fail to account for the upward bias and are generally more responsive to a recommendation with a buy rating (see Malmendier & Shanthikumar, 2007). The data set we compiled for this study allows us to analyze the reaction of retail clients of each bank located in Germany to the recommendations of their respective bank's affiliated analysts and state whether private investors' sensitivities to recommendations by their bank increased with the implementation of MiFID II. Second it also permits us to study whether banks abused this elevated sensitivity and used analyst recommendations more extensively to push their customers into stock that the bank simultaneously sold off from its proprietary portfolio. The key results of our paper indeed indicate that retail clients of an affiliated bank became more responsive to that bank's analyst recommendations but not to other banks' analyst recommendations. More importantly, however, we can show that banks use this elevated sensitivity to steer their retail clients' investments into stocks that the respective bank is actually selling off from its proprietary portfolio.

Our findings have important policy implications. On the positive side, we can confirm results already pointed out in the previous literature that the cost unbundling introduced by MiFID II indeed makes sell-side research more informative and that investors also respond more sensitive to recommendations, especially to those of their bank. However, on the negative side, we can also show that exactly this higher sensitivity to affiliated analyst recommendations after MiFID II can be abused by banks by allowing them to steer their clients' portfolio investments. Thus, to further improve transparency and mitigate this opportunistic behavior, MiFID II should not only require banks to report if they hold a certain stock in their own account when issuing a recommendation but, given our findings, the regulation should be complemented by a reporting requirement on contemporary banks' (net) stock sales subsequent to a buy recommendation in the past. This way, investors are better able to judge potential conflict of interest.

The existence of universal banks in Germany that cater all lines of banking services, including sell-side research, private wealth management and proprietary trading provides us with a unique empirical setup to analyze the effects of the cost unbundling regulation introduced with MiFID II. For our empirical strategy, we use the Securities Holdings Statistics (SHS) provided by the Deutsche Bundesbank for the time period between January 2014 to September 2019: This highly granular data reports for each of the roughly 1,700 German banks' proprietary (i.e. own) account holdings as well as the holdings of their respective retail clients on a security-by-security level. Second, we match the SHS data set on the bank-stock level to the IBES database that contains information on all individual stock recommendations of analysts affiliated to a particular bank (i.e. on the level of each bank registered in Germany). More precisely, we identify the bank to which each analyst is affiliated, and match the affiliated analysts' recommendations to the bank's proprietary stock holdings as well as its clients holdings of that stock on a bank-and-security level.

With this unique data set and the special setup of the German banking system, we shed light on three empirical questions with regards to the effectiveness of MiFID II: First, we analyze if sell-side analyst recommendations become more informative after the implementation of the cost unbundling introduced with MiFID II. Here, previous findings in the literature were mixed, with Guo and Mota (2019) and Lang et al. (2021) showing that the forecast accuracy improved after the cost unbundling while Fang et al. (2020) could not find significant evidence for an improvement in the quality of sell-side research reports. Second, we analyze whether the sensitivity of private investors to sell-side analyst recommendations of their affiliated bank increased after MiFID II was enacted. While Fang et al. (2020) already showed that market reactions to analyst recommendations after MiFID II generally became stronger, it remains an open question whether this effect is largely due to a stronger response by bank clients to the analyst recommendations of their affiliated bank only. Third – and related to the second question – in the case the sensitivity of private investors to recommendations by sell-side analysts indeed increased, in particular to the recommendations of the affiliated bank, we then investigate if banks exploited the increased sensitivity using analyst recommendations to steer their clients' portfolio more opportunistically towards stocks that the bank actually intends to sell off. Doing so, we are the first paper that sheds some light on the bank recommendation channel hypothesized by Fecht et al. (2018).

Related to the empirical questions raised above, our work generated insights along three dimensions. First, we show that sell-side analyst recommendations became indeed more informative: By comparing each individual analyst's forecast error for her earnings per share (EPS) prediction before and after the introduction of MiFID II in 2018, we find that after the regulation came into effect, forecast errors were significantly lower even after controlling for a variety of bank, analyst, and stock controls as well as stock-bank fixed effects. At the same time, we find that the number of recommendation changes significantly declined post-MiFID II. Placebo tests confirm that this observation is only significant for 2018 when MiFID II was introduced. Thus, our results confirm earlier work by Guo and Mota (2019) who also find that the quality and information content of analyst forecasts increased subsequent to the introduction of MiFID II, possibly because analysts are putting more effort on their remaining coverage as argued by Lang et al. (2021).

Second, while we do not find any evidence that after the introduction of MiFID II, private investors respond more sensitively to the average analyst recommendation changes, we do find significant evidence that private investors react more sensitive to recommendations of affiliated analysts of the bank at which they have their account. More precisely, when we regress a bank's retail clients' purchases of a particular stock on the contemporaneous analyst recommendations to buy this stock, then only the recommendations issued by their own (i.e. affiliated) bank have an effect on the investors' investment decision, while changes in the average recommendation level do not influence their investment decision. This finding for the affiliated bank's recommendation holds even after controlling for other analysts' average recommendations and the results are relatively robust to the inclusion of fixed effects. Thus, contrary to Fang et al. (2020), we cannot confirm for our sample that the overall market reaction post-MiFID II to analyst recommendations increased but it seems that private investors only react stronger to recommendations of affiliated analysts of their bank.

Third, we regress the propensity of a banks' retail clients to buy a particular stock pre- and post-MiFID II on three dummy variables indicating i) that the bank simultaneously sells the stock, ii) that the bank issued a buy recommendation, and iii) that the bank sells while issuing a buy recommendation. While generally, customers' propensity to buy a stock is negatively correlated with the bank selling it, when the bank issues simultaneously a buy recommendation, clients are more likely to buy the stock that the bank sells, especially in the post-MiFID II period. We also find similar results when we regress the amount that a banks clients buy of a particular stock on the amount the bank sells while recommending to buy: Post MiFID II retail clients tend to buy significantly more of a stock the more the bank sells while its analyst recommends to buy the stock. Both results are robust even when we fully saturate the model with bank-time, stock-time and stock-bank fixed effects. These findings suggest that after MiFID II, by using their affiliated analyst recommendations, banks could easier induce their clients to buy stocks that they sold off from their own account. In order to assess whether this is more pronounced opportunistic behavior post-MiFID II we additionally analyze whether this behavior also impaired bank customers' investment returns. For this, we compare the trading profits that clients make when following their bank's buy recommendations while the bank was selling. Here we find that when customers follow their bank's buy recommendation – while the bank was selling – customers invested in these stocks more severely underperformed post-MiFID II.

In sum, although MiFID II might have improved the overall analyst research quality, the results from our work show that for those stocks that a bank wants to sell off, MiFID II might have allowed banks a more effective abuse of their analyst recommendations to opportunistically steer their clients investments into those stocks. Thus, while MiFID II's general objective is to increase transparency and to contain the opportunistic abuse of analyst recommendations, our results indicate that it might have even increased the abuse of analyst recommendation in facilitating banks' proprietary trading.

Our paper extends the literature in several ways. First, it adds to the existing literature on sell-side research and how analyst recommendations can be biased due to various conflicts of interest. Lin and McNichols (1998) and Michaely and Womack (1999) for example show the existence of an investment banking underwriting bias, whereby a bank's growth forecast or recommendation for a company are more optimistic if the bank acts in a capacity as an underwriter for that company when compared to the forecasts and recommendations issued by analysts from non-affiliated banks for the same company. Malmendier and Shanthikumar (2014) add to that and show that when underwriting stocks, the analysts affiliated to that bank speak "two-tongues" by biasing their ultimate recommendation but not the forecasts. Another bias, the management and director relationship bias, found by Das, Levine, and Sivaramakrishnan (1998) and Lim (2001), shows that analysts deliberately give upward biased recommendations to maintain accessibility to a firm's managers and thus, to obtain more information about the company directly from the management. Lourie (2019) find that analysts issue more positively-biased predictions at the revolving year if they are hired by the firm they are covering as the biased prediction helps them to secure their career, while Mathew and Yildirim (2015) show that if a director or upper manager of the firm is on board of the brokerage house for which the analyst works, then the analyst will issue an upward biased recommendation for that firm. Sell-side research can also be biased to generate a higher trading flow: Jackson (2005) was one of the first to show that analysts issue upward biased recommendations that help to generate more trades for the bank while Cowen et al. (2006) further reveal that analysts make the most optimistic forecasts if they are mainly funded by brokerage services which by far ought-weights the previously mentioned underwriting affiliation bias. A recent paper from Shi (2020) also demonstrates that analysts make noisy recommendations to the general public while providing more precise information to their clients, typically mutual fund managers.

Our paper adds to aforementioned literature by showing that analysts' recommendations can be biased upwards if the bank intends to contemporaneously sell a company's stock out of its own trading portfolio after issuing a buy recommendation. More precisely, we argue that a bank-proprietary portfolio affiliation bias may exist in analysts' sell-side research, whereby analysts have a larger chance to recommend customers to buy a stock that the bank intends to sell compared to other stocks that the bank doesn't want to sell. Whereas Michaely and Womack (1999) and Fecht et al. (2018) mention a potential conflict of interest that may arise due to a bank's proprietary trading, these papers do not elaborate on this direction. We even go one step further and analyze whether the bank-proprietary portfolio affiliation bias might have become worse with the cost unbundling regulation introduced with MiFID II. Indeed, the limited empirical literature that exist on the effects of the MiFID II implementation show that market reactions to analyst recommendations are significantly larger after MiFID II (see Pope et al., 2019; Fang et al., 2020), which means analysts' recommendations seem to have a larger ability to influence the decisions of investors and this may allow banks to steer their customers even more opportunistically. Indeed, one of our key findings is that the cost unbundling introduced with MiFID II has significantly enlarged the conflict of interest in banks' proprietary trading. That is, the bank-proprietary portfolio affiliation bias has existed even before MiFID II, but the cost unbundling has significantly enlarged it. Although we can show that a bank-proprietary portfolio affiliation bias exists and that it has been enlarged with MiFID II, we find that at the same time the quality of analysts' research has improved in terms of better EPS predictions. This is surprising but may be explained by the fact that other empirical studies have shown that analysts' compensation and promotion are are not only linked to the commission revenue they earned for their brokerage houses but also to their reputation (see Groysberg, Healy, & Maber, 2011). Thus, analysts may be concerned about their reputation to maintain the subscription of their research reports and the corresponding subscription income (see also Jackson, 2005)[3]. In addition, analysts may put more effort into producing higher-quality research reports as it has already been shown by Guo and Mota (2019) and Lang et al. (2021) for the post MiFID II period.

The second contribution of our paper to the existing literature relates to the impact of financial market regulations, in particular on the effect of MiFID II. A survey on the effects on MiFID II in

[3] Jackson (2005) reveals that, beside an upward biased analysts may trigger generations, a more accurate analyst can gain higher reputation, which can also help to generate more trades. Analysts' concern for reputation may help to decrease the upward bias.

2017 (Preece) predicted that MiFID II may improve the research quality, while, one year after the implementing of MiFID II, a subsequent survey on MiFID II (Preece) shows that buy-side and sell-side professionals now have contrary attitudes, with buy-side professionals feeling the quality of research is not changing, while sell-side professionals even feeling that the quality of research is decreasing. The academic literature on the empirical effects of MiFID II has also been largely mixed, inconsistent and was difficult to reconcile. While Guo and Mota (2019) and Lang et al. (2021) found that analyst report quality has been improved after price unbundling, Fang et al. (2020) do not find significant evidence on it.

Our data set allows us to distinguish between the stocks with and without conflict of interest on the bank level and to state if their respective analysts report qualities are different. Analysts can make better predictions for the unaffiliated stocks, which lead investors to have higher returns and makes the whole market more rely on analysts; but when it comes to the affiliated stocks, i.e. stocks that parent banks intend to sell from their proprietary portfolio, analysts may make biased recommendations and still benefit from the increased market reactions that has been seen post MiFID II. In addition it remains unclear what exactly drives the increased market reactions found by Guo and Mota (2019) and Lang et al. (2021) given that with the cost unbundling, access to external research has become more limited. In our paper, we can show that it is the research of the affiliated bank that leads clients to invest, whereas the average change in the recommendation has no effect for private clients' investments. Thus, the increased market reactions found by studies for the time period post MiFID II is not because investors as a whole react more strongly to analyst recommendations but it is the reaction of investors to research of their own banks which seem to drive the market reactions to a given recommendation.

The remainder of this paper is structured as follows: Section 2 provides more background information about MiFID II and the institutional environment in Europe. Section 3 introduces the data sources and outlines the construction process. The results are then discussed along our three research questions: In Section 4, we present the findings with respect to whether or not the the quality of analyst reports after MiFID II improved. Section 5, shows the results with respect to investors' reactions to recommendations post MiFID II. Finally, Section 6 sheds light on whether banks use analyst recommendations to steer their investors more opportunistically after MiFID II. The final section concludes.

2 Institutional background

Unlike in the U.S., the asset management business in Germany is mostly not catered by independent firms. Instead, asset management companies are usually affiliated to universal banks that typically provide all lines of business, ranging from sell-side research, investment banking to wealth management services. Thus, typically one and the same bank serves as broker or portfolio manager to their private clients and at the same time provides research to its clients either directly in form of analysts' research reports or indirectly via financial or private wealth advisors.

The second *Markets in Financial Instruments Directive* (MiFID II) is an updated package of regulations that aim to increase the transparency across the *European Economic Area* (EEA)financial markets[4] and all types of financial instruments (see European Securities and Markets Authority, 2014a). Particularly, MiFID II aims to increase the amount of information available to investors, reduce the use of dark pools and OTC trading through standardizing the regulatory disclosure requirements for firms operating in the EEA. In this paper, we focus on two aspects of MiFID II that may have an impact on how investors react to sell-side research reports, namely the price unbundling aspect and the information content requirements of MiFID II.

