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Abstract:

This paper analyzes the effects of providing forward-looking metrics on employee decision making. We use data from a southern European bank that, in April 2002, started providing its branch managers with customer lifetime value (CLV) information about mortgage applicants. The data allows us to gauge the effects of enriching the information set of these employees in an environment where incentives and the allocation of decision rights remained unchanged. We find that CLV availability resulted in a significant shift in attention towards the more profitable client segments (the weight of the top segment in the portfolio of customers increases from 26% to 34%), but we do not find evidence of improved cross-selling (except for an increase in the sale of insurance products). Moreover, the use of CLV information did not have a negative impact on pricing, as some of the literature suggests, nor on default risk, indicating that managers increased sales to more profitable customers by providing better customer service.

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I. Introduction

In this paper we analyze whether the introduction of forward-looking information influences employee decision making when there is no accompanying change in incentives or decision rights. Firms use forward-looking metrics such as customer satisfaction or customer lifetime value (CLV) to overcome the myopia created by the use of short-term financial metrics such as accounting profits in compensation schemes (Hauser, Simester and Wernerfelt, 1994, Hemmer, 1996, Ittner, Larcker and Rajan, 1997). For instance, a software company may include customer satisfaction in the compensation of a sales person to avoid a situation in which that sales person might lose the future sales of a customer by pushing the sale of a product that does not really fill the customer's needs in order to meet his sales quota.

However, a forward-looking metric may not be necessary to align the incentives of the firm and its employee. In essence, a forward-looking metric is a noisy assessment of future performance that will be superseded at a later day by the actual performance. The lower customer satisfaction score will eventually translate into lower sales for the firm. In this sense, short-term profits would be sufficient for a firm to control its employee's allocation of effort between short-term and long-term actions if the firm and employee were engaged in a long-term contract and the underlying moral hazard problem in the employee's actions did not change over time (Dikolli, 2001, Dutta and Reichelstein, 2003).

Even in the latter case, forward-looking metrics may impact managerial decision making without explicit inclusion in the incentive contract of the decision maker. An employee may change his decisions when confronted with a leading indicator if this metric brings new information to the decision making process. For instance, measures of customer satisfaction may inform the employee about the effectiveness of certain customer interactions. Moreover, even CLV that is a derivative metric of information already available to the decision maker (observable customer characteristics and past behavior of similar customers) may alter decision making if the bounded rationality of the decision maker limits the possibility of processing the existing information in an unbiased manner (Chakravarti, Mitchell and Staelin, 1981).

In this paper we analyze a situation in which the firm enlarged the information set of customer-facing employees with a forward-looking metric—CLV—while maintaining the incentives linked to short-term accounting profits. The firm also kept constant the decision rights of the employees to limit actions that could jeopardize future value creation (e.g. excessive price discounting). Specifically, we analyze how customer-facing employees modify their sales decisions when CLV estimates are added to their information set. Thus, we consider a situation in which the information set was altered while the other two mechanisms of control, incentives and decision rights, remained the same.

We conducted our research at a mid-sized southern European bank that had recently introduced a mortgage simulator as a decision aid for branch managers. The mortgage simulator helped managers visualize the expected future value of a mortgage applicant. This information enabled managers to better gauge the trade-offs between the value derived from the mortgage and the value of simultaneous and potential future sales. We found that branch managers altered their efforts most in the dimension of customer selection. Managers increased the share of mortgage sales in attractive customer segments. In contrast, aside from insurance contracts, we saw very little difference in cross-selling (the number of additional products sold with the mortgage), price concessions, or the way that managers incorporated risk considerations in their lending decisions.

Our research contributes to a variety of management literatures. Whether changes in information can independently effect changes in decision making is a question that has long captured the attention of management scholars. However, there is very little empirical evidence of how pure changes in the information set affect the outcome of decision processes. Aside from scant experimental information (for example, Fudge and Lodish, 1977) and a few studies that analyze the congruence between decisions and new information paradigms (Narayanan and Sarkar, 2002) or qualitative evidence of changes in decision outcomes (Ryals, 2005), most of the research in this area is affected by the impossibility of separating the impact of changes in the information set from the effect of simultaneous modifications in the incentive system. We contribute to this literature by analyzing changes in decision outcomes before and after the introduction of CLV while maintaining incentives and decision rights unchanged.

The CLV concept emerges from a conceptualization of the firm as a portfolio of customers (Gupta, Lehmann and Stuart, 2004). As a performance metric, CLV enables firms to concentrate their resource allocation in acquiring customers that create more value for the firm or in transforming existing customer relationships to increase their value through loyalty or cross-selling (Blattberg and Deighton, 1996; Zeithaml, Rust and Lemon, 2001; Reichheld, 1993). However, some researchers have cautioned that in competitive environments the promise of a customer's future value may lead to overinvestment in customer acquisition, and thus to the destruction of value (Klemperer, 1987; Villanueva, Bhardwaj, Balasubramanian and Chen, 2007). Most of the literature has focused on models to better estimate CLV (Hansotia and Wang, 1997; Villanueva and Hanssens, 2007), its link to the firm's financial value (Gupta et al., 2004; Amir and Lev, 1996), or the relationship between non-financial performance and the sustainability of a customer relation (Ittner and Larcker, 1998). However, there is very little research on how managers actually use CLV estimates in their decision making processes; a rare example is Ryals's (2005) qualitative study. We complement this literature by analyzing how the availability of CLV estimates affects the sales decisions of customer-facing employees.

In 1939, reflecting on the banking industry, Schumpeter noted the need for information that transcends the individual contract: "the banker must not only know what the transaction is which he is asked to finance and how it is likely to turn out, but he must also know the customer, his business, and even his private habits, and get, by frequently 'talking things over with him,' a clear picture of his situation." This point remains relevant today. Customer knowledge developed through a lending relationship may create opportunities to cross-sell other banking products (Bharath, Dahiya, Saunders and Srinivasan, 2007) or to widen the informational gap with competitors and exploit it through higher interest rates (Hauswald and Marquez, 2003). CLV estimates are a potentially promising addition to the tools that banks use to manage customer relationships and create value. We contribute to this literature by analyzing how the availability of CLV affects the way retail-banking branch managers deal with a very important event in the development of the relationship, such as the sale of a mortgage.

In summary, our paper enhances the literature on the use of forward-looking metrics for performance management by showing that firms can use the provision of such metrics to implicitly control the effort allocation of its employees between long-term and short-term actions. The paper also contributes to the literature on information economics and performance measurement by documenting that changes in the information set alone—without adjustments to decision rights or the incentive system—may change the behavior of decentralized decision-makers. Additionally, the paper contributes to the management and marketing literature by illustrating a case in which customer-facing employees find it easier to increase customer value by adjusting their selection of customers than by changing customer behavior, consistent with the evidence suggested by Casas-Arce and Martínez-Jerez (2009). Moreover, the paper advances the literature in frontline compensation to show that employees do not unnecessarily destroy firm value by trying to please customers with a "race to the bottom" in pricing when they are armed with a full understanding of the economic implications of their decisions for the firm. Finally, by documenting how decentralized customer-facing employees use CLV estimates in allocating their sales efforts, the findings of this paper contribute to the customer management literature by showing that CLV could be an effective tool for a firm's relationship management strategy.

Our contributions should be viewed in the context of our study, which was restricted to a single institution that offered freedom of action and responsibility for profitability and value-creation to the more than 300 decision-makers we observed. Human capital has been one of the cornerstones of the strategy of our subject bank, whose efforts to build a committed workforce have resulted in an industry-low employee turnover rate of 5%. Hence, this is a setting where, as suggested by Dikolli (2001) and Dutta and Reichelstein (2003), because of the long-term nature of the employment relationship, we could expect the agent to appropriately weight the future consequences of his actions in line with the firm's interests, even in the absence of an explicit use of CLV in the incentive scheme. The same result may not hold in environments with higher employee turnover.

The structure of the paper is as follows. Section II provides the institutional background of the research site and the market in which it operates. Section III provides motivation for the empirical tests. The sample is described in Section IV. Section V explores the empirical evidence on the changes in customer selection efforts by branch managers, while Section VI analyzes the cross-selling efforts and Section VII studies the use of pricing discretion to support the commercial action. Section VIII analyzes how managers incorporate risk in their lending decisions, and section IX concludes.

II. Institutional Background

The Bank

Our study focuses on a mid-sized commercial bank based in southern Europe. In 2002, it had over 300 branches in operation and employed more than 1,000 agents. Most branches were located in urban areas and the typical branch employed four employees (a branch manager, two account managers, and a teller). The bank held total assets of more than €22 billion and total customer funds of nearly €19 billion. It was known in the industry for its highly educated workforce (over 60% college graduates) and sophisticated technology. Employee turnover was, at 5%, the lowest in the industry.

The bank employed a multichannel strategy to serve five major segments: individuals (mainly professionals and those in upper-middle income segments), private banking (high net worth clients), personal finance (very high net worth clients), corporate banking, and small businesses. The bank played a niche strategy in each of these segments by concentrating on groups that valued its distinct capabilities (e.g. innovative products) and avoiding segments that required special services (e.g. syndicated loans) that its relatively small resources could not sustain. By 2002, small business and home mortgage financing were central to the bank's strategy.

The Mortgage Market

The national economy where the bank operates grew significantly during the 1990s and early 2000s. During this period, home ownership was made more broadly achievable by higher incomes, lower unemployment, increasing foreign immigration, and historically low interest rates. By the turn of the century, the number of mortgages sold and the size of the average mortgage had both increased significantly.

