Misselling in Financial Advice

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Abstract

Financial advisors often steer clients toward high-commission products, leading to poor advice quality. Yet, uncertain investment returns make it challenging to detect deliberate misselling. Our study leverages Chinese Wealth Management Products (WMPs) with implicit guarantees, enabling clear identification of misselling as recommending objectively suboptimal low-return products. Using transaction data from a large Chinese retail bank, we document pervasive misselling (74%). To capture the role of advisors, we find that performance pressure, peer effects, and promotion prospects drive misselling, while client complaints deter it. Stressed advisors particularly target inexperienced clients and private banking clients, and female advisor-male client dyads.

Keywords: Financial advisors; Misselling; Conflicts of interest; Moral hazard; Wealth Management Products

JEL Classification: G21; D82; D86

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1. Introduction

The quality of financial advice for retail clients remains a central debate in the finance literature (see Reuter and Schoar 2024 for a review). While some studies show that conflicts of interest lead advisors to steer clients toward high-commission products, resulting in underperformance of advisor-managed investments (e.g., Inderst and Ottaviani 2009, 2012a; Hoechle et al. 2018), proving deliberate misselling is difficult. This is because investment returns are inherently risky ex-ante, making it challenging to conclude whether poor investment outcomes stem from limited advisor ability (Linnainmaa, Melzer, and Previtero 2021) or from deliberate misselling. Consequently, the true scale of such biased recommendations, if any, and their erosion of clients' realized returns remain largely unknown.

This paper addresses this challenge by leveraging the distinctive *gangdui*—rigid repayment, i.e., an implicit guarantee of both principal and interest—in China's wealth management product (WMP) market. WMPs are asset-backed vehicles that pool investor funds into a wide range of underlying assets, including money market instruments, bonds, and equities. A key feature of these products, despite prospectus wording suggesting otherwise, is an "expected" return that is, in practice, implicitly guaranteed.[2] Transactions involving WMPs constitute a significant, often the largest, component of retail services in many Chinese commercial banks.

The implicit guarantee in WMPs makes them particularly suited for our research. Because the implicit guarantee makes the investment's return virtually

[2] Commercial banks distributing WMPs typically ensure investors receive both principal and expected returns, regardless of underlying asset performance. For banks, these products are attractive because they help circumvent regulatory constraints imposed on traditional deposits, and many of them can even be structured off-balance-sheet. Offering an implicit guarantee allows banks to stay competitive and safeguard their reputations. Relying on the perceived credibility of commercial banks, retail investors accept risk premia on WMPs far below what their true risk warrants, treating them as risk-free, high-return deposit substitutes.

predictable ex-ante—so the advisor's forecasting skill is irrelevant—an ethical advisor should direct clients to the product that offers the highest yield within the same type and maturity. In contrast, if advisors deliberately steer clients toward lower-return products, such practice constitutes unequivocal misselling.

Our empirical analyses rely on transaction-level data provided by a major commercial bank in China (hereafter "The Bank"), whose core retail business involves underwriting and distributing Wealth Management Products (WMPs). The sample comprises 19,577 randomly selected retail clients and their complete transaction records from June 2019 to June 2020. Of these, 5,518 clients were uniquely matched to 463 financial advisors for the entire sample period, forming our primary advised client sample for analysis. The sample of un-advised clients serves as a placebo benchmark. We define misselling as the sale of *low-return products*—WMPs offering the lowest expected return among all concurrently available alternatives of the same product type and maturity at the time of sale.[3] Summary statistics reveal a strikingly high prevalence of low-return product sales: an average of 73% of WMPs sold were low-return. This proportion is 74% for advised clients, compared to 69% for un-advised clients, a differential that suggests potential advisor-driven misselling. However, the high incidence may stem from several alternative explanations. For instance, low-return products are more actively marketed, while higher-return products are sometimes subject to sales caps or "rush purchase" policies, making low-return products more consistently accessible.

To identify advisor-driven misselling, we construct advisor-month-level indicators capturing the time-varying incentives to missell. By incorporating client-advisor and time fixed effects, our empirical strategy exploits within-pair variation over

[3] During the sample period, an average of 6.6 distinct product type-maturity categories were available daily, with each containing approximately 4.52 individual products. Across these, the average expected return for the highest-return products was 4.15%, compared to 3.96% for the lowest-return products.

time. Consequently, if clients purchase more low-return products precisely when their advisors face heightened incentives to missell, this pattern is more plausibly attributed to advisor-driven behavior than to other explanations.

We explore three types of incentives for misselling.

First, we investigate performance pressure arising from The Bank's monthly sales quotas. Prior research shows that quota design systematically influences agents' effort and selling tactics (e.g., Chung, Narayandas, and Chang 2021; Jindal and Newberry 2022). We proxy performance pressure with a binary variable, *Missed quota*, which equals one when an advisor failed to meet the previous month's target, thereby heightening the incentive to boost sales performance in the current month. At the same time, The Bank's performance assessment system creates a conflict of interest, where products offering lower client returns often yield higher advisor performance scores. Consequently, advisors can improve their performance scores more effectively by steering clients toward low-return products. Our regression results show that advisors under performance pressure significantly increase misselling. Specifically, failing to meet the prior month's quota is associated with a 30.7% increase in low-return WMP sales volume and a 7.5% rise in their sales ratio (low-return to total WMPs sold).

Second, we examine the impact of peer effects, another key driver of agents' work effort (DeMarzo and Kaniel 2023; Dimmock, Gerken, and Graham 2018), on misselling. Within The Bank, peer effects are institutionalized via performance rankings that foster internal competition. We proxy for peer pressure using peer group size, hypothesizing that larger groups intensify competitive pressure to outperform. To establish causality, we exploit an exogenous shock—a structural reorganization of The Bank's branch families in November 2019, which altered advisors' peer comparison groups. Using a Difference-in-Differences (DiD) strategy, we find that financial advisors who transitioned into larger peer groups significantly increased misselling. Our findings reveal that although peer pressure spurs advisors to boost their performance metrics, the resulting gains are achieved at the clients' expense.

Finally, our investigation extends to "softer" forms of motivation—career-based promotion prospects. At The Bank, promotion (advancement to higher-level advisor positions) is highly competitive among advanced-level advisors: a select group of top-performing advisors is shortlisted annually based on prior-year performance. This nomination triggers a formal evaluation period that may heighten promotion candidates' incentive to boost performance through misselling. Using The Bank's January 2020 announcement of promotion candidates as an event, we employ a DiD research design. The findings offer tentative evidence that misselling can be driven by the pursuit of career advancement, though its effects are less robust compared to the impact of quota pressure or peer effects.

After investigating incentives that motivate misselling, we now explore factors that mitigate misselling. Using The Bank's complaint records, we find that quota-driven performance pressure loses much of its effect on misselling when clients lodge complaints about WMP products or service quality. This evidence suggests that timely client feedback imposes a credible cost on advisors and thus helps curb unethical sales practices.

Section 5 pinpoints whom advisors missell to by mapping vulnerable client segments to the attributes of the advisors who target them. Our analyses explore three dimensions: experience, client wealth, and gender. First, we find that client investment experience (proxying financial literacy) plays a critical role: less experienced clients are significantly more susceptible to purchasing low-return products when their advisors face performance pressure. Second, regarding client wealth, our results indicate that while advisors may preserve relationships with premium clients, very wealthy (private banking) clients are disproportionately targeted for misselling. This is potentially due to their perceived lower oversight concerning WMPs, and the higher efficiency gained from a single large transaction in boosting advisors' performance. Finally, gender dynamics reveal a nuanced pattern, with the propensity for misselling significantly concentrated in female advisor-male client dyads.

This study relates to three strands of literature.

First, this paper contributes to the long debate on the quality of financial advice. A substantial body of literature indicates that conflicts of interest lead advisors to recommend high-commission products (Mehran and Stulz 2007; Mullainathan, Nöth, and Schoar 2012; Christoffersen et al. 2013; Egan, Matvos, and Seru 2024), which likely results in the underperformance of advisor-directed investments (Foerster et al. 2017; Hoechle et al. 2018). However, this view is contested. One challenge in evaluating advisor effectiveness is constructing a valid counterfactual (Chalmers and Reuter 2020) because choice to seek advice is itself endogenous (Kramer 2016). Evidence shows that advisors can temper clients' behavioral biases when they invest (Shapira and Venezia 2001; Von Gaudecker 2015; Hoechle et al. 2017). A second, more fundamental challenge lies in distinguishing intentional misselling from limited advisor skill. In particular, Linnainmaa, Melzer, and Previtero (2021) show advisors often achieve poor returns themselves, suggesting skill deficits, not exploitation, may drive poor client outcomes. Our paper offers a clear identification strategy to distinguish ability-driven outcomes from deliberate opportunistic behavior.

Second, our study speaks to the broader principal-agent literature (Ross 1973), and especially to common-agency settings in sales-driven industries where one agent (financial advisor) simultaneously serves two principals—the firm (The Bank) and the client (Bernheim and Whinston 1986). Conflicting principal pay-offs naturally push agents toward biased recommendations (Bolton, Freixas, and Shapiro 2007; De Cornière and Taylor 2019), making misselling mechanical in common-agency settings (Inderst and Ottaviani 2009). Firms exploit this by designing commission schemes that steer agents toward high-margin products (Inderst and Ottaviani 2012b), thereby boosting their own profits (Lazear 2000). Moreover, quotas have been shown to significantly influence agents' in-period effort and selling tactics (Oyer 1998; Chung, Narayandas, and Chang 2021; Jindal and Newberry 2022). Yet these gains by firms and salespeople come at clients' welfare cost (e.g., Levitt and Syverson 2008; Anagol et al.

2017). Within the financial advisory industry, Hackethal, Haliassos, and Jappelli (2012) document lower advisor quality among bank financial advisors compared to independent financial advisors. This aligns with Hoechle et al. (2018), who conclude that advisors prioritize bank interests over client interests. Regulators have sought to curb these conflicts of interest—for example, the U.S. SEC's Regulation Best Interest (Reg BI, SEC 2019) aims to push the traditional commission model toward a quasi-fiduciary standard. The strikingly high incidence of low-return product sales we document implicates misselling not only by advisors but also by The Bank. While our study does not evaluate any specific regulation, the sizable welfare cost borne by clients in such a common agency setting underscores the importance of independence- and disclosure-enhancing regulation.

Third, this study connects to the literature on implicit guarantees. In China, implicit guarantees on WMPs were believed to mitigate capital misallocation by favoring non-SOEs (Allen et al. 2023), yet also creating moral hazard by distorting market incentives (Huang, Huang, and Shao 2023). Media reports suggest these guarantees fueled the real estate market, as investors, relying on the guarantee, may have reduced scrutiny and taken excessive risks (Bloomberg News 2017, 2019, 2021). This parallels findings on government implicit guarantees more broadly, which can distort markets and create risks (Strahan 2013; Dong, Hou, and Ni 2021; Jin, Wang, and Zhang 2023). While our paper does not primarily address the financial risks engendered by implicit guarantees themselves, it leverages the unique implicitly guaranteed WMP setting to demonstrate how, under information asymmetry, financial advisors with an information advantage can arbitrage this institutional feature for profit.

The paper is structured as follows: Section 2 introduces the institutional background of the Chinese WMP market and The Bank. Section 3 describes the data structures and key variable measurements. Section 4 explores different incentives for misselling and examines the moderating role of client complaints. Section 5 investigates heterogeneity, analyzing how advisor and client characteristics influence misselling dynamics. Finally, Section 6 offers concluding remarks and discusses implications.

2. Institutional background

2.1. The Bank

The data for this study are provided by a state-controlled joint-stock commercial bank in China (referred to as "The Bank" in this paper), which operates over 1,100 branches across 122 cities nationwide. As of year-end 2021, The Bank held total assets exceeding 3 trillion RMB and reported operating income approaching 100 billion RMB, ranking it among the top 50 banks globally (The Banker, 2022).