The first aspect, the price unbundling regulations, are mainly covered in Article 11, 13 and 27 of *Commission Delegated Directive (EU) 2017/593*. Before MiFID II, payments for market research were usually bundled with commissions paid by asset managers to brokerage houses and these costs were ultimately passed to their clients. Price bundling induces a conflict of interest between asset managers and end investors: Asset managers may place orders with a broker that doesn't align to the best interest of their clients (e.g. in terms of best execution etc.) to receive research reports from this broker for which clients with a higher commission fees. Asset managers have no clear incentives to negotiate a lower commission rate. With the implementation of MiFID II, the research costs must be unbundled from the commission fees, thus making the true costs to the client transparent. As a result, brokerage houses have to price each of their analyst reports separately and properly.[5] The cost of research is not allowed to be linked with volume or values created by the (potential) client firm.[6]

The second aspect, the information provision requirements, are covered in Article 24(3)(4)(7) of *Directive 2014/65/EU*, and Article 44 of *Commission Delegated Regulation (EU) 2017/565*.

[4]MiFID II in total applies to 31 countries in the EEA, including 28 EU members and Iceland, Liechtenstein, and Norway.

[5]Article (13) of Commission Delegated Directive (EU) 2017/593

[6]Article (27) of Commission Delegated Directive (EU) 2017/593

These requirements impose regulations on the content of all information, even including marketing communications (see European Securities and Markets Authority, 2014a), with the aim to mitigate asset managers' misuse of the behavioural biases of investors (see e.g. Brenncke, 2018). One of the most prominent requirement concerns the full transparency on the costs (such as product costs, service costs, research costs, and payments to third parties) that need to be disclosed to clients. The key implication here is that the cost for obtaining information from analysts can no longer be bundled with the commissions paid by investors. If asset management firms would like to pass this cost to clients, they are supposed to notice their clients explicitly.

Under the MiFID II regime, banks can now either absorb the research cost by themselves or pass the cost on to end investors through a pre-agreed *Research Payment Account* (RPA). According to a survey on MIFID II from CFA Institute (see Preece, 2017) and an industry report from Oliver Wyman (see Turner, Edelmann, Davis, & Blomkvist, 2017), the majority of surveyed asset management firms decided to absorb the cost by themselves, especially the larger ones. Some investment managers, particularly the small and mid-sized asset management firms, are however not able to both afford external research costs and to expand their internal research teams, and they have to cut down their research consumption costs and adjust their strategies to use the limited available information more efficiently. The CFA survey on MiFID II in 2019 (see Preece)) shows 57% of buy-side professionals felt that they have less access to research than in the pre-MiFID II environment. The survey also mentions that investment managers who hold larger portfolios or who run well-diversified portfolios may also decrease their consumption of external research. Instead of receiving analyst reports from a variety of providers, they may focus only on a few external providers and may depend more on their affiliated bank's (internal) research, as the latter is assumed to be "cost-free".

Thus, within universal banks – even after MiFID II – wealth managers, financial advisors, and asset managers are not charged for the bank affiliated (internal) analyst recommendations. MiFID II requires a Research Payment Account to be set up only for external (third-party) research but not for internal research.[7] Therefore, while MiFID II might have affected the demand for research by independent wealth or asset managers (forcing analysts also to improve precision of their forecast due to the fiercer competition) (see Siobhan, 2019, Murphy, 2017), MiFID II did not enforce a more efficient cost accounting for analyst recommendations within a universal bank.

[7] See Commission Delegated Directive (EU) 2017/593 of 7 April 2016, supplementing Directive 2014/65/EU of the European Parliament.

3 Data Set and Key Variables

For our empirical investigation, we match five granular data sets for the time period between January 2014 to September 2019: First, we use the monthly *Security Holding Statistics* (SHS) from the Deutsche Bundesbank that records each German bank's own security holdings and its clients' security holdings on a security-by-security level. Specifically, for a bank's clients, we look at the holdings of private households and for a bank's own holding we look at the trading book records. Second, we obtained all sell-side analyst research information from the *Institutional Brokers' Estimate System* (I/B/E/S, or IBES).[8] In addition, the daily exchange rate from all other currencies to USD is also retrieved from IBES.

Third, we match three further data sets at the security level: For balance sheet information, SIC industry code, as well as security trading prices, we revert to Compustat and match it on a monthly basis to the IBES data set by using the CUSIP code. We further augment this with data from Datastream on the free-float market capitalization and for the matching of the IBES ticker ID and *International Securities Identification Number* (ISIN). Finally, some (smaller) German stocks do not have corresponding free-float market capitalization records in Datastream, and for those, the company's book capital is applied as a substitute. The latter is retrieved from *Bundesbank Centralised Securities Database* (CSDB) and mapped on a monthly basis to the SHS data set on the security level.

Starting from October 2018, Thomson Reuters made some significant changes to their IBES products, responding to the implementation of MiFID II, and anonymized some of the large brokerage houses and their analyst names.[9] Therefore, this paper uses the version of data retrieved in February 2020 for which analyst reports data were available up to September 2019 by that time. To solve the anonymization problem, we first identified the anonymous brokers' exact names by

[8] IBES records an observation only when the analyst updates his (her) evaluation. To avoid losing the first analyst evaluation change measure, we started the IBES sample from 2005. By doing so, we can also retrieve analyst-brokerage and analyst-brokerage-firm working experiences. If the analyst ID appeared in 2005, we consider this analyst has 1-year of working experience.

[9] IBES keeps changing the Estimid (brokerage house) names and codes for each broker. In February 2020 version IBES data, more analysts are anatomized, and unique analyst IDs are also randomly re-assigned, makes the data updates process almost impossible. Details can be found through *PRODUCT CHANGE NOTIFICATION*. Retrieved from: https://wrds-www.wharton.upenn.edu/documents/1030/Product_Change_Notification-IBES_Detail_History-_PreApproval_Contributor..._.pdf?_ga=2.42040288.4333705.1590694008-1092399374.1571994388

matching bulk observations from the February 2020 version to a prior 2018 version of the IBES database. If the majority observations (around 90% of the observations prior 2018) of a particular anonymous broker matches, we then restore the original IBES brokerage abbreviation name for that anonymous broker.[10]

Using that version of the IBES data set, we then manually match the IBES brokerage abbreviation name with the bank name in the SHS data set and filter out all German based brokerage houses. In total, we could identify 27 unique banks which have a brokerage house. Since the securities in SHS are identified by a unique ISIN code whereas IBES uses the CUSIP and SEDOL codes we used Datastream to match the full-digit CUSIP and SEDOL codes to the ISIN codes.[11]

Having matched the IBES and SHS data set on the bank-stock level, we next merged the Datastream data set with the free-float market capitalization and the CSDB data set with firm book capital, trading volume, bank-own gain on the level of each stock by using the ISIN code.[12]

To model the investment behavior of banks and their affiliated clients, we construct two dependant variables from the monthly SHS data set: First, $\Delta HH_{i,j,t}$ measures at the end of each month t, the relative change in the holdings of stock i for all private households that have their account at bank j. As in Fecht et al. (2018), we use the corresponding free float market capitalization ($FFMC_{it}$) for each stock i to normalize the monthly changes,[13]

$$\Delta HH_{i,j,t} = \frac{Holdings_{ijt}}{FFMC_{it}} - \frac{Holdings_{ijt-1}}{FFMC_{it-1}}. \tag{1}$$

We proceed in an analogous manner for the measure for bank j's relative holdings change of stock i at the end of each month t, $\Delta Bank_{i,j,t}$,

$$\Delta Bank_{i,j,t} = \frac{Holdings_{ijt}}{FFMC_{it}} - \frac{Holdings_{ijt-1}}{FFMC_{it-1}}. \tag{2}$$

[10]Due to job mobility of analysts, however, we cannot retrieve the analyst ID to name anymore

[11]Specifically, regarding the eight-digit CUSIP, we apply the WRDS - Analytics "CUSIP Converter" tool (retrieved from: `https://wrds-www.wharton.upenn.edu/pages/grid-items/cusip-converter/`) to translate in to nine-digit CUSIP; regarding the six-digit SEDOL code, we add up the 7th check digit via its generation rules (London Stock Exchange Group, 2018 November)

[12]The Trading volume and Bank-own gain two variables are sparsely available and once include in the regression, the effective number of observations enters in regression will sharply decrease: The baseline regression without any control variables will contain 27 banks but if we include all controls and fixed effects, there remain 19 banks in the pre-MiFID subsample and 18 banks in the post-MiFID subsample.

[13]This takes care of price changes, newly issued stocks, and stock splits.

To conduct the extensive margin analysis and assess bank j's customers' propensity to buy a certain stock i in month t, we define the dummy varibale $HHBuy_{i,j,t}$ which equals to 1 if $\Delta HH_{i,j,t} > 0$ and 0 otherwise:

$$HHBuy_{i,j,t} = \begin{cases} 1 \text{ if } \Delta HH_{i,j,t} > 0 \\ 0 \text{ otherwise} \end{cases}. \tag{3}$$

Analogously, we define $BankSell_{i,j,t}$ as a dummy variable taking the value 1 if $\Delta Bank_{i,j,t} < 0$ and 0 otherwise.

Form the IBES data set, we first construct the forecasting error for the earnings per share (EPS) prediction, $EPS\,Error_{i,j,t}$ and follow Mikhail, Walther, and Willis (1999). This variable measures the firm i's earnings per share prediction from the analyst research issued by bank j in month t, less the realized earnings per share of that firm, the method is marginally used by Mikhail et al. (1999) and Hong and Kubik (2003):

$$EPS\,Error_{i,j,t} = \frac{|EPS\,prediction_{i,j,t} - EPS\,realization_{i,j,t}|}{YearEndPrice_{i,y-1}} \tag{4}$$

All prices are converted into US dollars to avoid the measurement errors from different predictions and realized value currencies. Further, in order to make the prediction error comparable across different firms and time, we normalized the absolute value of EPS errors by the previous year-end stock price (the closing price of the stock on the last trading day of the previous calendar year).[14] If the stock price is recorded in other currencies instead of USD, we also convert the stock price into USD with the exchange rate on the same day.[15]

From the IBES data set we also create the main explanatory variable for our analysis, namely $RecBuy\,Affi_{i,j,t}$ which measures the *upward changes in recommendation* of stock i made by an analyst affiliated to bank j in month t. With our focus on recommendation changes, rather than levels of recommendation, we follow Stickel (1995).[16] Earlier literature showed that the change of a recommendation has a larger market impact (see Boni & Womack, 2006). In addition, looking

[14]Note that Mikhail et al. (1999) normalize by the beginning of quarter stock price, whereas we normalize the absolute difference with previous year-end price.

[15]Note that the $EPS\,Error_{i,j,t}$ is inherited from the previous month measure if a bank does not update the EPS prediction of the stock in the current month. The motivation of repeatedly using the EPS prediction error is to account for the endogeneity of updating the EPS prediction, as a less precisely measured bank may update more frequently.

[16]However, changes in recommendation are defined in different ways in literature. Jegadeesh, Kim, Krische, and Lee (2004) studies the the heterogeneous publication time of recommendations and their different values. This paper define 5 = strong buy, 3 = hold, 1 = sell, and takes the difference between the changes to measure

at changes also avoids ambiguity (Stickel, 1995). In order to calculate $RecBuy\,Affi_{i,j,t}$, we first translate the recommendations *Sell, Underperform, Hold, Buy*, and *Strong Buy* given by IBES into the respective numerical code as follows[17]

$$Recommend_{i,j,t} \in \{\text{-}2,\ \text{-}1,\ 1,\ 2,\ 3\}.$$

We then define the dummy variable $RecBuyAffi_{i,j,t}$ indicating recommendation changes from {-2,-1} to {1,2,3}, or {0,1} to {2,3} on stock i by an analyst affiliated with bank j in month t. The dummy $RecSellAffi_{i,j,t}$ indicates if the recommendation is changed from {0,1,2,3} to {-1,-2}; all other recommendation updates are considered neither upgrades nor downgrades. If not otherwise mentioned, we use the $RecBuyAffi_{i,j,t}$ dummy to identify "Buy-Recommendation" throughout the paper.[18] More precisely, the $RecBuyAffi_{i,j,t}$ measure takes the following values,[19]

$$RecBuyAffi = \begin{cases} 1 \text{ if } Recommend_{i,j,t-1} \in \{-2,-1\} \text{ to } Recommend_{i,j,t} \in \{1,2,3\} \\ 1 \text{ if } Recommend_{i,j,t-1} \in \{0,1\} \text{ to } Recommend_{i,j,t} \in \{2,3\} \\ 0 \text{ otherwise.} \end{cases} \tag{5}$$

The next three sections present the three main research questions of the paper. Each section contains the hypothesis, identification strategies, model design, followed by the empirical results. Further explanatory variables not mentioned in this section will be introduced as needed.

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the recommendation change. For the corporate analyst consensus recommendation, they also group the firm-observations into quintiles, 1.00 = strong buy, 0.25 = hold, 0.00 = sell. Loh and Stulz (2011) studies when did analyst recommendation change influence, and they defines 5 = sell, 1 = strong buy, and record the recommendation change with the difference bweteen the subsequent two recommendations from the same analyst, Loh and Stulz (2018) studies if analyst recommendation is more effective in bad macroeconomic times. They categories the recommendation changes into upgrade and downgrade two classes. Stickel (1995) studies the performance of analyst recommendations, they firstly let 1 = strong buy, 5 = sell, and then define "buy (sell) recommendations" according to to be all upward revisions to a strong buy recommendation (designated 1) and all revisions to a 2 = buy recommendation coming from a recommendation of hold, sell, or strong sell (3, 4, or 5, respectively). Sell recommendations are defined as all revisions to a 5, all revisions to a 4 coming from a recommendation of 1, 2, or 3, and all revisions to a 3 from a 1 or 2 recommendation.

[17]Category code 0 is given for "no recommendation", i.e. stocks that do not have analyst coverage since the beginning of 2005 (as we start to collect observations from 2005).

[18]We call the above-introduced procedure the "'Rec-Buy' categorizing rule" for simplicity in the following paper.

[19]Compared to Stickel (1995), we also consider changes from $\{-2,-1\}$ to $\{1\}$ as buy recommendations. According to Barber, Lehavy, Mcnichols, and Trueman (2001), when recommendations changes from "Underperform(-1)" or "Sell(-2)" to the "Holding(1)" level, the stock will also show a sizeable three-day percentage positive market-adjusted returns. The percentage return change is similar size as if change from "Underperform(-1)" to "Buy(2)" or "Strong Buy(3)", and being around 40 times as if the recommendation reiterated "Holding(1)".