The banking sector in this country was relatively concentrated and the five largest savings and commercial banks accounted for 45% of the total lending market.

Over the last quarter of the 20th century, mortgages had become progressively more important for banks' lending portfolios. One reason was the sheer size of the market: mortgage lending as a percentage of total lending increased from 12.4% in 1970 to 50% by 2002. Financial institutions also focused on mortgages because of their perceived value as a loyalty-building product, as refinancing and prepayment were rare transactions in this market. Although banks competed for market share by attempting to offer the lowest rate, they also strove to make mortgages more easily accessible through extended customer-service points, multichannel service, and online mortgage applications. The majority of mortgages sold at the turn of the 21st century in this market had extended terms (over 20 years) and variable interest rates.

By 2002, the bank in our study had achieved a fairly strong showing in the mortgage market relative to its size by leveraging its product design abilities and the commercial acumen of its retail network. Although the bank's market share in terms of branches was less than 1%, it captured 3% of mortgages.

Incentive Compensation

Branch managers' compensation included both a fixed and variable component. The variable component, typically about 20-25% of fixed income, was relatively high for the banking industry at the time. Variable compensation was calculated mainly according to the financial performance of the branch; a minor proportion (about 25%) was linked to some non-financial measures of performance such as customer satisfaction and managerial ability. Financial performance was measured by the branch's residual income, or the net income less a capital charge.

In addition to the general incentives of the variable compensation system, branch managers occasionally received product campaign incentives, an exception to the bank's explicit policy of avoiding product targets for variable compensation purposes. This policy was intended to foster long-term customer loyalty by keeping front-line employees focused on the unique needs of each client rather than on short-term goals for a specific product.

Overall, the bank's compensation system was designed to encourage branch managers to treat the branch as an entrepreneurial venture. The branch manager was responsible for value creation, or residual value, and enjoyed a high level of freedom in this respect. For example, a branch manager could decide to sell a product at a loss if s/he believed that the client purchasing the product would generate other, more lucrative sources of revenue in the future. The central office of the bank was responsible for providing managers with the tools to achieve their goals. As a result of the high level of freedom accorded branch managers, the better managers were motivated to work harder to achieve higher performance, which identified them as high-potential professionals within the firm (Holmstrom, 1999),

Information

The bank used a sophisticated activity-based costing (ABC) system that provided profitability per contract (such as a checking account or loan). The contract profitability information was aggregated by customer, by organizational unit, and by segment. Branch managers received monthly reports on the profitability of the bank as a whole, the overall profitability of all branches in their geographic zone, and the profitability of their own branch.

Branch managers could view the monthly and quarterly profitability of individual clients in their branch using a support system that was provided to each commercial representative. The client profitability data included a "potential" field based on the client's segment that estimated the value the client could produce for the bank at the peak of their relationship. This target value was less than the maximum value achieved in the client's segment but higher than the average.

The Mortgage Simulator

In April 2002, the bank deployed an Excel-based mortgage simulator intended for use in the branches at the moment of sale. The simulator generated a suggested interest rate and a suggested list of products for cross-selling based on the customer's segment (identified through information input by the branch manager). It also analyzed the potential impact of mortgage characteristics and additional product purchases on the customer's estimated lifetime value. Thus, the CLV that the simulator generated was not an average value for the segment but an individualized estimate that incorporated customer characteristics and actual purchase behavior (Hogan et al., 2002). Table 1 describes how the simulator estimated the CLV. The CLV was limited to a horizon of five years in order to curtail the relevance of residual values in the estimates, a not uncommon modeling choice (Donkers et al., 2007).

The basic function of the simulator was to describe the expected behavior and value of an individual customer. These predictions helped to quantify the long-term consequences of some of the manager's decisions (such as the mortgage price and items chosen for cross-selling). However, many aspects of the mortgage sale still relied on the manager's judgment. For instance, the simulator could not measure the potential impact of a price concession on the likelihood of purchase, or where a client fit in the spectrum of a particular segment. Branch managers had the freedom to set the interest rate independent of the simulator's suggestion and to tailor the list of cross-selling products according to their knowledge of each customer.

Although managers accessed the mortgage simulator and the transactional system from the same computer, the two applications were not integrated. Therefore, it was possible to sell a mortgage without using the simulator. The bank did not store data on simulations performed or on the acceptance/rejection rate of mortgage offers when the simulator was used. Information on accepted mortgage offers was observable only in the transactional system. The transactional system did not indicate whether the accepted mortgage offers were made with or without the help of the simulator.

III. Motivation of Empirical Analysis

The position of the branch manager at our bank was designed to make each branch resemble a small entrepreneurial venture. Managers were free to shape their own business agenda, price products, and discriminate between levels of service offered to different customers. They were rewarded according to the total economic impact of their actions as measured by branch residual income (profitability after a charge for capital usage). Branch managers would allocate their efforts in areas where they expected a higher return for a given level of effort (Holmstrom and Milgrom, 1991). In this context, managers selling a mortgage had to decide which customers merited more attention, how much effort should be exerted to selling additional products, and how large a discount might be justified to gain a mortgage sale.

In this section we develop a simple model to gain some intuition on the potential effects of the CLV information. This model allows us to derive some hypotheses that we test in the empirical section.

A simple model of the use of customer information

Consider a decision-maker (DM) who must choose how much effort to exert when serving a potential customer. There are two dimensions to the effort choice: a_m captures the effort towards the mortgage sale, and a_{xs} represents the effort towards cross-selling. Effort comes at a cost of $c_m(a_m) + c_{xs}(a_{xs})$. Initially, the DM chooses a_m to increase the probability of a sale of a mortgage, $\pi_m(a_m)$. The value of a sale is normalized to one. If the sale materializes, then the DM chooses a_{xs} to produce additional value $\tilde{\theta}\pi_{xs}(a_{xs})$ by selling additional products to the customer. We assume that $\tilde{\theta}$ is random and can take values $\overline{\theta}$ and $\underline{\theta}$, with $\overline{\theta} > \underline{\theta}$. This formulation captures the idea that customers differ in how valuable they are for the DM. Some customers are not responsive to cross-selling appeals (therefore, the return to cross-selling effort is low), and generate a low CLV as a result. On the other hand, other customers are more open to being cross-sold (the return to cross-selling effort is high), and therefore can potentially generate a high CLV.

To obtain a well-behaved problem, we assume that c_m and c_{xs} are increasing and convex, while π_m and π_{xs} are increasing and concave. To guarantee an interior solution, we also assume that $c'_m(0) = c'_{xs}(0) = 0$ and $\pi'_m(0), \pi'_{xs}(0) > 0$.

The DM is initially uncertain about the type of customer he faces. He believes that $\tilde{\theta} = \overline{\theta}$ with probability p, and $\tilde{\theta} = \underline{\theta}$ with probability $1-p$. He can decide to gather additional information at a cost of K. To simplify the exposition, we assume that paying this cost conveys the full information about the realization of $\tilde{\theta}$.

If the mortgage sale goes through, by backward induction the DM solves:

$$\max_{a_{xs}} E\left[\tilde{\theta}\pi_{xs}(a_{xs})\right] - c_{xs}(a_{xs})$$

where the expectation is taken over the information available to the DM at the time of choosing a_{xs}. Denote by a_{xs}^* the optimal effort level, and by V_{xs} the resulting value for the DM. Cross-selling effort is characterized by the first-order condition:

$$E\left[\tilde{\theta}\right]\pi'_{xs}(a_{xs}^*) = c'_{xs}(a_{xs}^*)$$

Notice that cross-selling effort a_{xs}^* is higher when the DM knows he faces a customer who is open to purchasing more products ($\bar{\theta}$), than when he does not know the type of the client (and hence expects an average type $p\bar{\theta} + (1-p)\underline{\theta}$), or when the client cannot be cross-sold ($\underline{\theta}$). Likewise, the value of cross-selling, V_{xs}, increases in the expected type of the customer.

Anticipating the value he will obtain from cross-selling, the DM chooses a_m to solve:

$$\max_{a_m} \pi_m(a_m) + \pi_m(a_m)V_{xs} - c_m(a_m)$$

The optimal effort a_m^* is characterized by the first-order condition:

$$\pi'_m(a_m^*)(1 + V_{xs}) = c'_m(a_m^*)$$

Notice there is a complementarity between the value of cross-selling and the value of selling a mortgage: the higher V_{xs} is, the higher the incentives to increase a_m. As a result, the DM exerts more effort to sell the mortgage when he knows that the customer is of a $\bar{\theta}$-type than when he does not know the client's type, or when the type is $\underline{\theta}$.

The value of the CLV information lies in the improvement of the effort allocation choices. If the DM does not acquire any information, then he exerts the same average effort on all types of customers. On the other hand, if he acquires the CLV information, he exerts a higher effort (both on the mortgage sale and on cross-selling) on the valuable customers and a lower effort on the less profitable ones.

To the extent that the mortgage simulator lowers the cost of acquiring this information K, we would expect to find branch managers exerting more effort on valuable customers, and lower effort on customers with a low CLV. As a result, the probability of selling a mortgage to a profitable client increases, while it decreases for less profitable client segments.

Hypothesis I: The proportion of mortgages sold to the most attractive segments will increase after CLV information is provided to branch managers.

