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Costs: Evidence from Retail Banking

Douglas FRANK
Tomasz OBLOJ
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by

Douglas Frank *

and

Tomasz Obloj**

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* Assistant Professor of Strategy at INSEAD, Boulevard de Constance 77305 Fontainebleau, France
Ph: +33 (0)1 60 72 93 57, Email: douglas.frank@insead.edu

** PhD Candidate in Strategy at INSEAD, Boulevard de Constance 77305 Fontainebleau, France
Ph: +33 (0)1 60 72 91 70, Email: tomasz.obloj@insead.edu Corresponding author.

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ABSTRACT

The literature on incentive contracting suggests that the optimal performance pay contract depends on a tradeoff between productivity and agency costs. The effect of employee ability on this tradeoff is theoretically ambiguous, as the employee's private gains (through more sophisticated gaming responses) may exceed the employer's productive benefits. Similarly, employees' "adverse learning" about how to game their incentives may outweigh their productive learning. Existing research has not examined these possible perverse effects. We observe branch managers of a large retail bank following the introduction of a new incentive plan. We use a novel empirical strategy to estimate the profits the bank loses through managers' manipulation of loan sizes and interest rates, and find that these agency costs are between three and twelve percent of profits on average. Managers' formal education ("book smarts") has no impact on agency costs, but their ability to infer undisclosed information about the incentive plan ("street smarts") does. More-able managers in the latter sense cost the bank an extra two percent of profits. Finally, agency costs are increasing over time, suggesting that adverse learning dominates productive learning. We find suggestive, but inconclusive, evidence that higher levels of "street smarts" are associated with a higher rate of adverse learning.

Keywords: agency costs, incentives, performance pay, multitasking, employee learning, adverse learning, ability, human capital

1. INTRODUCTION

Performance-based pay plans are a common way in which organizations try to solve the agency problem that exists between owners and employees.¹ Theoretical models typically ascribe the agency problem to one of two types of information asymmetry: moral hazard (the principal doesn't know how hard the agent has worked) or adverse selection (the principal doesn't know the agent's productivity, or "type"). The optimal performance pay contract therefore attempts to achieve two main personnel objectives: attracting highly able employees and inducing them to work hard (Lazear 1986).

A variety of empirical work confirms the increase in employees' productive effort that can result from performance pay plans (Paarsch and Shearer 1999, Lazear 2000, Lach and Schankerman 2008). On the other hand, these incentives can be problematic due to the well-known multitasking problem (Holmstrom and Milgrom 1991, Baker 1992), and there is a growing body of evidence documenting distortionary "gaming" responses to explicit performance incentives (Chevalier and Ellison 1997, Oyer 1998, Dranove 2003, Courty and Marschke 2004, Larkin 2007).²

Some research suggests a mutually reinforcing relationship between strong performance-based incentives and employee ability (Milgrom and Roberts 1990, Milgrom and Roberts 1995, Ichniowski, Shaw and Prennushi 1997, Bresnahan 1999, Black and Lynch 2001, Caroli and Van Reenen 2001, Bresnahan, Brynjolfsson and Hitt 2002, Rajan and Wulf 2006, Bartel, Ichniowski and Shaw 2007, Lemieux, MacLeod and Parent 2009). The explanation is simple and intuitive: strong incentives and ability are complements, because the marginal returns to effort (induced by the incentives) are increasing in the employee's ability. However, there may be some settings in which this is not the case. The multitasking and gaming literature highlights that the optimal incentive contract depends on a tradeoff between productive effort and agency costs. The effect of ability on this tradeoff is theoretically ambiguous. While a worker's ability affects her productivity, it also potentially affects her capacity to game her incentives – to identify and exploit weaknesses in the

¹ For example, Lazear and Shaw (2007) cite statistics showing that, in 1999, two-thirds of large firms had individual incentives for at least 20 percent of their employees.

² See also Lazear and Oyer (2007) for a recent review.

system arising from imperfections in monitoring effort and performance. In environments where the agent's private gains from ability are relatively high, the principal's optimal response might be to weaken or eliminate explicit performance-based incentives. This link between ability and agency costs has not been studied theoretically or empirically.

Because they deal with information asymmetry and revelation, agency contracting models also incorporate, implicitly or explicitly, an element of learning. In all these models, it is generally the principal who learns about the agent's ability, or attempts to. In the simplest static models, learning occurs instantaneously. In dynamic models, such as those of "ratcheting" (Baron and Besanko 1984, Freixas, Guesnerie and Tirole 1985, Lazear 1986, Laffont and Tirole 1988) and "signal-jamming" (Holmström 1999), learning takes place over time, and agents may even take actions to inhibit the principal's learning. In practice, however, agents are learning alongside principals – not just about how to do their jobs better (Arrow 1962, Jovanovic and Nyarko 1996, Benkard 2000, Thompson 2001), but also about aspects of the incentive plan that the principal might prefer to keep hidden: the nature and intensity of monitoring, the decision rules for changing performance targets or imposing sanctions, etc.. Such "adverse learning" could give rise to increasing agency costs over time. This has not been studied theoretically or empirically.

In this paper, we study the effects of employee ability and learning on the employer's profits in the presence of strong performance-based incentives. We observe branch managers of a large Polish retail bank over a 13-month period following the introduction of a new incentive plan. Managers' pay is tightly tied to performance (the number of new loan customers acquired), with the variable share of pay averaging over 40 percent. Managers have discretion over the loan size and interest rate, which they can potentially manipulate to earn higher bonuses each month.

Managers' abuse of their delegated autonomy is constrained by several features of the plan's design and administration, many of which the bank deliberately keeps opaque. Some loans must pass through centralized credit controls, bank managers can be dismissed if performance is "too low", or they can be sanctioned if loan terms are too favorable. Also, the bonus for new customer acquisitions has a "ratcheting" element built in, as it depends on

managers' performance against an individual sales target that is revised monthly. Therefore, managers must trade off high current bonuses against more challenging future performance targets. However, the bank does not share any information with the managers about how their targets are determined.

In this context, there is therefore a twofold role for ability and learning. On the one hand, more able managers should be more productive at selling loans at terms favorable to the bank, and managers' productivity generally should increase over time as they learn more about their markets, effective sales techniques, etc. On the other hand, managers may direct their ability and learning toward discerning the undisclosed aspects of the incentive plan's design and administration. This would enable them to distort their effort toward actions that are privately beneficial but costly to the bank, while at the same time avoiding detection, sanctions or more difficult performance targets.