4 Does MiFID II improve the quality of analyst reports?

For our first research question we analyze whether MiFID II improved the quality of sell-side analyst reports. As outlined in Section 1, surveys in the industry (Preece, 2017, 2019) and academic papers (Fang et al., 2020; Lang et al., 2021; Pope et al., 2019) gave rather inconsistent results on whether or not the information content of analyst reports has improved. Thus, we first test the effect of MiFID II on the information content by analyzing if the EPS forecasts become more informative and whether analysts put more effort into their coverage in the post MiFID II period for the 25 banks in our sample (we exclude the 2 online banks as they used the same brokerage house as their affiliated offline banks and the recommendations are repeatedly used).

4.1 Did the EPS forecasts become more precise post-MiFID II?

To empirically identify whether the quality of analysts' reports with regards to the precision and accuracy improved, we run a panel regression model for the sample period from January 2014 to September 2019 estimating the forecast error in month t of the earnings per share estimate[20] for a given stock i for an analyst working at bank j as

$$EPS\ Error_{i,j,t} = \beta_0 PostMiFID_t + Controls_{j,t} + Controls_{i,t} + Controls_{j,i,t} + \gamma_{j,i}, \tag{6}$$

where $PostMiFID_t$ is a dummy variable that equals 1 for the time period after January 2018, $Controls_{j,t}$ are analyst and brokerage specific characteristics, comprising the number of industries and the number of firms covered by a particular analyst during one year as well as analyst brokerage and brokerage-stock specific working experience, and the size of the brokerage house.[21] As stock level characteristics, $Controls_{i,t}$, we use the number of analysts following the company (yearly basis), the Debt-to-asset ratio (quarterly basis, debt ratio for short), the moving average and the moving volatility of the stock price over the last 12 months (monthly basis).[22] All

[20]Following the previous literature, e.g. Clement (1999) and Guo and Mota (2019), we remove forecasts issued within 30 days of the fiscal year-end.

[21]Note that the size of the brokerage house is measured by the number of analysts publish at least one of the three products (recommendation, price targets, and earnings per share prediction) within one year. The brokerage house measure somewhat captures the ability of an analyst, as the larger brokerage house, the better its reputation and can attract higher ability analysts. All $Controls_{j,t}$ are counted or computed with year y frequency. Also note that because the change of IBES Detail structure, we can only access the anonymous analyst ID. If an analyst move to another brokerage house, their unique ID will change, so the real work experience is no longer retrievable.

[22]The last three variables are computed by firm data from Compustat, whose coverage scope are not fully match with the I/B/E/S. So after including these two past 12 month average variables, number of observations that

stock controls enter the regression with a one quarter lag. $Controls_{j,i,t}$, are bank-specific controls, including bank j's own $Volume - traded$ in stock i in month t, the one month lagged $Own\_Gain\_bank\_Lag$ which is the gain made by bank j on stock i in the previous month, and the $\Delta OtherHH$ which is the percentage of stock outstanding that is held by customers affiliated to other banks (except bank j). Finally, $\gamma_{j,i}$ is the analyst-firm fixed effect and captures the unobserved bank and stock specific linkages (e.g. bank j underwriting the IPO of stock i etc). Including this fixed effect allows us to compare the impact of MiFID II on the same analyst's forecast precision when covering a particular firm.

If the implementation of MiFID II indeed improved the quality of analysts' research, we should observe β_0 to be negative since post-MiFID II, prices of analyst research are unbundled from the transaction fees and the users of the research should become pickier, pushing analysts to produce more accurate and informative predictions. A negative sign for β_0 would imply a decrease of the prediction error and thus an improvement in the prediction precision. Our results for Model 6 are outlined in Panel A of Table 1.[23] Column pairs in the table are gradually saturated with the control variables and fixed effects. In the most rigorous model in column (5), we include all control variables, as well as the $stock \times bank$ fixed effects.

[Table 1]

Looking first at our key variable of interest, *MiFID*, which equals one after the new regulation come into force, we find β_0 to be highly significant and negative across all of our models. This means that the realized EPS predictions have smaller errors or a higher precision in the post-MiFID II period. Thus, based on the prediction precision alone, we can conclude that the quality of analysts reports improved significantly after January 2018. It is important to note that this holds even after including *Bank* fixed effects in column (3) that accounts for unobserved bank-specific characteristics that cannot be captured by bank-related control variables like bank sophistication, for any unobserved stock-specific characteristics in column (4) and for $stock \times bank$ fixed effects in column (5). Looking at the other explanatory variables that can explain the EPS prediction precision, we find that, on average, more experienced analysts make more precise predictions whereas other brokerage house specific characteristics are irrelevant. In addition, the

effetely enter into regressions will decrease (but will not influence the number of banks enter into regression).

[23] When retrieving data, the IBES only have EPS prediction values for 2019 but do not have the realized value for 2019 yet, so we drop the observations after 2019 for EPS prediction precision tests.

EPS prediction becomes less precise (the EPS prediction error becomes larger) if the company has higher debt ratios.

4.2 Do analysts put more effort in their research post-MiFID II?

A second method to test for the quality improvement in sell-side analyst research reports is to look at the publication frequency of recommendations. As Lang et al. (2021), we interpret a less frequent publication of a recommendations is an indication of analysts putting more effort on their reports. With more effort being invested, less frequent revisions are needed. We thus regress for the sample period from January 2014 to September 2019 $REC\,Count_{i,j,t}$, which represents a count indicator reporting the number of new recommendations issued by analysts affiliated with bank j on stock i in month t, on the same variables as introduced in Equation 6 before,

$$REC\,Count_{i,j,t} = \beta_0 PostMiFID_t + Controls_{j,t} + Controls_{i,t} + Controls_{j,i,t} + \gamma_{j,i}. \tag{7}$$

If β_0 is negative then the implementation of MiFID indeed induced analysts to put more effort into their coverage. The results of this analysis are displayed in Panel B of Table 1. Indeed, we find the *MiFID* dummy coefficient to be negative across all models. Thus, the number of recommendations on a particular stock issued within one bank decreases after MiFID was enacted. This aligns with our hypothesis that after the MiFID II, the analyst research payments are no longer bundled with the commissions; thus, triggering trading is not as attractive as before, so analysts decrease the number of recommendations published in general.

4.3 Robustness check and implications

MiFID II has been discussed since 2014 and should originally been implemented by 2017. However, in the end, the implementation had to be postponed to January 2018. A natural question that arises is whether banks already started taking actions in 2017 or 2016 to prepare the conceived implementation? If this would be the case for most banks in our sample, then the "MiFID" effects may be found at some earlier cutoff year.

[Table 2]

In Table 2 we depict the results for different cutoff dates for our previous regression analysis with respect to the research quality. The left part of Table 2 shows the results for the the EPS prediction error (analyst research precision), where Panel A1 takes *MiFID2016* $= 1$ for observations after January 2016 and Panel A2 takes *MiFID2017* $= 1$ for observations are after January 2017. Looking at the results, we find that the EPS prediction error does not have a significant difference before and after the 2016 cutoff and that the EPS Error becomes even higher after the 2017 cutoff. We can conclude that only if the post MiFID II dummy is indeed set at the 2018 cutoff as in our baseline analyses, then we will see the coefficients being negative and thus, the increase in the precision of sell-side analysts is only found for the time period after January 2018.

The right part of Table 2 shows the results for *MiFID2016* $= 1$ in Panel B1 and *MiFID2017* $=$ 1 in Panel B2 for the recommendation publication counts. We find that the coefficients in Panel B1 are mostly positive and thus find that after 2016, analysts even increased their number of reports. The coefficients in Panel B2 are not significant for columns (2) to (5), which means the number of publications does not significantly differ before and after 2017. Thus, similiar to the pausbility test for the EPS prediction error, we find the decrease in the number of studies and an associated increase in the quality of sell-side research reports only if we set the cutoff at January 2018 and hence at the time when MiFID II was enacted.

Thus, based on our two analysis and the robustness checks, we can conclude that after MiFID II was introduced in January 2018, sell-side research has become more precise and the publication frequency decreased, implying that analysts put more effort into their research and the research quality improved.

5 Do investors react stronger to recommendations post MiFID II?

Our second research question on the empirical effects of MiFID II concerns investors' responsiveness to sell-side research recommendations after the regulation come into force. As we have shown in the previous section, the quality of sell-side research improved significantly after MiFID II and this increased quality can be one reason why investors may react stronger to recommendations post MiFID II. A second rational for a stronger responsiveness can also be found more directly embedded in the regulation itself. MiFID II requires asset managers to provide additional information in a balanced way on any instrument they recommend (e.g. on the risks and benefits). Hence, due to the higher transparency requirements, investors are more likely to put a higher credibility on analyst recommendations and investors may thus follow the advice more closely by believing that the advice is delivered more transparently and that the bank acts in the clients' best interest (European Securities and Markets Authority, 2014b).

In order to empirically test the differences in the investors' reactions to the sell-side research recommendations before and after the implementation of MiFID II, we first split our sample into two sub-samples and start our analysis by looking only at the security (and not at the bank) level and changes in the average recommendation (consensus recommendation): Using a pre- and a post-MiFID II sub-sample – with the cutoff set at the 1st January 2018 – we conduct Fisher's Permutation test to check whether the coefficients for our main variables of interest are significantly different from each other.[24]

Contrary to previous papers analyzing the impact of MiFID II by using cumulative abnormal returns as the measure for the market reactions (Fang et al., 2020; Guo & Mota, 2019; Pope et al., 2019), we are able to use the direct investors' security holding changes across all banks. This allows us to go even further in the second step of our analysis, by further breaking our analysis up to the bank-security level. More specifically, we look at the reaction of each bank's private clients to changes in the recommendation by their respective bank. We thus compare the effects of the bank's buy recommendation on its customers' investment decisions and separate the effects before and after MiFID II.

5.1 Investors' reactions to average recommendation changes

In our first regression, we estimate the changes in holdings of stock i by all retail customers across all sample banks against the changes in the average recommendation level across all analysts and various control variables to analyze whether retails clients in general react stronger if analysts' opinions change to buy. More precisely, we run the following regression

$$\Delta AggHH_{i,t} = \beta_0 RecBuyAllAvg_{i,t} + Controls_{i,t} + \overline{Controls_{j,t}} + \overline{Controls_{j,i,t}} + \gamma_i \tag{8}$$

where $\Delta AggHH_{i,t} = \sum_j \Delta HH_{i,j,t}$, is the aggregate percentage change in the market value of customers holdings for stock i (in relation to the FFMC) across all 27 sample bank in month t. $RecBuyAllAvg_{i,t}$ is the average recommendation change across *all* existing analyst recommen-

[24]Fisher's permutation test is basically testing whether $Vardiff = Coef(preMiFID) - Coef(postMiFID)$ being significantly different from zero. In order to test the p-value of *Vardiff*, we need to know the distribution of the Vardiff statistics. Fisher's permutation test allows to obtain the empirical distribution of the *Vardiff* statistics through repeated sampling, and to compute the empirical p-values.

dations in the IBES system.[25] $Controls_{i,t}$ represent time varying stock controls, $\overline{Controls_{j,t}}$ represents the time varying bank controls, averaged across all sample banks, and $\overline{Controls_{j,i,t}}$ is the average of the stock-bank controls across all banks as introduced in Section 4. The model in Equation (8) is the intensive margin estimation and allows us to analyze the direct impact of the explanatory variables on the relative changes in customers' holdings. Using the same equation, we can also estimate the extensive margin for which we run the same regression but use $AggHHBuy$ as the dependant variable. This is a dummy variable equalling one if the aggregate customers' holding changes on stock i across all sample banks in month t is positive and 0 otherwise:

$$AggHHBuy = \begin{cases} 1 \text{ if } \Delta AggHH > 0 \\ 0 \text{ otherwise.} \end{cases} \tag{9}$$

Table 3 presents the regression result for Model (8) where Panel A at the left displays the result from extensive margin analysis and Panel B displays the result of intensive margin analysis. To test our hypothesis whether retail customers react stronger to the average recommendation changes by sell-side analysts, we first regress the dependent variable for the pre- and post- MiFID II phase on the average change in the level of recommendations for stock i without any further controls (column 1), and then gradually saturate the model with control variables (column 2), add industry fixed effects (column 3) and finally reach our most rigorous model specification that includes stock-time fixed effects (column 4). At the bottom of the table we present the results for Fisher's Permutation test to test if there is a significant difference for the pre-MiFID and post-MiFID time.[26]

Looking at the results in Panel A and our key variable of interest, $RecBuyAllAvg$, which records the average upward recommendation change from all newly published research on the stock i at time t, we do not find any significant results that a positive change in the average

[25]To compute $RecBuyAllAvg_{i,t}$, we first take the rounded average value of all newly published recommendations of stock i in month t of all analyst recommendations available in IBES, $\overline{recommend_{i,j,t}} \in$ {-2, -1, 1, 2, 3}, and then assign the value 1 if the subsequent two months $\overline{recommend_{i,j,t}}$ value changes fits the "'Rec-Buy' categorizing rule" outlined previously. As an example, if bank1, bank2, and bank3 out of our sample banks updated the recommendation for stock ABC during a month, the recommendation value is 1, 1, and 2 respectively; bank3 and bank4 updated recommendation for this stock in the following month, the value is 1 and 3. We first average the values across all updated recommendations in the same month, i.e. 1.33 (rounded to 1) and 2 sequentially. According to the "'Rec-Buy' categorization rule" (see Equation 5), the $RecBuyAllAvg_{i,t} = 1$.

[26]The Vardiff equals the coefficient from Pre-MiFID subsample minus the Post-MiFID subsample. This paper takes 100 times repeats of the sampling and computed the empirical p-value of this Vardiff based on the 100 times samplings.

recommendation leads to a higher probability that retail clients will buy stock i. Thus, there is also no evidence that the aggregate customers' likelihood of buying a stock is significantly different before and after the implementing of MiFID II.

In Panel B, that depicts the results for the aggregate households stock holdings in terms of the percentage of the outstanding stock, we find that customers bought significantly larger amounts of stock i if the market average recommendation for stock i changed upwards before MiFID II was implemented. This holds even if we include all sets of control variables and the stock fixed effects. Thus, before the cost unbundling introduced with MiFID II, retail investors reacted to changes in the average market recommendation by buying larger quantities of a stock if the consensus amongst analysts increased. However, after MiFID II, the coefficient on $RecBuyAllAvg$ becomes insignificant after controlling for industry or the stock fixed effects. As in Panel A, the empirical p-values for the pre- vs post-MiFID coefficients tests are also not significant.