Retail finance is a key strategic focus for The Bank, which reported a personal finance balance of 456.9 billion RMB at year-end 2021. Its retail operations primarily encompass deposit and loan services and the distribution of Wealth Management Products (WMPs), supplemented by sales of other offerings like insurance and precious metals. Notably, bank-distributed WMPs constitute 60% of client Assets Under Management (AUM) at The Bank; deposits account for another 30%.

2.2. Implicit guarantees in WMPs

In China, Wealth Management Products (WMPs) are investment instruments that commercial banks offer to retail investors. Functioning as asset-backed vehicles, these products pool investor funds for investment in a diverse range of underlying assets. Low-risk WMPs primarily invest in assets such as money market instruments, bonds, and equities. High-risk WMPs further include non-standard credit assets like trust loans.

WMP prospectuses typically disclose a fixed or a range of expected returns. Although regulations prohibit formal guarantees of principal or return, in practice, promised returns are almost, if not always, fulfilled. This phenomenon—widely known in Chinese as *gangdui*, or an implicit guarantee—refers to the *de facto* rigid repayment of both capital and interest regardless of underlying asset performance.

In practice, the expected returns of WMPs are effectively guaranteed because commercial banks honor payouts even if underlying assets underperform or default. Banks provide such guarantees to maintain their market competitiveness and protect reputations (Huang, Huang, and Shao 2023). Such behavior reinforces an entrenched investor belief that WMPs are "risk-free, high-return" instruments, prompting investors to treat them as deposit-like assets with enhanced yields, despite the lack of any formal guarantee (Reuters 2017).

Implicit guarantees in China emerged as a form of regulatory arbitrage during the 2000s, particularly following the 2008 financial crisis (Allen et al. 2023). Faced with strict controls on deposit interest rates, commercial banks sought alternative channels to attract funds by offering higher-yielding products. WMPs served this purpose well. As WMPs are classified as financial market instruments, banks were able to bypass regulatory constraints such as the loan-to-deposit ratio and risk provisioning rules (Chen, Ren, and Zha 2018). This flexibility allowed them to invest in high-yield, high-risk sectors like real estate, thereby offering attractive returns to investors.

For years, regulators tolerated these implicit guarantees because WMPs played a vital role in supporting economic growth and alleviating pressure on the formal banking system, notably by facilitating credit access for non-state-owned enterprises (Allen et al. 2023). By the mid-2010s, however, growing concerns over moral hazard began to draw serious attention (Bloomberg News 2017). The belief among investors that they would invariably be bailed out led them to allocate capital to high-yield, high-risk assets without demanding returns commensurate with the underlying risk.

In response to these concerns, Chinese regulators introduced reforms aimed at dismantling the implicit guarantee regime. The Asset Management Rules (*Ziguan Xingui*), issued in April 2018, explicitly prohibited financial institutions from offering or implying guaranteed returns (People's Bank of China (PBOC) et al. 2018).

Although the transition period for full compliance was initially set to conclude in 2020, it was extended to 2021 due to the COVID-19 pandemic (People's Bank of China (PBOC) 2020). Nevertheless, despite these regulatory efforts, implicit guarantees persisted widely in practice. Crucially for this study, until the end of our sample period, The Bank had consistently delivered the promised return on all its WMPs.

To ensure clarity, we offer two clarifications on WMPs in the context of this study.

First, our study focuses exclusively on low-risk WMPs[4], whose underlying assets primarily comprise money market instruments, bonds, and equities. We explicitly exclude high-risk, trust-based WMPs[5] from our analysis for several reasons. Trust products are inherently riskier and subject to more stringent investor eligibility requirements. At The Bank, for example, they are offered exclusively to qualified investors with net assets of at least RMB 5 million and a minimum investment of RMB 1 million. These substantial financial thresholds create a distinct investor base and different client-advisor interaction dynamics compared to those for lower-risk WMPs. Moreover, unlike low-risk WMPs that typically disclose a single expected return, many trust products specify a range of expected returns. This return variability in trust products complicates the systematic identification of misselling, further justifying their exclusion.

Second, we clarify why clients, even assuming implicit guarantees, might not invariably select the highest-yielding WMP. Imperfect information is a necessary condition for moral hazard in principal-agent settings to arise (Holmström 1979; Bolton, Freixas, and Shapiro 2007; Mehran and Stulz 2007; Povel and Strobl 2024). To steer

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[4] Commonly referred to in Chinese as *licaichanpin*, whose direct translation is also Wealth Management Products. High-risk WMPs, or trust products, are named *xintuo* in Chinese.

[5] Trust products are issued by trust companies, typically backed by projects in real estate development, infrastructure, and corporate loans. They were believed to play a prominent role in fueling the rapid growth of China's shadow banking sector and real estate markets (Allen et al., 2023; Bloomberg News, 2019, 2021).

clients towards financial advisors, commercial banks intentionally obfuscate product details or complicate information access, for example, through complex digital interfaces (Célérier and Vallée 2017).[6] Additionally, banks often publicly advertise only a limited selection of WMPs, reserving a wider array of products for discussion and exclusive offering through direct advisor consultations. At The Bank, clients receive product options within categories consistent with their declared risk appetite. Within these risk-matched offerings, the choice set is further constrained by products that are readily available or actively recommended by advisors.

The Bank categorizes its financial products into five risk levels (1–5), and our sample comprises WMPs from risk levels 2 and 3. Risk level 2 products primarily consist of money market instruments and high-grade bonds, whereas risk level 3 products permit limited equity exposure.[7] Within each such risk level, WMPs demonstrate high homogeneity in structure and underlying assets. Since WMPs are riskless in practice, to avoid confusion, we refer to risk level as product type in this study, referring to the types of underlying assets.

Throughout our sample period, The Bank distributed a total of 2,177 distinct Wealth Management Products (WMPs) of risk level 2–3. Excluding those with infinite maturity, these products had maturities ranging from one month to three years (average: 5.6 months). Their expected annual returns varied from 2.29% to 5.40%, with a mean of 4.00%.

Each WMP was available for public sale only during a specified offering period. On any given day during the sample period, an average of 22.26 financial products were available (ranging from 6 to 40). These daily offerings spanned approximately 6.6 distinct product type-maturity categories, from which a client could typically choose

[6] In Chinese WMP markets, crucial product details, such as the precise composition of underlying assets, are frequently opaque or not readily disclosed.
[7] Risk level 1 products are deposit-type products, while trust products are categorized as risk level 4-5.

among 4.52 products within each specific type-maturity group. Note that we constrained the daily "available product set" to products purchased by at least one client, accounting for potential sales caps on high-return products that could render them de facto unavailable.

2.3. Misselling

Misselling refers to instances where a salesperson prioritizes personal gain over the client's best interest (Inderst and Ottaviani 2009). Within the retail financial advisory industry, this occurs when a financial advisor deliberately recommends suboptimal financial products—often to enhance personal sales performance or commission gains—rather than selecting products aligned with a customer's specific needs.

Detecting or proving misselling presents a significant empirical challenge. Because investment returns are inherently risky and ex-ante uncertain, it is difficult to ascertain whether poor outcomes stem from deliberate misselling or merely from an advisor's limited skill.

Two features unique to our setting offer a distinct opportunity to identify misselling with greater precision.

First, the implicit guarantee prevalent in Chinese WMPs effectively mitigates, if not removes, the ex-ante uncertainty typically associated with investment returns. Under such a guarantee, an ethical advisor acting in the client's best interest should consistently recommend the product offering the highest available return for a given product type and maturity. Consequently, the recommendation or sale of a lower-return product, when higher-yielding alternatives with similar characteristics are accessible, constitutes an objectively observable instance of misselling.

Second, a structural conflict of interest inherent in The Bank's operations directly incentivizes advisors to engage in misselling. Specifically, The Bank's internal performance assessment mechanism creates a negative correlation between a financial product's client-guaranteed expected return and the advisors' simulated profits (their key performance metric). This system, therefore, motivates advisors to recommend products that, while offering lower returns to clients, generate higher sales performance and commissions for themselves. The subsequent section further details the construction and implications of this simulated profit metric.

In this paper, we measure misselling by the sale of *low-return products*. These are defined as WMPs offering the lowest expected return to clients among all concurrently available alternatives with an identical product type and maturity on the client's day of purchase.[8]

On average, the expected return guaranteed to clients for these low-return products was 3.96% during our sample period, compared to 4.15% for high-return products (defined as WMPs offering the highest available return for the same product type and maturity).

2.4. Performance assessment and a conflict of interest

This section explains how a conflict of interest is institutionalized within The Bank. Similar to many sales-driven organizations, The Bank mandates a monthly quota for its retail financial advisors, benchmarked against a *simulated profit* target. Because this simulated profit mechanism inherently fosters a conflict of interest, and the pressure to meet quotas directly incentivizes misselling, we now detail The Bank's advisor evaluation process.

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[8] As explained in Section 2.2, "product type" corresponds to The Bank's internal risk level classification; specifically, risk level 2 products primarily involve investments in money market instruments and high-grade bonds, while risk level 3 products may include limited equity exposure. Product maturities in our sample range from one month to three years, or open-ended (infinite).

Financial advisor performance at The Bank is assessed using simulated profit (measured in RMB). This metric has three components, with the largest contribution stemming from the simulated profit generated through new sales of financial products. The Bank calculates and assigns this specific simulated profit value to the responsible advisor for each product sold through the following three-step process:

1. Estimate the *total* expected return of the product: The Bank first assesses product risk to establish an internal, proprietary expected rate of return—its estimate of the product's actual return potential. This figure, designated as the real expected return or total expected return, is inherently risky and not disclosed to clients.
2. Allocate the *total* expected return: Next, The Bank decides how to allocate this estimated total expected return between itself and the client, a division made on a product-by-product basis according to internal policies. Clients are informed only of their allocated portion, which corresponds to the expected (but guaranteed) return specified in the product prospectus.
3. Assign simulated profit to advisor: Finally, The Bank calculates its own expected profit from a financial product sold as the difference between the total expected return and the client's return, multiplied by the purchase amount. The selling advisor is then credited with 70% of this expected profit as simulated profit for new sales. This 70% allocation remained stable during our sample period and is reviewed annually for potential adjustment.

A numerical example helps to clarify this process:

1. Consider *Product A*, where The Bank anticipates a 6% total expected return.
2. The Bank decides to share the return with clients at a 1:2 ratio, meaning clients are informed of a 4% expected (guaranteed) return.
3. Suppose a financial advisor sells RMB 1 million of *Product A*, The Bank's expected profit is 2% of this amount, that is, 20,000 RMB. Of this, 70% (14,000 RMB) is credited to the financial advisor's simulated profit.

In other words, an advisor registers 14,000 RMB in simulated profit for that month by selling 1 million RMB worth of *Product A*. When an advisor sells multiple products, their total simulated profit is the sum of the simulated profits from each product sold.[9]

The Bank's simulated profit system inherently creates a conflict of interest between its financial advisors and their clients. For any given total expected return, a higher client return necessarily reduces the advisor's simulated profit, and vice versa. While advisors should ideally recommend products maximizing client returns, this principle often fails in practice. Advisors may be more likely to missell to meet quotas (thereby securing their job and increasing commissions), pursue promotions, or conform to peer pressure.

The Bank's quota system operates as follows. Financial advisors are categorized into six levels based on experience and performance, and each level has a specific monthly simulated profit quota.[10] Advisors exceeding their quota receive cash bonuses. Missing the quota for one or two consecutive months results in lost bonus eligibility but no formal sanctions. However, missing it for three consecutive months triggers a human resources review, potentially leading to a reassessment of the advisor's position or level.

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[9] In addition to "simulated profit for new product sales," financial advisors earn (1) "simulated profit for Assets Under Management (AUM)", which reflects the interest spread (from financial products and deposits) that existing assets generate for the bank; and (2) "simulated profit for acquiring new clients". However, these two components typically make up only a small portion of an advisor's overall performance evaluation.

[10] The quotas remain relatively stable over time but may be adjusted in response to broader economic conditions or changes in internal policy.