In line with the human capital literature, we measure managers' ability as cognitive ability. Usually, the literature assumes that ability is one-dimensional (Heckman and Rubinstein 2001). However, in popular writing and common speech, one finds terms that acknowledge many distinct dimensions of cognitive intelligence, such as "book smarts", "street smarts" and "creativity". This taxonomy is not simply the result of a layperson's imprecision in language. It corresponds closely to Aristotle's three "excellences" of intelligence (theoretical, practical and productive) (Tigner and Tigner 2000), as well as to Sternberg's (1985) triarchic theory of intelligence, which encompasses analytical, practical and creative dimensions.

In our analysis, we focus on two of these three dimensions: theoretical/analytical ("book smarts") and practical ("street smarts"). A natural measure for the former is educational attainment, which we use. For the latter, we introduce a measure called "plan knowledge", which captures how well managers understand aspects of the incentive plan that the firm does not reveal. Sternberg et al. (2000) cite evidence that, not only is practical intelligence distinct from the type of intelligence that produces academic achievement, the two may even be negatively correlated. In our case, plan knowledge is positively correlated

with an advanced education, but only weakly so, suggesting that the two scales do indeed measure distinct types of ability.

We have five main sets of findings. First, managers' pricing and loan size choices suggest that they use their decision making autonomy for private benefit. Managers give more favorable interest rates when further behind their target sales rate, and they sell smaller loans after reaching the eligibility threshold for the new-customer bonus. Second, this behavior varies by ability. Managers with high "plan knowledge" give lower interest rates on average, their pricing is more sensitive to their position in the incentive plan, and they more heavily emphasize small loans above the highest bonus threshold. These results suggest that they better understand the dynamic aspect of their private optimization problem, under which high performance in one month is penalized with more-challenging future performance targets. We find no effect of the second dimension of ability – education – on managers' behavior. Our third set of findings concerns the bank's foregone profits. We estimate the bank's demand function for loans and find that lost profits due to manipulation of loan sizes and interest rates are between three and twelve percent of the theoretical maximum, depending on the benchmark used. Furthermore, the profit loss is two percentage points greater for the managers with high plan knowledge, irrespective of the benchmark. Our fourth set of results shows that the bank loses more profits as time passes. Over the 13 months of the incentive plan, the profit loss increases by four percentage points, irrespective of the benchmark. This suggests that managers' adverse learning outpaces their productive learning. While we document that high-plan-knowledge managers generate higher agency costs, we do not find conclusively that they have a higher rate of adverse learning, although our results do point in that direction. Finally, we analyze outlets' loan portfolio quality and find that the rate of nonperforming loans is 0.7 percentage points higher for high-plan-knowledge managers. We find further evidence to suggest that this difference is due to their active management of borrower risk.

We make several contributions with these results. First, we advance the novel proposition that employee ability and learning may be net liabilities for the principal in certain performance pay contexts, and we document this empirically. In addition to

providing a valuable counterpoint to the research cited above, which focuses on the principal's positive returns to ability and learning, our results shed light on an unresolved puzzle in the literature – why do some employees game their incentive plans while others do not? Nagin et al. (2002) find that a large fraction of employees under an output-contingent pay plan does not respond opportunistically to variations in monitoring output quality. They find that this is partly explained by employees' feelings about how the employer treats them. A further, unexplored, hypothesis is that employees differ in their ability to make correct inferences about how the monitoring rate is changing. Our results suggest that a similar type of cognitive ability – the ability to infer undisclosed information about the incentive plan – does drive opportunistic behavior in the firm we study, and we find that the more “able” employees in this regard are more costly to the bank.

Our second contribution is to measure the costs to the bank of the employees' behavior against the benchmark of profit maximization. We obtain this benchmark through a novel empirical strategy. Since managers price loans according to where they stand in their incentive plan, their plan status can be used as an instrument for the supply of loans to identify the bank's demand function. This, in turn, permits us to compare the profitability of observed and hypothetical pricing decisions. In the only other paper we know of that estimates agency costs (Larkin 2007), the product in question – enterprise software – is highly customized and sold to heterogeneous customers. In that paper, our method would not be feasible, and the author instead relies on a partially subjective matching technique in order to estimate the agency costs.

Our third contribution is the empirical setting. Most micro evidence concerning employees' responses to performance pay comes from blue-collar and agricultural workers. Ours is one of a small number of detailed analyses of incentives in white-collar, service sector jobs, and the only one we know of for the banking industry. One common theme in popular analyses of the 2008 global financial crisis is the belief that bankers' strong incentives destabilized the system by rewarding short-term profits without regard to longer-term risk. While we can offer no insight into the systemic impact of our bankers' behavior,

we do find evidence consistent with a link between incentives and loan quality, particularly for the managers with high plan knowledge.

Finally, we should comment on the issue of optimal contracting. Because the bank has one uniform incentive plan for all its branches, we would expect the contract to be suboptimal with respect to certain subsets of employees. Furthermore, we suspect that the contract is not the globally optimal one, as our analysis has uncovered information that bank executives did not have when the contract was written. It is not even immediately evident what the optimal contract should look like. First, the manager characteristic uncovered by our analysis – “plan knowledge” – is only weakly associated with observable measures such as output, so any revelation mechanism is likely to be complex. Second, the contracting problem could be generically framed as one of an imperfectly informed principal facing boundedly rational agents.³ We know of no existing theory that treats this problem, nor do we attempt in this paper to solve it. Rather, our contribution is to offer the first empirical evidence of an economically important relationship between cognitive ability and agency costs and, we hope, to stimulate further theoretical and empirical research on this type of contracting problem.

The paper is organized as follows. In section 2, we present the institutional background and the bank’s incentives. In section 3, we present a simple model of ratcheting to motivate parts of the empirical analysis. In section 4, we describe the data. In section 5, we present preliminary evidence of agency problems. In sections 6 and 7, we estimate the effects of gaming on discounting and loan size respectively. We calculate the magnitude of agency costs via demand estimation in section 8. In section 9, we present evidence of adverse learning among branch managers, and in section 10 we investigate the time series of loan portfolio quality. Section 11 concludes.

³ The low-plan-knowledge managers in our study could be considered boundedly rational in that they appear not to perceive information relevant to choosing their optimal response to the bank’s incentive plan.

2. INSTITUTIONAL BACKGROUND

2.1. Bank Description

We study a private retail bank operating in Poland. The bank is among the twenty largest financial institutions in the country, employing several thousand people and serving loans to hundreds of thousands of customers yearly.⁴ Its focus is on the sales of simple banking products, such as deposit accounts and small consumption loans, to mass market customers. The bank operates through a network of several hundred outlets located in large to mid-size towns. A typical outlet employs three to four salespeople including the outlet manager. The manager is responsible for meeting the outlet's sales target and has discretion over a small marketing budget, as well as freedom in approving and pricing some loans. Outlets are aggregated into five "macro-regions", each supervised by its own manager. Macro-region managers report directly to the sales director, who is the second-ranking person in the bank.