[Table 3]

In sum, we don't find evidence that MiFID II contributed to a stronger responsiveness of private clients to changes in the average recommendation level, neither in terms of a higher probability of a reaction nor in terms of higher demanded quantities. Given that (Fang et al., 2020) show that the overall market reaction to sell-side analyst research actually increases after MiFID II and given that we find that before MiFID II, private customers reacted somewhat to changes in the average sell-side research recommendations, a natural question that arises is whether private customers may only react to their own bank's sell-side research recommendation after the implementation of MiFID II, given that the cost unbundling led to a reduction of external research that is provided to private clients. In the next section we elaborate on this question.

5.2 Investors' reactions to their own bank's recommendation changes

In the previous regression in Model 8, we only looked at the change in the average recommendation that includes all recommendations issued for stock i and that are available in IBES. Our key finding was that post MiFID II, retail investors don't react stronger to changes in the average recommendation. However, with MiFID II, the pricing for research is unbundled and financial advisors need to pay separately for recommendations from external providers. Thus, due to budget constraints, financial advisors and wealth managers may reduce their usage of external analyst reports from other institutions post MiFID II. Still, however, they can freely access their own banks' sell-side research reports and may thus rely more heavily on their own bank's research and recommendations. We test this hypothesis using the following regression model

$$\begin{aligned}\Delta HH_{i,j,t} = {} & \beta_0 RecBuyAffi_{i,j,t} + \beta_1 RecBuyAllOtherAvg_{i,-j,t} \\ & + \gamma_{i,t} + \gamma_{j,t} + \gamma_{i,j} + Controls_{i,t} + Controls_{j,t} + Controls_{j,i,t} + \epsilon_{i,j,t}\end{aligned} \tag{10}$$

where $RecBuyAffi_{i,j,t}$ is the key variable of interest and represents the average change in the recommendation of bank j on stock i in month t (see section 3 for the detail calculation). The variable $RecBuyAllOtherAvg_{i,-j,t}$ serves as a control and is the average level of all newly updated recommendations (-2,3) of a stock from other banks, except the recommendation of bank j.[27] In Equation (10) we thus test if bank j's buy recommendation on stock i has a direct impact for the contemporaneous holdings of their (bank j's) retail customers. As before, we also estimate bank j's customers propensity to buy stock i in month t using the dummy variable $HHBuy_{i,j,t}$ which equals 1 if private households increased their holdings of stock i in month t ($\Delta HH_{i,j,t} > 0$) and equals 0 otherwise. Since the regression in Equation (10) is based on a stock-bank-month level, we can apply both *Stock* fixed effects, γ_i, and monthly *Time* fixed effects, γ_t. The *Time* fixed effects will absorb the aggregate effect of all unobserved, time-variant, explanatory variables for the household aggregate holding changes like general macroeconomic conditions that affect all stocks equally. The *Controls* constitute the same sets of explanatory variables as introduced in the previous section.

Table 4 presents the results for the likelihood of customers buying a stock *HHBuy* on the affiliated bank's buy-recommendation dummy *RecBuyAffi*, where a significant β_0 will reflect the add-on effect for the probability that retail customers react to their affiliated bank's analyst report. Column pair (1) includes the *Bank*, *Industry*, and monthly *Time* fixed effects, capturing the bank and industry time-invariant characteristics and in column pair (2), we add the *Stock* × *Bank* fixed effects, which allows to compare customers' reaction in the same bank and to the same stock along the time. Looking at the results, we see that customers increase their likelihood of buying stocks if their affiliated bank has issued a Buy-Recommendation in the pre-MiFID II period. However, their behaviour to follow the recommendations of their own bank stops in the post-MiFID II period. These results hold if we change the *Time* fixed effects into *Bank* × *Time* fixed effects as

[27] We take the variable $RecBuyAllOtherAvg_{i,-j,t}$, all other sample banks' (except for the affiliated bank) average recommendations, to control the market average opinion. We do not directly use the market average recommendation $RecBuyAllAvg_{i,t}$ as a control variable because the latter will perfectly multicollinear with the *Stock* × *Time* fixed effects $\gamma_{i,t}$ that we finally add in the model.

in column pair (3) and if we further add stock-time-varying control variables as in column pair (4). The last column pair (5) includes a full set of fixed effects instead of the control variables. The $Stock \times Time$ fixed effects fully capture the market average recommendations on this stock during these months, as well as all other stock-time varying events (e.g. earning announcements). $Bank \times Time$ captures bank reputation events or profit announcements and $Stock \times Bank$ captures effects like a bank underwriting particular stocks or bank's own trading gain on this stock. All these fixed effects together allow us to separate the customer stock demand just due to their affiliated banks' recommendation issuance in this particular month out from the average market activity. Looking at the coefficient on *RecBuyAffi* we find it significant and positive for the pre-MiFID II subsample period and insignificant in the post-MiFID II subsample. This implies that on top of the market average recommendations, customers react on average more to their own banks' recommendation. Nevertheless, this effect disappears after MiFID II. Throughout column pairs (2) to (5), the vardiff statistics for the *RecBuyAffi* variable is significantly positive at 10% confidence level. This figure confirms that conditional on the affiliated bank issuing a buy recommendation, the likelihood of a customer buying that stock in the post-MiFID II period is significantly smaller compared to the pre-MiFID II period. Finally, when looking at the $RecBuyAllOtherAvg_{i,-j,t}$ variable, we find that customers react to the average recommendation stronger in the post-MiFID II period than in the pre-MiFID II period, although this significance in column (5). All in all we can conclude that retail customers in general more likely to increase their holdings of a given stock if analysts in general shift to a positive stance but we don't find an add-on effect of their own bank's recommendation change on top of that.

[Table 4]

Table 5 shows the regression results for the *extent* customers will buy a stock in response to their affiliated bank's recommendation change on top of consensus change of all other analysts. The extent of bank j's customers is measured by the percentage change of stock outstanding, ΔHH. Otherwise, Table 5 is structured in the same way as Table 4.

Looking at the results in column pairs (1) to (4) we find that when the affiliated bank issued a buy recommendation, its customers will increase their holdings of this stock. The size of the coefficients are slightly larger for the post-MiFID II period than for the pre-MiFID II period. In column pair (4), the coefficient of *BuyAffi* equals 0.0022 for pre-MiFID II, and 0.0034 for post-MiFID. Customers will thus increase their bought quantity if their affiliated bank issues a buy recommendation in the post-MiFID II period. Column pair (5) replaces stock-time varying controls with $Stock \times Time$ fixed effects. Results there are not significant which suggests that on top of the market average within the same bank in the same month, customers do not have different preferences over different stock recommendations issued by the affiliated bank. Although the size of Vardiff for column pair (5) is larger than other pairs, the p-value is still not significant. All in all we can conclude that although customers decreased the likelihood of buying a stock after a buy-recommendation of their own bank, they will buy a larger quantity in the post-MiFID II period for those stocks when their affiliated bank has a buy-recommendation.

[Table 5]

5.3 Robustness test

After the baseline model, we apply another measure of the affiliated bank upward change of recommendations to check whether private investors react more to their affiliated banks' recommendations on top of the market average. We first compute $RecommendExcess_{i,j,t}$ as gap between the bank's own recommendation and the average recommendations published by all other banks during the same month: $RecommendExcess_{i,j,t} = Recommend_{i,j,t} - \overline{Recommend}_{i,t}$. We also define the $RecommendDiff_{i,j,t} = Recommend_{i,j,t} - Recommend_{i,j,t-1}$. We then define $RecBuyAffiExcess_{i,j,t}$ = 1 if (1) the bank raised their recommendations comparing to the previous month; (2) after the raise-up, their recommendation is still higher than the market average recommendation during this month on this stock.[28]

$$RecBuyAffiExcess_{i,j,t} = \begin{cases} 1 \text{ if } Recommend\,Excess_{i,j,t} > 0 \,\&\, Recommend\,Diff > 0 \\ 0 \text{ otherwise} \end{cases} \tag{11}$$

Regression specifications and the table display patterns are the same as the baseline results above. This categorization is stricter than the usual one and can capture the stocks that bank really "strongly recommend". As we have accounted for the average recommendations in the construction process of dummy variable *RecBuyAffiExcess*, we did not use the control *RecBuyAllOtherAvg* here. Results can be found in Table A1 and Table A2. We find the results

[28]As an example: if Bank A had recommendation HOLD (Rec. category = 1), and this months upward changed to strongly buy (Rec. category = 3), while after this change, the average market recommendation is between buy and strong buy (e.g.average Rec. category = 2.5), then we record $RecBuyAffiExcess_{i,j,t} = 1$. If Bank A moved from hold to buy, and the market average category is 2.3, then $RecBuyAffiExcess_{i,j,t} = 0$ still. This is a more strict measure than the $RecBuyAffi_{i,j,t}$, it records the "Excess" movements of the recommendations that the private investors' affiliated bank has published.

from this excess recommendation measure to be mostly consistent with our baseline results. For the extensive margin analysis we again find that for the pre-MiFID II period, households tend to follow the excess buy-Recommendations but don't find this for the post-MiFID II period. Also, the differences between *RecBuyAffiExcess* coefficients are significantly positive which indicates that customers has a significantly larger likelihood to buy a stock if the affiliated bank issues an above average buy recommendations in the pre-MiFID period compared to the post MiFID period.

[Table A1]

From the intensive margin analysis, the result is somewhat different from the baseline model. Customers only show a positive reaction to affiliated banks' excess buy-recommendation in the pre-MiFID II period and do not react more in the post-MiFID II period. Coefficients for pre- and post-MiFID subsample are not significantly different from each other. This misalignment could be because analysts are indeed more cautious in the post-MiFID II period and do not issue recommendations far above the market average.

[Table A2]

6 Do banks use analyst recommendations to steer their investors more opportunistically post MiFID II?

The results in Section 5 indicate that investors became slightly more reactive to the analyst recommendations after MiFID II was implementation, in particular to their own bank's recommendation changes. A natural questions that follows from this observation is whether banks may use this somewhat stronger responsiveness to more opportunistically steer their affiliated customers.

6.1 Bank proprietary trading analysis

To test the hypothesis that banks issue a buy recommendation for those stocks that they actually intend to sell, we run two types of regression models and split the sample into a pre- and post-

MiFID sample. First, we test the intensive margin,

$$\begin{aligned} HHBuy_{i,j,t} =& \beta_0 RecBuyAffi_{i,j,t} + \beta_1 BankSell_{i,j,t} \\ &+ \beta_2 RecBuyAffi_{i,j,t} \times BankSell_{i,j,t} \\ &+ \gamma_{i,t} + \gamma_{j,t} + \gamma_{i,j} + Controls + \epsilon_{i,j,t}, \end{aligned} \tag{12}$$

where $HHBuy_{i,j,t}$ is the Dummy variable of households decision equalling 1 if we observe that households at bank j bought stock i in month t. Second, we test the intensive margin, where $\Delta HH_{i,j,t}$ is the outstanding stock percentage changes held by customers at bank j for stock i in month t,

$$\begin{aligned} \Delta HH_{i,j,t} =& \beta_1 \Delta Bank_{i,j,t} + \beta_2 BankSell_{i,j,t} + \beta_3 BankSell_{i,j,t} \times \Delta Bank_{i,j,t} \\ &+ \beta_4 RecBuyAffi_{i,j,t} + \beta_5 RecBuyAffi_{i,j,t} \times \Delta Bank_{i,j,t} \\ &+ \beta_6 RecBuyAffi_{i,j,t} \times BankSell_{i,j,t} \\ &+ \beta_7 RecBuyAffi_{i,j,t} \times BankSell_{i,j,t} \times \Delta Bank_{i,j,t} \\ &+ \gamma_{i,t} + \gamma_{j,t} + \gamma_{i,j} + Controls + \epsilon_{i,j,t}. \end{aligned} \tag{13}$$

The $BankSell_{i,j,t}$ and $\Delta Bank_{i,j,t}$ in Equations 12 and 13 represent the extensive and intensive measures for bank portfolio allocation changes respectively. The $BankSell_{i,j,t}$ equals to 1 if stock i has a negative aggregate value change in bank j's portfolio in month t, i.e. $\Delta Bank_{i,j,t} < 0$ equals to 0 otherwise. $RecBuyAffi_{i,j,t}$ is again the customers' affiliated bank j's decision dummy of an upward change in the recommendation for stock i in month t. $\gamma_{i,t}$, $\gamma_{j,t}$ are stock-time and bank-time fixed effects respectively and $\gamma_{i,j}$ captures the bank-stock specific nexus (e.g. the underwriting relationship).[29] To compare the effects under pre- and post-MiFID II periods, we again split the sample ia pre- and post-MiFID II period.

Starting with the extensive margin, the likelihood of a customer to buy a stock, we present the results in Table 6. As before, within each column pair, pre-MiFID II results are on the left and the post-MiFID II results are on the right. In column (1) we include stand-alone bank, industry,

[29]Note that the CSDB variable for the *Volumn_traded* and *Own_Gain_bank_lag1* are sparsely available. Once we include the three controls in the regression, the effective number of observations will shrink significantly. If so, it will be hard to determine whether the change of significance pattern is due to the change of model setting or is due to the change of the number of observations. To make coefficients across model settings being comparable, we thus restrict the regression in a subsample where all control variables are available, which leaves around 28000 observations (20 banks) before MiFID II and 18000 observations (19 banks) post-MiFID II in the proprietary trading analysis. When the model is saturated with both control variables and fixed effects, the number of effective observations decreases further, but the change is trivial.

and month fixed effects and than gradually move to higher-dimension fixed effects in columns (2) to (7).[30] Looking at the $BankSell$ dummy in the first raw of the Table 6 that records the relationship between bank selling and customers' likelihood of buying for a given stock i we find that the coefficients are mostly negative and significant. Thus, if a bank sells a particular stock ($BankSell = 1$), the likelihood of its affiliated retail customers buying this stock is smaller than if the bank does not sell it, and hence, the trading direction of banks and customers is positively correlated. The coefficient for $BankSell$ is significant for both pre and post-MiFID II subsamples in column pairs (2) to (5) and the post-MiFID II coefficient has a larger absolute value, which implies that the positive correlation between the bank and affiliated customers' trading direction is getting stronger after MiFID II was enacted.