3. Data and variables

3.1. Sample

Our dataset, obtained from The Bank, comprises the full population of 620 financial advisors in Beijing (2019–2020) and a random sample of 19,577 retail clients. Of the sample, 5,518 clients were advised clients, each managed by a single financial advisor. For these clients, all transactions contributed to their assigned advisor's performance metrics. Conversely, transactions by un-advised clients (those without an assigned advisor in The Bank's system) were registered only to the branch's performance account. The 5,518 advised clients were served by 463 distinct financial advisors, representing approximately 75% of The Bank's advisors in Beijing.[11] The client-advisor pairings remained unchanged throughout the sample period. This matched group of advised clients constitutes our main sample for analysis, while the un-advised clients serve as a placebo sample.

The dataset includes three layers: financial advisors, retail clients, and financial products.

For each financial advisor, the dataset provides monthly information on the advisor's level (within six levels), sales quota (i.e., target simulated profits), realized simulated profits, and total value of individual and corporate loans under their management from June 2019 to June 2020. The dataset also contains personal characteristics such as branch affiliation, gender, and time of entry into the financial industry. As shown in Table 1, 30% of the 463 financial advisors in our sample are male, and they have an average of 11.6 years of professional experience.

[11] Appendix Figure A1 shows the geographical distribution of sampled advisors and the population advisors across districts in Beijing.

[Insert Table 1 about here]

For each customer, we obtain her transaction records for deposits and financial products (including WMPs and others), and the daily total value of financial assets held at The Bank from June 2019 to June 2020. The full sample contains 186,944 transaction records. Reported personal information includes the branch and date of account opening, age, gender, and risk appetite[12]. Our main sample of 5,518 clients had an average age of 52.8 years, an average investment duration of 4.4 years, and average daily asset holdings of RMB 0.55 million at The Bank (including WMPs and deposits). Based on self-reported risk appetite, 26.3% were classified as risk-averse. The sample was 44.1% male, with age and risk appetite distributions broadly similar across genders.[13]

For each financial product sold during the sample period, we obtained the corresponding product brochures, which contain detailed information on product type, investment maturity, the expected return disclosed to clients, and other investment rules. The Bank offers a wide range of financial instruments, including term deposits, low-risk WMPs, trusts (high-risk WMPs), securities, securities-in-transit, insurance, and precious metals. Among these, low-risk WMPs and deposits were the most commonly held, with the former accounting for over 60% of clients' AUM and the latter nearly 30%. This study focuses on low-risk WMPs, which are characterized by "implicitly guaranteed" returns.

[12] Client risk appetite is assessed via survey questions and categorized by The Bank into five levels: risk-averse (levels 1–2), risk-neutral (level 3), and risk-loving (levels 4–5).

[13] Appendix Table A1 presents summary statistics for un-advised clients and compares them with advised clients. To ensure comparability, particularly given the non-negligible proportion of inactive un-advised clients, both samples exclude "inactive" client-months, defined as periods where the client made no WMP transactions for three or more consecutive months. T-tests reveal that un-advised clients have similar gender distribution (45% male). However, they are slightly less experienced in investing (4.3 years average), younger (45.6 years old), less risk-averse (19.11% risk averse), and held less wealth (average daily asset holdings: RMB 0.32 million).

3.2. Variables

3.2.1. Misselling

As detailed in Section 2.3, this study measures misselling by the sales of low-return WMPs, defined as WMPs that offer the lowest expected return to clients among all concurrently available products of the same type and maturity on the client's purchase date.

Within the full 19,577-client sample and over the study period, low-return products accounted for 72.9% of total WMP sales (RMB 52.04 billion out of RMB 71.38 billion). This proportion was 74.0% for advised clients (RMB 40.05 billion out of RMB 54.13 billion) and 69.5% for un-advised clients (RMB 11.99 billion out of RMB 17.24 billion). These statistics yield three key insights: (1) The high prevalence of low-return product sales overall strongly suggests a profit-driven sales strategy by The Bank and its advisors. (2) Advised clients' higher propensity to purchase low-return products points to advisor-initiated misselling. (3) The markedly higher transaction volume among advised clients, contrasted with the notable inactivity of many un-advised clients, suggests an endogenous client-advisor relationship where The Bank and its advisors prioritize active clientele.

To investigate whether most low-return products were purchased by a small group of targeted clients, we refine our analysis of misselling to the client level. For each client-month, we construct three variables of misselling: (1) a sales dummy, which equals one if the client made any purchase of low-return products during the month (extensive margin); (2) sales volume, measured as the logarithm of the total transaction amount of low-return products (in RMB) plus one (intensive margin); and (3) sales ratio, calculated as the RMB volume of low-return products divided by the total RMB volume of all WMPs purchased by the client in that month.[14]

Table 1 reveals that misselling is pervasive at the individual client level. Among advised clients, an average of 48% of client-months contained low-return product transactions. When conditioned on actual WMP sales (55.9% of client-months), this proportion is approximately 85.5%. In terms of sales volume, low-return products account for RMB 558 thousand per client-month, representing 74% of the total WMP volume sold (RMB 755 thousand). When averaging the low-return product sales ratio per client-month, the ratio is 36%.[15] All the three measures of misselling are higher among advised clients than un-advised clients (Appendix Table A1).

Conversely, the purchase of high-return products occurs much less frequently. Only 8% of advised client-months involve the transaction of a high-return product, and these transactions constitute only 11.7% of the total WMP sales volume (RMB 88.5 thousand / RMB 754.77 thousand). Among un-advised clients, 13.0% WMPs sold were high-return products (RMB 54.1 thousand / RMB 416.1 thousand).

Comparing the average expected returns (3.96% for low-return products versus 4.15% for high-return products), clients who select low-return products miss out on a potential 0.19% in annual returns per product purchased, or a potential 0.14% in total annual return considering the percentage of low-return product purchased (74% ×

[14] When a client-month dyad has no WMP transactions, we set the low-return product sales ratio to zero. This approach treats a client's non-purchase as an active choice; for instance, if a client declines recommended (low-return) products and consequently chooses not to purchase any WMPs in the month, this client-month is considered a 0% low-return product sales ratio. This conservative approach leads to an underestimation of the low-return product sales ratio in summary statistics. In Appendix, we perform robustness tests using active client-month sample by removing periods when clients were not engaged in any WMP transactions (e.g., their funds were already invested and not yet matured) for three or more consecutive months.

[15] This average sales ratio is lower than the volume-based ratio (74.0%) because we conservatively assign a value of zero to client-months with no WMP transactions (see previous footnote for explanation). In Appendix Table 1, we present the summary statistics of active client-month sample. This refinement increases the proportion of client-months with non-zero WMP sales from 55.9% in the full sample to 83.2%. In this active sample, the average low-return product sales ratio is 54.1%. Mechanically this refinement would not alter the volume-based ratio.

0.19%). For the average client in our sample, this results in an estimated annual loss of roughly RMB 12,730 (RMB 558,360 low-return product purchased per month × 12 months × 0.19% annual loss per product). This represents a significant sum, equivalent to approximately 1.5% of the 2019 annual per capita disposable income for Beijing residents.[16]

3.2.2. Incentives for misselling

To better understand the drivers of misselling, we investigate the specific scenarios where financial advisors face increased incentives to missell.

First, we consider performance pressure, proxied by a dummy variable, *Missed quota*. This indicator equals one if the financial advisor failed to meet his assigned sales quota in the preceding month ($t-1$), and zero otherwise. The *Missed quota* variable thus captures an advisor's underperformance against internal benchmarks, serving as a proxy for the heightened pressure they may feel to increase current-period (t) sales. The details of The Bank's quota system are provided in Section 2.4.

Missing quota is not uncommon: 44.92% of advisors in our sample missed their quota at least once. This suggests that our findings are not driven by a small group of chronically underperforming advisors. On average, 26.10% of financial advisors failed to meet their sales quota in a given month (Table 1).

Second, we examine peer pressure as another incentive for misselling. This analysis leverages a quasi-natural experiment arising from a structural reorganization of The Bank's branch families in November 2019. We hypothesize that advisors whose branches were merged into larger branch family (larger peer groups) experienced intensified peer pressure, leading to an increase in misselling behavior. This

[16] 2019 national per capita disposable income data for Beijing residents is sourced from Beijing Statistical Yearbook, https://nj.tjj.beijing.gov.cn/nj/main/2021-tjnj/zk/indexch.htm [Accessed: 5th May 2025].

institutional change motivates a DiD research design: the treatment group comprises advisors from branches that transitioned into these larger branch families, and the post dummy variable marks the period following the branch family reorganization (November 2019). More details will be further elaborated in Section 4.2.

Third, we investigate a more nuanced, career-based incentive for misselling: promotion prospects. At The Bank, annual promotion opportunities for advanced-level advisors are highly competitive and typically reserved for the top 5% of performers within this group, who then undergo another evaluation period after this candidate list is announced. This institutional feature motivates again a DiD research design: the treatment group comprises these top 5% of candidates for promotion, and the post dummy variable marks the period following the announcement of these candidates (January 2020). More details will be further elaborated in Section 4.3.

3.2.3. Controls

We include all available variables that would affect the financial advisor's efforts to sell. First, we include the logarithm of the advisor's monthly bonuses (plus one) in the previous month to capture the monetary incentive to perform.[17] Second, we include the logarithm of the amount of individual loans and corporate loans that are supervised by financial advisors[18]. In The Bank, financial advisors also assist clients in obtaining loans, but loan assignments are distributed by bank branch managers. While financial advisors may face little performance pressure in loan services, it may influence their working efforts since it impacts their bonus.

[17] The monthly bonus is awarded as compensation for financial product sales exceeding the quota and is calculated as a proportion of the excess simulated profit.

[18] Precisely, we calculate the average daily stock amount of individual loans and corporate loans within a month.

4. Advisor incentives and misselling

Summary statistics indicate that a significant portion (74%) of WMP sales involve low-return products, suggesting evidence of potential misselling. However, this observation could have alternative interpretations than advisor-led misselling. For example, clients, even advised ones, might bypass direct advisor consultation when transacting (Bhattacharya et al. 2012). Additionally, low-return products are more actively marketed, while higher-return products are sometimes subject to sales caps or rush purchase policies, making lower-return products more consistently accessible. To isolate the contribution of advisors, this section investigates specific situations where advisors have clear incentives to missell.

4.1. Quota pressure

First, we conjecture that advisors are incentivized to missell when under pressure to meet their sales quota. At The Bank, financial advisors are mandated to meet a monthly sales quota; missing this quota incurs penalties related to both career prospects and bonuses. Failing to achieve this quota in the previous month (*t−1*) thus creates a strong and direct incentive for advisors to use misselling tactics in the subsequent period (*t*) to restore performance expectations.

We investigate this hypothesis with the following regression model:

$$\begin{aligned} \textit{Sales of low-return WMPs}_{i,j,t} = {} & \alpha + \beta \times \textit{Missed quota}_{i,t-1} + \gamma_1 \times \boldsymbol{X}_{i,t-1} + \\ & \textit{client-advisor}_{i,j} + \textit{year-month}_t + \varepsilon_{i,j,t} \end{aligned} \tag{1}$$

where i represents the financial advisor, j represents the client, and t represents the month. Each client is served by only one advisor, and client-advisor pairings remain constant throughout the sample period. The dependent variable measures sales of low-return WMPs by advisor i to client j in month t, captured by (1) a dummy variable indicating whether the client purchased any low-return WMP (extensive margin), (2) the logarithm of low-return WMP sales volume plus one (intensive margin), and (3) the sales ratio, defined as the volume of low-return products sold divided by the total volume of WMPs sold. The key explanatory variable is quota pressure, captured by the *Missed quota* dummy, which equals one if the advisor failed to meet their sales quota in the previous month. ***X*** represents a vector of control variables, including the bonus of the financial advisor in the previous month (log plus one), the amount of client loans under his supervision (log plus one), and the corporate loans under his supervision (log plus one). In the regression, client-advisor fixed effects and year-month fixed effects are included. The standard errors are clustered at the financial client-advisor level. The sample contains 5,518 clients corresponding to 463 financial advisors, with a sample interval of June 2019 to June 2020.

