The Distribution Side of Insurance Markets

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Abstract

This paper provides causal evidence for the impact of sales channels on insurance product adoption. Specifically, we utilize policy-level data provided by one of the largest life insurers in China, where we observe granular information on policy features and investor characteristics. We then exploit a regulatory change in the aftermath of the Global Financial Crisis that requires at least a portion of the insurance contracts sold through bank agents in each quarter to be long-term insurance products. Using a discontinuity-in-slope design, we show that bank agents falling below their target qualified ratios in the first two months of a quarter make up for the shortfall in the third month; conversely, bank agents that have exceeded their target ratios in the first two months do not alter their behavior in the last month of the quarter. This shift in qualified ratio in the last month of the quarter is entirely driven by a product-composition change – switching from short-term life insurance to long-term annuity products. We further show that this switch is not achieved by changing the relative pricing (or features) of insurance contracts or client compositions.

JEL classification: G02, G12, G23, N22

1 Introduction

Households face a difficult search problem when choosing from a large menu of financial products – from bank savings products to mutual fund and insurance products, to more complicated structural products. To mitigate search costs, households often rely on the advice of intermediaries (e.g., local brokers and bank branches) in their financial decisions. These financial intermediaries serve a number of useful functions: to introduce a diverse range of financial products to otherwise uninformed clients, to explain the technical details of innovative, sometimes difficult-to-understand products, and to facilitate transactions. An increasingly important concern with the interactions between households and their advisors is that financial intermediaries – in pursuit of own benefits – may not offer their clients the best (most suitable) products. Recent studies indeed show that intermediaries and advisors recommend dominated products to their clients for higher sales commissions.[1]

Unlike prior studies that examine purchase decisions of (nearly) identical financial products with different sales commissions or fees, our aim in this paper is to analyze the extent to which distribution channels affect *the types* of financial products acquired by households of similar characteristics. The answer to this question has important implications for household welfare. An obvious challenge to this exercise is credible identification: for instance, one needs to a) know the fair price of each product, and b) solve a difficult matching problem between households and products, in order to establish causality. To this end, our identification strategy involves a two-pronged approach.

First, we have access to granular policy-level data provided by one of the largest life insurers in China. Our data include a 10% random sample of all insurance policies sold in 9 large Chinese cities for the period 2012-2016. We observe the mutually-agreed contractual docu-

[1]For instance, Hortacsu and Syverson (2004) find that price dispersion exists across identical S&P 500 index funds, and there was a marked shift in capital flows to more expensive (often newly entered) index funds in their sample period. Egan (2020) shows that between two products with identical payoffs, advisors often recommend the one with higher sales commissions (so lower net-of-fee returns) to households.

ments which include all policy features (product types, contract lengths, payout structures, etc.), investor characteristics (age, gender, income, etc.) and sales channels (bank branches or personal agents). This granularity allows us to examine subtle changes in contractual details and investor characteristics both through time and across investors.

Second, we exploit an important regulatory change in 2014 in China (in response to the Global Financial Crisis) that imposes a constraint on the types of insurance polices sold through banks agents. Specifically, before 2014 life insurers mostly sold short-term life insurance products through bank agents (as a way to obtain short-term financing). The 2014 regulation requires that at least 20% of the insurance products sold through each bank (aggregated at the provincial level) in each quarter must be long-term products – in order to curb short-term financing by insurers. This new regulation provides a relatively clean discontinuity design to identify large swings in product adoption. A unique feature of our setting is that there is no change in the sales commissions paid to banks (or other distribution channels) across different insurance products around the policy shock, so the effect we document is orthogonal to the traditional channel of variation in sales commissions.

Our empirical strategy exploits branch-quarter variation in the distance-to-constraint and examines how bank branch sales near quarter-ends vary as a function of the distance-to-constraint, before vs. after the policy change. Note that the regulatory constraint is binding at the bank-quarter-province level; we argue that, in practice, banks in each city of the province have a specific target qualified ratio to accommodate the heterogeneity in clienteles across cities. We proxy for the city-level target ratio using the average qualified ratio across all branches within each city in the preceding year (which is then applied to all branches in the city for the next quarter).[2]

More specifically, our identification strategy exploits the fact that bank branches falling

[2]From our private conversation with our data provider, this is a common practice of how banks implement and achieve the regulatory sales target. Later we will provide empirical evidence to show that this construction is a good approximation of how banks distribute its provincial-level target to each of its branches.

below their target qualified ratios in the first two months of a quarter have strong incentives (i.e., are likely required by the provincial headquarter) to make up for the shortfall in the third month; conversely, bank branches that have exceeded their target qualified ratios in the first two months have no incentive to alter their behavior in the final month of the quarter. In other words, we expect a discontinuous jump in the relation between the qualified ratio minus target ratio in the last month of a quarter and that in the previous two months as the lagged ratio crosses from above to below the target ratio (i.e., from having slacks to having deficits).[3].

Our predictions are strongly borne out in the data. We start our analyses with new insurance contracts signed in the final month of each quarter (March, June, September, and December). For bank branches that fall below their target qualified ratios in the first two months of the quarter, the relation between the qualified ratio (minus the target ratio) in the final month and that in the first two months is statistically more negative than the same relation for bank branches above their target ratios in the first two months. The difference between the two is -0.528 with a t-statistic of -2.41. We also examine the same difference (between bank branches above and below the threshold) in the response coefficient for non-quarter-end months (i.e., the other eight months). Since the constraint is only binding at quarter ends, we expect to see a smaller difference. Indeed, the difference in the response coefficient in non-quarter-end months is statistically insignificant from zero, and with a wrong sign. We further separate all insurance contracts into two groups: life insurance contracts and annuity contracts, and find that virtually all our documented effect comes from changes in annuity products (with a difference in the response coefficient of -0.700 and a t-statistic of -4.17).

We then repeat our analyses with the total premium from all insurance contracts – both those signed in the final month of the quarter (new) and those signed before the final

[3]In an ideal setting, we expect the slope to be exactly 0 for bank branches with qualified-ratio slacks in the first two months and a slope of -1 for branches with qualified ratio deficits (on a value-weighted basis)

month (existing). We see very similar patterns. The response coefficient of the distance-to-target-ratio in the final month of the quarter on the lagged distance for bank branches above the threshold is statistically more negative than that for bank branches below the threshold. Again, there is no discernible difference in the response coefficient for non-quarter-end months.[4]

To validate our target construction, we conduct a placebo test by introducing random noise to the average qualified ratio across all branches in the city from the preceding year. As the variance of the noise term increases, the observed pattern weakens monotonically. A second approach is to reduce the informational granularity of the target calculation (e.g., replacing bank $\times$ city $\times$ year-month information with city $\times$ year-month information). As the targets become less specific, the results further weaken. These analyses provide support for the premise of empirical design that bank branches in the same city have similar target qualified ratios.

An interesting feature of the insurance contracts offered by our firm is that while most life insurance contracts have a short maturity (less than 10 years), so do not qualify for long-term investments, virtually all annuity products have a maturity longer than 10 years, so qualify as long-term investments. We find that the shift in the qualified ratio almost driven entirely by a composition change – to switch from short-term unqualified life insurance products to long-term qualified annuity products, with the total premium unchanged.

An obvious concern with our results so far is that households may take out long-term annuity products but then decide to cancel these contracts shortly after, so there is no change in the effective investment horizon. At least in our sample period, from 2012 to 2016, we do not see an increase in the lapsation rate for long-term contracts signed in the final month of the quarter in response to a target-qualified ratio deficit. We further show that the switch

[4] We also provide evidence that bank branches with qualified-ratio deficits in the first two months of a quarter delay the payment of their existing short-term insurance products to the following quarter to improve the qualified ratio in the current quarter.

from life insurance products to annuity contracts introduces changes in mortality delta. Although this is mostly mechanical (as annuity contracts have larger life components than life insurance products, the change in mortality delta have important welfare implications.)

Although our analysis focuses on a particular regulatory change in the Chinese insurance market, our results have broader implications for other financial products in other countries. Sales team/distribution channels often face quotas and sales targets (for example, a sales person needs to sell $X of a product by year end); these sales targets can have very similar impacts on sales and production adoptions as the regulatory constraint examined in this paper.

A natural follow-up question is how do distribution channels achieve their sales targets? First, distribution channels, together with product providers, can change the (relative) pricing of products. Second, distribution channels can spend more effort/resources courting clients more suited for the product in question, therefore forgoing other types of clients (so a change in client composition). Third, distribution channels can persuade their clients to adopt certain products (not through pricing, but through communication and perhaps manipulation). This is also a substitution away from other products, but with no change in client characteristics.

To differentiate the first channel from the other two channels, we examine the pricing markups of different products. Following the standard procedure to calculate insurance products' markups in prior research, we find no significant change in markups of insurance product pricing in the last month of the quarter in a way that would lead investors to switch from short-term insurance products to long-term products.

To differentiate the second channel from the third, we examine changes in client characteristics that are associated with insurance purchase decisions. Our firm collects three client characteristics: gender, age, and income.[5] We find no significant change in client character-

[5]The firm also collects information on clients' marital status and the number of children, but this infor-

istics near quarter ends as a function of the qualified ratio in the first two months of the quarter. In other words, while there is a change in the type of products sold, at least based on important observables (which our firm cares about), there is no discernible change in investor characteristics or composition.