The key variable of interest is the interaction term $BankSell = 1 \times RecBuyAffi = 1$. This coefficient indicates if a bank is selling a stock and issues a buy-recommendation at the same time. We find this interaction to be positively significant for the post-MiFID II subsample. Looking at the size of the coefficients, we can see that it is almost five times larger in the post-MiFID II when compared to the pre-MiFID II subsample. Even if we included the stock-time-varying and bank-stock-time varying controls, together with the $Bank \times Time$ and $Stock \times Bank$ fixed effects (column (5)), the coefficient for the interaction term is still significant in the post-MiFID II subsample. This implies that within the same bank in the same month, conditional on the bank selling off a given stock i, customers in the post-MiFID II period have a higher likelihood to buy this stock if the bank issues a buy-recommendation, compared to the case if the bank does not issue a buy-recommendations.

In column (6), we remove the control variables and add $Industry \times Time$ fixed effects, which captures the industry-time varying characteristics. We also replace the $Stock \times Bank$ fixed effects with the $Industry \times Bank$ fixed effects to relax the bank-stock specific nexus into bank-industry preferences. The finding is very similar as in previous columns and we find that only in the post-MiFID II subsample a significantly positive coefficient for the interaction term.

In column (7) we go one step further and include $Bank \times Time$, $Stock \times Time$, $Stock \times Bank$ fixed effects. The $BankSell = 1$ coefficients in both pre- and post-MiFID sub-samples turn

[30] We include $Volumn\_traded$ and $Own\_Gain\_bank\_lag1$ in analyses for information content and the aggregate level customer reaction on the average recommendations as well (Table 1, 2, and 3). In those analyses, we include the full set of control variables in all columns except for the very first column, which does not influence our interpretations of the coefficients. Therefore, did not drop singleton observations for the very first columns in those tables

insignificant, and the $BankSell = 1 \times RecBuyAffi = 1$ in the post-MiFID subsample becomes also insignificant. Thus, in the most rigorous setting, when comparing the same stock being bought by customers in the same month and from the same bank, customers' likelihood of buying this stock is not correlated with the bank's selling behaviour and thus, the likelihood of customers buying a certain stock can not be influenced by the recommendations issued by the bank at which the customers have their account. However, this insignificance may be mainly due to the three sets of two-way fixed effects absorbing too much of the variation of the variable.

[Table 6]

In sum we can conclude that when a bank is selling a given stock and issues a buy-recommendation for that stock at the same time, its affiliated customers have a significantly higher likelihood to buy this stock. While this phenomenon is not significant before MiFID II, it becomes significant after MiFID II. This inference is further confirmed by the vardiff statistics and corresponding p-values at the bottom of the table: The vardiff statistics are negative across all settings and the p-values are significant at 1% for column pairs (1) to (6).

[Table 7]

In 7 we present the empirical results for the intensive margin analysis presented in Model 13 where we take ΔHH, i.e. the household stock holding changes in the percentage of the total outstanding amount, as the dependent variable. In addition we include the variable $\Delta Bank$ which is the bank stock holding changes in the percentage of the total outstanding amount as well as its interaction terms in the analysis. The $BankBuy$ dummy separates the bank sell and not-sell cases. The control variables and fixed effects settings are analogue to the extensive margin. Each column pair again contains the pre-MiFID II subsample result on the left and the post-MiFID II subsample result on the right.

Looking at the results, we find that the coefficients of $\Delta Bank$ in the first row are positive and significant in all column pairs (1) to (6). This means that if a bank is not selling a stock, nor issuing a buy-recommendation, its affiliated customers' trading amount has a strong positive relationship with bank's own trading amount. At the same time, the size of coefficients is slightly larger for post-MiFID II subsample. $BankSell = 1$ serves as a control variable and displays a similar pattern as in Table 6: if a bank is selling off a stock from their own trading account, their customers will sell as well.

The coefficients for the $BankSell = 1 \times \Delta Bank$ are mostly significantly negative, indicating that conditional on a bank selling a stock, the more of the stock the bank sells (i.e. the more negative $\Delta bank$), the more are customers buying. Thus if the bank is selling a lot, customers will buy in, or at least sell off less. Additionally, We find that the absolute value of coefficients for this interaction term is larger in the post-MiFID II period than in the pre-MiFID period. All in all these results so far give evidence that for the existence of the proprietary trading channel whereby a bank offloads some portion of a stock that it intends to sell to the portfolios of its own customers.

Looking into the impact of banks' buy-recommendation on the extent of affiliated customers' investment behaviour, we find the coefficients of $RecBuyAffi = 1 \times \Delta Bank$, for the post-MiFID subsample in column pairs (4), (5) and (7) to be significantly positive. Thus, a buy-recommendation will increase the positive relationship between the bank and its affiliated customers in the post-MiFID II period but does not have a significant enhancement effect in the pre-MiFID II period. The triple interaction term $RecBuyAffi = 1 \times BankSell = 1 \times \Delta Bank$ coefficients are significant and negative for post-MiFID II subsample in column pairs (4) and (7). The P-values for the coefficients comparison in column pairs (4) and (7) are also significant at 5% level. Column pair (7) displays the most rigorous setting, which contains $Bank \times Time$, $Stock \times Time$, and $Stock \times Bank$ all three fixed effects. So, the result tells that within the stock-month groups and removing the bank-stock and bank-time varying control variables, a Buy-Recommendation will make customers buy even more (or selling even less) compare to the case when there are no recommendations $BankSell = 1 \times \Delta Bank$ (As in column (7), without the Buy-Recommendation, the coefficient for $BankSell = 1 \times \Delta Bank$ is -0.0801; while with a Buy-Recommendation, the coefficient for $RecBuyAffi = 1 \times BankSell = 1 \times \Delta Bank$ is -0.6567, at the same direction). Affiliated bank's Buy-Recommendations only show impact in the post-MiFID II period. MiFID II makes the analyst recommendation to be a better channel for banks to exercise proprietary tradings. This could be the potential downside of the implementation of MiFID II.

If we compare coefficients for $RecBuyAffi = 1 \times \Delta Bank$ (β_5) to the coefficients for $BankSell = 1 \times \Delta Bank$ plus $RecBuyAffi = 1 \times BankSell = 1 \times \Delta Bank$ ($\beta_3 + \beta_7$), which can tell how bank-sell cases are asymmetric to the banks-non-sell cases under the condition of issuing a Buy-Recommendation of a stock. From column (7), $\beta_3 + \beta_7 = -0.7368$ and $\beta_5 = 0.6431$, two numbers have a similar size but different signs, which almost cancels out with each other. So, under the condition of issuing a Buy-Recommendation, when a bank is not selling, the customer-bank's positive relationship almost cancels out with the negative impact from the affiliated bank selling behaviour. This finding is actually valid in both pre- and post-MiFID II period since the pre-MiFID II subsample $\beta_3 + \beta_7$ (= - 0.1417)and $\beta_5(= 0.1212)$ also have a similar size but opposite sign, though the coefficients are not significant.

6.2 Extension to profitability check

Results above show that MiFID II introduces back the proprietary tradings. Facing stocks that banks are selling off and issuing a Buy-Recommendation at the same time, customers are buying more when the bank is selling off more. Under such circumstances, how customers' portfolio return becomes is an essential issue. We then test if this behavior of banks makes customers' portfolio returns worse off.

$$\begin{aligned} ProfitHH_{i,j,t} = & \beta_0 RecBuyAffi_{i,j,t} + \beta_1 BankSell_{i,j,t} \\ & + \beta_2 RecBuyAffi_{i,j,t} \times BankSell_{i,j,t} \\ & + \gamma_{i,t} + \gamma_{j,t} + \gamma_{i,j} + Controls + \epsilon_{i,j,t} \end{aligned} \tag{14}$$

To calculate $ProfitHH_{i,j,t}$, first compute the realized return of stocks during month t with the month end closing price, $StockReturn_{i,t} = log(price_{i,t}/price_{i,t-1})$. Then, we multiply the realized return with the positive part[31] of the bank j's *client holding unit changes.* client holding unit changes applied here is different to the previous stock holding value changes $\Delta HH_{i,j,t}$. Unit Holding is indeed the change of number of stocks, so it is not adjusted for stock splitting of stock i in month t.

$$ProfitHH_{i,j,t} = StockReturn_{i,t} \times Max[\Delta HH_{i,j,t}, 0] \tag{15}$$

To decrease noise introduced here due stock splitting, we define $BankSell_{i,j,t}$ in a similar way, i.e. equals to one if the unit of stock i in bank j's portfolio is negatively changed in month t.

If banks have higher extent misbehave, then customers in the post MiFID II period may have even lower profit when they are buying. i.e. β_2 in the pre-MiFID II is larger than it is in the post-MiFID II sub-sample.

[Table 8]

[31] In detail, we multiply the realized return $Return_{j,t}$ with the bank j affiliated clients' unit changes on stock i get the $ProfitHH_{i,j,t}$, and Make $ProfitHH_{i,j,t} = 0$ if the clients holding unit change is zero or negative.

Table 8 displays results of customer profitability analysis under pre and post MiFID II subsamples. Regressions follow Model (14). Dependent variable is $ProfitHH_{i,j,t}$, which measures the bank's affiliated customers' portfolio return whenever customer is buying stocks. To construct this variable, we firstly computed the stock price changes during one month ($return = ln(price_{i,t} - price_{i,t-1})$). Then, we interact this return variable with **positive part of**[32] Bank j's household holding unit changes on Stock i, and call the variable $ProfitHH_{i,j,t}$.

Need to mention that the $ProfitHH_{i,j,t}$ takes the customer stock holding *unit* changes in the computation, which is different to the *HHBuy* dummy used in the previous analysis as the latter one is defined by the customer stock holding change in percentage of the total outstanding amount of this stock. So, the stock unit change measure, passing to the $ProfitHH_{i,j,t}$ measure used in the current analysis, do not adjust for the stock splitting case. To keep consistency and without introducing measurement error, we define $BankSell_{i,j,t}$ here with the bank holding unit changes as well. $BankSell_{i,j,t}$ equals one if bank j has a negative unit changes in holding of stock i during month t. The *RecBuyAffi* is the dummy equals to one if bank j has issued an upward change recommendation on stock i during the month t. Results under Pre- and Post-MiFID subsamples are again displays one column next to another.

Coefficients for *BankSell* dummy are mostly positive, and the size of the coefficient is larger for the post-MiFId subsample. So without a Buy-Recommendation, whenever a bank is selling and customer is buying, they will have a positive return, which becomes even larger in the Post MiFID II period.

Coefficients for *RecBuyAffi* and the interaction term $BankSell = 1 \times RecBuyAffi = 1$ are not significant in models (1) to (6). However, when we compare the coefficients for interaction terms from Pre- and Post-MiFID subsamples, we found that, the coefficients are significantly larger in the pre-MiFID period than in the post-MiFID period according to the table bottom p-value. It indicates that when bank is selling a stock and issuing a buy recommendation at the same time, customers who buy this stock in the same month earns more (or lose less) in the pre-MiFID period compare to in the post-MiFID period. Model (7) changes the industry related fixed effects into the stock related fixed effects, but the above mentioned pattern disappears.

This profit analysis supports the conclusion that MiFID II makes analyst Buy-Recommendation be a wider channel for banks to misuse their affiliated customers and make their customers economically worse.

[32]Interact this return variable with 0 if the customer stock holding *unit changes* are negative or being zero.

7 Conclusion

This paper conducts three sets of analysis. First, this paper answers the question that after MiFID II has been implemented, whether the information content of the analyst research has been improved? We find some evidence to support the information-content-improvement hypothesis that the earnings per share prediction (EPS) as an important input of analyst recommendation. Its prediction error has decreased since 2018, and this decrease is not found since 2017 nor 2016. Also, the number of analyst recommendation published each month decreased since the implementation of MiFID II, and this decrease is not found in the years. The result aligns the hypothesis that analysts have lower motivation to trigger trading after analyst research price unbundling

Second, we are looking for the response of the households to the analyst recommendations. Results tell that customers, on average, do not show much difference in the likelihood of buying a stock when facing the market average analyst upward change recommendations pre- versus post-MiFID II period. Notwithstanding, customers in all will buy more stocks in the post-MiFID II period than in the pre-MiFID II periods when facing the market average analyst upward change recommendations. On top of the market average conditions, customers have a higher likelihood of buying a stock when their affiliated bank issues a Buy-Recommendation in the pre-MiFID II period. This ”following recommendation” behaviour stops in the post-MiFID II period. Although customers decreased the likelihood of buying, they will buy more in the post-MiFID II period for those stocks their affiliated bank has a Buy-Recommendation once they buy.

With a higher dependence of customers on the affiliated banks' recommendations in the post MiFID II era, we are concerning whether banks will steer their MiFID II to trade more when banks want to sell off one stock. Results from our paper show that MiFID II indeed makes the analyst recommendations to be a wider channel for banks to exercise proprietary tradings. MiFID II introduces back proprietary trading that when a bank sells more, its affiliated customers buy more or sell less of this stock. In the meantime, a Buy-Recommendation issued by the bank issued simultaneously will make the situation worse, i.e. customers buy more or sell even more negligible. We also find evidence to show that in the post-MiFID II era, bank proprietary trading makes customers economically worse.

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8 Appendix

Table A1: Customer Reactions to the Above-Average Recommendation (Extensive Margin Analysis)

This table presents part of the test results for **H3:** on top of the average analyst recommendations, investors become more responsive to affiliated bank's analyst reports. Sample is from 01Jan2014 to 30Sept2019, Pre- and Post-MiFID subsample cutoff is on 01Jan2018. Dependent variable HHBuy equals 1 if the customer stock holding changes in percentage of outstanding stocks is positive. The explanatory variable RecBuyAffiExcess equals 1 if the following two conditions are satisfied: (1) Analyst affiliated to a bank has upward moved their recommendations on a stock in one month; (2) the recommendation is higher than the market averages (after counting the self upward movement). Constant terms are not displayed in the table. Where, StockControl contains: Debt ratio, Avg price 12m, Stdev 12m. In each column pair, the left column is the result for the Pre-MiFID II subsample, and the right column is the result for the Post-MiFID II period.