The effects on cross-selling are ambiguous. Assuming that the DM does not obtain any additional information from the time of the mortgage sale until the cross-selling takes place, the mortgage simulator should also increase cross-selling to the profitable clients and decrease cross-selling to less profitable clients. On the other hand, before the introduction of the simulator the DM may, through further interactions with the client, have learned the customer type $\tilde{\theta}$ after selling the mortgage but before making the cross-selling effort. In this case, the ex-ante information is of no additional value at that stage, and no change in cross-selling would be appreciated. Finally, since the simulator also aided the branch managers in their cross-selling effort, it could also have increased cross-selling to all clients by reducing the cost of the activity overall.

Hypothesis II: After CLV information is provided to branch managers, the number of products sold along with a mortgage will increase for the customers in the most attractive segments, will decrease for the least attractive segments, and will increase for the average customer.

In practice, branch managers' effort choice is multidimensional. They can increase the probability of the sale of a mortgage by providing better customer service, by lowering the price of the mortgage (at the cost of a lower profit), or by accepting riskier customers (at the cost of higher future defaults). On first blush, it might seem appropriate that branch managers lowered prices for customers of high lifetime potential. However, this may be inconsistent with a strategy of competing on service to build long-lasting relationships with loyal and high-potential customers. If the branch manager discounts prices, she might attract the high-potential but highly price-sensitive customers who might switch to another bank before they can be cross-sold. Thus, while more effort would be desirable for the bank, lowering prices or adding risk to the mortgage portfolio may not be. We also test whether the CLV information affected these dimensions.

Hypothesis III: The average price of a mortgage sold to the customers in the most attractive segments will drop after CLV information is provided to branch managers.

Hypothesis IV: The default risk of a mortgage sold to the customers in the most attractive segments will increase after CLV information is provided to branch managers.

Of course, the CLV introduction may have had no effect on the branch managers' behavior and we may not observe any of the effects hypothesized above if managers already had access to this information and considered its implications at the time of the mortgage sale, or if they ignored this information outright and favored their own judgments (Gupta and Steenburgh, 2008). Scholars have argued that these measurements may lack the necessary credibility among managers because they are not simple and robust enough to appear as an extension of what managers do (Little, 1970), because they have been devised by consultants foreign to the management group (Narayanan and Sarkar, 2002) or because they lack the relevant organizational conditions (Shields, 1995; Foster and Swenson, 1997).

In the next sections we analyze whether the behavior of branch managers in our site changed in the aforementioned dimensions after the introduction of the simulator. Ideally, we would have liked to study the simulator's impact using changes in effort, measured as time allocated to commercial actions and/or the amount of discount offered in all mortgage applications regardless of whether customers accepted the offers or not. However, our observations were limited to outcomes, or the mortgages actually sold. Our analyses rest on the assumption that changes in outcome are a consequence of, and consistent with, changes in the effort branch managers exerted.

IV. Sample Description

To assess the effects of providing branch managers with information on the lifetime value of a customer, we obtained data on the bank's transactions for a two-year window around the introduction of the mortgage simulator. The data contains information on all the customers that purchased a mortgage between April 2001 and April 2003.[†] We selected the timeframe to be sufficiently close to the time of implementation in order to minimize the impact of other changes in the economy, industry, or the bank itself. At the

[†] We excluded the subrogation market, in which mortgages were awarded to the developer of a set of units and automatically transmitted to the buyer without branch input.

same time, we wanted to allow enough time to pass after the deployment date to ensure that branch managers would be familiar with the tool.

To control for additional factors that may be changing at the same time (either at this bank, or in the market as a whole), we also collected data on the bank's internet banking clients who purchased a mortgage during this period. Internet customers received automatic offers from the bank according to pre-established algorithms, and decided to accept or decline the offer based on its perceived attractiveness. Thus, any change in the bank's strategy, its product offering, or a shift in the competitive environment that altered the relative attractiveness of the bank's offerings should be felt by this group of customers as well. In contrast with branch sales, internet sales are not affected by any changes in the sales effort of the customer-facing employees. Moreover, in our period of analysis the CLV tool was only implemented in the branch channel, and therefore had no impact on how the bank interacted with internet customers.

Table 2 shows the descriptive statistics for brick-and-mortar and internet clients who purchased a mortgage at some point during the observation period. The table suggests that for both groups the types of customers and the mortgages they bought are similar.

Table 2 shows that the mortgages of internet and branch customers have a similar size, around €100,000, and a similar duration, on average over 20 years. The internet mortgages, however, generally have higher value-to-loan ratios than branch mortgages (159% vs. 151%), consistent with the bank requiring more collateral when the lack of personal contact may increase the opportunity for fraud. In addition, internet mortgages have lower spreads (43 basis points vs. 53 basis points), reflecting the lower cost of serving these customers. The low interest rate spreads for both internet and branch mortgages suggest that competition in the market where our bank operates preempts predatory behavior despite certain mortgage characteristics—high collateralization, prepayment penalties, and little refinancing—that may favor predatory lending behavior (Bond, Musto and Yilmaz, 2009).

In the table we can also see that internet and branch mortgage customers are roughly the same age and have similar potential annual profitability. Branch customers, however, show deeper relationships with the bank than the internet control group. On average, they have been with the bank for over 17 months, whereas internet mortgage clients have average tenures of 6.5 months. Branch customers also hold a higher average number of products than internet customers (6.7 vs. 5.9), larger average balances of deposits (€6,500 vs. €3,300), and slightly larger loans (€106K vs. €95K), although the latter is mainly driven by the mortgage amount.

Table 2 also provides the descriptive statistics on branch activity. It shows that a branch sells, on average, slightly more than 20 mortgages per year, with an average loan size of around 103,000€.

These summary statistics suggest that brick-and-mortar and internet customers are indeed very similar, thus justifying the use of the latter as a control group in the empirical analysis.

V. Impact of CLV Availability on the Segment Composition of Mortgage Sales

In this section we compare the segment composition of mortgages sold before and after the CLV estimate was introduced to determine how the new information affected the choices of the bank's branch managers. In particular, we analyze whether CLV influenced managers to focus their sales efforts on more attractive customers.

In an ideal situation, we would have analyzed the impact of the CLV on branch managers' decisions by studying the complete set of customer interactions surrounding the mortgage sales. However, we were not able to observe situations in which an applicant rejected a mortgage offer, nor were we able to observe the actual CLVs that managers viewed at the time of a mortgage sale as they input alternative scenarios (e.g. characteristics of the mortgage, actual products sold, etc.). Instead, we know that the main input in the calculation of CLV was the customer segment, with more attractive segments generating a higher CLV. Because we do know the segment each customer belonged to at the time of the mortgage signing, we will use segment identification to perform the analyses in this section.

The bank defined thirteen customer sub-segments as a combination of income and age criteria. To produce more parsimonious analyses, we follow the bank's practice of aggregating these sub-segments into four main segments, which are largely driven by income. In ascending order of attractiveness, these groups are D, C, B, and A.

If the availability of CLV information influenced the amount of time or effort managers allocated to attractive customers, we would expect the weight of more attractive segments in the distribution of mortgages purchased to increase after the deployment of CLV estimates. Panel 1 of Table 3 compares the weight of each of the four main segments in the portfolios of mortgages sold before and after the tool was introduced. In the mortgages sold to branch customers after the introduction of CLV, we see an increase in the share of customers in segment A (from 26% to 34% of the mortgages sold), and a decrease in customers in other segments (especially those in segment C). The X^2 test of homogeneous distribution clearly rejects the possibility that both sets of mortgages were extracted from the same population.

These changes could be due to a shift in the overall composition of the bank's customers, or to a change in the strategy of the bank, rather than an effect of the CLV information. However, when we look at the evolution of the segments for internet customers, we see that the proportions in this group remain more stable relative to those of branch customers. Indeed, the fraction of segment A customers decreases slightly (from 33% to 31%), while the proportion of segment B increases. Segment C also decreases, but less so than A.

Comparing the changes in the brick-and-mortar segment composition relative to the changes in the internet channel, we can safely say that branch managers shifted their effort towards the segments with higher CLV after this estimate became available. The difference-in-differences shows an increase of over 10% in the emphasis of segment A, to the detriment of segments B and C. (Segment D also increases, but it is too small to play a relevant role.)

We perform similar comparisons for both new and existing customers. CLV information is potentially more useful for the branch managers when they are dealing with new clients. Presumably, they have better information about the profitability of the customers they already serve, and thus the CLV estimate might have less of an impact on decisions for that group.

To examine this conjecture, we define a new customer as one who became a customer of the bank during the 60-day period prior to the date of the mortgage signing.[‡] Although the proportion of customers in the top segment is smaller among new customers throughout the sample, the deployment of CLV estimates increases the share of segment A for new customers more than for existing customers. Conversely, after CLV availability, the share of C customers among new clients drops more than among existing customers. When we compare these changes with the evolution of segment composition for new and existing customers in the internet channel, the difference-in-differences remains at the 10% level. Although the portfolio of new customers shows a larger increase in the weight of segment A and a larger decrease of segments B and C relative to existing customers, these differences are not very large.

In table 4 we provide more evidence of this shift in the segment composition using the difference-in-differences estimator from a regression model. This table corroborates the above results. It shows that internet customers typically belong to better segments. However, there is no difference in the segment composition before and after the distribution of CLV information for the internet channel. The diff-in-diffs coefficient measures the effect of the CLV, comparing the changes in mortgage sales before and after its introduction for branch and internet customers. It shows a very significant impact of the deployment of CLV estimates, increasing the average segment score of the branch mortgage portfolio vis-à-vis the internet mortgage portfolio by 0.13.[§] The results are robust to several alternative specifications, controlling for the geographical location of the client and adding a time trend.