In our last set of analyses, we repeat our empirical exercises on the subset of contracts sold through the personal agent (PA) channel. We do not find similar patterns in qualified vs. non-qualified insurance premium in the last month of the quarter. This is consistent with the fact that personal agents are not subject to the new regulation.

In sum, our analysis (with the difference-in-slope test) reveals that as bank branches fall below their target qualified ratios in the first two months of the quarter, they increase the sales of qualified long-term products, which are predominantly annuity products, and reduce the sales of unqualified short-term products, which are mainly life-insurance products. We also provide suggestive evidence that bank branches achieve this switch in composition via persuasion, rather than by changing the relative pricing of their products or changing the client compositions.

The main contribution of our paper is twofold. First, prior research on the incentives of the distribution channel shows that distributors persuade their clients to adopt "overpriced" products (compared to other products with identical or similar payoffs), because these overpriced products pay a higher sales commission. Our paper instead shows that distributors also promote "wrong" products. In particular, we show in a discontinuity setting that nearly identical clients buy short-term life insurance in the pre-2014 period but long-term annuities in the post-2014 period. Almost by definition, short-term life products are vastly different from long-term annuities, both in terms of contract duration and mortality benefits. Our results highlight the narrative that (many) retail investors lack basic financial knowledge about *what kind of financial products* are suitable for their goals and preferences. Second, while

mation is missing for about half of the policyholders.

prior studies examine the relation between incentive/commission fees and products recommended, our paper focuses on regulatory and contractual constraints imposed on financial intermediaries.

Related Literature Our study contributes to the body of literature that underscores the importance of supply side factors in insurance markets. Koijen and Yogo (2015) show that insurance companies sold their policies at discounted prices when they suffered from balance sheet shocks. This heavy price discount on one hand attracts demands from policy buyers and on the other hand increases accounting profits (hence ratings) as long as it is still above the reserve value set by statutory reserve regulation in the United States. Ge (2022) extends Chevalier's pioneering study on how financial constraints affect product pricing in the context of insurance market and also Koijen and Yogo (2015). This study shows that premiums fall (rise) for life policies that immediately increase (decrease) insurers' financial resources. In a similar vein, Ge and Weisbach (2021) study how operating losses (e.g., due to adverse weather conditions) for insurers affect their asset portfolio allocations. Koijen and Yogo (2016) show that life insurance companies shifted their liabilities to shadow reinsurers which are less regulated and unrated off-balance-sheet entities within the same insurance group. While such shifting reduced the marginal cost of issuing policies, it increases the default risk of the industry.

2 Data and Empirical Strategy

2.1 Data and summary statistics

We exploit a unique dataset provided by one of the largest life insurers in China. The dataset contains a 10% random sample of all contracts signed in the period of 2009-2016 in 9 large cities in China: Beijing, Shanghai, Guangzhou, Chengdu, Nanjing, Wuhan, Shenyang, Zhengzhou, and Lanzhou. The total insurance premium in our sample was over 3B RMB in 2016. For our main analyses, we focus on the period from 2012 to 2016, centering on the policy change in 2014.[6]

The dataset contains comprehensive details from the contractual documents for each policy, encompassing several sets of information. Firstly, it provides insights into policy details, such as product type, contract length, annual premium and premium payment period. In total, there are 231 products included, categorized into four product types: life insurance, annuities, health insurance, and accident insurance. Notably, all life insurance or annuities in our sample are combined products and contain features of both life and annuity components. We use the following classification rule: products are categorized as annuities if they have a maturity period of more than 10 years and the expected present value of all annuity claims is at least equal to the insurance value. All others are classified as life insurance. Additionally, any life insurance or annuity products that include health and accident components are still categorized solely as life insurance or annuities.[7]

Secondly, the dataset encompasses buyer characteristics, including gender, age, annual income, occupation, and marital status. Thirdly, we can track all transactions related to the contracts, such as premium payments, contract lapsation, and insurance claims.

Lastly, important for our purpose, we also observe information on the distribution channel. Insurance policies are distributed through diverse channels. Figure 1 shows the premium revenue in our sample from each distribution channel. The majority of observations, over 95%, are sold by either banks or personal agents. We observe sales by each bank branch or personal agent with anonymous IDs, but we do not have information on the bank identity.

Table 1 presents summary statistics and describes the basic characteristics of our sample.

[6] The total premium collected in each quarter comprises premiums from newly issued policies as well as those from existing policies. By 2012, the impact of policies issued before 2009 (not in our sample) diminishes significantly.

[7] Health and accident components typically correspond to much lower value compared to life insurance and annuities.

Panel A provides an annual breakdown of insurance sales from all channels, detailing the number of contracts and the premium revenue generated from new contracts initiated each year. The majority of premium contributions come from two product types – life insurance and annuities – which together account for more than 96% of the total premiums across all years in our sample. Life insurance premiums represent over 80% of the total, but this percentage declines after 2014 as the share of annuities increases. A similar trend is observed in the number of contracts as well. In contrast, accident and health insurance policies (A&H) make up a substantial number of contracts, though they are generally of considerably lower value.

Focusing on the bank channel, Panel B reports the summary of insurance sales at the bank branch-month level. On average, a bank branch collects a total premium of 53,760 RMB, with 16,300 RMB qualifying for the policy's long-term requirement. New contracts are sold in about half of all bank branch-month combinations. Conditional on these branch-months with new sales, a branch sells an average of 1.8 contracts per month in our 10% random sample, generating around 83,780 RMB in premiums. The average contract lapsation rate within the first 12 months is 1%..

Panel C summarizes the policy-level characteristics of both the contracts and the buyers for those sold through the bank channel. The typical buyer is more likely to be female, with an average age of 48 and an annual income of 69,127 RMB. Life insurance contracts have an average duration of 6.38 years, while annuities average 20.25 years.

Panel C also reports statistics that capture contract pricing. The markup is defined as the ratio of the expected present value of the total premium to the expected claims amount over the contract's duration, calculated as follows:

$$M_{i,t} = \left(\sum_{k=t}^{t+T_0} P_{i,k} \pi_{L,k|i,t} d_{k|t} \right) / \left\{ \sum_{s=t+1}^{t+T} \left[A_{i,s}(1 - \pi^*_{D,s|i}) + C_{i,s} \pi^*_{D,s|i} \right] \pi_{L,s-1|i,t} d_{s|t} \right\}. \quad (1)$$

$\pi_{L,k|i,t}$ is the probability of being alive at period k given the insuree's characteristics for contract i and being alive at period t. $\pi^*_{D,s|i}$ is the probability of death at period s, conditional on being alive at $s-1$, for the insuree of contract i. These mortality rates, based on the Sixth National Population Census of China (2010), vary by age and gender.$A_{i,s}$ is the expected annuity payment at period s, including any dividends. $C_{i,s}$ is the death claim for contract i at period s. $P_{i,k}$ is the premium amount at period k. Values for $A_{i,s}$, $C_{i,s}$, and $P_{i,k}$ are manually collected from each policy. T is the contract maturity, and T_0 is the premium payment period. For whole life insurance, T ensures the insuree reaches age 110.[8] $d_{k|t}$ is the discount rate based on the $(k-t)$-year China Government Bond yield at t, and is obtained from the WIND financial database. For any rate $k-t$ lacking a corresponding treasury bond, we interpolate linearly between the two bonds with the closest maturities. The mean markup across all new contracts is 1.085. We also perform a cross-sectional regression of the markups on various contract and insuree characteristics, detailed in Section 4.2; the residual markup reflects pricing variations not explained by observable factors.

We also calculate the mortality delta (δ) to capture the differential payoff that a policy delivers at death. Following **?**, δ is calculated as the payoff that a policy delivers at death relative to being alive in the next period:

$$\delta_{i,t} = C_{i,t+1} - \left\{ A_{i,t+1} + \sum_{s=t+2}^{t+T} \left[A_{i,s}(1-\pi^*_{D,s|i}) + C_{i,s}\pi^*_{D,s|i} \right] \pi_{L,s-1|i,t+1} \frac{d_{s|t}}{d_{t+1|t}} \right\}. \quad (2)$$

After normalizing by insurance value, the ratio Delta/Value have a mean of 0.18 across all policies.

[8] In our sample, most policies set the maximum insured age to 110. For $t > 90$, terms in the numerator decrease to zero as $\pi^*_{D,s|i}$ approaches 1.

2.2 Identification Strategy

Our empirical strategy levers a policy shock and exploits how branch-quarter variation in compliance pressure affect bank branch sales before and after the policy change. In 2014, the China Banking Regulatory Commission and the China Insurance Regulatory Commission jointly issued a notice to standardize the practices of insurance sales in the bank agent channel (CBRC [2014] No.3). Before 2014, banks primarily sold short-term life insurance products; the new regulation, implemented in April 2014, mandates that bank-insurance sales channels to prioritize long-term products. Specifically, each bank is required to ensure that at least 20% of the quarterly premiums (aggregated at the province level) originated from 'qualified' long-term insurance products. These qualified products include annuities, long-term life insurance, health insurance, and accident insurance, all with terms exceeding 10 years. Figure 2 shows that all of the annuities in our sample are qualified and around 8% of life insurances are qualified.