	HHBuy									
	(1)		(2)		(3)		(4)		(5)	
	Pre	Post	Pre	Post	Pre	Post	Pre	Post	Pre	Post
ExcessAffiBuy=1	-0.0230***	-0.0274***	0.0177***	0.0069	0.0180***	0.0056	0.0094	0.0171	0.0175***	-0.0044
	(-4.74)	(-3.35)	(3.91)	(0.86)	(3.99)	(0.69)	(0.56)	(0.73)	(3.81)	(-0.54)
StockControl							Yes	Yes		
Bank fixed effects	Yes	Yes								
Industry fixed effects	Yes	Yes								
Time fixed effects	Yes	Yes	Yes	Yes						
Bank-time fixed effects					Yes	Yes	Yes	Yes	Yes	Yes
Stock-time fixed effects									Yes	Yes
Stock-bank fixed effects			Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Robust st.error	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	225,096	94,456	726,012	307,874	726,010	307,874	27,981	17,631	725,423	307,737
num.Banks	26	26	27	27	27	27	19	18	27	27
R-squared	0.08	0.09	0.29	0.36	0.30	0.36	0.27	0.30	0.40	0.44
Vardiff	0.0043		0.0107		0.0124		-0.0076		0.0219	
P-value	0.33		0		0		0.48		0	

Table A2: Customer Reactions to the Above-Average Recommendation (Intensive Margin Analysis)

This table presents part of the test results for **H3**: on top of the average analyst recommendations, investors become more responsive to affiliated bank's analyst reports. Sample is from 01Jan2014 to 30Sept2019, Pre- and Post-MiFID subsample cutoff is on 01Jan2018. Dependent variable ΔHH is the changes of the month end stock values held by bank or customers that normalized by the corresponding stock free float market capitalization. The explanatory variable RecBuyAffiExcess equals 1 if the following two conditions are satisfied: (1) Analyst affiliated to a bank has upward moved their recommendations on a stock in one month; (2) the recommendation is higher than the market averages (after counting the self upward movement). Constant terms are not displayed in the table. Where, StockControl contains: Debt ratio, Avg price 12m, Stdev 12m. In each column pair, the left column is the result for the Pre MiFID II subsample, and the right column is the result for the Post MiFID II period.

	\Delta HH									
	(1)		(2)		(3)		(4)		(5)	
	Pre	Post	Pre	Post	Pre	Post	Pre	Post	Pre	Post
ExcessAffiBuy=1	0.0036***	0.0032**	0.0037***	0.0039**	0.0038***	0.0036**	0.0058	-0.0017	0.0015**	0.0008
	(4.92)	(2.18)	(4.96)	(2.37)	(4.99)	(2.18)	(1.32)	(-0.28)	(2.03)	(0.53)
StockControl							Yes	Yes		
Bank fixed effects	Yes	Yes								
Industry fixed effects	Yes	Yes								
Time fixed effects	Yes	Yes	Yes	Yes						
Bank-time fixed effects					Yes	Yes	Yes	Yes	Yes	Yes
Stock-time fixed effects									Yes	Yes
Stock-bank fixed effects			Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Robust st.error	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	225,096	94,456	726,012	307,874	726,010	307,874	27,981	17,631	725,423	307,737
num.Banks	26	26	27	27	27	27	19	18	27	27
R-squared	0.02	0.03	0.06	0.10	0.06	0.11	0.15	0.26	0.34	0.37
Vardiff	0.0004		-0.0002		0.0002		0.0075		0.0007	
P-value	0.31		0.35		0.33		0.49		0.11	

Table A3: Variable description and source

Variable	**Description**	**Source**
Avg price 12m	Moving average of the price from the current month to the past 12th month	Compustat*
Debt Ratio	Total debts (liabilities) of previous quarter divided by total assets of previous quarter	Compustat*
Prccd (price)	Stock close price, daily frequency	Compustat
Prccq	Stock close price, quarter frequency	Compustat
Sic2digit	Two digits SIC industry classification ID	Compustat
Stdev 12m	Moving average of the price volatility from the current month to the past 12th month	Compustat*
MARKET CAP EUR	Market Capitalisation in EUR	CSDB
MARKET CAPITAL	Market capitalisation	CSDB
Own_Gain_bank_lag1	The affiliated bank's previous month gain	CSDB
Volume_traded	The value of stocks traded by one bank	CSDB
FreeFloatMarketCap(FFMC)	Month end free float market capitalization of a company	DataStream
Broker analyst exp	Number of years the analyst work in this broker	IBES*
Broker size	Number of analysts work in this broker during this year	IBES*
EPS Prediction	Estimate Value	IBES
IBTKR	IBES system unique ID for each stock	IBES
Num. analyst follow	Number of analyst that is following this firm during this year	IBES*
Num. firm covered	Number of firms is covered by an analyst during this year	IBES*

Continued on next page

Table A3 – continued from previous page

Variable	Description	Source
Num. ind. covered	Number of industries is covered by an analyst during this year, contains missing	IBES*
Rec Count	Number of recommendations of one broker-stock pair	IBES*
RecBuyAffi	Dummy variable, equals 1 if the change of my affiliated broker's recommendation for a stock in a month follows the "Rec-Buy" categorizing rule upward change side.	IBES*
RecBuyAllAvg	Dummy variable, equals 1 if the change of average value of all brokers' last recommendations for a stock in a month follows the "Buy-Recom" categorizing rule upward change side.	IBES*
RecBuyAllOther Avg	Dummy variable, equals 1 if the change of average value of all other brokers' (except my own affiliated broker) last recommendations for a stock in a month follows the "Buy-Recom" categorizing rule upward change side.	IBES*
Broker id	Bundesbank data unique ID for each broker	ID, Mannual
ISIN	The most current ISIN as it would also appear in IBES	ID, SHS, DataStream
REFERENCE MONTH	Data is reported for last day of this month	ID, Mannual
$\Delta Bank$	Value changes of one stock held by a bank, normalized by free float markt capitalization of the stock	SHS*
ΔHH	Value changes of one stock held by all customers from the same bank, normalized by free float markt capitalization of the stock	SHS*
$\Delta OtherHH$	Value changes of one stock held by all customers from all other sample bank except for the affiliated bank, normalized by free float markt capitalization of the stock	SHS*
B_Stock_Raw	Unit changes of one stock holding by a bank	SHS

Continued on next page

Table A3 – continued from previous page

Variable	Description	Source
BankSell	Dummy variable equals 1 if the $\Delta Bank$ is negative (or, OWN STOCK RAW is negative); otherwise equals 0	SHS*
C_Stock_Raw	Unit changes of one stock holding by all customers from the same bank	SHS
HHBuy	Dummy variable equals 1 if unit changes of one stock holding by all customers from the same bank is increased; otherwise equals 0	SHS*
Profit_HH	The stock return times the positive change of C_Stock_Raw	SHS and Compustat*

Notes: Star sign * means the variable is computed, rather than directly take, from the source indicated

Table A4: Descriptive Statistics, pre- and post-MiFID sub-sample comparison

Panel A: Dependent Variables

	Pre-MiFID II					Post-MiFID II					diff		
	count	mean	sd	p25	p75	count	mean	sd	p25	p75	count	b	t
EPS Error	309,520	0.459780	12.8397	0.0022	0.0205	122,102	2.810106	126.5126	0.0021	0.0204	431,622	-2.3503***	(-6.48)
REC Count	1,149,184	0.047086	0.2695	0.0000	0.0000	506,594	0.036878	0.2341	0.0000	0.0000	1,655,778	0.0102***	(24.66)
ΔHH	1,149,184	0.000080	0.0523	0.0000	0.0000	506,594	0.000491	0.0565	0.0000	0.0000	1,655,778	-0.0004***	(-4.41)
$\Delta Bank$	1,149,184	0.000005	0.0267	0.0000	0.0000	506,594	-0.000096	0.0200	0.0000	0.0000	1,655,778	0.0001**	(2.67)
ProfitHH	1,111,938	-215.547816	-3.29e+07	0.0000	3160780.7500	501,916	-351.305356	-2.03e+07	0.0000	4942300.0000	1,613,854	135.7575	(1.85)

Panel B: Explanatory Variables

	Pre-MiFID II					Post-MiFID II					diff		
	count	mean	sd	p25	p75	count	mean	sd	p25	p75	count	b	t
RecBuyAffi	970,057	0.008670	0.0927	0.0000	0.0000	393,277	0.007511	0.0863	0.0000	0.0000	1,363,334	0.0012***	(6.95)
RecBuyAllOtherAvg	1,149,184	0.023365	0.1511	0.0000	0.0000	506,594	0.022205	0.1474	0.0000	0.0000	1,655,778	0.0012***	(4.63)
RecBuyAllAvg	1,149,184	0.023438	0.1513	0.0000	0.0000	506,594	0.022288	0.1476	0.0000	0.0000	1,655,778	0.0012***	(4.59)

Panel C: Control Variables

	Pre-MiFID II					Post-MiFID II					diff		
	count	mean	sd	p25	p75	count	mean	sd	p25	p75	count	b	t
Avg price 12m	1,026,515	996.112567	24226.5193	11.9203	76.5022	459,793	986.092421	22964.4704	13.9974	92.8474	1,486,308	10.0201	(0.24)
Stdev 12m	1,026,507	141.743307	4867.8461	1.1571	7.1191	459,793	201.002952	10732.7028	1.3347	8.9195	1,486,300	-59.2596***	(-3.58)
Debt ratio	474,640	0.600974	0.2265	0.4569	0.7409	218,711	0.605006	0.2288	0.4621	0.7439	693,351	-0.0040***	(-6.84)
Volume traded	600,207	3722.380802	47879.7776	20.4689	404.8984	407,108	3636.387708	50115.9376	20.5064	423.8601	1,007,315	85.9931	(0.86)
Own_Gain_bank_lag1	145,357	401824.428118	1.1916e+08	-62977.8633	66735.3438	60,620	306347.105584	23914149.6516	-54107.5234	81172.7852	205,977	95477.3225	(0.29)
Broker analyst exp	340,393	6.827514	3.3017	4.0000	10.0000	143,743	7.462882	4.1273	4.0000	11.0000	484,136	-0.6354***	(-51.79)
Broker size	537,089	244.440730	146.3807	55.0000	354.0000	247,446	216.471380	120.0109	115.0000	340.0000	784,535	27.9693***	(89.30)
Num. firm covered	495,127	14.602811	7.7110	10.0000	18.0000	231,859	14.309943	7.4651	9.0000	18.0000	726,986	0.2929***	(15.43)
Num. ind. covered	499,142	2.312430	2.6787	0.0000	4.0000	233,709	1.935860	2.5696	0.0000	4.0000	732,851	0.3766***	(57.68)
Num. analyst follow	532,159	34.887695	19.3475	20.0000	49.0000	232,664	30.393254	17.2805	16.0000	42.0000	764,823	4.4944***	(100.83)
$\Delta OtherHH$	1,149,184	0.071252	88.7938	-0.0708	0.0455	506,594	-0.136233	45.5667	-0.0827	0.0629	1,655,778	0.2075*	(1.98)

Details about the IBES data set

We can identify US, Canadian, and international firms with the following rules:

- US firm are those: IBES ticker 1st digit != "@" & usfirm == 1
- Canadian firms are those: IBES ticker 1st digit != "@" & usfirm ==0
- Other international firms are those: IBES tickers 1st digit == "@" & usfirm == 0

* IBES ticker: the unique identification for stocks in IBES dataset.

* usfirm: dummy variable, equals to 1 if the firm is registered in the US.

Table 1: Information Content Analysis

This table presents the test results for **H1a:** Research information environment is improved, with regard to the precision and accuracy of the earnings per share forecast. **H1b:** Research information environment, in general, does not have a significant improvement in precision. Sample is from 01Jan2014 to 30Dec2018 for Panel A and to 30Sept2019 for Panel B. Dependent variable in Panel A is EPS $\text{Error}_{i,j,t}$, firm i's earnings per share prediction from the analyst research issued by brokerage house affiliated to bank j in month t, less the realized earnings per share of that firm. All prices are converted into US dollar; the EPS prediction error is further normalized by the last year-end stock price. Dependent Variable in Panel B is $\text{REC Count}_{i,j,t}$, the number of recommendations of stock i an analyst affiliated to bank j has been issued in month t. The explanatory variable MiFID is the post-MiFID II dummy variable, equals 1 if the observation is after 1st January 2018.