[Insert Table 2 about here]

Table 2 presents the baseline regression results. Columns 1-3 examine the effect of performance pressure on misselling. The effects of *Missed quota* are positive and statistically significant on all three measures of misselling. In column 1, the coefficient of 0.027 on the sales dummy indicates that advisors who missed their sales quota in the previous month have a 2.7 percentage point higher probability of selling a low-return WMP in the current month. This effect represents a 5.6% increase relative to the sample mean of the low-return product sales dummy (0.48). Furthermore, advisors who missed their prior month's quota sell 30.7% more low-return WMPs by volume (column 2). This could be translated into an additional RMB 171.4 thousand in sales of low-return WMPs per client-month by advisors under performance pressure. Regarding the sales ratio (column 3), advisors under performance pressure sell 2.7 percentage points more low-return WMPs to each client, representing a 7.5% increase relative to the mean sales ratio.

Columns 4-6 of Table 2 present results from placebo tests using the sales of high-return WMPs as the dependent variable. In these regressions, the coefficients on *Missed quota* are statistically insignificant and economically small. This finding supports the interpretation that quota pressure specifically drives misselling to boost performance, rather than increasing overall sales efforts across all product types.

For robustness, Appendix Table A2 reports results using an active client sample. This sample differentiates from the main analysis by excluding client-months in which no WMP transactions occurred for three or more consecutive months (e.g., due to funds being invested and not yet matured). The results confirm the robustness of our main findings, with larger estimated magnitudes within this active client sample.

As a placebo test, Appendix Table A3 replicates Table 2 using active un-advised clients. The hypothesis is that advisors would not target these clients for misselling, as their transactions would not contribute to the advisor's performance metrics. We construct a hypothetical *Missed quota* variable for each client-month, defined as the average *Missed quota* for the branch where the client opened their account. The results confirm no significant variation in the purchase of low-return products among un-advised clients.

Appendix Table A4 investigates whether quota pressure effectively boosts advisor performance, measured by the growth in completion rate (the month-over-month change in the ratio of simulated profits to the sales quota). The results indicate that advisors who missed their quota in the previous month achieve significantly greater growth in their completion rates in the current month. Specifically, advisors who underperformed in the prior month increased their completion rate by 0.41 (column 1), or 41% of their target. This effect is substantial, particularly given that the average growth in completion rate is close to zero.

Overall, the findings suggest that underperforming financial advisors tend to promote low-return products to meet their sales quota, even at the expense of client profits. The fact that clients purchase more low-return products recommended by pressured advisors provides clear evidence of advisor-driven misselling.

4.2. Peer pressure

This section investigates another less direct source of performance pressure: peer effects. While not a formal, enforced performance target, peer dynamics are relevant for understanding working behavior, e.g., sales efforts and tactics. DeMarzo and Kaniel (2023) argue that strong peer effects, for example wage comparisons, significantly influence employee utility and effort; sufficiently strong peer effects can even undo performance benchmarking. We extend the literature by examining whether, when banks leverage peer competition to motivate advisors, advisors exhibit misselling to increase sales performance.

Within The Bank, peer effects are institutionalized through the periodic dissemination of advisor performance rankings designed to foster internal competition. Directly measuring peer pressure is inherently challenging; therefore, we use peer group size as a proxy. The underlying intuition is that larger peer groups amplify competition for top rankings and associated rewards, potentially intensifying the pressure to outperform. Conversely, smaller groups might foster stronger social ties and mutual support, potentially mitigating such competitive pressures.

To establish a causal link between peer group size and misselling, we exploit an exogenous shock to The Bank's peer group composition. The Bank's organizational structure is hierarchical, encompassing levels such as branch, branch family, city, city family, province, and national, each managed by a designated leader. In June 2019, the 63 branches in our sample were organized into six branch families in Beijing. To optimize communication and oversight, branch family memberships are periodically reconfigured. Since performance rankings are disseminated across all organizational tiers, these reconfigurations alter an advisor's relevant peer comparison group. Notably, an advisor reassigned from a smaller to a larger branch family experiences an increased number of direct peers, which could heighten competitive pressure even if overall performance standards remain constant.

A significant such branch family rotation occurred in November 2019. During this event, 44 of the 63 branches in our sample were reassigned to larger branch families, 12 were moved to smaller families, and 7 experienced no change in family size. We leverage this organizational reshuffling as a quasi-natural experiment and implement a DiD strategy to identify the causal effect of an increased peer group size on misselling. The treatment group comprises financial advisors from the 44 branches that transitioned into larger branch families. The control group consists of advisors from the remaining 19 branches (those moving to smaller families or experiencing no change). To distinguish the effect of peer pressure from that of direct performance targets, the model includes *Missed quota* as a control variable. Our estimation employs the following DiD specification:

$$\begin{aligned} \textit{Sales of low-return WMPs}_{i,j,t} = {} & \alpha + \beta \times \textit{Enlarged Group}_i \times \textit{Post-Nov2019}_t + \\ & \gamma_1 \times \textit{Missed quota}_{i,t-1} + \gamma_2 \times \boldsymbol{X}_{i,t-1} + \textit{client-advisor}_{i,j} + \textit{year-month}_t + \varepsilon_{i,j,t} \end{aligned} \quad (2)$$

[Insert Table 3 about here]

As shown in Table 3, the coefficients on the DiD interaction term are positive and statistically significant across misselling outcomes. For financial advisors in the treated group, the propensity to sell low-return products increased significantly post-reorganization. For instance, the volume of low-return products sold per client-month rose by 74.9% (column 2), consistent with the hypothesis that heightened peer pressure incentivizes misselling. This effect is economically substantial: it translates to an increase in monthly low-return product sales of approximately RMB 418.2 thousand per client (74.9% × RMB 558.36 thousand).

[Insert Figure 1 about here]

Figure 1 illustrates the parallel trends assumption by presenting the coefficients for dynamic DiD estimations, which show how the difference in sales dummy (Panel A), sales volume (Panel B) and sales ratio (Panel C) of low-return products between advisors from the treated and control groups changes over time. The results demonstrate clear trends, with financial advisors from the 44 branches exhibiting significantly higher performance and more misselling behavior after their branches were merged into larger branch families in November 2019.

Appendix Table A5 presents a placebo test using the un-advised client sample. The results demonstrate that un-advised clients did not alter their purchase behavior, even when advisors in their local branch faced heightened peer pressure. Unlike the more attenuated placebo test in Appendix Table A3, which relied on hypothetical quota pressure measures, the peer pressure changes in this test directly impacted all advisors within affected branches. This approach minimizes measurement error associated with hypothetical constructs, thereby providing strong placebo evidence confirming that advisors only missell to relevant (advised) clients for performance enhancement.

4.3. Promotion prospects

Prior analysis demonstrated that performance pressures from different sources are associated with increased misselling. This section investigates whether a more nuanced incentive—promotion prospects—similarly contributes to misselling, even without immediate penalties tied to explicit performance targets.

To identify the causal effects of promotion prospects on misselling, we exploit an institutional arrangement within The Bank's promotion system. Financial advisors at The Bank are categorized into two primary ranks: a starter level (with three sub-levels) and an advanced level (also with three sub-levels). Advancement within the starter level is typically non-competitive, based mainly on tenure and adherence to conduct standards, usually resulting in quasi-automatic promotion. In contrast, promotions within the advanced level are highly competitive. Eligibility for promotion consideration in a given year is restricted to the top 5% of advanced-level advisors, determined by their prior-year performance. Final promotion decisions further incorporate both new performance records and peer evaluations conducted during the first half of the current year. Ultimately, a small proportion (approximately 5%-20%) of the candidates could be promoted to the next level.

During our sample period, The Bank announced its list of advanced-level advisors eligible for promotion consideration—the aforementioned top 5% of performers—in January 2020. Following this announcement, these candidates entered a formal competitive evaluation period, thereby experiencing increased promotion-related pressure from that point onward.

Leveraging this institutional arrangement, Table 4 presents DiD estimates gauging the effect of promotion pressure on misselling. The treatment group comprises the top 5% of advanced-level advisors selected as promotion candidates, while a post dummy variable equals one for periods in and after January 2020. To distinguish the effect of promotion pressure from that of direct performance targets, the model includes *Missed quota* as a control variable. The regression model is specified as follows:

$$\begin{aligned} &\textit{Sales of low-return WMPs}_{i,j,t} = \alpha + \beta \times \textit{Top 5\%}_i \times \textit{Post-Jan2020}_t + \\ &\gamma_1 \times \textit{Missed quota}_{i,t-1} + \gamma_2 \times \boldsymbol{X}_{i,t-1} + \textit{client-advisor}_{i,j} + \textit{year-month}_t + \varepsilon_{i,j,t} \end{aligned} \tag{3}$$

[Insert Table 4 about here]

Table 4 provides mixed evidence on misselling by advanced-level advisors nominated for promotion. After the nomination, their clients become more likely to purchase low-return products and to do so in larger amounts. Yet the coefficient on the ratio of low-return-product volume to total WMP sales remains statistically insignificant. Because this sales ratio measure is conservatively defined—in particular downward-biased—we cannot draw a firm conclusion. On balance, the results imply that promotion prospects are a weaker driver of misselling than either quota pressure or peer effects.

As a placebo test to strengthen causal interpretation, we use starter-level advisors, who are not subject to competitive promotion and therefore lack this specific incentive to missell. As shown in Appendix Table A6, the top 5% performers among starter-level advisors (based on total simulated profits in 2019) did not exhibit a similar increase in any misselling after January 2020.

These findings offer tentative evidence that misselling can arise under multiple incentive schemes. While strict performance targets clearly create pressure, less direct incentives (promotion prospects) may nudge some advisors toward recommending low-return products. Although the promotion effect is weaker and mixed in statistical significance, the pattern cautions that both explicit and implicit reward structures can, in certain cases, distort advisor behavior to the detriment of clients.

4.4. Client complaints as a moderator

Customer complaints can serve as a deterrent to misconduct and unethical behavior, as they are a key indicator of branch performance for the bank headquarters. Upon receiving a customer complaint, performance appraisal points may be deducted from the financial advisor and their branch, affecting the performance-based compensation of all branch staff. To test whether sales complaints restrain misselling, we utilize records on customer complaints about WMPs (product and services)[19] at each branch[20] and conduct a regression analysis based on Equation (1), including interaction terms between *Missed quota* and a *Complaint* dummy variable.

[19] Complaints about WMPs encompass product-related complaints (such as disappointing returns, difficulty in redeeming funds, etc) and service-related complaints (such as delays of errors in processing transactions, inadequate customer service when addressing queries, etc).

[20] Unfortunately, customer complaints at the individual level were not available in our study. However, if a branch receives a complaint, the branch family or city manager is likely to pay closer attention to the

[Insert Table 5 about here]

Table 5 shows that customer complaints sharply weaken the quota-pressure effects on misselling. In column 1, the interaction term *Missed quota* × *Complaint (all)* is negative and significant, indicating that when a branch receives a complaint, advisors who failed to meet the previous month's quota sell 0.019 (0.028 − 0.047) fewer low-return products (as a ratio of total sales of WMPs) than they otherwise would.[21] Column 3 demonstrates that service-related complaints generate the strongest corrective effect (−0.065). This suggests clients' direct feedback on advisory conduct creates immediate behavioral constraints.

5. Targets of misselling: client-advisor match

Financial advisors may strategically target specific client groups for misselling. For example, extant research has shown that advisors tend to exploit less financially sophisticated clients (Egan, Matvos, and Seru 2019).[22] Motivated by this stream of literature, the current section investigates the client characteristics associated with an increased likelihood of purchasing low-return products, thereby identifying potential targets of such practices. Furthermore, we explore advisor-specific attributes correlated with a greater propensity to missell.

branch and take steps to rectify any irregularities.