2.2. Incentives

During our sample period, the incentive scheme is constant and uniform across outlets. The pay of the outlet managers and salespeople is tightly linked to outlet performance. Compared to the banking industry in Poland, the bank's incentives are relatively strong, with the variable share of managers' monthly pay averaging over 40 percent.

There are two main types of loans that outlets can sell – "primary" and "secondary". A primary loan, which is the bank's focus at the time of our study, is a loan sold to first-time customers. Typically, such customers can borrow up to their monthly income (approximately 2000 zloty⁵ at the time of the study). Secondary loans are reserved for repeating clients. Because we focus on sales of primary loans, we report the detailed incentive structure for this product only.⁶

⁴ Exact figures suppressed for confidentiality.

⁵ One US Dollar equals approximately 3 zloty (zl) (as of December, 2008).

⁶ There are two main concerns with omitting the secondary loans. One is that demand for these loans might vary with outlet characteristics, varying the effect of the incentives for the primary loans. We include detailed controls for outlet type, region, calendar periods and their interactions to mitigate this possibility. As we show below, the outlet type appears to capture most of the unobservable sources of variation in performance across

Each month, an outlet is assigned a sales target (in zloty) for primary loans. The sales targets are set centrally, with the regional managers having only very limited influence. Outlet managers receive a “piece rate” bonus for each new loan sold once the outlet’s sales exceed 80 percent of the plan. The bonus rate increases in a stepwise fashion up until 130 percent of the sales target, after which it stays constant. Figure 1 illustrates the incentive plan. While we do not know (and neither do the outlet managers) the exact algorithm by which the sales targets are set, from our data we do know that the sales targets for primary loans are based on (a) the outlet’s performance in the past, (b) similar outlets’ performance in the past and (c) headquarters’ analysis of national, regional and local market trends.

 Insert Figure 1 about here

3. A SIMPLE MODEL OF RATCHETING

Because an outlet’s monthly sales target is a function of past performance, managers’ incentives contain an element of ratcheting. However, unlike the other elements of the incentive plan (sales targets, bonus rates, etc.), the ratcheting element is not explicitly communicated to employees. If employees vary in their ability to infer the presence of ratcheting, we might expect different responses to the bank’s incentive plan.

To motivate the empirical analysis, we present a simplified and reinterpreted version of the model in Weitzman (1980). An outlet manager produces output y_t with a strictly convex cost function, $C(y_t)$. The manager earns a bonus b for output above a target, q_t , i.e., $b(y_t - q_t)$.

First, assume there is no ratcheting, i.e., $q_t = q$ for all t . It is evident that the manager’s optimal output solves:

$$C'_t(y_t^*) = b \tag{1}$$

units. The second, related, concern is that certain outlets might be more likely to “bundle” primary and secondary loans. However, bundling is almost entirely ruled out in our data. Clients are not eligible for a secondary loan until they have repaid their primary loan, typically after a year or more. Therefore, it is virtually impossible that a primary and a secondary loan would be issued to the same client in the same month (i.e., bonus cycle).

Now, assume that the current period's target is set by bank executives as a function of the previous period's target and production:

$$q_t = q_{t-1} + \lambda_t (y_{t-1} - q_{t-1}) \quad (2)$$

where the nonnegative adjustment coefficient λ_t measures the extent of ratcheting. "Naïve" managers are ignorant of the ratcheting and continue to supply output according to (1). "Sophisticated" managers view the λ_t as independently distributed random variables with expected value λ .

Proposition: The sophisticated manager's optimal output choice satisfies

$$C'_t(y_t^*) = \frac{b}{1 + \frac{\lambda}{r}}, \quad (3)$$

where r is the discount rate.

Proof: See proof of Theorem 1 in Weitzman (1980), with $\delta_t = 0$.

Corollary: Sophisticated managers will restrict their output (choose lower y_t^*) relative to naïve managers.

Proof: Follows from (1) and (3), using the fact that $\frac{\lambda}{r} > 0$.

The model formalizes the simple intuition that sophisticated managers recognize the intertemporal externality of high current performance, while naïve managers do not. We should point out here that the model is intended only to sharpen the basic intuition about heterogeneous agents' responses to ratcheting. It is not intended as a literal description of the bank's incentive plan. In particular, while the performance target is in units of aggregate loan value, the bonus is paid per loan. We explore the implications of this in the empirical analysis.

4. DATA DESCRIPTION

Our analysis draws on (a) archival sales (panel) data, (b) interviews with bank executives and managers, yielding detailed knowledge of the production process and

incentive systems, and (c) a large-scale survey of outlet managers, yielding information on a variety of the managers' personal characteristics. Appendix A describes the interview and survey methodologies. In this section, we discuss in detail the archival data and the most important data from the interviews and surveys – our ability measures.

4.1. Archival Data

Our dataset contains confidential archival data on sales, loan performance and incentives, spanning the 13 months following the bank's introduction of the incentive plan described above. . The dataset encompasses all primary loans granted by all outlets during this time (over 500,000) and contains the following information.⁷

4.1.1. Loan-Level Data

Table 1 presents a typical loan-level data structure for each outlet.

Insert Table 1 about here

Loan size and interest rate: Due to confidentiality concerns, the bank did not release the exact size and interest rate of each loan. Instead, loans were aggregated into groups of similar size and interest rate. For each group, the data contain (a) the loan size category (on a scale of one to five), and (b) the interest rate category (on a scale of one to five). We worked closely with the bank's data coders to ensure that (i) the category definitions are stable over time and (ii) the categories are equidistant. The latter means that our loan size and interest rate data are essentially a linear transformation of the confidential values, and standard linear techniques are still appropriate.⁸ We also observe the exact total value of sales of all primary loans by an outlet on a particular day.

Number of loans: We observe the number of loans in each aggregated bundle corresponding to an observation in our data.

⁷ For analyses that combine the archival and survey data, we drop outlets for which (a) there is turnover in the outlet manager position or (b) there is missing data due to survey nonresponse. In the most restricted case, we retain 69 percent of outlets. We find no evidence to suggest that these remaining outlets are nonrepresentative of the broader sample. See Appendix A for further discussion.

⁸ While aggregating continuous interest rate and value variables into categories introduces measurement error, 60% percent of all observations consist of individual loans, so the impact is not as severe as one might initially assume.