Our identification strategy essentially exploits the branch-quarter level variation of compliance pressure and examines how bank branch sales respond to the distance-to-target before and after the policy change. The regulatory constraint is binding at the aggregated bank-quarter-province level. We argue that, in practice, each bank in each city has a specific target qualified ratio to accommodate the diverse clientele it may encounter. This target ratio is proxied by the average qualified ratio across all branches within the city in the preceding year, and applies to all branches for the next quarter.[9] If a branch is below this target in the first two months of a quarter, it has a strong incentive to make up for the shortfall in the third month; conversely, if the branch surpasses this target, there is no incentive to alter its behavior.

Specifically, we employ the following regression model:

[9]From our private conversation with our data provider, this is a common practice how banks implement and achieve the regulatory sales target. Later we will provide empirical evidence to show that this construction is a good approximation of how banks distribute its provincial-level target to each of its branches.

$$
\begin{aligned}
Y_{i,j,t} &= \beta_1 D_{QR^{L2}_{i,j,t}<C_{j,t}} \times (QR^{L2}_{i,j,t} - C_{j,t}) + \beta_2 D_{2014} \times D_{QR^{L2}_{i,j,t}<C_{j,t}} \times (QR^{L2}_{i,j,t} - C_{j,t}) \\
&+ \sum_{y=2012}^{2016} \gamma^1_y \times D_y \times (QR^{L2}_{i,j,t} - C_{j,t}) + \sum_{y=2012}^{2016} \gamma^2_y \times D_y \times D_{QR^{L2}_{i,j,t}<C_{j,t}} + \theta_t + \eta_i + \epsilon_{i,t} \qquad (3)
\end{aligned}
$$

$Y_{i,j,t}$ is our outcome variable of interest and is the qualified ratio (premium of qualified contracts/premium of all contracts) in the third month of the quarter by branch i in bank-city combination j in quarter t in most analyses. $C_{j,t}$ is the bank-city level target, proxied by the average qualified ratio in the previous four quarters across all branches under that bank in that city. $QR^{L2}_{i,j,t}$ is branch i's qualified ratio in the previous two months (the first two months in the quarter). $D_{QR^{L2}_{i,j,t}<C_{j,t}}$ is a dummy variable indicating whether branch i's qualified ratio in the first two month falls below the threshold. D_{2014} is a dummy variable that is equal to 1 after 2014 Q2, indicating time periods before and after the policy change.

Our main variable of interest is the triple interaction term $D_{2014} \times D_{QR^{L2}_{i,j,t}<C_{j,t}} \times (QR^{L2}_{i,j,t} - C_{j,t})$. We conjecture that the distance to target in the first two months, $QR^{L2}_{i,j,t} - C_{j,t}$, would have an negative impact on the sales composition (qualified ratio) in the third month, only when it's after the policy change and if the branch's qualified ratio in the first two month falls below the threshold ($\beta_2 < 0$). $D_{QR^{L2}_{i,j,t}<C_{j,t}} \times (QR^{L2}_{i,j,t} - C_{j,t})$ is the double interaction term and β_1 captures the effect of distance to target on the third-month sales when a bank branch falls short of the threshold before the policy change. We expect β_1 to be zero. Instead of including the other two double-interaction terms, $D_{2014} \times (QR^{L2}_{i,j,t} - C_{j,t})$ and $D_{2014} \times D_{QR^{L2}_{i,j,t}<C_{j,t}}$, we control for the interaction terms between $(QR^{L2}_{i,j,t} - C_{j,t})$, $D_{QR^{L2}_{i,j,t}<C_{j,t}}$ and a series of year dummies; this serves as a finer version of control that allows the effect to change every year. Additionally, we include quarter fixed effects θ_t and bank branch fixed effects η_i.

3 Main Results

3.1 Distance-to-constraint and qualified ratio near quarter-ends

In this subsection, we analyze the impact of branch-level compliance pressure on the sales composition of long-term versus short-term products when it approaches quarter ends.

We start by focusing on premiums from new contracts, as these are more susceptible to manipulation by the sales force compared to revenues from existing contracts. Table 2 reports the results. In Panel A, the dependent variable is the abnormal qualified ratio from new contracts, calculated as the qualified ratio (qualified premium/total premium) of newly signed contracts for each branch in the last month of each quarter, minus the same ratio from the previous four quarters for the same branch. By subtracting the branch's historical ratio, we control for time-varying, branch-specific factors influencing sales composition. The first column (Sample Month) presents estimates of β_1 and β_2 in Eq. 3 using data from the last month of each quarter. Consistent with our conjecture, the coefficient of the triple interaction term, β_2, is significantly negative, indicating that a shortfall of the target in the first two months of a quarter leads to make-up actions in the third month, resulting in a significantly higher qualified ratio. This effect is observed only after the policy change. In contrast, β_1, which captures the same relationship before the policy change, is not significantly different from zero. In terms of the magnitude, when a branch's qualified ratio falls 1% below the bank-city target in the first two months, its qualified ratio increases by 0.528% in the last month after the policy change.

One potential concern is that there may be time-series correlations in sales composition across consecutive months, or that the sales composition in the first two months of a quarter could be influenced by branch-specific characteristics and correlate with sales in the third month. To address these concerns, we conduct a placebo test by focusing on non-quarter-ending months (e.g., January, referred to as placebo months). We calculate the distance-to-target using the two months preceding the focal month (e.g., November and December) and then repeat the regression analysis, with the results presented in the second column (Placebo Month). This approach captures any branch-specific time-series patterns in sales composition, with the key difference being that, unlike in the sample months, banks are not subject to regulatory assessment during the placebo months. In sharp contrast to column (1), β_1 and β_2 in the placebo months are both not significantly different from zero. The last column shows a significant difference in the response when comparing the coefficients of β_2 between the sample and placebo months.

To further understand which types of insurance products are used in response to compliance pressure, we decompose the numerator of the abnormal qualified ratio into the qualified premium from life insurance and that from annuities, such that the sum of these components corresponds to the total abnormal qualified ratio.[10] We conduct this decomposition because life and annuity products are vastly different – over 90% life insurance products have durations under 10 years, whereas all annuities are qualified with durations over 10 years (with an average duration of 20 years). We then repeat the analysis using the abnormal qualified ratio from life insurance and annuities, with the results presented in Panels B and C, respectively. The findings reveal that the effect of compliance pressure comes entirely from increased annuity sales: β_2 for life insurance is near zero (Panel B, sample months), while β_2 for annuities is significantly negative (Panel C, sample months). This suggests that bank branches are more likely to substitute unqualified life insurance products with annuities, while maintaining the sales of qualified life insurance products unchanged. This is likely because designing and promoting new life insurance products with qualified longer durations within a short time frame could be costly for the insurance company.

Thus far, we have focused on analyzing the premiums collected from new contracts, which we consider the best reflection of sales effort in the current month. However, the qualified

[10]Health and accident insurance, taken together, contribute negligibly to the total premium, as shown in Table 1 Panel A.

premium, as required by regulation, includes premiums from both new contracts and those from existing contracts sold previously. We therefore repeat the analyses in Table 2, but replace the dependent variables with the ones calculated using total premiums and present the results in Table 3. The results remain qualitatively identical: when there is a shortfall in meeting the target during the first two months of a quarter, bank branches increase their sales of qualified (long-term) products in the third month. This pattern emerges only after the policy change and during the sample months, with the response primarily driven by increased annuity sales.

Given that the 2014 regulation requires compliance at the aggregated bank-province level, a valid concern arises about whether our construction of the sales target at the bank-branch level accurately reflects how banks distribute and enforce this regulatory requirement across branches. To address this, we empirically test the validity of our target construction using two approaches. In the first set of analyses, we introduce a random component with varying standard deviations to the target faced by each branch each quarter, then repeating our analyses. The rationale is that the correct target should result in the largest kink in slopes; if our constructed target accurately reflects the true threshold, the results should weaken as we introduce more noise into the calculation.

Table 4 Panel A presents regression estimations of βs using random thresholds. We generate random thresholds using the following process:

$$C^*_{i,t} = C_{j,t} + \sigma\epsilon^{'}_{i,t}.$$

$C_{j,t}$ is the bank-city level target as in the main analysis. We simulate $\epsilon^{'}_{i,t}$ from a standard normal distribution, $N(0,1)$, and set σ to 0.1, 0.2, and 0.3, with the results reported in columns (1), (2), and (3), respectively. Due to space constraints, we present only the difference in coefficients between sample months and placebo months, corresponding to the third column in Table 2 Panel A. we see that both the magnitude and significance of β_2 decrease as σ increases, indicating that our constructed targets capture the most pronounced kink in slopes. This supports the accuracy of our target construction, as deviations from the correct target weaken the results.