[21] The positive and significant coefficient on *Complaints* indicates endogeneity between complaints and misselling, as branches with more misselling are expected to receive more complaints.

[22] On the other hand, other research has shown that financial literacy significantly influences clients' engagement with and reliance on financial advice (e.g., Calcagno and Monticone 2015; Reuter and Schoar 2024; Egan, Matvos, and Seru 2024).

5.1. Experience

First, we assess whether a client's investment experience tempers misselling exposure, using the length of time they have held an account with The Bank as a proxy. Clients who have maintained an account for longer periods are likely to be more financially literate as they have more experience in WMPs transactions. Sustained exposure to statements, product disclosures, and market news should sharpen their ability to judge WMP quality. If this is true, seasoned investors ought to be less willing to accept low-return products pushed by their advisors and therefore less likely to appear in the mis-sold pool.[23]

Table 1 shows that client account tenure in our sample ranges from 0 to 212 months (0 to 17.7 years). Using the top quantile as a cutoff, we classify clients with over 83 months (6.9 years) of account tenure as experienced and those with less as novice. Panel A of Appendix Table A7 presents summary statistics on WMPs sales by experienced and novice clients.

[Insert Table 6 about here]

Table 6, Panel A, formally examines the role of client investment experience by introducing an interaction term between *Missed quota* and the *Experienced client* dummy variable in Equation (1). The results indicate that when an advisor has missed their quota in the previous period, their experienced clients purchase significantly fewer

[23] We acknowledge that this measure, while the best indicator available in our dataset, is imperfect as it could capture not only clients' financial literacy but also the duration of their relationship with their advisor. Prior research has shown that advisor-client relationships can influence advisor behavior. For instance, Gurun, Stoffman, and Yonker (2021) find that when firms adopt policies allowing advisors to take clients with them to new employers, thereby weakening firm-level disciplinary power, the incidence of advisor misconduct rises. This suggests that stronger advisor-client ties may reduce firm oversight. The effect of relationship duration on misselling is therefore theoretically ambiguous: while long-term relationships may encourage advisors to preserve trust and avoid exploitation, they may also enable advisors to take advantage of clients' loyalty or inattention.

low-return products compared to novice clients served by the same advisor. This finding suggests that investment experience indeed equips clients to better mitigate the risk of being targeted for misselling, even when their advisors face heightened incentives to do so.

Parallel to analyzing client experience, we examine the role of financial advisors' working experience, proxied by their tenure in the finance profession. Advisor tenure in our sample ranges from 22 to 475 months (approximately 1.8 to 39.6 years). Based on the top quantile cutoff, we classify advisors with over 140 months (11.7 years) of tenure as experienced and those with less as novice. Panel B of Appendix Table A7 presents descriptive statistics comparing WMP sales by these advisor experience categories.

The impact of advisor experience on misselling behavior is hypothetically ambiguous. On one hand, more seasoned advisors might possess greater skill in deploying sophisticated sales tactics and a deeper understanding of product structures, potentially enabling more effective misselling. Conversely, experienced advisors may also have stronger incentives to preserve long-term client relationships and their professional reputation, making them more circumspect and less prone to opportunistic sales behaviors. Our empirical results (Panel B, Table 6) indicate that experienced advisors, while generally selling more low-return products, do not exhibit significantly different misselling responses to performance pressure compared to their novice counterparts.

To further explore the interplay of client and advisor experience, Table 7 presents a subsample analysis based on four distinct advisor-client experience dyads: (1) experienced advisor–experienced client, (2) novice advisor–experienced client, (3) experienced advisor–novice client, and (4) novice advisor–novice client. This segmentation allows for an investigation into how the combined experience levels of both parties influence misselling propensity.

[Insert Table 7 about here]

The results in Table 7 reveal that the adverse impact of advisor performance pressure on misselling intensity is most pronounced within novice client-advisor dyads. For the experienced advisor–novice client subgroup, the estimated coefficient for performance pressure (column 5) is more than double the magnitude observed in the baseline model (column 3, Table 2). This suggests that clients with lower financial literacy exhibit a significantly heightened susceptibility to opportunistic behavior, particularly when interacting with experienced advisors. Furthermore, experienced clients purchased fewer low-return WMPs when advised by novice advisors, which further underscores the importance of client financial literacy.

Collectively, the above findings provide robust evidence highlighting the critical role of client investment experience (or financial literacy) in mitigating susceptibility to misselling. In contrast, the influence of advisor experience appears more nuanced.

5.2. Client wealth

Next, we investigate whether financial advisors disproportionately target wealthier clients for misselling. The hypothesis is ambiguous: while advisors may prioritize relationships with high-net-worth clients for larger transactions and referrals, these clients might scrutinize low-risk WMPs less given the complexity of managing their larger, diversified portfolios, leading them to dedicate less attention to individual low-risk components. Furthermore, successfully selling a large volume of low-return products to one high-net-worth client can be more effort-efficient than making similar sales to multiple low-net-worth clients. This is consistent with the misconduct model proposed by Thanassoulis (2023), who shows that firms tend to extract higher margins from high-valuation customers while competing on price in more commoditized, massmarket segments. Empirically, Hoechle et al. (2018) further show that wealthier clients are targeted by advisors selling high-profit margin products.

We examine the role of client wealth in misselling by including interaction terms between *Wealthy client* dummies and *Missed quota* in Equation (1). Adhering to regulatory classifications within China's banking sector, clients are categorized by wealth: 68% are regular clients, 31% are premium clients (average daily balance exceeding RMB 500,000 in a given month), and 1% are private banking clients (average daily balance surpassing RMB 6 million). Appendix Table A8 provides descriptive statistics on WMPs transactions across these client wealth tiers.

The results (Table 8) indicate that only private banking clients are disproportionately targeted for misselling when advisors face performance pressure. This suggests that while advisors may try to preserve relationships with premium clients, they might exploit private banking clients, who are typically least involved in scrutinizing lower-return, guaranteed financial products.

[Insert Table 8 about here]

5.3. Gender

The influence of client and advisor gender on misselling behavior presents another avenue for investigation. Existing literature on gender differences in financial decision-making offers conflicting predictions regarding both client susceptibility and advisor propensity for misselling.

From the client perspective, recent research documents that female clients may face discrimination from financial advisors due to perceived lower financial literacy (Bucher-Koenen et al. 2023; Bhattacharya et al. 2024). However, findings on women's investment behavior are inconclusive. While some studies indicate women often exhibit greater caution in investment decisions (Byder, Agudelo, and Arango 2019), others suggest they might be more prone to certain irrational purchasing behaviors (Coley and

Burgess 2003). Conversely, although men tend to display higher overconfidence (a potential irrationality), Kramer (2016) notes that highly self-confident individuals (often men) are less inclined to seek financial advice, which could paradoxically increase their misselling vulnerability when they do interact with advisors.

On the advisor side, Egan, Matvos, and Seru (2022) document a gender punishment gap in the financial advisory industry, where female advisors are more likely to lose their jobs following misconduct. This could heighten the perceived risks of misselling for female advisors. In addition, gender differences in responses to stress are well-documented but inconclusive. For example, men are often more motivated to improve performance under pressure (Niederle and Vesterlund 2011), yet they also exhibit higher levels of overconfidence (Barber and Odean 2001), which may dampen the effects of performance pressure.

Descriptive statistics on WMPs sales, disaggregated by client and advisor gender, are presented in Appendix Table A9.

[Insert Table 9 about here]

[Insert Table 10 about here]

Table 9 formally investigates gender's moderating influence on misselling by interacting *Missed quota* with gender indicators (client gender in Panel A; advisor gender in Panel B). Table 10 further examines these gender dynamics through subsample analyses of four advisor-client gender pairings. The results reveal that male advisors show less misselling behavior under performance pressure. In addition, misselling by advisors under performance pressure is concentrated solely in female-advisor / male-client dyads. In other words, pressured female advisors significantly increase low-return product sales to their male clients, whereas other gender pairings show no statistically significant link between advisor performance pressure and misselling.

This concentrated effect within the female advisor–male client group is intriguing. It may suggest a complex interplay of factors. For instance, female advisors under pressure might perceive male clients as more receptive to certain sales tactics or less likely to scrutinize recommendations for lower-return WMPs, especially if these clients exhibit overconfidence or delegate investment decisions more readily. Alternatively, it could reflect specific communication styles or negotiation dynamics unique to this gender pairing under stressful conditions.

6. Conclusion

This paper depicts misselling in financial advice within the unique institutional context of China's wealth management product (WMP) market. Leveraging a granular dataset from a large retail bank, we provide compelling evidence that conflicts of interest induce financial advisors to sell low-return products—those offering lower returns to clients but generating higher simulated profits for advisors. The implicit guarantees in WMPs, which theoretically should simplify optimal client choice, paradoxically create a setting where deliberate misselling can be identified more clearly, distinct from issues of advisor ability. This study thus advances the financial advice literature by demonstrating a method to clearly distinguish deliberate misselling from limited advisor skill.

Summary statistics reveal that 74% of WMPs sold were low-return products. To isolate the proactive role of financial advisors, we examine specific scenarios that incentivize misselling: quota pressure, peer pressure, and promotion prospects. Our results indicate these incentives significantly increase advisors' engagement in misselling. Conversely, client complaints effectively curb misselling tendencies.

We also investigate which client characteristics are associated with a higher susceptibility to being missold, and which advisor attributes correlate with a greater tendency to missell. Specifically, we find that less experienced (less financially literate) clients are particularly vulnerable. In addition, private banking clients also appear disproportionately targeted, potentially due to lower scrutiny of these guaranteed products. Furthermore, gender dynamics reveal that performance pressure most significantly increases misselling by female advisors serving male clients.

This study provides robust evidence suggesting that poor outcomes associated with advice from financial advisors stem, at least partially, from their unethical intentions rather than merely limited investment skill. Our findings carry important implications for regulators, financial institutions, and investors. For regulators, there is a clear need for enhanced oversight of sales practices, a re-evaluation of incentive structures that might inadvertently promote misselling, and initiatives to bolster investor financial literacy. Financial institutions should consider the long-term reputational damage and erosion of client trust stemming from such practices and implement more robust internal controls and ethical training. For investors, this research underscores the importance of vigilance, seeking independent information, and understanding potential biases that can influence financial advice.