Columns 6, 7, and 8 compare the effects of the CLV introduction for new and existing customers. Although they show a slightly higher effect for new clients, this difference is never significant (see the coefficient for the interaction of the difference-in-differences variable with the dummy for new customers). Therefore, CLV information

[‡] The same analysis was performed with two alternative definitions of a new customer. The first classified new customers as those whom the bank identified as inactive as of 60 days before the mortgage sale. The second classified new customers as those who did not hold any product with the bank 60 days before the date of the mortgage sale. The results obtained using all three definitions were essentially identical.
[§] In our regression framework we define the dependent variable as a variable that takes the value of 4 if the customer purchasing the mortgage belongs to segment A, 3 if she belongs to segment B, 2 if C, and 1 if D. The portfolio score would be the arithmetic mean of the segment value so defined for the mortgages in the portfolio.

seems to affect new and existing customers equally, suggesting that branch managers found it valuable for both groups of customers and incorporated insights from CLV in all of their decisions.

In summary, the evidence found in this section suggests that the availability of CLV information at the time of the mortgage sale did influence managers to reallocate their efforts towards more attractive segments. Moreover, the evidence suggests that managers considered CLV regardless of whether they were serving new or existing customers.

VI. Cross-selling

In this section we analyze whether the introduction of CLV resulted in an increase in the average number of products sold to customers acquiring a mortgage. We also analyze whether CLV availability affected the average diversity of products held by these customers.

One of the rationales of customer as opposed to product orientation is that it is easier to sell more products to an existing customer than to capture new customers (Blattberg and Deighton, 1996; Reichheld, 1993). CLV can help branch managers understand how to convert customers into more valuable assets through cross-selling (Zeithaml, et al, 2001).

Cross selling was a salient component of the CLV estimates provided to the branch managers. At the time of the mortgage sale, the system generated a checklist of various products that a customer with similar demographic criteria would be likely to purchase. In addition, the CLV estimates showed branch managers the estimated effect of additional product sales on the expected lifetime value of the customer. Thus, the tool encouraged managers to cross-sell in two ways: by suggesting actions (products to sell) and by showing the impact of those actions on current and future branch performance.

At the same time, several factors had the potential to inhibit any positive effect on cross-selling. For instance, if branch managers were already capturing information on the likely buying patterns of different mortgage customers and in the habit of applying a mental checklist of additional products, we would expect the simulator to have little additional effect. We would also expect cross-selling to remain stable if branch managers were unable or unwilling to change consumer purchasing behavior. In addition, branch managers may have regarded the mortgage sale as an acquisition event and considered cross-selling more appropriate for an expansion of the relationship at a later date (Dwyer, Schurr, Oh, 1987).

The results in Table 5 show that there was a significant increase in the average number of products sold to mortgage purchasers after the introduction of the CLV estimates (from 6.53 to 6.79). However, we see a similar increase for internet customers. Controlling for the change in the number of products of internet mortgage customers, the number of products held by a branch mortgage customer post-CLV increased by a mere 0.06 (or 1% of the average number of products held by branch customers). Therefore, it is difficult to conclude that CLV introduction had much of an impact on cross-selling.

If we disaggregate the effects for the different segments, we do see that the introduction of CLV led to a larger decrease in the number of products sold to segments C and D vis-à-vis the internet channel. In turn, there is a moderate increase in cross-selling for customers in segment B (especially new customers), and to existing segment A customers. Therefore, the lack of an aggregate effect can mask differences in the allocation of cross-selling effort across different segments. Branch managers do not seem to devote more resources to cross-selling. But they may be distributing those efforts differently across the various segments. In particular, they may be devoting less attention to segments with lower customer equity and spending more resources on cross-selling to segments with higher customer equity (Blattberg and Deighton, 1996).

The results in Table 6 corroborate these results in a regression framework. Column 1 shows a significant increase in the number of products held by customers in the second year of our sample, with branch customers tending to have more products than internet customers. However, the CLV introduction has no effect at the aggregate level. The coefficient on the diff-in-diffs is small, and it is not statistically significant. Moreover, the small, but positive coefficient, seems to be due to changes in the segment composition of the mortgage customer portfolio in the branches. Once we control for customer segment in column 2, the coefficient is negative but not significant, consistent with an increase in the fraction of segment A, which holds more products than the other segments.

Columns 3 and 4 show that the results are robust to including controls for geographic location, and a time trend. Column 5 to 7 look for a differential effect for new and existing customers. Again, we see no effect for new or existing customers (both the coefficients of the diff-in-diffs, and the interaction between diff-in-diffs and a dummy for new customers are small and statistically insignificant). Columns 8 to 11 look at the effect of CLV for the different customer segments. The coefficients on the diff-in-diffs variable suggest that branch managers reduce their efforts to cross-sell to segments C and D, i.e., those with lower customer equity.

In addition to the number of additional products sold, we may consider whether CLV affected the *kind* of products purchased by customers. Did the pattern of product consumption change after the CLV estimates were introduced? Banks that opt for what Porter calls needs-based positioning (Porter, 1996) value cross-selling across product families more than sales within families, as the more products a customer holds in different families, the more financial needs the banking relationship satisfies. This in turn makes it costlier for a customer to change banks and thus increases customer loyalty.

To measure the diversity of financial needs that customers filled with the bank's products, we were given a set of dichotomic variables indicating whether or not a customer held a product (or products) related to that need.[**] We further grouped the product types used by the bank into a set of nine product families. Table 7 examines the type of products that customers purchased before and after the introduction of CLV.

Overall, both branch and internet mortgage customers hold slightly more product families after the introduction of CLV (3.77 vs. 3.61 for branches and 2.97 vs 2.80 for internet channel). However, an analysis of the effect of CLV availability on the different product families shows that the apparent increase in the breadth of products sold to branch mortgage customers is due to an increase in the consumption of insurance products. The latter are typically sold with the mortgage and may require little additional effort by the branch manager. There is no corresponding increase in insurance product consumption for internet customers, suggesting that the increase in branch sales is due more to the managers' effort than to insurance product improvements. For internet

[**] For instance, if a customer held two short-term CDs, only one product type would be marked (the field for "short-term deposits" would be 1). If a customer held one CD and one credit card, two product types would be marked.

mortgage customers, the increase in product families is concentrated in payment products (basically ATM cards) for new customers.

Overall, these results suggest that the introduction of CLV estimates did not encourage branch managers to increase cross-selling effort. However, it may have stimulated them to reallocate that effort differently among the various customer segments, and to grab the low-hanging fruit of low-effort incremental cross-selling as in the case of insurance products.

VII. Pricing

In this section we analyze whether the CLV introduction altered the way branch managers priced mortgages. The bank's branch managers had complete freedom in setting the price of a mortgage and, in theory, could have offered mortgages interest-free to customers likely to generate profits through other sources. CLV estimates made other sources of value salient at the time of the mortgage sale. Thus, they may have motivated managers to make different trade-offs between mortgage price and total customer value.

Mortgage prices usually reflect a combination of risk and commercial considerations. Banks may try to assign higher interest rates to riskier customers who are more likely to default and lower interest rates to customers who are more likely to pay the bank back or who have more valuable collateral (Manove, Padilla and Pagano, 2001). However, risk-based pricing has traditionally been difficult to implement. Instead, banks have often used loan acceptance as the main mechanism for managing risk.

In addition to risk considerations, mortgage prices may be determined by a bank's commercial purposes. For example, a bank may emphasize the importance of gaining new customers or customers in more valuable segments. Branch managers may be willing to lower the price of the mortgage if a lower interest rate will convince these customers to accept the offer. Moreover, they may lower the interest rate in accordance with the attractiveness of the customer.

There is no theoretical consensus on how the existence of a relationship should affect loan pricing. While some argue that the existence of informational advantages may lead to higher interest rates in relationship lending (Hauswald and Marquez, 2003), others suggest that the informational advantage translates into a better risk assessment that allows lenders to provide loans at lower cost and pass these savings along to customers (Cassar, Cavalluzzo and Ittner, 2007). Because mortgages are not a frequent purchase, and because there is very little refinancing in the market where our bank operates, they entail important switching costs for customers. This may induce mangers to overinvest in customer acquisition through low prices (Klemperer, 1987). For instance, Villanueva et al. (2007) argue that CLV use can be detrimental to profitability because managers will tend to compete for customers with high potential future value by offering very steep discounts.

Another commercial consideration that may affect mortgage price is cross-selling. Branch managers may condition a discount in the mortgage interest rate on the acquisition of other banking products in a sort of rudimentary bundle pricing. CLV may affect this bargain by explicitly calculating the trade-off between interest pricing and cross-selling and by providing branch managers with a checklist of the products that the customer may be more prone to buy.

To find out whether the introduction of CLV changed the way branch managers priced mortgages, we analyze changes in the spread charged to customers acquiring a mortgage. At the time of the study an overwhelming majority (more than 99%) of the mortgages sold by the bank had an adjustable rate and were denominated in Euros. The interest rate was the sum of a reference interest rate (usually the EURIBOR Europe-Inter-Bank-Offer-Rate) and a spread, and was adjusted annually following the market changes in the reference rate. Branch managers could not influence the reference rate but had complete discretion over the spread.