A second approach to validate our target construction is to reduce the information content in the target calculation and assess whether the results weaken as the targets become less informative. Specifically, the target we construct—calculated as the average qualified ratio over the previous four quarters for all branches of a given bank in a specific city—contains bank $\times$ city $\times$ year-month level information. We create three alternatives, less-informative targets: (1) the previous qualified ratio from another bank in the same city and year-month, (2) the ratio from the same bank in a different year-month, and (3) the ratio from a bank in another city in the same year-month. We then repeat our baseline regression using these less-informative targets, with results presented in Table 4 Panel B. As expected, removing bank-specific information reduces the effect by half (target 1, column 1), and further reducing information leads to estimates close to zero (targets 2 and 3, columns 2 and 3). These results support that our main construction effectively captures sales targets at the bank-branch level.

3.2 The (lack of) effect on total premiums and contract lapsation

The previous section analyzed how compliance pressure at the bank branch-quarter level influences sales composition. A natural follow-up question is whether compliance pressure also impacts total sales, beyond just composition. In this section, we investigate the effect on total premiums within our identified framework (Eq 3).

Table 5 presents the results. In Panel A, the dependent variable is the logarithm of the total premium from new contracts sold in a given month at a bank branch. The estimated β_2 is insignificant for both sample and placebo months, indicating no discernible on total premiums. In Panels B and C, we break down the total premium into life insurance contracts and annuities, respectively. For the last month of each quarter (sample months), β_2 is significantly positive for life contracts and significantly negative for annuities. By contrast, the effects are near zero during placebo months. Taken together, these results suggest that near quarter-ends, when there is a shortfall in meeting compliance targets, bank branches do not increase overall sales. Instead, they shift sales from short-term life products to long-term qualified annuities, indicating a substitution effect.

A potential concern with our findings thus far is that households might purchase long-term annuity products but decide to cancel them soon after, meaning there would be no real impact on the hosueholds' product adoption. We thus examine whether the lapsation rates change at those quarter ends with more intensive compliance pressure. Table 6 presents results using lapsation rates as the dependent variable. Panel A reports equal-weighted lapsation rates, defined as the proportion of lapsed new contracts relative to all new contracts, where a lapsed contract is one that was signed in a given month but terminated by the buyer for personal reasons within the following 12 months. The estimates are close to zero and statistically insignificant, suggesting that while compliance pressure affects sales composition, it has little impact on overall lapsation rates. Panel B shows that this finding holds true when considering value-weighted lapsation rates, calculated as the total premium of lapsed new contracts relative to the total premium of all new contracts.

4 Mechanisms: How Do Banks Achieve Sales Targets?

In this section, we explore the mechanisms that help explain how distribution channels meet their sales targets. Several possibilities could account for this. First, distribution channels, in collaboration with product providers, may adjust the pricing of various products, making certain offerings more attractive to investors. Second, these channels might focus on targeting clients who are more inclined or suited to specific products, leading to a shift in the composition of policyholders. Thirdly, distribution channels could persuade their clientele to adopt certain products through communication, possibly manipulation. This could lead to a shift away from other products, even without any alteration in client characteristics. We examine each of the possible mechanisms in the following analyses.

4.1 Do banks change relative pricing?

One way banks might influence buyers' choices is by adjusting the relative pricing of qualified versus unqualified products. Naturally, the pricing of each policy depends on its characteristics and the demographics of the buyer. To explore this, we first examine how pricing relates to these factors. We calculate the $Markup_{i,k,t}$ for each contract according to Eq 1, and then regress the markup on a set of contract-level characteristics. These include the insured person's gender, age, and annual income, as well as whether the policy pays dividends and the contract's duration.[11] We also include the interaction terms of these characteristics. These results are presented in Table 7. We perform separate analyses for life insurance and annuities, and further divide the sample into pre- and post-policy change periods (with 2014 as the cutoff). This allows us to account for potential differences in pricing dynamics over time and between product types.

For our purposes, we want to examine whether bank branches adjust the relative pricing of different products when facing compliance pressure near the end of each quarter. We assess the pricing of each contract using both the raw markup and the residual markup derived from the pricing equation in Table 7.[12] The residual markup reflects pricing deviations that cannot be explained by the contract's inherent features. We then estimate our baseline regression as in Eq 3, with the dependent variable set to be the raw markup or residual

[11] Both life insurance and annuities can pay dividends based on the insurance company's investment profits, which are usually variable but determined at the time of signing the new contract.

[12] To calculate the residual, we run this regression separately for each year and for life insurance and annuities.

markup. The results, shown in Table 8 Panels A and B, indicate that neither the markup of qualified nor unqualified products is affected by the shortfall to sales targets at quarter-ends.

4.2 Shift of clientele or persuasion aimed at the same client base?

The previous subsection shows that bank branches do not change relative pricing to affect sales composition. Another possibility is that they may make sales effort to attract clienteles that are more suitable for long-term products, which will result in a different clientele composition when they face compliance pressure. We test this conjecture by re-run our baseline regression (as in Eq 3) at the contract level and set the dependent variable to be a battery of insuree's characteristics.

Table 9 presents the impact of compliance pressure on insuree characteristics, including gender, age, and annual income, shown in Panels A, B, and C, respectively. We report estimations for all contracts, as well as separately for qualified and unqualified products. The results show that nearly all β_2 coefficients are not significantly different from zero, both in placebo and sample months. This suggests that, following the regulatory reform, bank branches do not adjust their clientele at the quarter ends with increased compliance pressure. Instead, they shift product sales within the same client pool.

5 Additional Results: The Personal Agent Channel

In this section, we validate our empirical findings by testing the impact of placebo target ratios on personal agents' insurance sales. As the policy change is exclusive to the bank agent channel, analyzing the personal agent sales channel serves as a placebo test. This allows us to rule out the possibility that the observed results are driven by broader market trends rather than the policy's specific effects on bank agents.

We apply our baseline empirical strategy but now analyze the impact on personal agents' sales. Similar to the construction of qualification targets for bank branches, we create a placebo target for each salesman by averaging the qualified ratio over the previous four quarters across all salesmen within a given institution in the same city.[13]

In Panel A of Table 10, we repeat the regression analyses in Table 2, but now focus on relation between the abnormal qualified ratio and distance to target for personal agents. The results show that all β_2 estimates, in both sample and placebo months, are close to zero and statistically insignificant. This indicates that whether qualified sales in the first two months of a quarter exceed or fall short of the target has no discernible impact on the sales composition in the third month. In Panels B and C, we further break down new sales into life insurance and annuity categories. Again, β_2 estimates are generally indistinguishable from zero.

Table 11 evaluates the effect of the placebo target on total premiums (Panel A) and lapsation rates (Panel B) for personal agents, mirroring the analyses conducted in Table 5 Panel A and Table 6 Panel B. Consistent with earlier findings, the β_2 estimates are generally close to zero and statistically insignificant. These results further confirm that the sales targets imposed by the policy regulation, which are specific to the bank channel, have no impact on the sales behavior of personal agents.

6 Conclusion

This paper studies the impact of distribution channels on insurance product adoption. We exploit a regulatory change in 2014 that requires at least 20% of the insurance products sold by bank insurance agents in each quarter to be qualified long-term insurance products. Leveraging an unique policy-level data provided by one of the largest life insurers in China,

[13] As in the bank channel, we aggregate smaller institutions with annual revenue below 100,000 RMB from the previous year into a "virtual" institution for each city and quarter.

we analyse how branch-quarter variation in distance-to-constraint affect sales composition in each of the bank branches. Exploiting a discontinuity-in-slope empirical design, we show that bank agents falling below their target qualified ratios in the first two months of a quarter make up for the shortfall in the third month; conversely, bank branches that have exceeded their target ratios in the first two months do not alter their behavior in the final month of the quarter. This shift in the qualified ratio in the last month of the quarter is entirely due to a composition change – to switch from short-term unqualified life insurance products to long-term qualified annuity products.

Further analyses on the mechanisms show that this change in sales composition is achieved mainly via persuasion, rather than by changing the relative pricing of the products or changing client compositions. Our results highlight the fact that many retail investors may have very limited financial knowledge about what kind of financial products are suitable for their goals and preferences. Constraints that distribution channels face can therefore generate a large impact on financial product adoption and investor welfare.