	Panel A: EPS prediction error					Panel B: Recommendation publication counts				
	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
MiFID	-0.0110***	-0.0106***	-0.0043***	-0.0037***	-0.0039***	-0.0146***	-0.0099***	-0.0075*	-0.0098**	-0.0097*
	(-2.68)	(-5.07)	(-4.63)	(-8.46)	(-6.26)	(-9.78)	(-2.79)	(-1.77)	(-2.25)	(-1.90)
Broker analyst exp		-0.0004	-0.0003	0.0002**	0.0007***		-0.0046***	-0.0050***	-0.0039***	-0.0078***
		(-1.43)	(-1.35)	(1.97)	(4.25)		(-9.25)	(-9.79)	(-6.35)	(-6.94)
Broker size		-0.0000**	0.0004***	-0.0000*	0.0000		-0.0000	0.0001	-0.0001**	0.0001
		(-2.30)	(2.96)	(-1.94)	(0.05)		(-1.23)	(1.62)	(-2.48)	(1.36)
Num. firm covered		0.0003	0.0004	0.0000	-0.0000		0.0013***	0.0017***	0.0007	0.0020**
		(1.32)	(1.37)	(0.70)	(-0.12)		(3.83)	(4.38)	(1.48)	(2.52)
Num. ind. covered		-0.0013	-0.0012	-0.0005**	-0.0003		-0.0014	-0.0027**	-0.0005	-0.0061**
		(-1.63)	(-1.56)	(-2.46)	(-0.94)		(-1.30)	(-2.31)	(-0.37)	(-2.03)
Num. analyst follow		-0.0008***	-0.0008***	0.0000	-0.0000		-0.0008***	-0.0007***	0.0007	0.0002
		(-4.17)	(-4.18)	(0.06)	(-0.22)		(-7.06)	(-6.40)	(1.60)	(0.39)
Debt ratio		0.1003***	0.1006***	0.1216***	0.1258***		-0.0169*	-0.0184**	0.0558	0.0694
		(3.50)	(3.50)	(2.69)	(2.71)		(-1.88)	(-2.02)	(1.16)	(1.37)
Avg price 12m		-0.0000*	-0.0000	-0.0000***	-0.0000***		-0.0000	-0.0000	-0.0000	-0.0000
		(-1.72)	(-1.45)	(-4.25)	(-4.18)		(-0.51)	(-0.15)	(-0.85)	(-0.78)
Stdev 12m		0.0000***	0.0000***	0.0000	0.0000		-0.0000	-0.0000	-0.0000	-0.0000
		(3.10)	(2.97)	(1.40)	(1.38)		(-0.27)	(-0.44)	(-0.90)	(-0.93)
Volume_traded		0.0000	0.0000	-0.0000	-0.0000		0.0000	0.0000	-0.0000	-0.0000
		(1.42)	(1.30)	(-1.43)	(-1.45)		(1.17)	(1.10)	(-0.16)	(-0.22)
Own_Gain_bank_lag1		0.0000	0.0000	0.0000	0.0000		0.0000	0.0000	0.0000	0.0000
		(0.75)	(0.76)	(1.10)	(1.05)		(0.43)	(0.42)	(0.38)	(0.47)
ΔOtherHH		0.0000	0.0000	-0.0000	-0.0000		0.0000	0.0000	0.0000	0.0000
		(0.76)	(0.85)	(-0.62)	(-0.57)		(0.10)	(0.13)	(0.24)	(0.34)
Constant	0.0320***	0.0084	-0.1245***	-0.0565**	-0.0650**	0.1025***	0.1502***	0.1265***	0.0497	0.0585
	(13.18)	(1.53)	(-2.65)	(-2.02)	(-2.53)	(121.92)	(15.68)	(7.69)	(1.39)	(1.42)
Bank fixed effects			Yes					Yes		
Stock fixed effects				Yes					Yes	
Stock-bank fixed effects					Yes					Yes
Robust st.error	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	80607	13733	13733	13632	13623	189407	24678	24677	24546	24461
R-squared	0.00	0.03	0.03	0.87	0.87	0.00	0.01	0.01	0.06	0.10

Standard errors in parentheses; * p<0.1, ** p<0.05, *** p<0.01

Table 2: Information Content Analysis - Plausible tests

This table presents the robustness check results for **H1a** and **H1b**, which takes plausible MiFID II cutoffs and conduct the same analysis. Sample is from 01Jan2014 to 30Dec2018 for Panel A and to 30Sept2019 for Panel B. Dependent variable in Panel A1 and A2 is EPS Error, a firm's earnings per share prediction from the analyst research issued by the brokerage house affiliated to a bank in a month, less the realized earnings per share of that firm. All prices are converted into US dollar; the absolute value of EPS prediction error is further normalized by the last year-end stock price for allowing cross stock comparison. Dependent Variable in Panel B1 and B2 is REC Count, the number of recommendations of a stock that a bank-affiliated brokerage house has been issued in one month. Explanatory variable MiFID2016 in A1 and B1 equals 1 if the observation is after 1st January 2016. The explanatory variable MiFID2017 in A2 and B2 equals 1 if the observation is after 1st January 2017. Constant terms are not displayed in the table. Where, BrokerControl contains: Broker analyst exp, Broker size, Num. firm covered, Num. ind. covered; StockControl contains: Num. analyst follow, Debt ratio, Avg price 12m, Stdev 12m; AffiBankControl contains: Volume_traded, Own_Gain_bank_lag1, Δ OtherHH. Results show the plausible cutoffs do not have similar effects on the information content of analyst research.

	Panel A1: EPS prediction error - MiFID2016					Panel B1: Rec. publication counts - MiFID2016				
	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
MiFID2016	-0.0010	-0.0045*	0.0005	0.0014	0.0020	-0.0131***	0.0103	0.0130*	0.0158**	0.0154**
	(-0.22)	(-1.65)	(0.16)	(0.53)	(0.79)	(-8.90)	(1.55)	(1.93)	(2.26)	(2.18)
BrokerControl		Yes	Yes	Yes	Yes		Yes	Yes	Yes	Yes
StockControl		Yes	Yes	Yes	Yes		Yes	Yes	Yes	Yes
AffiBankControl		Yes	Yes	Yes	Yes		Yes	Yes	Yes	Yes
Bank fixed effects			Yes					Yes		
Stock fixed effects				Yes					Yes	
Stock-bank fixed effects					Yes					Yes
Robust st.error	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	80,607	13,733	13,733	13,632	13,623	189,407	24,678	24,677	24,546	24,461
R-squared	0.00	0.03	0.03	0.87	0.87	0.00	0.01	0.01	0.06	0.10
	Panel A2: EPS prediction error - MiFID2017					Panel B2: Rec. publication counts - MiFID2017				
	(1)	(2)	(3)	(4)	(5)	(1)	(2)	(3)	(4)	(5)
MiFID2017	-0.0087**	-0.0094***	-0.0052**	0.0011*	0.0017***	-0.0111***	-0.0028	-0.0004	-0.0004	0.0022
	(-2.29)	(-3.03)	(-2.29)	(1.92)	(2.78)	(-8.01)	(-0.75)	(-0.09)	(-0.08)	(0.48)
BrokerControl		Yes	Yes	Yes	Yes		Yes	Yes	Yes	Yes
StockControl		Yes	Yes	Yes	Yes		Yes	Yes	Yes	Yes
AffiBankControl		Yes	Yes	Yes	Yes		Yes	Yes	Yes	Yes
Bank fixed effects			Yes					Yes		
Stock fixed effects				Yes					Yes	
Security-bank fixed effects					Yes					Yes
Robust st.error	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	80,607	13,733	13,733	13,632	13,623	189,407	24,678	24,677	24,546	24,461
R-squared	0.00	0.03	0.03	0.87	0.87	0.00	0.01	0.01	0.06	0.10

Standard errors in parentheses; * p<0.1, ** p<0.05, *** p<0.01

Table 3: Aggregate Customer Reactions to the Average Market Recommendations

This table presents the test results for **H2a:** Investors do believe that financial advisors delivers more transparent information and ”acts with your best interest in mind”, so they are more willing to following analyst researches. **H2b:** On contrary, because indeed more risks are revealed to customers after MiFID II implementation, client inducements behavior is decreased and customers are thus more rational and independent, and their reaction to analyst recommendation will be lower than before. Sample is from 01Jan2014 to 30Sept2019, Pre- and Post-MiFID subsample cutoff is on 01Jan2018. Dependent variable in Panel A is $textAggHHBuy$, a dummy variable, equals 1 if the aggregate customers’ holdings on a stock across all sample banks in the month is positive. Dependent variable in Panel B is $text\Delta AggHH$, the aggregate customers’ holding changes on a stock measured in the percentage of total stock outstanding amount. The explanatory variable $RecBuyAllAvg$ equals 1 if monthly average stock recommendations from all newly published research on the same stock is upward changed and fits ”Rec-Buy” categorizing rule. Constant terms are not displayed in the table. Where, BrokerControl contains: Broker analyst exp, Broker size, Num. firm covered, Num. ind. covered; StockControl contains: Num. analyst follow, Debt ratio, Avg price 12m, Stdev 12m; AffiBankControl contains: Volume_traded, Own_Gain_bank_lag1, ΔOtherHH. In each column pair, the left column is the result for the Pre-MiFID II subsample, and the right column is the result for the Post-MiFID II period.

	Panel A: Extensive Margin (AggHHBuy)								Panel B: Intensive Margin (AggΔHH)							
	(1)		(2)		(3)		(4)		(1)		(2)		(3)		(4)	
	Pre	Post	Pre	Post	Pre	Post	Pre	Post	Pre	Post	Pre	Post	Pre	Post	Pre	Post
RecBuyAllAvg = 1	-0.0276*	-0.0063	-0.0212	-0.0072	-0.0225	-0.0138	-0.0195	0.0059	0.0656**	0.1037**	0.0859**	0.1205*	0.0838*	0.1152	0.0825*	0.1256
	(-1.85)	(-0.25)	(-0.85)	(-0.20)	(-0.90)	(-0.39)	(-0.73)	(0.15)	(2.44)	(2.25)	(2.01)	(1.67)	(1.96)	(1.60)	(1.66)	(1.49)
(mean) BrokerControl			Yes	Yes	Yes	Yes	Yes	Yes			Yes	Yes	Yes	Yes	Yes	Yes
StockControl			Yes	Yes	Yes	Yes	Yes	Yes			Yes	Yes	Yes	Yes	Yes	Yes
(mean) AffiBankControl			Yes	Yes	Yes	Yes	Yes	Yes			Yes	Yes	Yes	Yes	Yes	Yes
Industry fixed effects					Yes	Yes							Yes	Yes		
Stock fixed effects							Yes	Yes							Yes	Yes
Robust st.error	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	48,257	19,807	20,693	12,651	20,684	12,651	20,507	12,436	48,257	19,807	20,693	12,651	20,684	12,651	20,507	12,436
R-squared	0.00	0.00	0.02	0.03	0.03	0.04	0.17	0.21	0.00	0.00	0.20	0.26	0.20	0.26	0.24	0.32
Vardiff	-0.0213		-0.0139		-0.0087		-0.0254		-0.0381		-0.0346		-0.0314		-0.0431	
P-value	0.19		0.36		0.34		0.18		0.2		0.29		0.23		0.23	

Standard errors in parentheses; * p<0.1, ** p<0.05, *** p<0.01

Table 4: Customer Reaction to the Analyst Research (Extensive Margin Analysis)

This table presents part of the test results for **H3:** on top of the average analyst recommendations, investors become more responsive to affiliated bank's analyst reports. Sample is from 01Jan2014 to 30Sept2019, Pre- and Post-MiFID subsample cutoff is on 01Jan2018. Dependent variable HHBuy equals 1 if the customer stock holding changes in percentage of outstanding stocks is positive. The explanatory variable RecBuyAffi equals 1 if the *changes in recommendation* of a stock made by the analyst affiliated to a bank in a month fits the "Rec-Buy" categorizing rule. RecBuyAllOtherAvg serves as a control variable equals 1 if the rounded average value of all banks' (except for the affiliated bank) contemporaneous recommendations fits the "Rec-Buy" categorizing rule. Constant terms are not displayed in the table. Where, StockControl contains: Debt ratio, Avg price 12m, Stdev 12m. In each column pair, the left column is the result for the Pre-MiFID II subsample, and the right column is the result for the Post-MiFID II period.

	HHBuy									
	(1)		(2)		(3)		(4)		(5)	
	Pre	Post	Pre	Post	Pre	Post	Pre	Post	Pre	Post
RecBuyAffi=1	-0.0327***	-0.0388***	0.0129***	-0.0013	0.0133***	-0.0029	0.0145***	-0.0018	0.0163**	-0.0147
	(-6.82)	(-4.81)	(2.92)	(-0.16)	(3.02)	(-0.37)	(3.09)	(-0.23)	(2.12)	(-1.09)
RecBuyAllOtherAvg	0.0115***	0.0181***	0.0021	0.0097***	0.0021	0.0097***	0.0028	0.0082**	-0.0324**	-0.0366
	(5.20)	(5.05)	(1.00)	(2.73)	(1.01)	(2.73)	(1.23)	(2.22)	(-2.15)	(-1.42)
StockControl							Yes	Yes		
Bank fixed effects	Yes	Yes								
Industry fixed effects	Yes	Yes								
Time fixed effects	Yes	Yes	Yes	Yes						
Bank-time fixed effects					Yes	Yes	Yes	Yes	Yes	Yes
Stock-time fixed effects									Yes	Yes
Stock-bank fixed effects			Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Robust st.error	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	225,096	94,456	231,604	96,414	231,594	96,409	207,762	89,913	225,102	93,940
Num.Banks	26	26	26	26	26	26	26	26	26	26
R-squared	0.08	0.09	0.21	0.24	0.22	0.25	0.22	0.25	0.29	0.30
Vardiff	0.0061		0.0142		0.0161		0.0164		0.0310	
P-value	.16		.03		.02		.04		.07	

Standard errors in parentheses; * $p<0.1$, ** $p<0.05$, *** $p<0.01$

Table 5: Customer Reaction to the Analyst Research (Intensive Margin Analysis)

This table presents part of the test results for **H3:** on top of the average analyst recommendations, investors become more responsive to affiliated bank's analyst reports. Sample is from 01Jan2014 to 30Sept2019, Pre- and Post-MiFID subsample cutoff is on 01Jan2018. Dependent variable ΔHH is the changes of the month-end stock values held by bank-affiliated customers that normalized by the corresponding stock free float market capitalization. The explanatory variable RecBuyAffi equals 1 if the *changes in recommendation* of a stock made by the analyst affiliated to a bank in a month fits the "Rec-Buy" categorizing rule. RecBuyAllOtherAvg serves as a control variable equals 1 if the rounded average value of all banks' (except for the affiliated bank) contemporaneous recommendations fits the "Rec-Buy" categorizing rule. Constant terms are not displayed in the table. Where, StockControl contains: Debt ratio, Avg price 12m, Stdev 12m. In each column pair, the left column is the result for the Pre-MiFID II subsample, and the right column is the result for the Post-MiFID II period.