Approval track: Depending on the information in the loan application, a computer algorithm assigns the client to one of three risk categories. For clients in the lowest risk category, the outlet manager has full discretion in granting the loan, and the loan can be issued immediately (“fast loans”). For the higher risk categories, the loan has to be approved by the bank’s risk department, with a delay of up to 30 days (“slow loans”). Our interviews suggest that the risk management procedures are independent of the characteristics of the outlet and outlet manager, and also independent of the outlet’s performance. One implication is that the delay in issuing slow loans is a random variable.

The data give only the loan issue date, not the loan approval date. However, for fast loans the approval and issue dates almost always coincide. In much of the analysis below, we need to know the date on which the outlet manager approved the loan. In these cases, we therefore restrict the data to the fast loans.

4.1.2. Outlet-Level Data

Sales target: We observe the exact value of the sales target for each outlet each month. Because we know the exact value of loans issued (across all approval tracks), we can compute the exact position of an outlet with regard to its sales target each day (“plan position”).

Outlet characteristics: Outlets are attributed by the sales department to one of six categories encompassing the type of location (hypermarket, city center, or suburban), outlet format (stand-alone vs. kiosk) and employment. Due to perfect correlation between some of the dimensions we observe six different “outlet types”. We also observe the geographical location of the outlet (the “macro region” referred to above).

Loan performance: At the end of each month, we observe the fraction of each outlet’s outstanding loans currently being paid back by bank clients. This measure allows us to observe the percentage of bad loans in the outlets’ portfolio. We cannot, however, observe this measure for different loan types or approval tracks.

4.2. Ability Measures

In addition to personal characteristics such as age, gender and marital status, our survey asked for the managers’ educational attainment. Since almost all managers have

university degrees, we asked whether they had a master's degree or above (which about half did). This question provides us with a standard measure of managers' ability, which in the economics literature is routinely associated with cognitive ability or intelligence (Heckman and Rubinstein 2001).

As mentioned in the introduction, it is reasonable to think that something as complex as cognitive ability cannot be reduced to a one-dimensional scale. The notion that there are other, distinct, dimensions dates at least to Aristotle and has modern proponents in the cognitive psychology literature (Sternberg et al. 2000, Tigner and Tigner 2000). One distinction that both the ancients and moderns have drawn is between theoretical/analytical and practical intelligence, corresponding closely to the layperson's concepts of "book smarts" and "street smarts". Research in psychology suggests that these two types of cognitive ability may be uncorrelated or even negatively correlated.⁹

One way of viewing the distinction between theoretical/analytical and practical intelligence is that the former is related to success in solving well-defined problems, while the latter is related to success in solving problems for which the parameters, relevant information and solution methods are ill-defined. A good illustration comes from Ceci and Liker (1986). They asked a group of men with a long history of regular horse race attendance to predict the post-time odds on a variety of races. This is a cognitively demanding task, but one with no clear path to a solution. The authors found that success in the handicapping task was unrelated to the men's scores on a standard IQ test.

The managers in our sample are similar to the horse handicappers in that, in order to formulate a personally optimal response to the bank's incentives, they need to make complex inferences about a variety of questions, such as: Where does the plan offer opportunities to simultaneously improve my measured performance and reduce my effort? What behaviors are likely to trigger sanctions, and what are those sanctions likely to be? What parts of the

⁹ Sternberg et al. (2000) cite numerous studies that reach this conclusion.

customer's loan application can I "fudge" to avoid credit controls, and how far can I carry this? How is my performance target determined?¹⁰

Linear regression provides a natural model for thinking about managers' ability to make sophisticated inferences about the incentive plan. In their study, Ceci and Liker (1986) found, using a regression model to represent the handicappers' decision making process, that the experts were more likely to incorporate into their predictions a variable capturing complex interactions in the horses' historical performance data. A basic result in linear regression is that, for a given sample size, prediction error decreases as more variables are added to the model. More formally, $E[\text{var}(y | x)] \geq E[\text{var}(y | x, z)]$, where $\text{var}(y | x) \equiv E[\{y - E[y | x]\}^2]$ (Wooldridge 2002, p. 31). Therefore, if we think of highly "able" managers as those who condition on a larger set of information (i.e., both x and z) when thinking about the incentive plan, these managers should make more precise predictions about the plan.

In our survey, we asked outlet managers to predict their sales targets for the next month. The survey took place after the 13-month period we analyze here, and the managers' predictions apply to a different incentive regime, under which they had separate targets for four different products. We compare the four predictions with the actual targets and define a binary variable, "plan knowledge", equal to one if the manager's average absolute prediction error is below the mean for all managers.¹¹ As discussed above, bank executives set monthly sales targets by a closely guarded algorithm¹². Therefore, managers' ability to predict their targets is a good proxy for their ability to reconstruct the bank executives' decision-making processes, priorities, etc., from a diffuse set of information. We expect plan knowledge to measure how well the managers understand undisclosed aspects of the incentive plan that might be useful in gaming it.

¹⁰ Note that this is similar to, but vastly more complex than, the problem that telephone fundraisers were trying to solve in Nagin et al. (2002). There, the question was whether and by how much to misreport the amount of a pledged donation. Fundraisers knew that their reports were subject to verification; the only information that was hidden was the monitoring rate.

¹¹ We standardize the prediction errors before averaging. Note that we observe the predictions only once. Because of learning, prediction error is likely to change over time. This is not a problem as long as learning does not change managers' relative prediction errors, which we assume.

¹² In our survey, 85 percent of outlet managers either disagree or strongly disagree with the statement: "The bank informs me about how the sales plan for my unit is constructed."

To confirm that the plan knowledge variable really does measure how well managers understand the incentive plan, we analyzed the transcripts of our interviews with a subset of the outlet managers. Two researchers independently coded the interviews as (a) demonstrating a relatively sophisticated knowledge of the incentive plan, (b) demonstrating a relatively unsophisticated knowledge of the incentive plan, or (c) inconclusive. For both raters, 11 of the 17 managers could be assigned to group (a) or (b), and 10 of the 11 assignments matched the plan knowledge variable inferred from the managers' prediction errors. This correlation between the archival and interview data is significant at the 0.01 level.¹³

Table 2 shows how our two ability measures – advanced education and plan knowledge – correlate with each other and with other typical human capital variables such as age and tenure. Plan knowledge is positively correlated with advanced education, but only weakly so, suggesting that it does indeed capture a different dimension of ability. Plan knowledge is most strongly correlated with age.

Insert Table 2 about here

Table 3 shows how selected measures of managers' productivity – sales target, average daily number of loans sold, average volume of loans sold and average plan position at the end of the month – differ by ability. The average values are all higher for more-able managers by either definition.¹⁴ However, the differences are also relatively small and only statistically significant in one case: high plan-knowledge managers issue significantly smaller loans on average.

Insert Table 3 about here

¹³ Even if the uncategorizable interview data were arbitrarily assigned to be all high- or all low plan knowledge, the correlation in the full set of 17 observations would be statistically significant.