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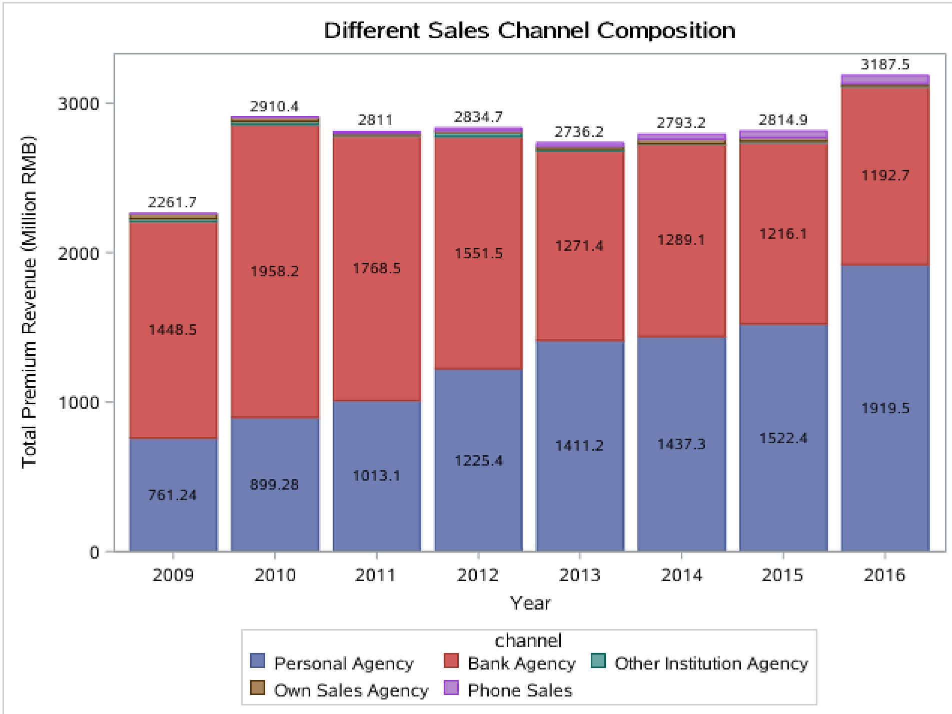

Figure 1: Premium revenue from different distribution channels

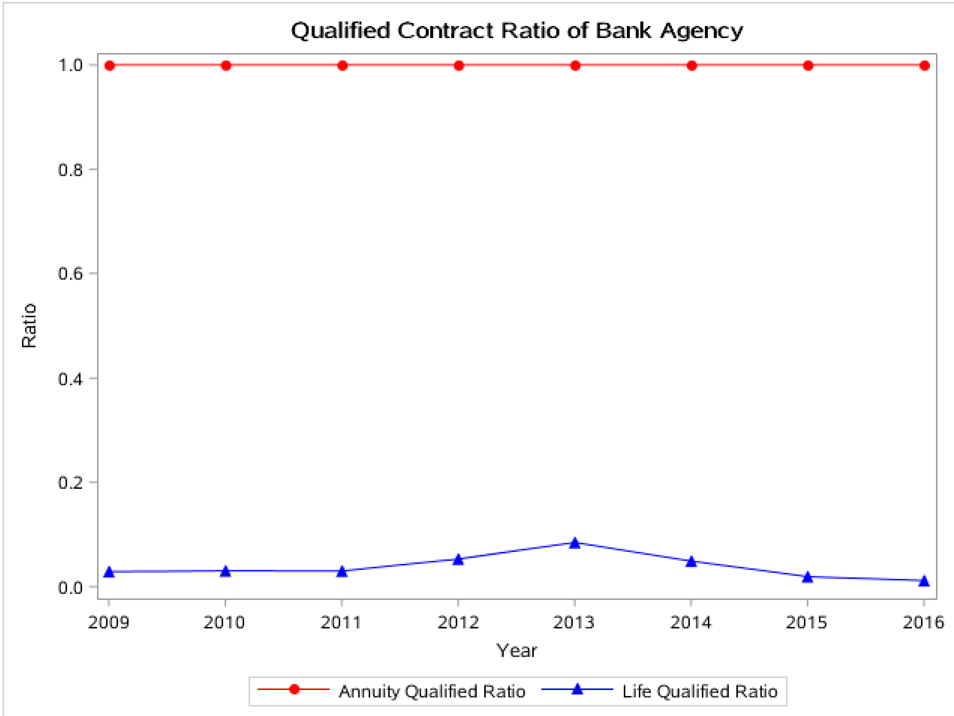

Figure 2: Qualified ratio of new contracts sold by bank channel

Table 1: Summary Statistics

This table reports the summary statistics of insurance selling of our sample for the period 2009 to 2016.

Panel A reports time-series insurance sales by SalesmanIDs from all sales channels. In the second column, the total number of insurance contracts sold in that given year is shown, along with the proportion of each type of insurance product. The term "A&H" stands for accident and health insurance combined. Column 6 reports the total insurance premium in million RMB from these new contracts in the given year. For contracts with multi-period payments, only the premium occurring in that year is taken into account. The following three columns show the proportion of each type of insurance product contributing to the premium.

Panel B reports premium revenue, average lapsation rate, and contract duration of each bank branch for each month. Qualified premiums refer to those from long-term products required by the 2014 regulation reform. In the second part of the panel, only branches with new contracts sold in a given month are reported. Lapsation refers to the proportion of new contracts lapsed within 12 months due to personal reasons. The last part of the panel focuses on branches with life insurance and annuity sales in a given month. The duration represents the maturity of the contract. For whole life products, it is assumed that the insured would die at 85 years old.

Panel C reports the characteristics of new contracts sold by bank agencies. The markup is the ratio of the present value of expected premium revenue to the present value of expected policy payment, considering all mortality rates. The Residual Markup stands for the residuals of the regression in Table 7, discussed in Section 2.1. Given that there are some missing values in buyer income, we substitute the missing values with the median income of the same age and gender group in the same city. The Delta/Value stands for the mortality delta following **?** at the point when the insurance is sold, divided by the insurance value.

Table 1: Summary Statistics

(a) All SalesmanID (Branch) Obs

year	# of New Contracts	Life	Proportion Annuity	A&H	Premium (New) (Million RMB)	Life	Proportion Annuity	A&H
2009	102348	52.66%	14.11%	33.24%	1657.35	88.35%	10.97%	0.68%
2010	155802	36.14%	6.67%	57.19%	2126.73	92.50%	5.96%	1.54%
2011	68574	63.69%	13.44%	22.87%	1629.86	93.20%	5.58%	1.23%
2012	65845	51.74%	14.39%	33.87%	1349.33	85.36%	11.53%	3.10%
2013	53832	51.85%	14.56%	33.60%	1037.21	88.60%	8.75%	2.65%
2014	62999	35.00%	15.87%	49.14%	1228.16	80.05%	16.31%	3.64%
2015	61173	22.45%	36.99%	40.56%	1357.89	39.18%	57.99%	2.83%
2016	86899	24.16%	45.29%	30.55%	1541.83	32.93%	64.90%	2.18%

(b) Branch-Month Obs. (Bank Agency)

	N	mean	std	p5	median	p95
Total Premium (K RMB)	119515	53.76	165.48	0.11	15.00	210.00
Qualified Premium (K RMB)	119515	16.30	81.07	0.00	0.06	65.66
Conditional on the branch having sold new contracts that month						
# of New Contracts	55517	1.854	1.930	1.00	1.00	5.00
New Premium (K RMB)	55517	83.78	229.13	0.10	340.00	20.00
New Annuity Premium (K RMB)	55517	18.45	109.67	0.00	90.00	0.00
New Life Premium (K RMB)	55517	65.20	201.87	0.00	290.00	10.00
Lapsation	55517	0.01	0.09	0.00	0.00	0.00

(c) New Contracts (Bank Agency)

	N	Mean	Std. Dev.	p5	Median	p95
Buyer Male	296091	0.383	0.486	0.000	0.000	1.000
Buyer Age	296116	48.140	13.302	26.000	48.000	70.000
Buyer Income (K RMB)	296103	69.127	95.979	20.000	50.000	150.000
Duration (Annuity)	16743	20.247	17.170	10.000	10.000	64.000
Duration (Life Insurance)	275845	6.381	5.785	5.000	5.000	10.000
Markup	146310	1.085	0.119	0.941	1.093	1.221
Residual Markup	146310	0.000	0.039	-0.058	0.001	0.054
Delta/Value	141513	0.180	0.201	0.038	0.101	0.564

Table 2: Distance-to-Constraint and Sales Composition: New Contracts

This table reports the estimated regression coefficients β_1 and β_2 from

$$\begin{aligned} y_{i,t} = \quad & \beta_1 D_{QR^{L2}_{i,t}<C_{i,t}} \times (QR^{L2}_{i,t} - C_{i,t}) + \beta_2 D_{2014} \times D_{QR^{L2}_{i,t}<C_{i,t}} \times (QR^{L2}_{i,t} - C_{i,t}) \\ & + \sum_j \gamma_{1,j} D_j \times (QR^{L2}_{i,t} - C_{i,t}) + \sum_j \gamma_{2,j} D_j D_{QR^{L2}_{i,t}<C_{i,t}} + \theta_t + \eta_i + \epsilon_{i,t}, \end{aligned}$$

where i stands for the bank branch and t stands for the year-quarter. The observations are in the branch-month level. $QR_{i,t}$ is the qualified ratio in the previous two months, which is heterogeneous for each branch i. Institution ID. $C_{i,t}$ is the city-level bank-specific target, namely the required qualified ratio in the previous four quarters defined in the data section, which is identical for all branches at each quarter with the same Institution ID. D_{2014} is a dummy for the post–2014 period. We allow the coefficient of the single terms $\{(QR^{L2}_{i,t} - C_{i,t}), D_{QR^{L2}_{i,t}<C_{i,t}}\}$ to have different coefficients $\{\gamma_{1,j}, \gamma_{2,j}\}$ in each year. The time-fixed effect θ_t is captured at the year-quarter level. The panel fixed effect η_i is captured at the bank branch level. All standard errors are double-clustered at year-quarter and branch level. T-stats are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

In Panel A, $y_{i,t}$ is set to be the ratio of qualified premium to total premium from all new contracts minus the branch's qualified new premium ratio in the last four quarters, i.e. abnormal qualified ratio. In the first column, only quarter-end month observations are included. In the second column, only observations in the first and second month within a quarter are included. In the last column, the differences of coefficients in the first two columns are reported, by running a pooling regression and introducing difference dummies. The coefficients change from $(\beta_1, \beta_2, \{\gamma_{s,j}\}_{1,2}, \theta_t, \eta_i)$ to $(\beta_1 + \delta^* \beta_{\delta,1}, \beta_2 + \delta^* \beta_{\delta,2}, \{\gamma_{s,j} + \delta^* \gamma_{\delta,s,j}\}_{1,2}, \theta_t + \delta^* \theta_{\delta,t}, \eta_i + \delta^* \eta_{\delta,i})$. Here, $\delta^* = 1$ for all sample month observations and 0 otherwise. The reported coefficients in the last column are $(\beta_{\delta,1}, \beta_{\delta,2}, \{\gamma_{\delta,s,j}\}_{1,2}, \theta_{\delta,t}, \eta_{\delta,i})$.