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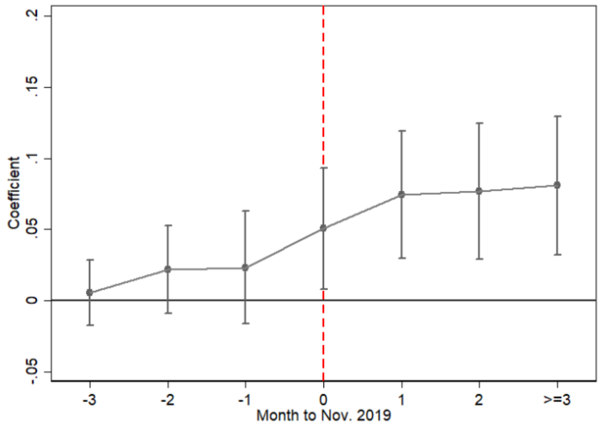
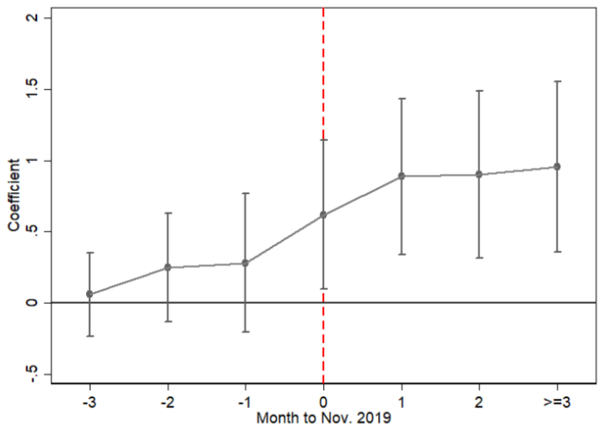
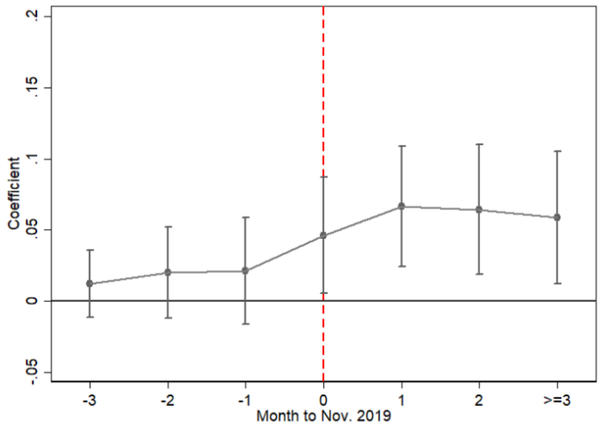
Figures and Tables



Panel A. *Sales dummy of low-return WMPs*



Panel B. *Sales volume of low-return WMPs*



Panel C. *Sales ratio of low-return WMPs*

Figure 1. Peer pressure and misselling: parallel trends.
This figure illustrates the parallel trends assumption for the DiD analysis examining the effect of peer pressure—proxied by exogenous changes in peer group size—on misselling behavior. The estimation follows Equation (2), replacing the *Post-Nov 2019* dummy with a set of month-specific dummies. November 2019, the event month, is set to be year 0. Years <= -3 are omitted as reference group. Panel A plots the coefficients for the sales dummy of low-return products; Panel B shows the results for the log of sales volume of low-return products; Panel C shows the results for the sales ratio of low-return products.

Table 1. Summary Statistics

	N	Mean	Std. Dev.	Min	p50	Max
Advisor-Month						
Missed quota	6015	0.26	0.44	0	0	1
Quota (in 1,000 RMB)	6015	763.60	668.90	0	780.00	2210.00
Simulated profits (in 1,000 RMB)	6015	854.82	1028.56	0	630.29	10225.14
Monthly bonus (in 1,000 RMB)	6015	3.03	3.65	0	2.24	33.40
Client loan (in 1,000 RMB)	6015	9867.66	25654.94	0	87.00	397830.84
Firm loan (in 1,000,000 RMB)	6015	28.28	129.45	0	0	1851.10
Advisor experience (month)	6015	139.65	68.27	22	126	475
Advisor gender (is male)	6015	0.30	0.46	0	0	1
Client-Advisor-Month						
Missed quota	71722	0.14	0.35	0	0	1
Sales volume – all WMPs (in 1,000 RMB)	71722	754.77	3765.35	0	77.00	228064.98
Sales dummy – all WMPs	71722	0.56	0.50	0	1	1
Sales dummy – low-return WMPs	71722	0.48	0.50	0	0	1
Sales volume – low-return WMPs (in 1,000 RMB)	71722	558.36	3530.04	0	0	227564.98
Sales ratio – low-return WMPs	71722	0.36	0.42	0	0	1
Sales dummy – high-return WMPs	71722	0.20	0.40	0	0	1
Sales volume – high-return WMPs (in 1,000 RMB)	71722	88.50	453.62	0	0	12980.00
Sales ratio – high-return WMPs	71722	0.08	0.22	0	0	1
Client complaints – all	71722	0.03	0.16	0	0	1
Client complaints – product	71722	0.02	0.15	0	0	1
Client complaints – service	71722	0.02	0.14	0	0	1
Client experience (month)	71722	52.91	36.67	0	54	212
Client risk appetite (1−5)	70240	3.01	0.77	1	3	5
Client wealth (in 1,000 RMB, daily average)	71722	552.67	1096.50	0	213.41	27819.52
Client age	71722	52.79	14.81	18	54	95
Client gender (is male)	70682	0.44	0.50	0	0	1

Table 2. Quota pressure and misselling

This table examines the effect of quota pressure on misselling at the client-advisor-month level, using data from 5,518 clients matched to 463 financial advisors between June 2019 and June 2020. Each client is served by a single advisor, and no client-advisor pairings change during the sample period. Columns 1–3 report results for misselling, measured by the sales of low-return WMPs (i.e., those offering the lowest expected return within each product type-maturity category). Three sales measures are constructed as dependent variables: (1) *sales dummy*, equal to one if any sales of low-return WMPs occurred during the month; (2) *sales volume*, defined as the log of total volume (in RMB) of low-return WMPs sold plus one; and (3) *sales ratio*, defined as the volume of low-return WMPs sold divided by the total volume of WMPs sold. Columns 4–6 focus on the sales of high-return WMPs (i.e., those offering the highest return within each product type-maturity category), serving as placebo tests. The key independent variable, *Missed quota*, is a binary indicator equal to one if the advisor failed to meet their sales target in the previous month. All regressions include the following control variables: lagged advisor compensation (log+1), lagged size of retail client loans (log+1), and lagged size of corporate loans (log+1) under the advisor's account. Client-advisor fixed effects and year-month fixed effects are included. Standard errors are clustered at the client level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Misselling: Low-return WMPs			Placebo: High-return WMPs		
	Sales dummy	Sales volume	Sales ratio	Sales dummy	Sales volume	Sales ratio
	1	2	3	4	5	6
Missed quota	0.027***	0.307***	0.027***	-0.008	-0.117	-0.005
	(0.008)	(0.101)	(0.008)	(0.006)	(0.072)	(0.003)
Advisor compensation	-0.002	-0.026	-0.001	-0.002	-0.022	0.001
	(0.002)	(0.023)	(0.002)	(0.002)	(0.021)	(0.001)
Client loan	-0.002	-0.015	-0.003*	0.001	0.017	-0.001
	(0.002)	(0.022)	(0.002)	(0.001)	(0.018)	(0.001)
Firm loan	0.003**	0.037**	0.003**	0.000	0.004	0.000
	(0.002)	(0.019)	(0.001)	(0.001)	(0.015)	(0.001)
Client-advisor FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-month FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	66,198	66,198	66,198	66,198	66,198	66,198
Adjusted R-squared	0.760	0.786	0.724	0.750	0.760	0.684

Table 3. Peer pressure and misselling

This table presents a DiD analysis leveraging an exogenous shock to peer group size within The Bank. In November 2019, a significant reorganization of branch families took place: 44 of the 63 branches in our sample were merged into larger families, 12 into smaller families, and 7 remained unchanged. The treatment variable, *Enlarged Group*, is a binary indicator equal to one for financial advisors in the 44 branches that merged into larger branch families, and zero otherwise. The *Post-Nov2019* dummy equals one for observations from November 2019 onward, and zero otherwise. The regressions are estimated at the client-advisor-month level, covering 5,518 clients matched to 463 advisors from June 2019 to June 2020. In columns 1–3, the dependent variables are measures of the sales of low-return WMPs, including: (1) *sales dummy*, equal to one if any sales of low-return WMPs occurred during the month; (2) *sales volume*, defined as the log of total volume (in RMB) of low-return WMPs sold plus one; and (3) *sales ratio*, defined as the volume of low-return WMPs sold divided by the total volume of WMPs sold. In columns 4–6, the dependent variables are measures of the sales of high-return WMPs, which serve as placebo tests. All regressions include *Missed quota*, as well as control variables identical to those in Table 2. Client-advisor and year-month fixed effects are included. Standard errors are clustered at the client level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Misselling: Low-return WMPs			Placebo: High-return WMPs		
	Sales dummy	Sales volume	Sales ratio	Sales dummy	Sales volume	Sales ratio
	1	2	3	4	5	6
Enlarged group × Post-Nov2019	0.063***	0.749***	0.045**	-0.004	-0.093	-0.016
	(0.021)	(0.251)	(0.019)	(0.020)	(0.252)	(0.013)
Missed quota	0.027***	0.302***	0.027***	-0.008	-0.116	-0.005
	(0.008)	(0.101)	(0.008)	(0.006)	(0.071)	(0.003)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Client-advisor FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-month FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	66,198	66,198	66,198	66,198	66,198	66,198
Adjusted R-squared	0.761	0.786	0.724	0.750	0.760	0.684

Table 4. Promotion prospects and misselling

This table examines the effect of promotion incentives on misselling, employing a DiD method. The regressions use the sample of advanced-level advisors, where the treatment group comprises the top 5% of advanced-level advisors selected for promotion consideration, and the post-treatment period begins in January 2020. In columns 1–3, the dependent variables are measures of the sales of low-return WMPs, including: (1) *sales dummy*, equal to one if any sales of low-return WMPs occurred during the month; (2) *sales volume*, defined as the log of total volume (in RMB) of low-return WMPs sold plus one; and (3) *sales ratio*, defined as the volume of low-return WMPs sold divided by the total volume of WMPs sold. In columns 4–6, the dependent variables are measures of the sales of high-return WMPs, which serve as placebo tests. All regressions include *Missed quota*, as well as control variables identical to those in Table 2. Client-advisor and year-month fixed effects are included. Standard errors are clustered at the client level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Misselling: Low-return WMPs			Placebo: High-return WMPs		
	Sales dummy	Sales volume	Sales ratio	Sales dummy	Sales volume	Sales ratio
	1	2	3	4	5	6
Top 5%×Post Jan-2020	0.034**	0.380**	0.018	-0.010	-0.133	-0.011
	(0.014)	(0.173)	(0.013)	(0.012)	(0.140)	(0.007)
Missed quota	0.039***	0.438***	0.043***	-0.012*	-0.157*	-0.007*
	(0.010)	(0.126)	(0.009)	(0.007)	(0.083)	(0.004)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Client-advisor FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-month FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	43,680	43,680	43,680	43,680	43,680	43,680
Adjusted R-squared	0.761	0.786	0.726	0.745	0.756	0.687

Table 5. Client complaints

This table examines how client complaints moderate the effects of quota pressure on misselling. Columns 1 and 2 focus on all complaints, with the *Complaint (all)* indicator equals one if the advisor's branch received any client complaints (regarding WMPs products or service) in the month. Columns 3 and 4 focus on complaints regarding advisor services. Columns 5 and 6 focus on complaints regarding products. In columns 1, 3 and 5, the dependent variable is the sales ratio of low-return WMPs, defined as the volume of low-return WMPs sold divided by the total volume of WMPs sold in a given client-month. In columns 2, 4 and 6, the dependent variable is the sales ratio of high-return WMPs, which serve as placebo tests. The key independent variable is *Missed quota*, a binary indicator equal to one if advisor *i* failed to meet their sales target in month *t−1*. All regressions include control variables identical to those in Table 2. Client-advisor and year-month fixed effects are included. Standard errors are clustered at the client level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	All complaints		Complaints regarding services		Complaints regarding products	
	Low. WMPs Sales ratio	High. WMPs Sales ratio	Low. WMPs Sales ratio	High. WMPs Sales ratio	Low. WMPs Sales ratio	High. WMPs Sales ratio
	1	2	3	4	5	6
Missed quota	0.028***	-0.005	0.028***	-0.005	0.028***	-0.005
	(0.008)	(0.003)	(0.008)	(0.003)	(0.008)	(0.003)
Missed quota×Complaint (all)	-0.047**	0.004				
	(0.023)	(0.010)				
Complaint (all)	0.027***	-0.008				
	(0.009)	(0.006)				
Missed quota×Complaint (service)			-0.065**	-0.002		
			(0.028)	(0.012)		
Complaint (service)			0.044***	-0.002		
			(0.013)	(0.008)		
Missed quota×Complaint (product)					-0.046*	0.003
					(0.024)	(0.011)
Complaint (product)					0.022**	-0.008
					(0.009)	(0.006)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Client-advisor FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-month FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	66,198	66,198	66,198	66,198	66,198	66,198
Adjusted R-squared	0.724	0.684	0.724	0.684	0.724	0.684