¹⁴ We observe similar differences when controlling for outlet characteristics.

5. PRELIMINARY EVIDENCE OF GAMING

Industry specialists in Poland note that demand for consumption loans tends to increase at the end of each month, driven partly by consumers' bridging to the next payday Money.pl 2005. One of the bank's executives told us:

There usually is a fourth week effect. In some months we do not observe it as clearly as in others but the demand tends to increase late in the month. Of course this gives [outlet] directors an opportunity to boost their sales. This is why we discourage them from lowering their prices late in the month.

Our data are consistent with the presence of a fourth-week effect. Figure 2 compares the average daily value of loans sold by interest rate group in the first three weeks of the month versus the fourth week.¹⁵ In each group, average daily sales are higher in the fourth week than in the first three weeks of the month (all differences are statistically significant). That is, conditional on the price, loan sales are higher in the fourth week, consistent with a spike in demand.

Insert Figure 2 about here

The bank's policy of discouraging fourth-week discounts is consistent with profit-maximizing behavior: ordinarily, we would expect to observe higher or at least unchanged prices during peak demand periods. This is not the case, as illustrated in Figure 3. In all but one loan size group (group 3), the average interest rate granted in the fourth week is significantly lower (t -statistic > 3, $p < 0.01$) than in the first three weeks.

Although a simple supply and demand model predicts that prices will rise in periods of peak demand, this prediction is occasionally violated empirically. Chevalier, Kashyap and Rossi (2003) discuss and test three classes of models that predict falling prices in peak demand periods: (a) cyclical demand elasticities (the level and elasticity of demand are positively correlated), (b) countercyclical collusion models (collusive agreements are more likely to break down when demand rises) and (c) loss-leader/advertising models (firms

¹⁵ We divide each month into four "weeks". Because these "weeks" are of unequal duration across different months, the table reports statistics at the daily level. We conduct robustness checks to ensure that our division pattern does not drive the results.

commit through advertising to offer low prices on certain goods in order to sell other, higher-margin, goods once consumers are in the store). None of these models appears to be relevant in our setting. Regarding (a), we estimate the bank's demand function in section 8 and find no evidence that the elasticity changes in week four.

There are two reasons to think that models of type (b) are not at work. First, the most prominent evidence in favor of these models indicates defection from collusive agreements during peak demand *seasons* (Borenstein and Shepard 1996). The cycle of the bank's demand is measured in weeks, not months. A collusive agreement that breaks down every fourth week for exactly one week seems a bit farfetched. Furthermore, anecdotal evidence from the bank is inconsistent with collusion. Branch managers report that they compete aggressively for new clients (see below), and if bank executives were engaged in countercyclical collusion, they would not discourage discounting in week four.

Finally, the loss-leader advertising model (c), for which Chevalier, Kashyap and Rossi (2003) find support in grocery retailing, has at least three features that are inconsistent with our setting: (i) advertising campaigns and promotional prices timed to coincide with the demand increase (in contrast, the bank's demand increase lasts roughly one week, while promotional campaigns are in effect for many weeks or even months), (ii) the potential for the retailer to "hold up" the consumer due to the latter's sunk travel costs (in contrast, a customer is more likely to walk away from an overpriced bank loan than from an overpriced can of green beans) and (iii) high-margin products that are bought *concurrently* with the "loss-leader" product (in contrast, the bank's complementary products are typically sold at a later date). Finally, if the bank were pursuing a loss-leader discounting strategy in week four, bank executives would not discourage price discounting during this time.

Given, then, that none of the caveats to the standard supply and demand model seems to apply, Figure 2 and Figure 3 collectively suggest an agency problem at the bank. The bank's demand for primary loans in week four must be either (a) weakly below demand in weeks one through three, or (b) higher. If managers are pricing optimally throughout the month, then (a) is not consistent with Figure 2 (because sales should be weakly lower in

week four), and (b) is not consistent with Figure 3 (because prices should be higher in week four). Below, we analyze this apparent gaming behavior in more depth.

Insert Figure 3 about here

6. LOAN PRICING

An obvious instrument that outlet managers can use to game the incentive system is the price (interest rate) of the loan. One manager told us:

When a client walks into an outlet asking for a loan and I need to sell, there's no way she's going out without one. I'll match any competitor's price and add something on top.

However, our interviews also suggest that managers use their discounting power sparingly:

Of course we give discounts. Everybody does. The trick is to give the discounts when you need to sell [loans] and the customer wants it, not just when the customer wants it.

What would dissuade managers from giving the maximum discount all the time? Two possibilities are fear of sanctions from their supervisors and dynamic considerations. Managers can pay a dynamic penalty from finishing the month too far behind or too far ahead of their sales targets. If an outlet manager finishes far behind plan, she risks being fired and incurring job search costs. In contrast, if she finishes far ahead of plan, as discussed in section 4, she risks having her sales target significantly raised in the following month, meaning that her expected pay, net of effort costs, will decrease. Interviews with managers suggest that some of them are sensitive to these dynamic considerations and seek to minimize deviations from their targets. One manager noted:

I know at all times where I stand with regard to the sales target. If I'm behind, I do all I can to catch up. If I'm ahead I take it easy.

Below, we investigate (a) whether managers use their discounting power to “fine-tune” their performance against target throughout the month, (b) how responsive the interest rate is to distance from the sales target, and (c) how these responses vary with managers’ ability.

6.1. Empirical Specification

We estimate variations on the following reduced-form equation:

$$r_{u,t} = \beta_0 + \beta_1 PD_{u,t} + \beta_2 K_u + \beta_3 Z_{u,t} + \varepsilon_{u,t} \quad (4)$$

The dependent variable, $r_{u,t}$, is the value-weighted interest rate on loans sold by outlet (unit) u on day t . The key independent variable, $PD_{u,t}$, is the “plan deviation” – how well the outlet is performing against its sales target at the beginning of day t . We measure this as the difference between (a) “expected performance” (the average daily sales rate implied by the outlet’s sales plan) and (b) “time- t required performance” (the average daily sales rate needed to meet 100 percent of the sales target from day t , given performance up until day $t-1$). Formally, the plan deviation is defined as

$$PD_{u,t} = \frac{ST_{u,m}}{T} - \frac{(ST_{u,m} - CV_{u,t,m})}{T-t}, \quad (5)$$

where T denotes the number of days in month m , ST the sales target and CV the cumulative value of loans sold up until date t in month m . Positive values of plan deviation indicate that the outlet is “ahead of schedule,” while negative values signal below-expected outlet performance. When plan deviation equals zero, the outlet is performing exactly at the rate needed to meet the sales target.¹⁶ The plan deviation measure is conceptually similar to the one used by Chevalier and Ellison (1997). There, a mutual fund manager’s behavior is a function of the difference between her fund’s current return and the return on a value-weighted market index (a benchmark for investors’ expectations). In our approach, the benchmark “expected performance” reflects bank managers’ expectations for that outlet’s average sales rate that month. We include the square of plan deviation in (4) to allow for a possible nonlinearity of its effect.