Panel B reports the regression results using the abnormal qualified ratio from new life insurance, i.e. the ratio of qualified premiums from new life insurance to the total new premium, subtracting this ratio in the last four quarters of a given branch, as $y_{i,t}$. All other settings are identical to Panel A.

Panel C reports the regression results using the abnormal qualified ratio from new annuities, i.e. the ratio of qualified premiums from new annuities to the total new premium, subtracting this ratio in the last four quarters of a given branch, as $y_{i,t}$. All other settings are identical to Panel A.

(a) Dependent Variable: Abnormal Qualified Ratio (New Contracts)

	Sample Months	Placebo Months	Diff.
β_1	0.082	-0.172	0.254
	(0.48)	(-1.47)	(1.25)
β_2	**-0.528****	**0.206**	**-0.735*****
	(-2.42)	**(1.20)**	**(-2.71)**
Obs.	6117	14740	20857
R^2	0.43	0.337	0.368

(b) Dependent Variable: Abnormal Qualified Ratio (New Life Insurance)

	Sample Months	Placebo Months	Diff.
β_1	-0.019	-0.084	0.066
	(-0.12)	(-0.70)	(0.35)
β_2	**0.174**	**0.175**	**-0.001**
	(0.81)	**(1.19)**	**(-0.01)**
Obs.	5807	14425	20232
R^2	0.362	0.314	0.329

(c) Dependent Variable: Abnormal Qualified Ratio (New Annuity)

	Sample Months	Placebo Months	Diff.
β_1	0.07	-0.062	0.133
	(0.66)	(-1.07)	(1.17)
β_2	**-0.700*****	**0.011**	**-0.711*****
	(-4.17)	**(0.09)**	**(-3.56)**
Obs.	5807	14425	20232
R^2	0.483	0.343	0.393

Table 3: Distance-to-Constraint and Sales Composition: All Contracts

This table reports the estimated regression coefficients β_1 and β_2 for the panel regression model identical to Table 2. In Panel A, $y_{i,t}$ uses the abnormal qualified ratio using the total premium, i.e. the total qualified premium to the total premium for each month of a given bank branch, subtracting this ratio calculated using the premium from the last four quarters. The qualified premium consists of the qualified premium from new contracts and also the qualified premium from old contracts. In Panel B, $y_{i,t}$ uses the abnormal qualified ratio from all life insurance contracts. Panel C substitutes $y_{i,t}$ into the abnormal qualified ratio from all annuities. All the other variable settings are identical to Table 2. T-stats are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

(a) Dependent Variable: Abnormal Qualified Ratio (All Contracts)

	Sample Months	Placebo Months	Diff.
β_1	0.086	-0.061	0.147
	(0.92)	(-0.80)	(1.24)
β_2	**-0.520*** **	**-0.065**	**-0.455*** **
	(-4.28)	**(-0.58)**	**(-2.79)**
Obs.	15075	31923	46998
R^2	0.453	0.317	0.362

(b) Dependent Variable: Abnormal Qualified Ratio (All Life Insurace)

	Sample Months	Placebo Months	Diff.
β_1	0.075	-0.017	0.091
	(0.87)	(-0.21)	(0.79)
β_2	**-0.238***	**-0.09**	**-0.148**
	(-2.01)	**(-0.85)**	**(-0.95)**
Obs.	14688	31629	46317
R^2	0.373	0.265	0.3

(c) Dependent Variable: Abnormal Qualified Ratio (All Annuity)

	Sample Months	Placebo Months	Diff.
β_1	-0.011	-0.058	0.047
	(-0.21)	(-1.19)	(0.67)
β_2	**-0.286*** **	**0.043**	**-0.329*** **
	(-4.80)	**(0.60)**	**(-3.64)**
Obs.	14688	31629	46317
R^2	0.336	0.249	0.279

Table 4: Alternative Sales Targets

This table reports the estimated regression coefficients β_1 and β_2 for the panel regression model similar to Table 2. The dependent variable $y_{i,t}$ is identical to the Panel A of Table 2. The only difference is that $C_{i,t}$s in Panel A are substituted by $C^*_{i,t} = C_{j,t} + \sigma\epsilon^{'}_{i,t}$, where $\epsilon^{'}_{i,t}$ is generated from $N(0,1)$ and σ is set to be 0.1, 0.2, or 0.3. $C_{i,t}$s in Panel B are substituted by $C^*_{i,t} = C_{l,k}$ that are randomly drawn from other time points k or banks l. In the first column $C^*_{i,t}$ is drawn from other banks $l \neq j$ in the same city and same year-month t. In the second column, $C^*_{i,t}$ is drawn from the same bank $l = j$ but different year-month $k \neq t$. In the third column, $C^*_{i,t}$ is drawn from the same time $k = t$ but different banks $l \neq j$ in our sample. All the columns reports the thrid column of the differences between sample months and placebo months in Table 2. All other settings are identical to Table 2. T-stats are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

(a) Adding Noise to the Constructed $C_{i,t}$

$\sigma =$	0.1	0.2	0.3
	Diff. (=Sample Months - Placebo Months)		
β_1	0.136	0.069	-0.044
	(0.91)	(0.55)	(-0.56)
β_2	**-0.567****	**-0.449****	**-0.095**
	(-2.47)	**(-2.57)**	**(-0.66)**
Obs.	20855	20855	20855
R^2	0.365	0.356	0.346

(b) Less Informative Targets

	Same YM + City	Same Bank	Same YM
	Diff. (=Sample Months - Placebo Months)		
β_1	0.037	-0.015	-0.117
	(0.30)	(-0.13)	(-1.06)
β_2	**-0.377***	**-0.205**	**-0.189**
	(-1.73)	**(-1.19)**	**(-1.13)**
Obs.	20855	20855	20855
R^2	0.331	0.327	0.327

Table 5: Distance-to-Constraint and Total Premium

This table reports the estimated regression coefficients β_1 and β_2 for the panel regression model identical to Table 2. In Panel A, the dependent variable $y_{i,t}$ is the logarithm of the total premium from the new contract selling of the branch in a given month. It is changed to the total premium from the new life insurance (annuity) contracts in Panel B (C). All other settings are identical to Table 2. T-stats are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

(a) Dependent Variable: Log(Total New Premium+1)

	Sample Months	Placebo Months	Diff.
β_1	0.266	0.172	0.075
	(0.57)	(1.47)	(0.12)
β_2	**-0.604**	**-0.206**	**-0.651**
	(-0.81)	**(-1.20)**	**(-0.70)**
Obs.	6187	14740	21066
R^2	0.411	0.337	0.411

(b) Dependent Variable: Log(Life New Premium+1)

	Sample Months	Placebo Months	Diff.
β_1	0.526	0.468	0.058
	(0.44)	(0.56)	(0.04)
β_2	**4.777****	**0.065**	**4.712***
	(2.44)	**(0.04)**	**(1.95)**
Obs.	6187	14879	21066
R^2	0.597	0.543	0.56

(c) Dependent Variable: Log(Annuity New Premium+1)

	Sample Months	Placebo Months	Diff.
β_1	0.507	-0.795	1.303
	(0.46)	(-1.30)	(1.06)
β_2	**-7.193*****	**0.307**	**-7.499*****
	(-4.27)	**(0.25)**	**(-3.67)**
Obs.	6187	14879	21066
R^2	0.674	0.623	0.639

Table 6: Distance-to-Constraint and Lapsation Rates

This table reports the estimated regression coefficients β_1 and β_2 for the panel regression model identical to Table 2. In Panel A (B), the dependent variable $y_{i,t}$ is the equal-weighted (value-weighted) lapsation rate of new contracts sold by the branch in a given month. The lapsed contract is defined as the contract lapses for personal reasons within the next 12 months. All other settings are identical to Table 2. T-stats are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

(a) Dependent Variable: Avg. Lapsation Rate (Equal Weighted)

	Sample Months	Placebo Months	Diff.
β_1	0.013	0.006	0.007
	(0.49)	(0.39)	(0.25)
β_2	**-0.021**	**-0.006**	**-0.015**
	(-0.61)	**(-0.29)**	**(-0.38)**
Obs.	6187	14879	21066
R^2	0.301	0.167	0.214