In Table 8 we use a multivariate regression framework to analyze how branch managers changed their mortgage pricing decisions once CLV became available. In column 1 we estimate the basic difference-in-differences model. The results show that the spreads of branch customers were 10 basis points larger than those of internet customers, consistent with the higher operating costs of the brick and mortar channel. These spreads do not seem to change over time, as the coefficient on the dummy for the post-CLV period is small and not significant. Moreover, the behavior of prices after CLV introduction is similar for internet and branch customers (insignificant coefficient of 0.5

basis points), suggesting that CLV estimates have no effect on branch managers' pricing decisions.

Nevertheless, branch and internet customers may have different risks and potential values that evolve differently over time. If we do not control for these factors, we may overlook the existence of an effect of the CLV introduction on the spreads. We analyze this possibility in columns 2 to 7.

Column 2 adds controls for the customer segment. Relative to segment A, customers in segments B, C, and D have increasingly higher spreads. This probably reflects the higher risk of these groups. However, the effect of the CLV introduction (the diff-in-diffs estimate) is still not significant. Column 3 adds controls for the mortgage characteristics (the amount of capital borrowed, the value-to-loan ratio, and the mortgage length). Columns 4 and 5 add individual characteristics: age, whether the customer was new to the bank, the number of products purchased, the monthly potential profitability of the customer, and the unrealized monthly potential profitability (potential minus actual profitability). Finally, columns 6 and 7 combine all these controls. CLV availability has no effect in any of these models. The diff-in-diffs coefficient remains insignificant throughout all the specifications, regardless of the controls for risk used.

The pricing evidence strongly suggests that the implementation of the CLV metric had no effect on the pricing decisions of branch managers. Our data does not support the theoretical predictions that branch managers will offer steep discounts in the hopes of capturing more loyal customers (Klemperer, 1987; Villanueva et al, 2007). Instead, the change in spreads over time is indistinguishable from the evolution of internet spreads. The evidence suggests that the additional information (CLV estimates) does not trigger a significant response in pricing by the branch managers.

VIII. Ex-post Risk Performance of the Mortgage Portfolios

One possible consequence of the introduction of CLV is a change in the way branch managers input risk in the loan-making decisions. If managers focus on potential increases in customer lifetime value (CLV), they may be less concerned with the risk of future defaults and the higher operating cost of managing workout mortgages. The trade-off between CLV and credit risk is different from the trade-off between CLV and price analyzed in the previous section because the economic impact of the two elements materializes years after the mortgage is signed. Thus, in this section we analyze whether the introduction of CLV estimates results in an increase in the realized credit risk of the mortgages that branch managers sold.

The risk we refer to in this section is above and beyond the measure of risk incorporated in the CLV calculations (Hogan et al., 2002). In short, this includes any risks that branch managers assess with the information they capture in their direct contact with the customer that cannot be systematically incorporated into the bank's systems.

In our site, mortgages that present any problematic situation are flagged by a system that indicates the level of risk associated with the client holding the loan. Thus, the system rates the client, not the loan itself. The quality of the classification is high because it determines both the amount of loan loss provisions and the level of capital required by banking regulators. The credit classification system identifies four levels of credit risk:

1. *Incidence.* Clients with any payment delayed for a period longer than 30 days.
2. *Tardy.* Clients with any payment delayed for longer than 90 days.
3. *Doubtful.* The risk management department (or the branch manager) manually indicates a higher level of risk. Typically, this situation applies to "incidence" clients or clients without any delay that have requested a bankruptcy protection procedure. It also includes "tardy" clients against whom the bank has initiated a judicial process of debt recovery.
4. *Defaulted.* Clients with written-off balances over €300 that had previously been fully covered by loan loss provisions.

A customer classified in any of these levels may remain in that category for as long as the qualifying conditions persist, evolve to a higher risk category, or return to the normal status if she normalizes her payment standing.

The mortgages are automatically approved by a system that gauges the borrower's credit risk and the characteristics of the loan. However, in our interviews with branch managers and officers of the risk management department, we learned that branch managers do have—and use—the option to override this system. They may approve an initially denied mortgage as long as it falls within certain parameters, sometimes pending the approval of a zone or regional manager. Conversely, if they feel that the risk of default is higher than the system suggests, they may quote a higher rate to discourage a customer from taking the mortgage. The use of this discretion is a consequence of the implicit incentives branch managers have to behave like entrepreneurs (Campbell et al., 2010). In contrast, mortgages sold through the internet channel rely on an entirely automated process, making them a good control sample in our analysis. Because internet contracts are more exposed to fraud, the risk criteria that the bank applies to them is slightly more restrictive. If the introduction of CLV estimates results in a change in the way managers use their discretion in lending decisions, this change should not be perceived in the internet mortgages.

Table 9 summarizes the frequency of risky classifications for the mortgages sold before and after CLV availability through the branch and internet channels. To simplify the analysis, we compare the frequency of risky classifications in the eight years following the mortgage contract.[††] We then focus our attention on the frequency of what we call bad risk standings, or classifications at every level higher than incidence (as the latter may reflect temporary or uncharacteristic oversight). Overall, the table shows that the level of defaults in this portfolio is very low, which is consistent with the bank's relatively conservative approach to risk management. Although 6.5% of the branch mortgage customers experience some incidence, only 0.7% suffer a bad risk situation in the period analyzed, and only 3 (less than 0.1%) are classified as default. For those customers who ever fall into a risky group, the average number of years in which the customer will be classified in any risk category is just below two. Finally, the lower frequency of risky situations in the portfolio of internet mortgages is consistent with the stricter risk criteria applied to this channel.

The frequency of risky classifications fails to reveal any major impact of CLV availability on the way branch managers sell mortgages. While the number of customers with a risky standing in the eight years after the mortgage is signed increases from 6.3% to 6.8% in the period post-CLV, when the analysis is limited to bad risk situations the proportion of customers affected falls from 0.7% in the pre-CLV period to 0.6% afterwards. Moreover, internet mortgages, which present a similar evolution in the frequency of risky classifications (2.9% vs. 3.2% in the pre- and post-CLV portfolios),

[††] These are year-end observations in the year the mortgage is sold and the 7 following years.

experience an increase in the frequency of customers with a serious risk standing, although the level remains very low (0.2% to 0.5% or 5 to 8 customers in the pre- and post-CLV periods, respectively).

In Table 10 we analyze whether there is a change in the way branch managers input risk in their lending decisions after the simulator with the diff-in-diffs framework. The dependent variables in these analyses are indicator variables that take the value of one if the customer is ever classified as risky in the eight year period following the mortgage contract and zero otherwise—with columns 1, 3, and 5 considering all risky categories and columns 2, 4, and 6 focusing on the bad risk standings. The explanatory variables are indicators of whether the mortgage was sold through the branches, whether it was sold before or after the deployment of the CLV estimates, and the interaction between both. The positive and significant coefficient on the branch channel indicator is consistent with the higher risk standards applied to internet mortgages. What is more relevant for our purposes, the coefficient on the interaction between the branch channel and post-CLV period fails to indicate a relaxation of the risk requirements by the branch managers. If anything, the negative and statistically significant (at the 10% level) coefficient on this interaction variable in the bad risk models would suggest that branch managers raise their risk standards after the introduction of CLV. Finally, these findings are robust to the inclusion of segment indicators in the regressions. The coefficients on these indicators are consistent with higher levels of risk associated with the segments with lower attractiveness.

In summary, an analysis of the ex-post risk performance of the mortgages sold before and after CLV availability does not support the hypothesis that branch managers relaxed risk standards in order to capture potential lifetime value. Rather, branch managers seem to put more weight on the potential negative consequences of a default, as the likelihood of a serious credit-risk classification for mortgages sold in the branches decreases vis-à-vis the control sample of internet mortgages.

IX. Conclusion

In this paper we analyze whether the addition of forward-looking metrics to the employees' information set influences their behavior when there is no accompanying change in incentives or decision rights. In particular, we look at a situation in which a firm introduced customer lifetime value (CLV) metrics in relation to transactional value while keeping employee decision rights and incentives the same. At the mid-sized southern European bank where we conducted our study, management had developed a mortgage simulator that calculated the expected value of a customer relationship and the trade-offs between mortgage terms and cross-selling profiles. We analyze how this decision aid affected the behavior of branch managers at the time of a mortgage sale.

We find that the higher visibility of an estimated relationship value compelled managers to increase their focus on the most attractive segments. Branch managers did not significantly increase the number of products sold to customers, with the exception of insurance. Moreover, the availability of CLV estimates did not encourage managers to attract these customers at the expense of making price concessions or increasing ex-post risk, suggesting that managers increased sales to more valuable customers by providing better customer service.

Our paper enhances the literature on the use of forward-looking metrics for performance management by showing that firms can use the provision of such metrics to implicitly control the effort allocation of its employees between long-term and short-term actions. The paper also contributes to the literature on information economics and performance measurement by documenting that, within our banking context, changes in the information set alone may indeed change the decision rules of customer-facing employees. Additionally, the paper contributes to the management literature by illustrating a case in which frontline employees find it easier to adjust their selection of customers than to change customer behavior, consistent with the evidence suggested by Casas-Arce and Martínez-Jerez (2009). Finally, the paper advances the literature in frontline compensation to show that employees do not unnecessarily destroy firm value by trying to please customers with a “race to the bottom” in pricing when they are armed with a full understanding of the economic implications of their decisions.

We leave to future research the analysis of how changes in other levers of organizational design, namely decision rights and performance measurement, interact with the use of information to affect frontline behavior. Ultimately, future studies on this subject may help to develop a contingency theory that would allow firms to choose the best combination of lever adjustments to achieve an optimal alignment of frontline action and the delivery of the firm's value proposition.