The vector K contains our two ability measures – advanced education and plan knowledge – and Z is a vector of controls, including region-quarter effects, outlet-type-quarter effects, week of the month effects and the Bank of Poland’s base interest rate.¹⁷ We

¹⁶ A reference value of 100 percent of the sales target, while consistent with our interviews, is in principle arbitrary. However, this has no bearing on the interpretation of the results, as a different reference value would merely imply a different normalization without changing the scale units.

¹⁷ The quarters are measured in running time, so that Q3 2006 and Q3 2007 have separate effects.

also introduce interaction terms between PD and K in some specifications. Summary statistics are in Table 4.

Insert Table 4 about here

We are careful to include in the vector Z controls for unobserved heterogeneity across outlets. As managers' characteristics, including plan knowledge, are time-invariant, we would not be able to identify our model using individual outlet fixed effects. We therefore use fixed effects at the level of the outlet type, defined in section 4. We provide several robustness checks to ensure that our estimates are not affected by unobserved heterogeneity within an outlet type.

One potential concern in estimating (4) is that our model suffers from a subtle type of endogeneity problem. Plan deviation measures how well managers stand with regard to their sales target; it could thus be affected by prior period discounting. If there is serial correlation in the error terms, this could lead to correlation between the plan deviation variable and the error term, leading to biased coefficient estimates Greene 2003, p. 266. Using the test proposed by Wooldridge (2002, p. 282), we reject the hypothesis of serial correlation in our panel ($F=0.43$, $p>0.05$).

6.2. Results

Table 5 presents results of the estimation of (4). Columns 1 and 2 present specifications of the restricted models without the influence of plan knowledge, with and without outlet fixed effects. Column 3 presents the specification with outlet type fixed effects. The individual coefficient estimates change relatively little from column 2 to column 3. We cannot reject the hypothesis of joint equality of coefficients across the two specifications ($\chi^2 = 8.34$, $p<0.01$). This makes us confident that the unobserved heterogeneity at the outlet level is well captured by the outlet type. The remaining specifications (columns 4-6) hence present estimates with fixed effects at the outlet type level. The specification in column 4 adds the time-varying controls. Column 5 adds the

ability measures, and column 6 includes their interactions with the main independent variable, plan deviation. The following discussion pertains to column 6.

Insert Table 5 about here

Recall that positive values of the plan deviation mean that the outlet is performing ahead of plan. Column 6 shows that the coefficient on this variable is positive and highly significant, indicating that outlets charge lower prices when they are “behind schedule” and higher prices when they are ahead. This suggests that managers might be offering suboptimal discounts (from the bank’s perspective) to meet their performance targets.

The coefficients on both the advanced education variable and its interaction with plan deviation are insignificant. On the other hand, the coefficients on plan knowledge and its interaction with plan deviation are significant. Managers with high knowledge of the sales plan give lower prices on average (column 5). The positive coefficient on the interaction term indicates that managers with high plan knowledge more rapidly increase prices as their performance relative to plan improves. This is consistent with the predictions of the model in section 3 – that sophisticated agents will restrict their output in the presence of ratcheting.

One possible concern about these results is that the plan knowledge variable may be correlated with other fixed outlet or manager characteristics, and that these characteristics are causing the outcomes we observe. To investigate this possibility, we constructed an alternate plan knowledge variable, replacing the raw sales plan prediction error with the residual from an OLS regression of the prediction error on the outlet type, location, and the managers’ gender, age, marital status and risk preferences. None of the results in the paper are materially affected by the change.

7. LOAN SIZE

As discussed above, in addition to the interest rate, outlet managers have discretion over the size of the loan they offer a client. Our interviews with managers indicate that

some of them have strong preferences over loan size and, especially, the timing of large loans.

The best thing that could happen to you is one big customer very early in the month. Such a customer can make up to 25 percent of the plan in my outlet. You don't have to worry that there'd be no bonus. At the same time, such a customer is a nightmare if he shows up on the 30th [day of the month].

Although loan size is partly driven by individual consumers' preferences, managers can influence it in at least two ways: (a) by "cutting" large loans into small loans ("slicing" in the managers' jargon) or (b) by proposing a loan below the client's borrowing capacity.¹⁸ Our interviews indicate that managers do manipulate loan size as a function of their position in the sales plan.

At the beginning of the month I always first propose the highest possible loan to clients. Sometimes even more. When we [the outlet] are already over the plan, I will never give a client what he can actually afford.

This last quotation suggests that we can understand the managers' incentives to manipulate loan size by thinking about two extremes of performance versus the sales plan. At the upper extreme, beyond 130 percent of plan, managers would ideally like to sell an infinite number of loans of size \mathcal{E} . This is because the bonus depends only on the quantity, not the value, of loans sold. In contrast, the manager derives no benefit from adding to the cumulative value of loans sold. There is no higher bonus rate to be attained, yet the expected costs of ratcheting continue to increase. At the other performance extreme, below 80 percent of plan, managers could never expect to earn a bonus in finite time by selling loans of size \mathcal{E} . We therefore expect to see loans sold when managers are above 130 percent of plan to be smaller than those sold when managers are below 80 percent of plan. Furthermore, we expect this effect to be stronger for managers with higher levels of plan knowledge.

7.1. Empirical Specification

We estimate variations on the following equation:

$$PS_{u,t} = \beta_0 G_{u,t} + \beta_1 PP_{u,t} + \beta_2 K_u + \beta_3 Z_{u,t} + \varepsilon_{u,t}. \quad (6)$$

¹⁸ Although an individual can only ever take out one primary loan, by definition, outlet managers can still "slice" primary loans by issuing separate loans to multiple members of the same household.

The dependent variable, $PS_{u,t}$, is the proportion of the number of small loans to all loans sold in outlet u on day t . We define a loan as “small” if it belongs to one of the first two of the five size categories.¹⁹ $PP_{u,t}$ measures outlet u ’s “plan position”, or percentage of sales plan met, at the start of day t . $G_{u,t}$ is a vector of indicator variables for various plan position thresholds. We define four intervals: 0-50 percent, 50-80 percent, 80-130 percent and above 130 percent. Other than the division at 50 percent, this partition reflects important thresholds in the managers’ piece rate incentive plan.²⁰ K_u is the vector of ability measures and $Z_{u,t}$ is a vector of controls as defined in (4). We suppress the constant so that we can include all the elements of $G_{u,t}$ in tests of their relative magnitudes. Some specifications include interaction terms between $G_{u,t}$ and K .