Table 6. Experience

This table examines how the impact of quota pressure on misselling varies with client investment experience (Panel A) and advisor working experience (Panel B). In Panel A, a client is classified as *experienced* if they have held an account at The Bank for more than 83 months (6.9 years). In Panel B, an advisor is classified as *experienced* if they have worked in the financial industry for more than 140 months (11.7 years). In columns 1 of both panels, the dependent variable is the sales ratio of low-return WMPs, defined as the volume of low-return WMPs sold divided by the total volume of WMPs sold in a given client-month. In columns 2 of both panels, the dependent variable is the sales ratio of high-return WMPs, which serve as placebo tests. The key independent variable is *Missed quota*, a binary indicator equal to one if advisor i failed to meet their sales target in month $t-1$. All regressions include control variables identical to those in Table 2. Client-advisor and year-month fixed effects are included. Standard errors are clustered at the client level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Misselling: Low-return WMPs Sales ratio	Placebo: High-return WMPs Sales ratio
Panel A. Investment experience of client	1	2
Missed quota	0.038***	-0.003
	(0.009)	(0.004)
Missed quota × Experienced client	-0.034***	-0.007
	(0.013)	(0.008)
Experienced client	-0.000	-0.013**
	(0.014)	(0.006)
Controls	Yes	Yes
Client-advisor FE	Yes	Yes
Year-month FE	Yes	Yes
Observations	66,198	66,198
Adjusted R-squared	0.724	0.684
Panel B. Working experience of advisor	1	2
Missed quota	0.019**	-0.002
	(0.009)	(0.004)
Missed quota × Experienced advisor	0.023	-0.009
	(0.016)	(0.007)
Experienced advisor	0.036**	0.003
	(0.016)	(0.010)
Controls	Yes	Yes
Client-advisor FE	Yes	Yes
Year-month FE	Yes	Yes
Observations	66,198	66,198
Adjusted R-squared	0.724	0.684

Table 7. Client-advisor experience match

This table examines how the impact of quota pressure on misselling varies with the match between client investment experience and advisor working experience. A client is classified as *experienced* if they have held an account at The Bank for more than 83 months (6.9 years), and as *novice* otherwise. An advisor is classified as *experienced* if they have worked in the financial industry for more than 140 months (11.7 years), and as *novice* otherwise. In columns 1, 3, 5 and 7, the dependent variable is the sales ratio of low-return WMPs, defined as the volume of low-return WMPs sold divided by the total volume of WMPs sold in a given client-month. In columns 2,4, 6 and 8, the dependent variable is the sales ratio of high-return WMPs, which serve as placebo tests. The key independent variable is *Missed quota*, a binary indicator equal to one if advisor i failed to meet their sales target in month $t-1$. All regressions include control variables identical to those in Table 2. Client-advisor and year-month fixed effects are included. Standard errors are clustered at the client level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Experienced advisor – Experienced client		Novice advisor – Experienced client		Experienced advisor – Novice client		Novice advisor – Novice client	
	Low. WMPs Sales ratio	High. WMPs Sales ratio	Low. WMPs Sales ratio	High. WMPs Sales ratio	Low. WMPs Sales ratio	High. WMPs Sales ratio	Low. WMPs Sales ratio	High. WMPs Sales ratio
	1	2	3	4	5	6	7	8
Missed quota	0.003	-0.012	-0.023*	-0.001	0.063***	-0.005	0.028**	-0.003
	(0.017)	(0.009)	(0.013)	(0.006)	(0.017)	(0.007)	(0.012)	(0.006)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Client-advisor FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,415	5,415	11,564	11,564	12,356	12,356	36,697	36,697
Adjusted R-squared	0.827	0.724	0.792	0.720	0.788	0.747	0.708	0.688

Table 8. Client wealth

This table examines how client wealth level influences misselling behavior. Clients are categorized based on their average daily asset holdings in The Bank in the previous month: *premium clients* hold more than RMB 500,000, while *private banking clients* hold more than RMB 6 million. In columns 1, the dependent variable is the sales ratio of low-return WMPs, defined as the volume of low-return WMPs sold divided by the total volume of WMPs sold in a given client-month. In columns 2, the dependent variable is the sales ratio of high-return WMPs, which serve as placebo tests. The key independent variable is *Missed quota*, a binary indicator equal to one if advisor *i* failed to meet their sales target in month $t-1$. All regressions include control variables identical to those in Table 2. Client-advisor and year-month fixed effects are included. Standard errors are clustered at the client level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Misselling: Low-return WMPs Sales ratio	Placebo: High-return WMPs Sales ratio
	1	2
Missed quota	0.022***	-0.003
	(0.008)	(0.004)
Missed quota×Premium Client	0.015	-0.005
	(0.015)	(0.009)
Premium Client	0.078***	0.014**
	(0.010)	(0.006)
Missed quota×Private banking Client	0.126**	-0.004
	(0.056)	(0.019)
Private banking Client	-0.003	-0.031
	(0.035)	(0.022)
Controls	Yes	Yes
Client-advisor FE	Yes	Yes
Year-month FE	Yes	Yes
Observations	66,198	66,198
Adjusted R-squared	0.725	0.684

Table 9. Gender

This table examines how the impact of quota pressure on misselling varies by client (panel A) and advisor (Panel B) gender. In columns 1, the dependent variable is the sales ratio of low-return WMPs, defined as the volume of low-return WMPs sold divided by the total volume of WMPs sold in a given client-month. In columns 2, the dependent variable is the sales ratio of high-return WMPs, which serve as placebo tests. The key independent variable is *Missed quota*, a binary indicator equal to one if advisor i failed to meet their sales target in month $t-1$. All regressions include control variables identical to those in Table 2. Client-advisor and year-month fixed effects are included. Standard errors are clustered at the client level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Misselling: Low-return WMPs Sales ratio	Placebo: High-return WMPs Sales ratio
Panel A. Client gender	1	2
Missed quota	0.023***	-0.012**
	(0.009)	(0.005)
Missed quota × Male client	0.011	0.018**
	(0.013)	(0.008)
Controls	Yes	Yes
Client-advisor FE	Yes	Yes
Year-month FE	Yes	Yes
Observations	65,238	65,238
Adjusted R-squared	0.724	0.683
Panel B. Advisor gender	1	2
Missed quota	0.037***	-0.004
	(0.010)	(0.004)
Missed quota × Male advisor	-0.030**	-0.003
	(0.014)	(0.006)
Controls	Yes	Yes
Client-advisor FE	Yes	Yes
Year-month FE	Yes	Yes
Observations	66,198	66,198
Adjusted R-squared	0.724	0.684

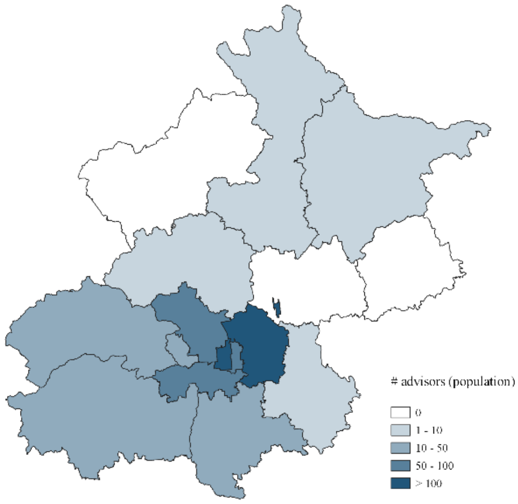
Table 10. Advisor-client gender match

This table examines how the impact of quota pressure on misselling varies with the match between client and advisor gender pair. In columns 1, 3, 5 and 7, the dependent variable is the sales ratio of low-return WMPs, defined as the volume of low-return WMPs sold divided by the total volume of WMPs sold in a given client-month. In columns 2,4, 6 and 8, the dependent variable is the sales ratio of high-return WMPs, which serve as placebo tests. The key independent variable is *Missed quota*, a binary indicator equal to one if advisor *i* failed to meet their sales target in month $t-1$. All regressions include control variables identical to those in Table 2. Client-advisor and year-month fixed effects are included. Standard errors are clustered at the client level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

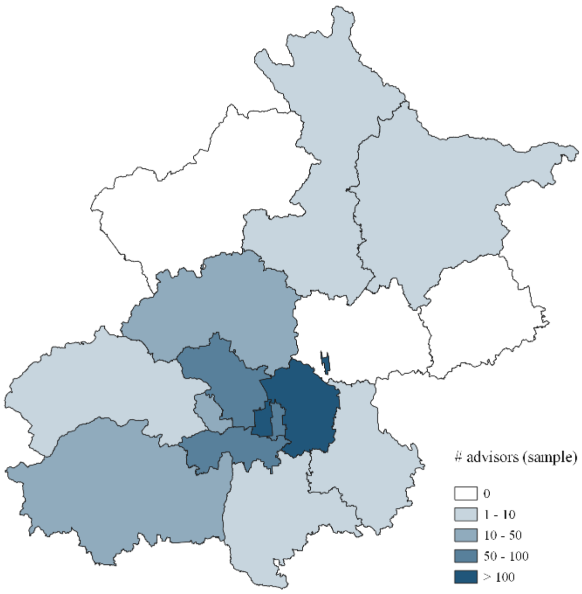
	Male advisor – Male client		Female advisor – Male client		Male advisor – Female client		Female advisor – Female client	
	Low. WMPs Sales ratio	High. WMPs Sales ratio	Low. WMPs Sales ratio	High. WMPs Sales ratio	Low. WMPs Sales ratio	High. WMPs Sales ratio	Low. WMPs Sales ratio	High. WMPs Sales ratio
	1	2	3	4	5	6	7	8
Missed quota	-0.006	-0.002	0.065***	0.006	0.019	-0.012	0.016	-0.008
	(0.015)	(0.004)	(0.018)	(0.007)	(0.012)	(0.008)	(0.013)	(0.006)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Client-advisor FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year-month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,035	4,035	24,738	24,738	4,545	4,545	31,920	31,920
Adjusted R-squared	0.761	0.738	0.730	0.688	0.744	0.689	0.712	0.674

Misselling in Financial Advice

Online Appendix



Panel A. Full sample



Panel B. Random draw sample (regression sample)

Figure A1. Distribution of advisors.
The figures depict the distribution of number of advisors in Beijing. Panel A corresponds to the full sample number (620 advisors) and Panel B corresponds to the random draw sample (463 advisors), i.e., the regression sample.

Table A1. Summary statistics: active advised and un-advised client samples

This table presents summary statistics for advised and un-advised client samples, as well as t-tests for variables' differences cross sample. To address the issue that an important proportion of un-advised clients are inactive in trading and depositing, this table focuses on "active" client-months, defined by excluding periods where no WMP purchases occurred for over three consecutive months. For the un-advised client sample, "missed quota" for a given client-month is hypothetically constructed as the average branch-level missed quota associated with that client's primary branch. The *Client risk appetite* variable exhibits significant missing data among un-advised clients, as risk surveys are primarily completed when clients engage with an advisor.