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Table 1. Customer Lifetime Value Model of the Mortgage Simulator

The mortgage simulator generates for the branch manager a suggestion of the appropriate price (spread over the Euribor rate) of the mortgage, a checklist of the products that the client may buy, and estimates of the customer's lifetime value. The CLV is calculated by adding the expected value of the mortgage and the expected value of other products the customer may buy. The estimated future volume of consumption of other products is a function of the customer segment and the actual products held at the time the mortgage is signed. The horizon of the calculations is five years (despite the fact that actual churn is below 10%). Below is a list of the different products considered in the estimation of CLV and a basic description of the calculations performed to estimate their contribution to the value of the customer.

Product	Value Calculation	Comments
Mortgage	NPV (financial margin + fees charged to the customer — closing costs — administrative costs — bad debt expense; K-equity mortgage business)	Prepayment risk estimated to decline over the life of the mortgage
Homeowners Insurance	f(value of the house; expected life of the mortgage)	
Life Insurance	f(value of the mortgage; age of the customer)	Increases with age until the effect of shorter remaining life expectancy dominates in older customers.
Checking Account	income level * age factor * employment factor – administrative costs	Higher-income clients and older clients keep larger balances. Self-employed clients are less valuable because their income level is less certain. Administrative costs estimated for the average customer per segment and fixed cost per account.
Payroll Account	income level * age factor – administrative costs	Higher value than the employee checking account because automatic payroll deposit leads to higher balances and higher loyalty
Credit Card	f(income level; risk level; gold/regular)	Gold card generates twice the value of the regular but the client needs to fulfill the income requirements
Pension Funds	f(personal income tax regulations; age)	Value decreases with age
Certificate of Deposit	f(income level; age)	The use of the product increases with age. Older customers are more loyal to the bank, but also have a shorter time horizon. Its use decreases with the financial sophistication of the consumer, for which a good proxy is income level.
Investment Fund	f(income level; age; family status)	It is assumed that the customer will invest most of its disposable income after consumption in financial instruments.
Brokerage Services	NPV of brokerage fees. Fees are f(income level; age; family status)	Customers who own a brokerage account will own some investment funds.

Table 2. Descriptive statistics

	Brick-and-mortar channel			Internet channel		
	All	**Pre-CLV**	**Post-CLV**	**All**	**Pre-CLV**	**Post-CLV**
Mortgage characteristics						
Number of clients	15503.00	8428.00	7075.00	2374.00	1549.00	825.00
Capital (€)	101712.26	95778.81	108780.39	96842.65	95678.78	99027.91
Mortgage length (years)	23.52	23.05	24.09	22.25	21.97	22.79
Value to loan ratio	151.49	151.55	151.41	158.92	158.48	159.74
Spread (%)	0.53	0.52	0.53	0.43	0.43	0.43
Client characteristics						
Number of products	6.65	6.53	6.79	5.89	5.82	6.02
Tenure at the bank	17.36	15.75	19.27	6.51	5.56	8.30
Age	35.55	35.48	35.63	34.59	34.44	34.88
Potential profitability (€)	969.57	926.28	999.17	962.17	945.58	974.85
Loans	105859.86	99438.93	112905.54	96350.22	94856.41	98825.98
Deposits	6506.25	5723.41	7438.58	3315.42	2779.27	4322.09
Branch characteristics						
Number of branches	351.00	337.00	329.00	-	-	-
Number of mortgages	44.17	25.01	21.50	-	-	-
Average mortgage size per branch(€)	102779.52	96809.91	108789.80	-	-	-

Notes. This table contains the basic descriptive statistics of the sample and control group. The sample is formed with all the mortgages sold between April 2001 and April 2003. It contains both mortgages sold through branches, and through the internet. The table presents the mean of several variables related to the mortgage characteristics, client characteristics, and branch characteristics.

Table 3. Segment composition of mortgage customers.

	Segment A	Segment B	Segment C	Segment D	Total	Chi-squared test of homogeneity (p-value)
All customers that bought a mortgage between 2001 and 2003						
All Branches	29.63%	50.05%	18.49%	1.83%	15503	
Pre-CLV	26.13%	50.81%	20.80%	2.27%	8428	151.78
Post-CLV	33.81%	49.16%	15.73%	1.30%	7075	(0.000)
Difference	7.68%	-1.65%	-5.07%	-0.97%		
All Internet	32.69%	50.08%	16.30%	0.93%	2374	
Pre-CLV	33.51%	48.55%	16.66%	1.29%	1549	9.75
Post-CLV	31.15%	52.97%	15.64%	0.24%	825	(0.021)
Difference	-2.36%	4.42%	-1.02%	-1.05%		
Difference-in-Differences	10.04%	-6.07%	-4.05%	0.08%		
New customers that bought a mortgage between 2001 and 2003						
All Branches	24.86%	52.65%	20.35%	2.14%	10256	
Pre-CLV	20.98%	53.18%	23.24%	2.61%	5711	145.28
Post-CLV	29.75%	51.99%	16.72%	1.54%	4545	(0.000)
Difference	8.77%	-1.19%	-6.52%	-1.07%		
All Internet	31.13%	51.38%	16.44%	1.05%	1709	
Pre-CLV	31.87%	49.65%	17.08%	1.40%	1142	7.40
Post-CLV	29.63%	54.85%	15.17%	0.35%	567	(0.060)
Difference	-2.24%	5.2%	-1.91%	-1.05%		
Difference-in-Differences	11.01%	-6.39%	-4.61%	-0.02%		
Existing customers that bought a mortgage between 2001 and 2003						
All Branches	38.96%	44.98%	14.85%	1.22%	5247	
Pre-CLV	36.95%	45.82%	15.68%	1.55%	2717	14.24
Post-CLV	41.11%	44.07%	13.95%	0.87%	2530	(0.003)
Difference	4.16%	-1.75%	-1.73%	-0.68%		
All Internet	36.69%	46.77%	15.94%	0.60%	665	
Pre-CLV	38.08%	45.45%	15.48%	0.98%	407	3.62
Post-CLV	34.05%	48.84%	16.67%	0.00%	258	(0.306)
Difference	-4.03%	3.39%	1.19%	-0.98%		
Difference-in-Differences	8.19%	-5.14%	-2.92%	0.30%		

Notes. This table analyzes the segment composition of customers that buy a mortgage between April 2001 and April 2003. We provide the proportion of clients belonging to a given segment in the portfolio of mortgages sold during that period. Segments are defined using criteria that combine income and age. The segments are listed in order of decreasing attractiveness, A being the most attractive, and D the least attractive. The sample is divided between branch customers, and customers that operate through the internet channel. We also distinguish between mortgages sold before and after the deployment of the CLV information. Customers who held at least one product from the bank as of 60 days before the sale date of the mortgage are labeled "existing customers;" those who did not, are labeled "new customers." The table reports the change in the fraction of customers of each segment before and after the deployment of CLV information. Difference-in-Differences computes the difference between the before and after change for branch customers and internet customers. The table also provides the total number of mortgages sold, and the Chi-squared test of homogeneity that compares the distribution of segments before and after the CLV information is provided (the null hypothesis being that the pre- and post-CLV observations comfrom the same distribution).

Table 4. Impact of CLV information on the segment composition of mortgage customers.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Post CLV	-0.005	-0.005	-0.076	-0.056	0.013	-0.056	-0.096	-0.068	-0.127
	(0.031)	(0.031)	(0.036)†	(0.058)	(0.037)	(0.058)	(0.067)	(0.043)	(0.061)†
Branch channel	-0.090	0.401	0.424	0.005	-0.145	0.005	0.385	-0.230	0.396
	(0.021)‡	(0.289)	(0.288)	(0.041)	(0.025)‡	(0.041)	(0.283)	(0.081)‡	(0.282)
Diff-in-Diffs	0.131	0.115	0.112	0.122	0.135	0.122	0.109	0.109	0.107
	(0.034)‡	(0.034)‡	(0.034)‡	(0.062)†	(0.041)‡	(0.062)†	(0.062)*	(0.040)‡	(0.062)*
Time trend			0.006				0.003	0.007	0.006
			(0.002)‡				(0.003)	(0.002)‡	(0.002)‡
New customer						-0.090			-0.089
						(0.044)†			(0.044)†
Post * New						0.069			0.073
						(0.069)			(0.069)
Branch * New						-0.149			-0.166
						(0.048)‡			(0.048)‡
Diff-in-Diffs * New						0.012			0.005
						(0.074)			(0.074)
Constant	3.192	2.660	2.575	3.258	3.168	3.258	2.773	3.106	2.741
	(0.020)‡	(0.294)‡	(0.293)‡	(0.038)‡	(0.023)‡	(0.038)‡	(0.293)‡	(0.028)‡	(0.287)‡
Customers	All	All	All	Existing	New	All	Existing	New	All
Region Fixed Effects	No	Yes	Yes	No	No	No	Yes	Yes	Yes
Observations	18834	18834	18834	6313	12521	18834	6313	12521	18834
R-squared	0.005	0.060	0.061	0.002	0.008	0.018	0.055	0.073	0.076

Notes. This table shows the effects of providing CLV information on the segment composition of customers that buy a mortage between April 2001 and April 2003. The dependent variable is the segment of the customer, coded as 4, 3, 2, and 1 for segments A, B, C, and D, respectively. *Post CLV* is a dummy taking a value of 1 for the months following the implementation of the CLV. *Branch channel* is a dummy taking a value of 1 for branch customers, and 0 for internet customers. *Diff-in-diffs* is the interaction of *Post CLV* and *Branch channel*. It measures the effect of the CLV. We also include a *time trend* in some of the regressions. *New customer* is a dummy that takes a value of 1 if the customer is new to the bank at the time of the mortgage purchase, and 0 if for existing customers of the bank. We also interact this dummy with *Post CLV, Branch channel,* and *Diff-in-diffs*. We also include region fixed effects on some specifications. Columns 1, 2, 3, 6, and 9 use the full sample of customers. Columns 4 and 7 use the subsample of existing customers. Column 5 and 8 use the subsample of new customers. Robust standard errors are in parentheses.
* p<0.1, † p<0.05, ‡ p<0.01

Table 5. Cross-selling to mortgage customers.