(b) Dependent Variable: Avg. Lapsation Rate (Value Weighted)

	Sample Months	Placebo Months	Diff.
β_1	0.012	-0.009	0.022
	(0.42)	(-0.46)	(0.63)
β_2	**-0.013**	**0.007**	**-0.02**
	(-0.33)	**(0.29)**	**(-0.44)**
Obs.	6187	14879	21066
R^2	0.304	0.163	0.21

Table 7: Determinants of Contract Pricing

This table reports the estimated regression coefficients for the panel regression model

$$Markup_{j,k,t} = \gamma_1 \mathbf{X}'_{\mathbf{j,t}} + \gamma_2 \mathbf{Z}'_{\mathbf{j,t}} + \gamma_3 \text{vec}(\mathbf{X}'_{\mathbf{j,t}} \mathbf{Z}_{\mathbf{i,t}}) + \theta_t + \eta_i + \epsilon_{i,t},$$

where k is the insurance products insured the person j in the branch i at the quarter t. $Markup_{j,k,t}$ is based on the ratio of the expected present value of the total premium to the expected claim amount within the contract maturity. $X_{j,t}$ represents insured characteristics, including the logarithm of annual income, a male dummy variable, and age. $Z_{j,t}$ is a vector of product characteristics, consisting of the duration and whether the product pays dividends. The time-fixed effect θ_t is captured at the year-quarter level. The panel fixed effect η_i is captured at the bank branch level. In the first three columns, the observations only consist of life insurance products. The first column uses the whole sample, while the second (third) column uses the sub-sample of contracts sold after (before) the regulation reform date. In the last three columns, the observations only consist of annuity products. These three columns follow the identical sub-sample division rule as the first three columns. All standard errors are double-clustered at the year-quarter and branch levels. T-stats are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively."

	Life Insurance			**Annuity**		
	Whole	After 2014	Before 2014	Whole	After 2014	Before 2014
Income	0.010*	0.005	0.001	-0.023**	-0.026**	0.014
	(1.92)	(0.89)	(0.03)	(-2.63)	(-2.71)	(1.11)
Dividend	(0.03)	0.039*	-0.133*	0.283***	0.258***	0.00
	(-1.41)	(2.02)	(-1.95)	(4.61)	(3.56)	(0.00)
Gender	-0.01	0.02	0.06	0.059***	0.085***	-0.02
	(-1.12)	(1.62)	(1.05)	(3.65)	(5.24)	(-0.91)
Age	-0.004***	-0.004***	-0.009***	0.00	0.002*	0.00
	(-11.02)	(-6.14)	(-4.69)	(1.66)	(1.78)	(-0.37)
Duration	0.004***	0.006**	0.002***	0.007***	0.007***	0.010***
	(2.73)	(2.52)	(4.95)	(11.47)	(9.93)	(12.07)
Income×Dividend	-0.015***	-0.017***	-0.01	0.025***	0.027**	0.00
	(-3.86)	(-3.65)	(-0.57)	(3.49)	(2.63)	(0.00)
Gender×Dividend	0.024***	0.020***	-0.07	-0.027***	-0.035**	0.00
	(5.20)	(3.13)	(-1.15)	(-2.68)	(-2.67)	(0.00)
Age×Dividend	0.002***	0.001***	0.007***	-0.003***	-0.003**	0.00
	(7.38)	(3.29)	(3.68)	(-2.82)	(-2.27)	(0.00)
Income×Duration	0.00	0.00	0.008***	0.008**	0.010**	0.00
	(0.90)	(0.78)	(3.34)	(2.16)	(2.46)	(-0.15)
Gender×Duration	-0.022***	-0.045***	0.00	-0.027***	-0.037***	0.01
	(-3.73)	(-4.68)	(-0.44)	(-3.40)	(-4.73)	(0.47)
Age×Duration	0.001***	0.00	0.001***	-0.001**	-0.001**	0.00
	(4.55)	(0.87)	(5.48)	(-2.04)	(-2.42)	(0.62)
Obs.	69787	26605	41972	6769	5784	759
Adjusted R^2	0.729	0.753	0.592	0.737	0.695	0.825

Table 8: Distance-to-Constraint and Contract Pricing

This table reports the estimated regression coefficients β_1 and β_2 for the panel regression model similar to Table 2 but uses contract-level observations. The $y_{i,t}$ in Panel A is the markup of each contract, and the $y_{i,t}$ in Panel B is the regression residual of the markup. These residuals are from regressions identical to Table 7 but conducted year-by-year and separately according to annuity or life insurance. In the first three columns of each panel, all contracts are included. In the middle three columns, we focus only on qualified contracts. The last three columns take the remaining unqualified sub-sample contracts. All independent and control variables are identical to Table 2 and at the branch level. The regressions use weighted OLS based on the contract's expected premium revenue. All standard errors are still double-clustered at year-quarter and branch level. T-stats are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

(a) Dependent Variable: Markup

		All			Qualified			Unqualified	
	Sample	Placebo	Diff.	Sample	Placebo	Diff.	Sample	Placebo	Diff.
β_1	-0.002	-0.031	0.029	0.037	-0.038	0.075	0.007	0.018	-0.011
	(-0.05)	(-1.37)	(0.69)	(0.66)	(-1.13)	(1.21)	(0.37)	(1.14)	(-0.48)
β_2	**0.007**	**0.022**	**-0.015**	**-0.048**	**0.000**	**-0.048**	**-0.001**	**-0.019**	**0.018**
	(0.12)	**(0.74)**	**(-0.22)**	**(-0.37)**	**(-0.00)**	**(-0.34)**	**(-0.05)**	**(-1.04)**	**(0.64)**
Obs.	11508	29695	41203	1996	4365	6361	9185	24952	34137
R^2	0.88	0.868	0.873	0.883	0.86	0.868	0.825	0.869	0.862

(b) Dependent Variable: Residual Markup

		All			Qualified			Unqualified	
	Sample	Placebo	Diff.	Sample	Placebo	Diff.	Sample	Placebo	Diff.
β_1	-0.01	0.007	-0.017	-0.012	-0.011	0.00	-0.018	0.010	-0.028
	(-0.63)	(0.56)	(-0.87)	(-0.65)	(-0.59)	(-0.01)	(-0.99)	(0.67)	(-1.20)
β_2	**-0.004**	**-0.002**	**-0.002**	**-0.038**	**0.001**	**-0.039**	**-0.002**	**0.001**	**-0.004**
	(-0.14)	**(-0.11)**	**(-0.07)**	**(-0.77)**	**(0.04)**	**(-0.67)**	**(-0.12)**	**(0.08)**	**(-0.14)**
Obs.	11508	29695	41203	1996	4365	6361	9185	24952	34137
R^2	0.32	0.24	0.268	0.427	0.341	0.374	0.317	0.232	0.26

Table 9: Distance-to-Constraint and Insurees' Characteristics

This table reports the estimated regression coefficients β_1 and β_2 for the panel (Probit) regression model identical to Table 8. The $y_{i,t}$ in Panel A is the buyer male dummy, and the regressions are based on the Probit model. The $y_{i,t}$ in Panel B is the insuree age, and the $y_{i,t}$ is the logarithm of the insuree's annual income in Panel C. All standard errors are still double-clustered at year-quarter and branch level. T-stats are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

(a) Dependent Variable: Insuree Gender

		All			Qualified			Unqualified	
	Sample	Placebo	Diff.	Sample	Placebo	Diff.	Sample	Placebo	Diff.
β_1	-0.061	0.331	-0.384	-1.201	-0.016	-0.84	0.44	0.629	-0.409
	(-0.15)	(0.74)	(-0.63)	(-1.37)	(-0.02)	(-0.87)	(0.97)	(1.34)	(-0.61)
β_2	**0.108**	**-0.468**	**0.576**	**1.073**	**0.134**	**1.021**	**-0.418**	**-0.854***	**0.457**
	(0.22)	**(-0.98)**	**(0.85)**	**(1.21)**	**(0.15)**	**(0.81)**	**(-0.61)**	**(-1.91)**	**(0.56)**
Obs.	11992	29816	41808	2395	4616	7011	9597	25200	34797
Pseudo R^2	0.004	0.001	0.002	0.014	0.003	0.006	0.006	0.002	0.003

(b) Dependent Variable: Insuree Age

		All			Qualified			Unqualified	
	Sample	Placebo	Diff.	Sample	Placebo	Diff.	Sample	Placebo	Diff.
β_1	0.433	0.625**	-0.192	0.397	1.064***	-0.668	0.078	-0.816*	0.894
	(0.94)	(2.23)	(-0.36)	(0.58)	(3.67)	(-0.92)	(0.10)	(-1.71)	(1.02)
β_2	**0.295**	**-0.302**	**0.597**	**0.364**	**-0.747**	**1.110**	**0.892**	**1.025***	**-0.133**
	(0.52)	**(-1.01)**	**(0.99)**	**(0.47)**	**(-1.59)**	**(1.16)**	**(0.98)**	**(1.90)**	**(-0.14)**
Observations	4180	10821	15001	1279	2917	4196	2653	7636	10289
R2	0.74	0.673	0.692	0.674	0.666	0.669	0.838	0.714	0.746