7.2. Results

Table 6 reports the results of the estimation of (6). The specification in column 1 reports results for the restricted model. In column 2 we add individual outlet fixed effects. In column 3 we substitute outlet type fixed effects for individual outlet fixed effects. Similarly to the estimation of (4), the estimated coefficients in column 2 and 3 do not statistically differ ($\chi^2 = 16.2$, $p < 0.01$). Column 4 adds the time-varying controls. Column 5 adds the advanced education and plan knowledge variables, and column 6 adds their interactions with the plan position thresholds.

 Insert Table 6 about here

In column 5, the coefficients on the plan position thresholds are positive, significant, and monotonically increasing. Each consecutive coefficient is statistically significantly greater ($F > 3.03$ ²¹, $p < 0.05$) than the former. These results indicate that managers steadily

¹⁹ Our results are robust to alternative classifications of small and large loans.
²⁰ Interviews with managers suggest that 50 percent is an important psychological threshold. Our results are robust to other partitions of plan position.
²¹ Three pairwise tests of four coefficients were involved. We report the smallest F-statistic of the three.

shift from large to small loans as they progress in their sales plan. This pattern is consistent with a steadily increasing marginal benefit to selling small loans as plan position improves.

Finally, we turn attention to the ability measures. There is no significant relationship between advanced education and loan size. In contrast, there is a relationship between high plan knowledge and loan size. Interestingly, we see the largest and most statistically significant effect at the 130 percent threshold. Above this level, the share of small loans in the day's portfolio is 6.3 percentage points higher for high-plan-knowledge managers. As already noted, above this threshold, the bonus rate stays constant, and the marginal benefit to selling a small loan is unambiguously greater than the marginal benefit to selling a large loan. Therefore, this is the threshold at which we would most expect to see a significant difference between more- and less-knowledgeable managers. This is again consistent with the prediction of the model in section 3 that more-sophisticated managers will restrict their output in the presence of ratcheting.

8. ESTIMATION OF AGENCY COSTS VIA DEMAND ESTIMATION

The results above suggest the presence of agency costs, arising from managers' delegated authority to set prices and influence loan sizes. In this section, we estimate these costs by comparing actual profits on primary loans with the profits the bank would have earned under two different counterfactual scenarios described below.

To estimate counterfactual profits, we need to know the bank's demand for primary loans as a function of the interest rate. We estimate this demand function using a novel identification strategy. As we have shown above, managers manipulate the price and size of loans in response to their plan position. On any given day, different managers in the same region will be at different positions in their incentive plan and will make different decisions about the price and average size of loans offered. Plan position is therefore an outlet-level supply shifter that can be used as an instrument to identify the demand curve for that region. With the estimated parameters for the demand function, we can compute demand under a variety of counterfactual scenarios. With some further information about the bank's costs

(described below), we can estimate actual and counterfactual profits, and also compute the price for primary loans that maximizes short-term profits.

We should note here that our demand-based estimation of agency costs encompasses both types of gaming behavior identified above – price manipulation and loan size manipulation. This can be understood by considering the three elements of our estimation strategy: (a) actual profits, (b) counterfactual profits and (c) the instrumental variables that help to identify (b). Actual profits are computed from the daily price-aggregate loan value pair observed for each manager. This will reflect any manipulation of prices or loan sizes. The benchmark counterfactual profits are what the manager could have earned in the absence of gaming. These profits are computed using the demand function. While the manager’s position in the incentive plan helps us to identify the demand function’s parameters, these parameters represent *consumers’* preferences, which are independent of managers’ incentives and behavior. Therefore, the demand function provides a gaming-free benchmark against which to compare the managers’ actual behavior. The difference between the observed and benchmark profits can be interpreted as the agency costs of price and loan size manipulation, provided the benchmark is computed using the bank’s profit-maximizing price, a point to which we now turn.

One benchmark for estimating agency costs is the profits managers would have earned had they chosen the price that maximizes profits under the short-run demand function. This benchmark is likely to overstate the true agency costs, because the bank’s objectives are more complex than simple short-term profit maximization. Since the bank is in a period of expansion during our study, and primary loan customers may buy complementary products in the future, it is likely that the price that maximizes long-run profits is lower than the price that maximizes short-run profits from primary loan sales.

Information gleaned from our interviews with bank personnel suggests a second, more conservative, benchmark. As discussed above, bank executives expressly discourage price discounting in the fourth week of the month, because demand increases during that time. Therefore, another benchmark is the profits the bank would have earned in week four, had managers maintained prices at their levels from the first three weeks of the month. This

benchmark is likely to understate the true agency costs, because our evidence suggests that outlet managers are gaming the system throughout the month. Therefore, prices in weeks one through three are likely below the profit-maximizing level.

The claim that this second benchmark is a conservative one is invalid if it is actually optimal for branch managers to reduce prices in week four, despite higher demand. As discussed above, among the models that can reconcile higher demand and lower prices, only those based on cyclical demand elasticities seem to be legitimate candidates in our context.

Therefore, as long as the demand elasticity does not change in week four, we argue that our agency cost estimates based on the second benchmark are conservative.

8.1. Empirical specification

We model an outlet’s daily demand for primary loans as follows:

$$Y_{u,t} = \beta_0 + \beta_1 r_{u,t} + \beta_2 r_{u,t} * I_{week4} + \beta_3 X_{u,t} + \varepsilon_{u,t} \quad (7)$$

where Y denotes the value of loans sold by outlet u on day t and $r_{u,t}$ denotes the value-weighted interest rate.²² The vector X includes controls for region (five macro-regions), month (thirteen months), outlet type (six dimensions defined above) and the week of the month.

Our specification therefore assumes that the level of demand can vary by region, time and outlet characteristics. We also allow the slope of the demand function to change in the last week of the month. The summary statistics for our variables are incorporated into Table 5Table 4.

To consistently estimate (7), we need an instrument for the price of the loan. As discussed above, our instruments are two measures of the managers’ performance against their incentive plan – “plan position” and “plan deviation”.

8.2. Results

Table 7 reports OLS and first- and second-stage estimates for the instrumental variables specification. The estimated slope of the demand function does not statistically

²² Although loans differ in size, the price does not differ statistically across the different size categories. We therefore estimate the demand function as daily demand for monetary value of loans. We obtain virtually identical results using the number of loans as the dependent variable.

differ in week four from that in the first three weeks of the month²³. We hence report results for pooled estimation.