	All segments	Segment A	Segment B	Segment C	Segment D
All customers that bought a mortgage between 2001 and 2003					
All Branches					
Pre-CLV	6.53	7.18	6.46	6.00	5.38
Post-CLV	6.79	7.31	6.67	6.18	5.48
Difference	0.26	0.13	0.21	0.18	0.10
All Internet					
Pre-CLV	5.82	5.98	5.79	5.59	5.40
Post-CLV	6.02	6.16	5.90	6.16	6.00
Difference	0.20	0.18	0.11	0.57	0.60
Difference-in-Differences	0,06	-0.05	0.10	-0.39	-0.50
New customers that bought a mortgage between 2001 and 2003					
All Branches					
Pre-CLV	5.91	6.20	5.97	5.62	5.08
Post-CLV	6.16	6.39	6.19	5.78	4.96
Difference	0.25	0.19	0.22	0.16	-0.12
All Internet					
Pre-CLV	5.58	5.66	5.61	5.35	5.06
Post-CLV	5.78	5.90	5.72	5.76	6.00
Difference	0.20	0.24	0.11	0.41	0.94
Difference-in-Differences	0.05	-0.05	0.11	-0.25	-1.06
Existing customers that bought a mortgage between 2001 and 2003					
All Branches					
Pre-CLV	7.82	8.36	7.66	7.16	6.45
Post-CLV	7.93	8.49	7.69	7.04	7.14
Difference	0.11	0.13	0.03	-0.12	0.69
All Internet					
Pre-CLV	6.50	6.74	6.36	6.33	-
Post-CLV	6.55	6.63	6.34	6.98	-
Difference	0.05	-0.11	-0.02	0.65	-
Difference-in-Differences	0.06	0.24	0.05	-0.77	-

Notes. This table analyzes the amount of cross-selling to customers who purchased a mortgage between April 2001 and April 2003. It reports the average number of products held by these customers. We also provide the average number of products held by customers that belong to a particular segment. Segments are defined using criteria that combine income and age. The segments are listed in order of decreasing attractiveness, A being the most attractive, and D the least attractive. The sample is also divided between branch customers, and customers that operate through the internet channel. We also distinguish between mortgages sold before and after the deployment of the CLV information. Customers who held at least one product from the bank as of 60 days before the sale date of the mortgage are labeled "existing customers;" those who did not, are labeled "new customers." The table also reports the change in the average number of products held before and after the deployment of CLV information. Difference-in-Differences computes the difference between the before and after change for branch customers and internet customers.

Table 6. Impact of CLV information on the number of products purchased by mortgage customers.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Post CLV	0.222	0.200	0.201	0.063	0.031	0.037	-0.059	0.172	0.105	0.572	0.600
	(0.066)‡	(0.066)‡	(0.066)‡	(0.080)	(0.188)	(0.073)	(0.159)	(0.131)	(0.081)	(0.164)‡	(0.230)‡
Branch channel	0.685	0.792	1.773	1.817	1.200	0.148	1.321	1198	0.678	0.417	0.054
	(0.046)‡	(0.046)‡	(0.332)‡	(0.333)‡	(0.339)‡	(0.142)	(0.398)‡	(0.090)‡	(0.061)‡	(0.102)‡	(0.271)
Diff-in-Diffs	0.040	-0.021	-0.027	-0.033	-0.034	-0.025	-0.007	-0.047	0.094	-0.388	-0.591
	(0.074)	(0.074)	(0.074)	(0.074)	(0.170)	(0.068)	(0.168)	(0.148)	(0.092)	(0.178)†	(0.334)*
Segment B		-0.613	-0.615	-0.612	-0.700	-0.184	-0.386				
		(0.037)‡	(0.037)‡	(0.037)‡	(0.072)‡	(0.031)‡	(0.033)‡				
Segment C		-1.036	-1.061	-1.056	-1.183	-0.492	-0.748				
		(0.044)‡	(0.046)‡	(0.046)‡	(0.098)‡	(0.039)‡	(0.042)‡				
Segment D		-1.647	-1.569	-1.560	-1.358	-0.948	-1.144				
		(0.114)‡	(0.115)‡	(0.115)‡	(0.316)‡	(0.098)‡	(0.106)‡				
Time trend				0.012	0.004	0.014	0.010				
				(0.004)‡	(0.009)	(0.003)‡	(0.004)‡				
New customer							-0.895				
							(0.106)‡				
Post * New							0.138				
							(0.166)				
Branch * New							-0.918				
							(0.118)‡				
Diff-in-Diffs * New							-0.030				
							(0.181)				
Constant	5.763	6.312	5.576	5.410	7.167	5.644	6.622	5.990	5.794	5.591	5.400
	(0.040)‡	(0.047)‡	(0.359)‡	(0.365)‡	(0.412)‡	(0.054)‡	(0.419)‡	(0.074)‡	(0.054)‡	(0.092)‡	(0.230)‡
Customers	All	All	All	All	Existing	New	All	Segment A	Segment B	Segment C	Segment D
Region Fixed Effects	No	No	Yes	Yes	Yes	Yes	Yes	No	No	No	No
Observations	18712	18026	18026	18026	6028	11998	18026	5406	9012	3295	313
R-squared	0.017	0.057	0.078	0.078	0.074	0.073	0.222	0.035	0.020	0.008	0.001

Notes. This table shows the effects of providing CLV information on the effort of branch managers to sell additional products to customers that buy a mortage between April 2001 and April 2003. The dependent variable is the number of products held by mortgage buyers at the bank. *Post CLV* is a dummy taking a value of 1 for the months following the implementation of the CLV. *Branch channel* is a dummy taking a value of 1 for branch customers, and 0 for internet customers. *Diff-in-diffs* is the interaction of *Post CLV* and *Branch channel*. It measures the effect of the CLV. The segment variables are dummy variables indicating the segment of the customer. We also include a time trend in some of the regressions. *New customer* is a dummy that takes a value of 1 if the customer is new to the bank at the time of the mortgage purchase, and 0 if for existing customers of the bank. We also interact this dummy with *Post CLV*, *Branch channel*, and *Diff-in-diffs*. We also include region fixed effects on some specifications. Columns 1, 2, 3, 4, and 7 use the full sample of customers. Column 5 uses the subsample of existing customers. Column 6 uses the subsample of new customers. And columns 8 through 11 restrict the sample to customers belonging to one of the segments. Robust standard errors are in parentheses.

* $p<0.1$, † $p<0.05$, ‡ $p<0.01$

Table 7. Product category cross-selling to mortgage customers.

	Number of product categories	Transactional products	Savings products	Investment products	Payment products	Personal loans	Home-acquisition products	Insurance products	Brokerage products	Other products
All customers that bought a mortgage between 2001 and 2003										
All Branches										
Pre-CLV	3.61	1.12	0.05	0.17	0.86	0.05	1.00	0.24	0.10	0.01
Post-CLV	3.77	1.12	0.04	0.16	0.91	0.05	1.00	0.36	0.11	0.01
Difference	0.16	0.00	-0.01	-0.01	0.05	0.00	0.00	0.12	0.00	0.00
All Internet										
Pre-CLV	2.80	1.06	0.05	0.01	0.44	0.01	1.00	0.15	0.07	0.00
Post-CLV	2.97	1.08	0.05	0.03	0.58	0.01	1.00	0.13	0.09	0.00
Difference	0.17	0.02	0.00	0.01	0.14	0.00	0.00	-0.02	0.02	0.00
Diff-in-Diffs	-0.01	-0.02	-0.01	-0.02	-0.09	0.00	0.00	0.14	-0.02	0.00
New customers that bought a mortgage between 2001 and 2003										
All Branches										
Pre-CLV	3.18	1.07	0.02	0.05	0.80	0.01	1.00	0.23	0.01	0.00
Post-CLV	3.34	1.06	0.02	0.06	0.85	0.01	1.00	0.34	0.01	0.00
Difference	0.16	-0.01	0.00	0.01	0.05	0.00	0.00	0.12	0.00	0.00
All Internet										
Pre-CLV	2.61	1.04	0.03	0.00	0.38	0.00	1.00	0.14	0.02	0.00
Post-CLV	2.75	1.05	0.02	0.00	0.55	0.00	1.00	0.11	0.01	0.00
Difference	0.14	0.01	-0.01	0.00	0.17	0.00	0.00	-0.03	0.00	0.00
Diff-in-Diffs	0.02	-0.02	0.00	0.01	-0.12	0.00	0.00	0.14	0.00	0.00
Existing customers that bought a mortgage between 2001 and 2003										
All Branches										
Pre-CLV	4.50	1.22	0.12	0.43	1.00	0.12	1.01	0.26	0.30	0.04
Post-CLV	4.54	1.23	0.08	0.36	1.03	0.12	1.02	0.38	0.28	0.03
Difference	0.04	0.01	-0.03	-0.07	0.03	0.00	0.00	0.12	-0.02	0.00
All Internet										
Pre-CLV	3.32	1.12	0.11	0.05	0.61	0.01	1.00	0.18	0.24	0.00
Post-CLV	3.45	1.14	0.10	0.09	0.65	0.02	0.99	0.16	0.28	0.00
Difference	0.13	0.03	0.00	0.04	0.04	0.01	-0.01	-0.01	0.04	0.00
Diff-in-Diffs	-0.09	-0.02	-0.03	-0.11	-0.01	-0.01	0.01	0.14	-0.05	0.00

Notes. This table analyzes the amount of cross-selling to customers who purchased a mortgage between April 2001 and April 2003. It reports the average number of product categories held by these customers, and the fraction of customers that hold each of these categories. The sample is also divided between branch customers, and customers that operate through the internet channel. We also distinguish between mortgages sold before and after the deployment of the CLV information. Customers who held at least one product from the bank as of 60 days before the sale date of the mortgage are labeled "existing customers;" those who did not, are labeled "new customers." The table also reports the change before and after the deployment of CLV information. Difference-in-Differences computes the difference between the before and after change for branch customers and internet customers.