(c) Dependent Variable: Insuree Income

		All			Qualified			Unqualified	
	Sample	Placebo	Diff.	Sample	Placebo	Diff.	Sample	Placebo	Diff.
β_1	0.617	0.520	0.097	1.082**	0.612	0.470	0.189	-0.590	0.779
	(1.39)	(1.62)	(0.18)	(2.54)	(1.68)	(0.86)	(0.27)	(-1.28)	(0.99)
β_2	**0.188**	**-0.240**	**0.428**	**-0.458**	**-0.453**	**-0.005**	**0.955**	**0.791**	**0.164**
	(0.33)	**(-0.68)**	**(0.66)**	**(-0.68)**	**(-0.91)**	**(-0.01)**	**(1.15)**	**(1.52)**	**(0.18)**
Obs.	4502	11577	16079	1410	3248	4658	2829	8052	10881
R^2	0.709	0.668	0.68	0.608	0.666	0.65	0.836	0.705	0.739

Table 10: Sales composition: Personal Agent Channel

This table reports the estimated regression coefficients β_1 and β_2 for the panel regression models similar to Table 2 but use the personal agency observations. The observations are at the SalesmanID level, corresponding to the bank branches. The virtual binding constraints are set at the InstitutionID level, corresponding to the bank of each city. The three panels are identical to the three panels in Table 2 respectively. All standard errors are still double-clustered at year-quarter and branch level. T-stats are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

(a) Dependent Variable: Abnormal Qualified Ratio (New Contracts)

	Sample Months	Placebo Months	Diff.
β_1	0.018	-0.035	0.052
	(0.12)	(-0.36)	(0.31)
β_2	**0.028**	**0.078**	**-0.05**
	(0.18)	**(0.79)**	**(-0.30)**
Obs.	4106	8146	12252
R^2	0.757	0.586	0.663

(b) Dependent Variable: Abnormal Qualified Ratio (New Life Insurance)

	Sample Months	Placebo Months	Diff.
β_1	0.246	-0.071	0.317
	(0.89)	(-0.62)	(1.10)
β_2	**0.04**	**0.205***	**-0.165**
	(0.14)	**(1.73)**	**(-0.55)**
Obs.	4106	8146	12252
R^2	0.534	0.558	0.551

(c) Dependent Variable: Abnormal Qualified Ratio (New Annuity)

	Sample Months	Placebo Months	Diff.
β_1	-0.228	0.036	-0.265
	(-0.66)	(0.22)	(-0.72)
β_2	**-0.012**	**-0.127**	**0.115**
	(-0.03)	**(-0.76)**	**(0.30)**
Obs.	4106	8146	12252
R^2	0.565	0.555	0.558

Table 11: Total Premium and Lapsation Rates: Personal Agent Channel

This table reports the estimated regression coefficients β_1 and β_2 for the panel regression models indetical to Table 10 using the personal agency observations. Panel A and Panel B are identical to Panel A of Table 5 and Panel B of Table 6 respectively. All standard errors are still double-clustered at year-quarter and branch level. T-stats are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

(a) Dependent Variable: Log(Total New Premium+1)

	Sample Months	Placebo Months	Diff.
β_1	0.102	0.203	0.203
	(0.12)	(0.40)	(0.40)
β_2	**-0.134**	**-0.271**	**-0.271**
	(-0.14)	**(-0.50)**	**(-0.51)**
Obs.	4137	8215	12352
R2	0.696	0.671	0.68

(b) Dependent Variable: Lapsation Rate (Value Weighted)

	Sample Months	Placebo Months	Diff.
β_1	0.068*	-0.041	0.109**
	(1.92)	(-1.63)	(2.58)
β_2	**-0.06**	**0.027**	**-0.086***
	(-1.55)	**(0.99)**	**(-1.89)**
Obs.	4137	8215	12352
R2	0.184	0.217	0.206

Table A1: Abnormal Qualified Ratio (New Contracts) in Different Areas

This table reports the estimated regression coefficients β_1 and β_2 for the panel regression models identical to Panel A of Table 2. Each panel use the subsample observations based on the cities. Panel A consists of tier 1 cities including Beijing, Shanghai and Guangzhou. Panel B includes observations in Nanjing, Chengdu and Wuhan as the tier 2 cities. Panel C focuses on observations in Zhengzhou, Lanzhou and Shenyang, which are tier 3 cities. All standard errors are still double-clustered at year-quarter and branch level. T-stats are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

(a) Tier 1 Cities

	Sample Months	Placebo Months	Diff.
β_1	-0.01	-0.207	0.198
	(-0.04)	(−1.43)	(0.73)
β_2	**-0.492***	**0.212**	**-0.703****
	(-1.76)	**(1.01**	**(-2.08)**
Obs.	4078	10185	14263
R^2	0.433	0.365	0.387

(b) Tier 2 Cities

	Sample Months	Placebo Months	Diff.
β_1	0.425	-0.183	0.608*
	(1.55)	(-0.90)	(1.82)
β_2	**-0.826***	**0.195**	**-1.021****
	(-1.98)	**(0.78)**	**(-2.17)**
Obs.	1333	2846	4179
R^2	0.413	0.336	0.362

(c) Tier 3 Cities

	Sample Months	Placebo Months	Diff.
β_1	-0.267	0.09	-0.356
	(-0.99)	(0.30)	(-0.92)
β_2	**0.632**	**-0.078**	**0.71**
	(1.33)	**(-0.21)**	**(1.28)**
Obs.	706	1709	2415
R^2	0.601	0.414	0.477

Table A2: Abnormal Qualified Ratio (All Contracts) in Different Areas

This table reports the estimated regression coefficients β_1 and β_2 for the panel regression models identical to Panel A of Table 3. Each panel use the subsample observations based on the cities. Panel A consists of tier 1 cities including Beijing, Shanghai and Guangzhou. Panel B includes observations in Nanjing, Chengdu and Wuhan as the tier 2 cities. Panel C focuses on observations in Zhengzhou, Lanzhou and Shenyang, which are tier 3 cities. All standard errors are still double-clustered at year-quarter and branch level. T-stats are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

(a) Tier 1 Cities

	Sample Months	Placebo Months	Diff.
β_1	0.064	-0.12	0.184
	(0.69)	(-1.39)	(1.47)
β_2	**-0.511*** **	**0.03**	**-0.542*** **
	(-4.27)	**(0.23)**	**(-3.05)**
Obs.	9904	21205	31109
R^2	0.456	0.338	0.377

(b) Tier 2 Cities

	Sample Months	Placebo Months	Diff.
β_1	0.489***	0.217*	0.272
	(3.02)	(1.73)	(1.32)
β_2	**-0.968*** **	**-0.410** **	**-0.558** **
	(-5.07)	**(-2.49)**	**(-2.27)**
Obs.	3174	6504	9678
R^2	0.436	0.292	0.336

(c) Tier 3 Cities

	Sample Months	Placebo Months	Diff.
β_1	-0.252***	-0.196	-0.056
	(-2.92)	(-1.06)	(-0.27)
β_2	**0.058**	**-0.028**	**0.086**
	(0.24)	**(-0.13)**	**(0.27)**
Obs.	1997	4214	6211
R^2	0.515	0.353	0.409

Table A3: Cosmetic Change in Old Contracts

This table reports the estimated regression coefficients β_1 and β_2 for the panel regression model identical to Table 2. The dependent variable $y_{i,t}$ is the ratio of delayed unqualified premiums to all scheduled premiums from existing contracts in a given month, also substracting this ratio in the previous four quarters. The delayed unqualified premium ratio is

$$\text{Delayed Unqualified Ratio} = \frac{\text{Delayed scheduled unqualified premium}}{\text{Total scheduled unqualified premium}},$$

and the total scheduled unqualified premium is the sum of delayed scheduled unqualified premium and observed unqualified premium. All other settings are identical to Table 2. T-stats are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Sample Months	Placebo Months	Diff.
β_1	0.238*	0.224***	0.014
	(1.78)	(3.01)	(0.09)
β_2	**-0.440****	**-0.153**	**-0.287**
	(-2.74)	**(-1.38)**	**(-1.47)**
Obs.	5615	11762	17377
R^2	0.355	0.241	0.278

Table A4: Mortality Deltas Due to the Binding Constraints

This table reports the estimated regression coefficients β_1 and β_2 for the panel regression models identical to Table 2 but with different $y_{i,t}$. The $y_{i,t}$ in this table is the total premium weighted mortality delta, normalized to the insurance value. The mortality delta follows **?**. All standard errors are still double-clustered at year-quarter and branch level. T-stats are reported in parentheses. ***, **, and * denote statistical significance at the 1%, 5%, and 10% levels, respectively.

	Sample Months	Placebo Months	Diff.
β_1	-0.193	0.03	-0.223
	(-1.47)	(0.17)	(-1.08)
β_2	**0.778****	**-0.223**	**1.002****
	(2.23)	**(-0.63)**	**(2.06)**
Obs.	4767	11870	16637
R^2	0.541	0.449	0.477