	Δ HH									
	(1)		(2)		(3)		(4)		(5)	
	Pre	Post	Pre	Post	Pre	Post	Pre	Post	Pre	Post
RecBuyAffi=1	0.0025***	0.0031**	0.0026***	0.0038**	0.0023***	0.0035**	0.0022***	0.0034**	0.0002	0.0029
	(3.38)	(2.02)	(3.49)	(2.25)	(3.17)	(2.20)	(2.72)	(2.09)	(0.12)	(1.04)
RecBuyAllOtherAvg	0.0045***	0.0038***	0.0046***	0.0045***	0.0046***	0.0045***	0.0053***	0.0048***	-0.0020	0.0087
	(8.93)	(4.04)	(8.81)	(4.45)	(8.97)	(4.55)	(9.48)	(4.65)	(-0.52)	(1.25)
StockControl							Yes	Yes		
Bank fixed effects	Yes	Yes								
Industry fixed effects	Yes	Yes								
Time fixed effects	Yes	Yes	Yes	Yes						
Bank-time fixed effects					Yes	Yes	Yes	Yes	Yes	Yes
Stock-time fixed effects									Yes	Yes
Stock-bank fixed effects			Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Robust st.error	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	225,096	94,456	231,604	96,414	231,594	96,409	207,762	89,913	225,102	93,940
Num.Banks	26	26	26	26	26	26	26	26	26	26
R-squared	0.02	0.03	-0.00	-0.03	0.03	0.03	0.03	0.04	0.22	0.25
Vardiff	-0.0006		-0.0012		-0.0012		-0.0012		-0.0027	
P-value	.24		.15		.15		.17		0.31	

Standard errors in parentheses; * p<0.1, ** p<0.05, *** p<0.01

Table 6: Proprietary Trading (Extensive Margin Analysis)

This table presents part of the test results for **H4 - part1**: Whether the correlation between bank holding changes and their retail customers' holding changes of a stock is still negative in recent years. If so, **H4 - part2**: Is the negative correlation between bank holdings and their customers' holding of a stock more or less affected by the bank's analyst recommendations after MiFID II? Sample is from 01Jan2014 to 30Sept2019, Pre- and Post-MiFID subsample cutoff is on 01Jan2018. Dependent variable HHBuy equals 1 if bank-affiliated customers stock holding changes in percentage of outstanding stocks is positive. Explanatory variables BankSell equals 1 if a bank's own stock holding changes in percentage of outstanding stocks is negative. RecBuyAffi equals 1 if the *changes in recommendation* of a stock made by the analyst affiliated to a bank in a month fits the "Rec-Buy" categorizing rule. Constant terms are not displayed in the table. Where, StockControl contains: Debt ratio, Avg price 12m, Stdev 12m; AffiBankControl contains: Volume_traded, Own_Gain_bank_lag1, ΔOtherHH. In each column pair, the left column is the result for the Pre-MiFID II subsample, and the right column is the result for the Post-MiFID II period.

	HHBuy													
	(1)		(2)		(3)		(4)		(5)		(6)		(7)	
	Pre	Post	Pre	Post	Pre	Post	Pre	Post	Pre	Post	Pre	Post	Pre	Post
BankSell=1	-0.0103*	-0.0099	-0.0244***	-0.0337***	-0.0241***	-0.0337***	-0.0262***	-0.0355***	-0.0260***	-0.0354***	-0.0088	-0.0025	-0.0069	-0.0044
	(-1.76)	(-1.36)	(-4.11)	(-4.55)	(-4.06)	(-4.55)	(-4.38)	(-4.71)	(-4.34)	(-4.70)	(-1.45)	(-0.32)	(-1.02)	(-0.50)
RecBuyAffi=1	-0.0122	-0.0394	0.0053	-0.0140	0.0067	-0.0131	0.0131	-0.0186	0.0146	-0.0180	-0.0230	-0.0487*	-0.0146	-0.0214
	(-0.60)	(-1.46)	(0.26)	(-0.50)	(0.33)	(-0.47)	(0.64)	(-0.66)	(0.71)	(-0.63)	(-1.10)	(-1.70)	(-0.59)	(-0.58)
BankSell=1 ×RecBuyAffi = 1	0.0210	0.0675	0.0187	0.0829*	0.0169	0.0824*	0.0078	0.0858*	0.0058	0.0856*	0.0192	0.1038**	0.0198	0.0672
	(0.58)	(1.51)	(0.52)	(1.79)	(0.47)	(1.78)	(0.22)	(1.83)	(0.16)	(1.82)	(0.53)	(2.22)	(0.49)	(1.18)
StockControl					Yes	Yes			Yes	Yes				
AffiBankControl					Yes	Yes			Yes	Yes				
Bank fixed effects	Yes	Yes												
Industry fixed effects	Yes	Yes												
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes								
Bank-time fixed effects							Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-time fixed effects											Yes	Yes		
Industry-bank fixed effects											Yes	Yes		
Stock-time fixed effects													Yes	Yes
Stock-bank fixed effects			Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes			Yes	Yes
Robust st.error	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	28,260	17,927	28,019	17,654	28,019	17,654	27,981	17,631	27,981	17,631	28,044	17,787	25,103	15,670
Num.Banks			20	19	20	19	19	18	19	18	19	18	18	17
R-squared	0.08	0.09	0.17	0.20	0.17	0.20	0.19	0.21	0.19	0.21	0.14	0.13	0.29	0.30
Vardiff	-0.0465		-0.0642		-0.0655		-0.0780		-0.0797		-0.0846		-0.0473	
P-value	0.01		0.00		0.00		0.00		0.00		0.00		0.15	

Standard errors in parentheses; * p<0.1, ** p<0.05, *** p<0.01

Table 7: Proprietary Trading (Intensive Margin Analysis)

This table presents part of the test results for **H4 - part1**: Whether the correlation between bank holding changes and their retail customers' holding changes of a stock is still negative in recent years. If so, **H4 - part2**: Is the negative correlation between bank holdings and their customers' holding of a stock more or less affected by the bank's analyst recommendations after MiFID II? Sample is from 01Jan2014 to 30Sept2019, Pre- and Post-MiFID subsample cutoff is on 01Jan2018. Dependent variable ΔHH is the changes of the month-end stock values held by bank-affiliated customers that normalized by the corresponding stock free float market capitalization. Explanatory variables BankSell equals 1 if a bank's own stock holding changes in percentage of outstanding stocks is negative. ΔBank is the changes of the month-end stock values held by bank that normalized by the corresponding stock free float market capitalization. RecBuyAffi equals 1 if the *changes in recommendation* of a stock made by the analyst affiliated to a bank in a month fits the "Rec-Buy" categorizing rule. Constant terms are not displayed in the table. Where, StockControl contains: Debt ratio, Avg price 12m, Stdev 12m; AffiBankControl contains: Volume_traded, Own_Gain_bank_lag1, ΔOtherHH. In each column pair, the left column is the result for the Pre-MiFID II subsample, and the right column is the result for the Post-MiFID II period.

	ΔHH													
	(1)		(2)		(3)		(4)		(5)		(6)		(7)	
	Pre	Post	Pre	Post	Pre	Post	Pre	Post	Pre	Post	Pre	Post	Pre	Post
ΔBank	0.0837***	0.1533***	0.0981***	0.1622***	0.0930***	0.1260***	0.1086***	0.1532***	0.1035***	0.1157***	0.0816***	0.1347***	0.0368*	0.0537
	(3.59)	(4.11)	(3.62)	(3.78)	(3.42)	(3.20)	(4.07)	(3.65)	(3.87)	(3.02)	(3.56)	(3.52)	(1.65)	(1.48)
RecBuyAffi=1	0.0032	0.0092	0.0046	0.0033	0.0039	0.0011	0.0044	0.0002	0.0038	-0.0018	0.0004	0.0063	-0.0091	-0.0059
	(0.72)	(1.05)	(0.97)	(0.37)	(0.84)	(0.12)	(0.93)	(0.03)	(0.81)	(-0.22)	(0.08)	(0.79)	(-1.48)	(-0.65)
RecBuyAffi=1 × ΔBank	0.1039	0.1436	0.0514	0.2903	0.0478	0.2595	0.0532	0.4924**	0.0492	0.4496**	0.1183	0.3637	0.1212	0.6431***
	(0.56)	(0.37)	(0.28)	(0.86)	(0.26)	(0.80)	(0.29)	(2.38)	(0.28)	(2.17)	(0.59)	(1.50)	(0.70)	(3.60)
BankSell=1	-0.0099***	-0.0058***	-0.0105***	-0.0070***	-0.0102***	-0.0052***	-0.0096***	-0.0061***	-0.0093***	-0.0040**	-0.0077***	-0.0042***	-0.0004	0.0022
	(-7.50)	(-3.67)	(-7.23)	(-3.94)	(-6.86)	(-3.03)	(-6.60)	(-3.44)	(-6.28)	(-2.37)	(-5.61)	(-2.65)	(-0.27)	(1.22)
BankSell=1 × ΔBank	-0.0399	-0.1368***	-0.0691*	-0.1706***	-0.0798*	-0.1295**	-0.0844**	-0.1605***	-0.0957**	-0.1198**	-0.0443	-0.1329***	-0.0235	-0.0801*
	(-1.21)	(-2.89)	(-1.68)	(-3.07)	(-1.94)	(-2.51)	(-2.05)	(-2.99)	(-2.33)	(-2.41)	(-1.31)	(-2.85)	(-0.66)	(-1.66)
RecBuyAffi=1 × BankSell=1	0.0042	-0.0103	0.0026	-0.0039	0.0026	0.0036	0.0006	-0.0063	0.0004	0.0014	-0.0016	-0.0153	-0.0008	-0.0127
	(0.51)	(-0.85)	(0.30)	(-0.32)	(0.30)	(0.28)	(0.06)	(-0.56)	(0.04)	(0.12)	(-0.18)	(-1.28)	(-0.07)	(-1.05)
RecBuyAffi=1 × BankSell=1 × ΔBank	-0.0813	-0.0958	0.0181	-0.2570	0.0314	0.0588	0.0014	-0.5040**	0.0133	-0.2035	-0.1497	-0.3636	-0.1182	-0.6567**
	(-0.34)	(-0.24)	(0.07)	(-0.71)	(0.12)	(0.15)	(0.01)	(-2.10)	(0.05)	(-0.72)	(-0.60)	(-1.36)	(-0.45)	(-2.08)
StockControl					Yes	Yes			Yes	Yes				
AffiBankControl					Yes	Yes			Yes	Yes				
Bank fixed effects	Yes	Yes												
Industry fixed effects	Yes	Yes												
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes								
Bank-time fixed effects							Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-time fixed effects											Yes	Yes		
Industry-bank fixed effects											Yes	Yes		
Stock-time fixed effects													Yes	Yes
Stock-bank fixed effects			Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes			Yes	Yes
Robust st.error	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	28,260	17,927	28,019	17,654	28,019	17,654	27,981	17,631	27,981	17,631	28,044	17,787	25,103	15,670
Num.Banks			20	19	20	19	19	18	19	18	19	18	18	17
R-squared	0.04	0.07	0.01	0.02	0.03	0.10	0.05	0.08	0.07	0.16	0.12	0.17	0.35	0.39
Vardiff	0.0145		0.2750		-0.0274		0.5054		0.2168		0.2139		0.5384	
P-value	0.47		0.11		0.33		0.02		0.16		0.12		0.04	

Standard errors in parentheses; * p<0.1, ** p<0.05, *** p<0.01

Table 8: Customer Portfolio Return Analysis

This table presents the test results for **H5-Part1**: If customers indeed buy stocks that bank is selling and issuing a Buy-Recommendation, then customers return will be lower than otherwise. **H5-Part2**: This phenomenon will be emphasized or mitigated according to banks' proprietary trading extent after implementation of MiFID II (depend on the result from H4). Sample is from 01Jan2014 to 30Sept2019, Pre- and Post-MiFID subsample cutoff is on 01Jan2018. Dependent variable ProfitHH is the realized return of a stock multiplies with the positive part of bank-affiliated customers' *unit changes* on that stock. Explanatory variables $\text{BankSell}_{i,j,t}$ equals 1 if the unit of a stock held by a bank is negatively changed in one month. *Holding unit changes* applied here is different to the previous stock holding value changes. RecBuyAffi equals 1 if the *changes in recommendation* of a stock made by the analyst affiliated to a bank in a month fits the "Rec-Buy" categorizing rule. Constant terms are not displayed in the table. Where, StockControl contains: Debt ratio, Avg price 12m, Stdev 12m; AffiBankControl contains: Volume_traded, Own_Gain_bank_lag1, ΔOtherHH. In each column pair, the left column is the result for the Pre MiFID II subsample, and the right column is the result for the Post MiFID II period.

	Profit_HH													
	(1)		(2)		(3)		(4)		(5)		(6)		(7)	
	Pre	Post	Pre	Post	Pre	Post	Pre	Post	Pre	Post	Pre	Post	Pre	Post
BankSell=1	270.0977**	771.4952*	403.1770***	667.0313**	373.9057**	656.7972**	468.6177***	585.4874**	435.4899***	574.5461**	325.7034**	585.6384	245.8034*	-26.5351
	(2.09)	(1.88)	(2.72)	(1.99)	(2.52)	(1.98)	(2.96)	(2.03)	(2.77)	(2.01)	(2.17)	(1.43)	(1.71)	(-0.06)
Buy Affi=1	-333.6893	290.1294	-361.3941	-208.5067	-361.1394	-148.9010	-424.5014	-46.0316	-423.6210	12.0610	-391.1135	-140.3976	-577.6018	-1345.5434
	(-1.08)	(0.46)	(-1.01)	(-0.34)	(-1.01)	(-0.24)	(-1.18)	(-0.07)	(-1.18)	(0.02)	(-1.22)	(-0.21)	(-1.17)	(-0.93)
BankSell1=1 × Buy Affi=1	1215.8503	-779.4493	1532.6292	-6.8809	1525.4492	30.9462	1259.7420	32.4509	1253.4167	89.1535	1145.3978	-136.5047	920.7563	1509.9230
	(1.35)	(-0.68)	(1.52)	(-0.01)	(1.50)	(0.03)	(1.17)	(0.03)	(1.15)	(0.08)	(1.07)	(-0.11)	(0.72)	(0.64)
StockControl					Yes	Yes			Yes	Yes				
AffiBankControl					Yes	Yes			Yes	Yes				
Bank fixed effects	Yes	Yes												
Industry fixed effects	Yes	Yes												
Time fixed effects	Yes	Yes	Yes	Yes	Yes	Yes								
Bank-time fixed effects							Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-time fixed effects											Yes	Yes		
Industry-bank fixed effects											Yes	Yes		
Stock-time fixed effects													Yes	Yes
Stock-bank fixed effects			Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes			Yes	Yes
Robust st.error	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	28,260	17,927	28,019	17,654	28,019	17,654	27,981	17,631	27,981	17,631	28,044	17,787	25,103	15,670
num.Banks	20	20	20	19	20	19	19	18	19	18	19	18	18	17
R-squared	0.01	0.01	0.07	0.10	0.07	0.10	0.08	0.11	0.08	0.11	0.09	0.08	0.45	0.35
Vardiff	1995.30		1539.51		1494.50		1227.29		1164.26		1281.90		-589.17	
P-value	0		0		0		0.06		0.07		0.04		0.23	

Standard errors in parentheses; * p<0.1, ** p<0.05, *** p<0.01