	Advised clients			Un-advised clients			
	N	Mean	Std. Dev.	N	Mean	Std. Dev.	T-test Diff.
Client-Advisor-Month							
Missed quota	48153	0.13	0.34	41446	0.18	0.17	-0.048***
Sales volume – all WMPs (in 1,000 RMB)	48153	1124.19	4549.97	41446	416.07	2102.37	708.120***
Sales dummy – all WMPs	48153	0.83	0.37	41446	0.35	0.48	0.485***
Sales dummy – low-return WMPs	48153	0.71	0.45	41446	0.30	0.46	0.414***
Sales volume – low-return WMPs (in 1,000 RMB)	48153	831.66	4281.73	41446	289.34	1782.27	542.321***
Sales ratio – low-return WMPs	48153	0.54	0.41	41446	0.22	0.37	0.316***
Sales dummy – high-return WMPs	48153	0.30	0.46	41446	0.13	0.33	0.172***
Sales volume – high-return WMPs (in 1,000 RMB)	48153	131.81	548.44	41446	54.06	399.34	77.754***
Sales ratio – high-return WMPs	48153	0.12	0.25	41446	0.05	0.17	0.072***
Client experience (month)	48153	52.60	35.96	41446	51.22	34.91	1.377**
Client risk appetite (1–5)	47925	3.05	0.75	17805	3.15	0.77	-0.103***
Client wealth (in 1,000 RMB)	48153	720.62	1237.39	41446	322.87	993.01	397.740***
Client age	48153	53.20	14.66	41446	45.62	14.36	7.579***
Client gender	47468	0.44	0.50	41446	0.45	0.50	-0.009

Table A2. Quota pressure and misselling, active advised clients

This table presents a robustness test of quota pressure effects on misselling. All variables and regression models are identical to those in Table 2, with the sole exception that the sample excludes "inactive" client-months, defined as periods where a client made no WMP transactions for three or more consecutive months. In all regressions, client-advisor fixed effects and year-month fixed effects are included. Standard errors are clustered at the client level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Misselling: Low-return WMPs			Placebo: High-return WMPs		
	Sales dummy	Sales volume	Sales ratio	Sales dummy	Sales volume	Sales ratio
	1	2	3	4	5	6
Missed quota	0.033***	0.359***	0.031***	-0.010	-0.134	-0.004
	(0.009)	(0.108)	(0.009)	(0.009)	(0.108)	(0.005)
Advisor compensation	0.001	0.008	0.003	-0.006***	-0.073***	-0.002
	(0.002)	(0.027)	(0.002)	(0.002)	(0.028)	(0.001)
Client loan	-0.002	-0.014	-0.002	0.001	0.013	-0.001
	(0.002)	(0.021)	(0.002)	(0.002)	(0.023)	(0.001)
Firm loan	0.001	0.009	0.001	0.000	0.002	0.001
	(0.002)	(0.021)	(0.002)	(0.002)	(0.023)	(0.001)
Client-advisor FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-month FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	39,312	39,312	39,312	39,312	39,312	39,312
Adjusted R-squared	0.677	0.730	0.715	0.774	0.784	0.761

Table A3. Quota pressure and misselling, active un-advised clients

This table presents a placebo test of quota pressure effects on misselling, focusing on un-advised clients. The original full sample includes 14,059 random clients not assigned a financial advisor in The Bank's system. To maintain comparability, the regressions focus on active client-months, excluding periods with no WMP transactions for three or more consecutive months. Dependent variables are identical to those in Table 2. Given that un-advised clients lack individual advisors, independent variables are hypothetically constructed using branch-month averages. Accordingly, *Missed quota* is the average missed quota of the client's branch from the preceding month. Control variables are similarly proxied at the branch-month level. All regressions include client fixed effects and year-month fixed effects. Standard errors are clustered at the client level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Misselling: Low-return WMPs			Placebo: High-return WMPs		
	Sales dummy	Sales volume	Sales ratio	Sales dummy	Sales volume	Sales ratio
	1	2	3	4	5	6
Missed quota	0.029	0.376	0.015	0.024	0.402	-0.003
	(0.044)	(0.509)	(0.038)	(0.047)	(0.561)	(0.022)
Advisor compensation	0.024	0.327	0.018	-0.010	-0.064	-0.009
	(0.022)	(0.253)	(0.020)	(0.022)	(0.266)	(0.012)
Client loan	-0.020	-0.132	-0.032	0.070	0.747	-0.002
	(0.045)	(0.543)	(0.041)	(0.049)	(0.585)	(0.023)
Firm loan	-0.001	-0.017	-0.002	0.002	0.027	0.001
	(0.002)	(0.022)	(0.002)	(0.003)	(0.033)	(0.001)
Client-advisor FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-month FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	14,131	14,131	14,131	14,131	14,131	14,131
Adjusted R-squared	0.677	0.733	0.710	0.757	0.766	0.758

Table A4. Quota pressure and performance (advisor level)
This table tests whether quota pressure improves financial advisors' performance. Column 1 uses *Completion rate growth*, defined as the month-over-month change in the ratio of simulated profits to the sales quota. Column 2 uses the log difference of month-over-month completion rate. The key independent variable, *Missed quota*, equals one if the advisor failed to meet their sales target in the previous month. Control variables follow those in Table 2. The regression is at the advisor-month level, covering 463 advisors from June 2019 to June 2020. All regressions include advisor fixed effects and year-month fixed effects. Standard errors are clustered at the client level. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

	Completion rate growth	Log diff. completion rate
	1	2
Missed quota	0.408***	0.252***
	(0.032)	(0.023)
Controls	Yes	Yes
Advisor FE	Yes	Yes
Year-month FE	Yes	Yes
Observations	5,550	5,550
Adjusted R-squared	0.061	0.102
Mean of dep. var	-0.00	-0.00

Table A5. Peer pressure and misselling, active un-advised clients

This table presents a placebo test of peer pressure effects on misselling, focusing on un-advised clients. The original full sample includes 14,059 random clients not assigned a financial advisor in The Bank's system. To maintain comparability, the regressions focus on active client-months, excluding periods with no WMP transactions for three or more consecutive months. All variables are identically defined as in Table 3. In all regressions, client-advisor fixed effects and year-month fixed effects are included. Standard errors are clustered at the client level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Misselling: Low-return WMPs			Placebo: High-return WMPs		
	Sales dummy	Sales volume	Sales ratio	Sales dummy	Sales volume	Sales ratio
	1	2	3	4	5	6
Enlarged group × Post-Nov2019	0.024	0.290	0.021	-0.014	-0.233	-0.004
	(0.037)	(0.447)	(0.032)	(0.041)	(0.515)	(0.020)
Missed quota	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Client-advisor FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-month FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	14,131	14,131	14,131	14,131	14,131	14,131
Adjusted R-squared	0.677	0.734	0.710	0.757	0.766	0.758

Table A6. Promotion prospect and misselling, starter-level advisors

This table presents a placebo test of promotion prospect effects on misselling, focusing on starter-level advisors, who are not subject to competitive promotion incentives. All variables are identically defined as in Table 4. In all regressions, client-advisor fixed effects and year-month fixed effects are included. Standard errors are clustered at the client level. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Misselling: Low-return WMPs			Placebo: High-return WMPs		
	Sales dummy	Sales volume	Sales ratio	Sales dummy	Sales volume	Sales ratio
	1	2	3	4	5	6
Top 5%×Post Jan-2020	-0.003	0.070	-0.005	-0.030	-0.280	-0.041
	(0.050)	(0.661)	(0.040)	(0.032)	(0.400)	(0.025)
Missed quota	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Client-advisor FE	Yes	Yes	Yes	Yes	Yes	Yes
Year-month FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	22,518	22,518	22,518	22,518	22,518	22,518
Adjusted R-squared	0.760	0.786	0.719	0.760	0.767	0.678

Table A7. Summary statistics by experienced and novice clients/advisors

This table reports the summary statistics of sales ratio by client/advisor experience. A client is classified as *experienced* if they have held an account at The Bank for more than 83 months (6.9 years), and as a *novice* otherwise. Panel B examines advisor experience, with advisors classified as *experienced* if they have worked in the financial industry for more than 140 months (11.7 years), and as *novice* otherwise.

Panel A. By client investment experience

	N	Mean	Std. Dev.	Min	p50	Max
Experienced clients						
Missed quota	18199	0.15	0.36	0	0	1
Sales volume – all WMPs (in 1,000 RMB)	18199	996.21	3818.88	0	96.00	66441.00
Sales ratio – low-return WMPs	18199	0.37	0.42	0	0	1
Sales ratio – high-return WMPs	18199	0.08	0.20	0	0	1
Novice clients						
Missed quota	53523	0.14	0.35	0	0	1
Sales volume – all WMPs (in 1,000 RMB)	53523	672.67	3743.46	0	70.00	228064.98
Sales ratio – low-return WMPs	53523	0.36	0.42	0	0	1
Sales ratio – high-return WMPs	53523	0.08	0.22	0	0	1

Panel B. By advisor working experience

	N	Mean	Std. Dev.	Min	p50	Max
Experienced advisors						
Missed quota	18752	0.21	0.41	0	0	1
Sales volume – all WMPs (in 1,000 RMB)	18752	878.12	3169.82	0	110.00	62658.93
Sales ratio – low-return WMPs	18752	0.39	0.42	0	0.21	1
Sales ratio – high-return WMPs	18752	0.08	0.21	0	0	1
Novice advisors						
Missed quota	52970	0.12	0.33	0	0	1
Sales volume – all WMPs (in 1,000 RMB)	52970	711.10	3953.84	0	60.00	228064.98
Sales ratio – low-return WMPs	52970	0.35	0.42	0	0	1
Sales ratio – high-return WMPs	52970	0.08	0.22	0	0	1

Table A8. Summary statistics by client wealth

This table reports the summary statistics of client wealth and sales ratio by client wealth level. Clients are categorized based on their average daily asset holdings in The Bank in the previous month: *premium clients* hold more than RMB 500,000, while *private banking clients* hold more than RMB 6 million.

	N	Mean	Std. Dev.	Min	p50	Max
Regular clients						
Client wealth (in 1,000 RMB)	49766	134.99	146.87	0	86.66	500.00
Missed quota	49766	0.15	0.36	0	0	1
Sales volume – all WMPs (in 1,000 RMB)	49766	213.34	1443.32	0	0	65370.00
Sales ratio – low-return WMPs	49766	0.29	0.41	0	0	1
Sales ratio – high-return WMPs	49766	0.06	0.20	0	0	1
Premium clients						
Client wealth (in 1,000 RMB)	21426	1316.75	1015.79	500.00	951.13	5997.82
Missed quota	21426	0.13	0.33	0	0	1
Sales volume – all WMPs (in 1,000 RMB)	21426	1634.08	4269.27	0	739.00	193284.98
Sales ratio – low-return WMPs	21426	0.53	0.39	0	0.59	1
Sales ratio – high-return WMPs	21426	0.13	0.24	0	0	1
Private banking clients						
Client wealth (in 1,000 RMB)	530	8881.82	3102.08	6000.29	7982.63	27819.52
Missed quota	530	0.19	0.39	0	0	1
Sales volume – all WMPs (in 1,000 RMB)	530	16046.43	26360.41	0	8500.00	228064.98
Sales ratio – low-return WMPs	530	0.67	0.38	0	0.83	1
Sales ratio – high-return WMPs	530	0.08	0.20	0	0	1

Table A9. Summary statistics by advisor/client gender
This table reports the summary statistics of sales ratio by client and advisor gender.

Panel A. By client gender

	N	Mean	Std. Dev.	Min	p50	Max
Male client						
Missed quota	31177	0.13	0.34	0	0	1
Sales volume – all WMPs (in 1,000 RMB)	31177	748.43	2782.19	0	80.00	65370.00
Sales ratio – low-return WMPs	31177	0.36	0.42	0	0	1
Sales ratio – high-return WMPs	31177	0.08	0.21	0	0	1
Female clients						
Missed quota	39505	0.15	0.36	0	0	1
Sales volume – all WMPs (in 1,000 RMB)	39505	765.86	4424.94	0	70.00	228064.98
Sales ratio – low-return WMPs	39505	0.36	0.42	0	0	1
Sales ratio – high-return WMPs	39505	0.08	0.22	0	0	1

Panel B. By advisor gender

	N	Mean	Std. Dev.	Min	Median	Max
Male advisor						
Missed quota	9456	0.25	0.43	0	0	1
Sales volume – all WMPs (in 1,000 RMB)	9456	703.09	3007.06	0	56.00	59088.00
Sales ratio – low-return WMPs	9456	0.35	0.42	0	0	1
Sales ratio – high-return WMPs	9456	0.07	0.20	0	0	1
Female advisor						
Missed quota	62266	0.13	0.33	0	0	1
Sales volume – all WMPs (in 1,000 RMB)	62266	762.61	3867.48	0	80.00	228064.98
Sales ratio – low-return WMPs	62266	0.36	0.42	0	0	1
Sales ratio – high-return WMPs	62266	0.08	0.22	0	0	1