Table 8. Impact of CLV information on the pricing of mortgages.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Post CLV	0.004	0.005	0.008	-0.003	-0.002	-0.002	-0.001
	(0.008)	(0.008)	(0.008)	(0.010)	(0.010)	(0.010)	(0.010)
Branch	0.098	0.094	0.100	0.098	0.101	0.098	0.099
	(0.006)‡	(0.006)‡	(0.006)‡	(0.010)‡	(0.010)‡	(0.010)‡	(0.010)‡
Diff-in-Diffs	0.005	0.008	0.008	0.009	0.006	0.011	0.010
	(0.009)	(0.009)	(0.009)	(0.012)	(0.012)	(0.012)	(0.012)
Segment B		0.020				0.011	0.016
		(0.004)‡				(0.006)*	(0.005)‡
Segment C		0.048				0.023	0.031*
		(0.006)‡				(0.010)†	(0.009)
Segment D		0.104				0.031	0.043
		(0.023)‡				(0.029)	(0.029)
Capital			-0.000			-0.000	-0.000
			(0.000)‡			(0.000)	(0.000)*
Value to loan			-0.000			-0.000	-0.000
			(0.000)‡			(0.000)†	(0.000)‡
Mortgage length			-0.000			-0.000	-0.000
			(0.000)‡			(0.000)‡	(0.000)‡
Age				0.001	0.001	0.001	0.001
				(0.000)‡	(0.000)‡	(0.000)‡	(0.000)†
New customer				-0.007	-0.004	-0.006	-0.005
				(0.005)	(0.005)	(0.005)	(0.005)
Number of products				-0.005	-0.006	-0.005	-0.005
				(0.001)‡	(0.001)‡	(0.001)‡	(0.001)‡
Potential				-0.000		-0.000	
				(0.000)‡		(0.000)‡	
Unrealized potential					-0.000		-0.000
					(0.000)‡		(0.000)‡
Constant	0.426	0.407	0.550	0.469	0.441	0.536	0.526
	(0.005)‡	(0.006)‡	(0.014)‡	(0.017)‡	(0.017)‡	(0.024)‡	(0.023)‡
Observations	17877	17877	17877	13276	13276	13276	13276
Adjusted R-squared	0.017	0.022	0.023	0.022	0.020	0.025	0.026

Notes. This table shows the effects of providing CLV information on the pricing decisions of branch managers regarding mortgages sold between April 2001 and April 2003. The dependent variable is the spread charged over the reference interest rate. *Post CLV* is a dummy taking a value of 1 for the months following the implementation of the CLV. *Branch channel* is a dummy taking a value of 1 for branch customers, and 0 for internet customers. *Diff-in-diffs* is the interaction of *Post CLV* and *Branch channel*. It measures the effect of the CLV. The segment variables are dummy variables indicating the segment of the customer. *Capital* is the amount loaned. *Value to loan* is the ration of the value of the property and the size of the loan. *Mortgage length* is the length (in months) of the loan. *Age* is the age of the customer. *New customer* is a dummy that takes a value of 1 if the customer is new to the bank at the time of the mortgage purchase, and 0 if for existing customers of the bank. *Number of products* measures the number of products held by the customer. *Potential* is the bank's measure of potential profitability of the customer (in Euros). *Unrealized potential* is the difference between the *potential* and actual profitability of the customer. Robust standard errors are in parentheses.
* p<0.1, † p<0.05, ‡ p<0.01

Table 9. Ex-post Risk of Mortgage Portfolios.

	Branch Mortgages						Internet Mortgages					
	Pre-CLV		Post-CLV		All		Pre-CLV		Post-CLV		All	
	Number	%	Number	%	Number	%	Number	%	Number	%	Number	%
All Risk Events	989	11.7%	894	12.6%	1,883	12.1%	135	4.9%	117	6.8%	252	5.6%
Customers with a Risk Event	530	6.3%	482	6.8%	1,012	6.5%	81	2.9%	55	3.2%	136	3.0%
Bad Risk Events	112	1.3%	70	1.0%	182	1.2%	11	0.4%	28	1.6%	39	0.9%
Customers with Bad Risk Events	62	0.7%	40	0.6%	102	0.7%	5	0.2%	8	0.5%	13	0.3%
Customers with Maximum Risk Classification:												
Normal	7,917	93.7%	6,605	93.2%	14,522	93.5%	2,676	97.1%	1,658	96.8%	4,334	97.0%
Incidence	468	5.5%	442	6.2%	910	5.9%	76	2.8%	47	2.7%	123	2.8%
Tardy	36	0.4%	17	0.2%	53	0.3%	0	0.0%	2	0.1%	2	0.0%
Doubtful	25	0.3%	21	0.3%	46	0.3%	5	0.2%	6	0.4%	11	0.2%
Default	1	0.0%	2	0.0%	3	0.0%	0	0.0%	0	0.0%	0	0.0%
Total Number of Customers	8,447	100.0%	7,087	100.0%	15,534	100.0%	2,757	100.0%	1,713	100.0%	4,470	100.0%

Notes. This table analyzes the amount of ex-post risk suffered by the mortgage portfolios of the bank containing those mortgages sold between April 2001 and April 2003. It reports the number and fraction of mortgages that show a risk event within an eight year period after their sale. The risk classification contains five levels. *Normal* refers to non-problematic mortgages. An *incidence* occurs when a client delays payment for longer than 30 days. Payment delays for longer than 90 days are classified as *tardy*. *Doubtful* indicates a higher level of risk, such as clients that have requested bankruptcy protection, or against whom the bank has initiated a judicial process of debt recovery. *Default* are clients with written-off balances over €300. *All risk events* include *incidence, tardy, doubtful,* and *default*. *Bad risk events* include only *tardy, doubtful,* and *default*. The sample is divided between branch customers, and customers that operate through the internet channel. We also distinguish between mortgages sold before and after the deployment of the CLV information.

Table 10. Impact of CLV information on the likelihood of a future risk deterioration.

	Risk Event	Bad Risk Event	Risk Event	Bad Risk Event	Risk Event	Bad Risk Event
	(1)	(2)	(3)	(4)	(5)	(6)
Branch channel	0.033	0.006	0.794	1.404	0.720	-1.292
	(0.005)‡	(0.002)‡	(0.121)‡	(0.465)‡	(0.122)‡	(0.466)‡
Post CLV	0.003	0.003	0.092	0.949	0.116	0.981
	(0.007)	(0.002)	(0.177)	(0.571)*	(0.178)	(0.571)*
Diff-in-Diffs	0.003	-0.005	-0.005	-1.213	0.033	-1.156
	(0.008)	(0.003)*	(0.189)	(0.606)†	(0.189)	(0.606)*
Segment B					0.311	0.609
					(0.077)‡	(0.265)†
Segment C					0.630	0.939
					(0.091)‡	(0.297)‡
Segment D					1.673	2.142
					(0.156)‡	(0.412)‡
Constant	0.029	0.002	-3.498	-6.311	-3.795	-6.849
	(0.004)‡	(0.001)	(0.113)‡	(0.448)‡	(0.125)‡	(0.491)‡
Model Class	OLS	OLS	Logit	Logit	Logit	Logit
Observations	20004	20004	20004	20004	20004	20004
R-squared	0.004	0.001				
Pseudo R-squared			0.010	0.010	0.024	0.027

Notes. This table shows the effects of providing CLV information on the risk management of branch managers regarding mortgages sold between April 2001 and April 2003. The dependent variables are *Risk event* and *Bad risk event*. *Risk event* is a dummy variable taking a value of 1 if the customer is classified as *incidence, tardy, doubtful*, or *defaulted* at any point within an eight year period after the purchase of the mortgage. *Bad risk event* is a dummy variable calculated in a similar way, but only taking a value of 1 if the customer is classified as *tardy, doubtful*, or *defaulted*. *Internet channel* is a dummy taking a value of 1 for internet customers, and 0 for branch customers. *After CLV* is a dummy taking a value of 1 for the months following the implementation of the CLV. *Internet after CLV* is the interaction of *internet channel* and *after CLV*. It measures the effect of the CLV. The segment variables are dummy variables indicating the segment of the customer. Columns 1 and 2 estimate an OLS model, while columns 3 to 6 use a logit model. Robust standard errors are in parentheses.

* p<0.1, † p<0.05, ‡ p<0.01