Insert Table 7 about here

As our focus is not on the parameters of the demand function itself, but rather to apply the demand function to estimate agency costs, we discuss Table 7 only briefly. The Hausman test rejects the null hypothesis of equality of coefficients obtained under OLS and 2SLS ($\chi^2 = 113.07$, $p < 0.01$). Additionally, the instruments are highly significant in the first-stage regression ($F = 95.33$). Furthermore, the IV estimation moves the point estimate on the price coefficient in the expected direction (we would expect OLS estimates to be biased upward). Finally, the Sargan overidentification test statistic is insignificant ($\chi^2 = 0.13$, $p = 0.72$). Collectively, these tests suggest that our instruments are valid and strong.

We should stress here that the demand function serves as a tool to estimate agency costs at the bank level; we are not interested in estimating conduct parameters for this industry. Still, one might wonder whether we are overlooking the effects of noncompetitive conduct in our analysis. We believe not. As noted above, our interviews indicate that branch managers are competing aggressively rather than colluding with their rivals. Furthermore, our demand function is not a market-level demand function, but rather the outlet's *own* demand function, conditional on whatever unobserved “game” the outlet is playing with its rivals. Therefore, even if competitive interactions are important in this industry, their impact on the bank is largely embedded in the demand function we estimate.

Using our estimated demand function, our goal is to compute profits and the profit-maximizing price for each outlet, in order to compare realized profits with maximum theoretical profits. To do this, we need information on marginal cost. We assume that the bank's marginal cost of loans is the interest rate offered on its savings deposit accounts.

²³ Since “week four” is an ambiguous concept in months of more than 28 days, we did robustness checks defining week four as the last 5, 6, 7, 8 and 9 days of the month. We do not find significant differences in the slope estimates for any of these specifications.

Because our loan interest rate data are disguised and rescaled by the bank, we need savings interest rate data on the same scale. We obtained this data through the following procedure. The bank provided data on the timing of television advertisements for its primary loans, from which we were able to trace the advertised interest rate. We took the rate offered during the first promotion in our sample period (which was in the first of the 13 months we study) as our baseline loan interest rate. We matched this to the interest rate offered on a deposit account during the same time period. We computed the savings interest rate scaled to our data as the product of (a) the ratio of the deposit to the loan interest rate and (b) the lowest loan interest rate value in our disguised data. Because the Bank of Poland's base interest rate was rising during our sample period, we do not believe that the bank's marginal cost stays constant. Therefore, we allow for the marginal cost to change proportionally to the changes in the central bank's base interest rate.

Table 8 compares the average observed daily price with the profit-maximizing price (Benchmark 1; short-run demand function), first pooled across all outlets, then separately for high- and low- plan knowledge managers. The table shows first of all that managers price well below the theoretical profit-maximizing level, at about 83 percent of the benchmark value. Furthermore, the table shows that managers with high plan knowledge give lower prices than managers with low knowledge, both in absolute terms and relative to the profit-maximizing price.

Insert Table 8 around here

In Table 9, we compare the bank's actual profits with the profits it would have earned under each of the two counterfactual pricing benchmarks discussed above. Because the profit levels have no economic meaning due to the bank's variable transformation, we report the ratio of actual to theoretical profits only. The first row of Table 9 reports the comparison with Benchmark 1, which assumes that managers choose the short-run profit-maximizing price.

Insert Table 9 around here

The table shows that, across all outlets, the bank loses as much as 12 percent of its profits due to managers' pricing decisions. This profit loss is greater for managers with high plan knowledge: 13 versus 11 percent. The difference between high- and low plan-knowledge managers is significant at better than the 0.01 level.

In the second row of Table 9, we compare the actual profits in week four with those the bank would have earned had managers continued to price at the level of weeks one through three (Benchmark 2). As discussed above, this is a valid estimate of the lower bound if demand increases at constant demand elasticity in week four, which is what we find in our demand estimation. The table shows that the bank loses at least three percent of its profits due to managers' pricing decisions. As for Benchmark 1, the lost profits are greater for the managers with high plan knowledge: a four percentage point loss versus a two percentage point loss from managers with low plan knowledge. This difference is significant at better than the 0.01 level.

These results are consistent with our earlier results and suggest that managers with high knowledge of the plan have a higher propensity to undertake actions that are costly to the bank. Both the upper and lower bound estimates of foregone profits are two percentage points higher for the managers with higher plan knowledge.

As discussed above, the agency costs estimated using Benchmark 1 must be treated with some caution. It is possible that the price that maximizes long-term profits is lower than the price that maximizes short-term profits. Therefore, high-knowledge managers could conceivably be acting in the bank's best interests by offering lower prices than their less-knowledgeable colleagues. However, the same caveat does not apply to the estimate based on Benchmark 2. Bank executives explicitly discourage fourth-week discounting. Therefore, to construe the observed price reductions as profit-maximizing behavior would require two rather unorthodox assumptions: (a) that the agents know better than the principals what the firm's objective function is and (b) that the agents are behaving altruistically.

In sum, the evidence broadly supports the conclusion that high plan knowledge is costly to the bank and that these costs outweigh any productivity benefits associated with the type of cognitive ability that is producing the plan knowledge (recall that plan knowledge is correlated with some indicators of productivity in our data). Thus, the bank appears to be a setting where the private marginal gains to this type of ability outweigh the employer's marginal gains.

9. ADVERSE LEARNING

As discussed above, managers' learning may work in two directions. On the one hand, it may increase their productivity, as much research would suggest (Arrow 1962, Jovanovic and Nyarko 1996, Benkard 2000, Thompson 2001). On the other hand, it may give rise to increasing agency costs if managers are mainly learning about opportunities to game their incentives. If the former dominates, we would expect to see the ratio of actual to theoretical profits increasing over time, whereas if the latter dominates, we would expect the reverse. Note that, because our estimated demand function (a) is the bank's, not the industry's, demand and (b) is allowed to vary in its level from month to month, it tells us what value of loans each unit could have sold as a function of the interest rate, allowing for any trends in consumer demand (the market was growing at the time). Therefore, the profit-maximization benchmark is already adjusted for changes in the market. Therefore, if no learning of any kind is going on, we should expect the ratio of actual to hypothetical profits to be constant.

Figure 4 shows a plot of the average agency costs, defined as $1 - (\text{actual profits} / \text{maximum profits})$ over time. From the plot, it is fairly clear that these costs are increasing over time. The plot also illustrates the higher average agency costs for the high-plan-knowledge managers already documented above. However, it is not evident from Figure 4 whether the rate of increase differs across the two ability types.

Insert Figure 4 around here

Table 10 gives the results for the nonlinear least squares estimation of the following specification:

$$AC_{u,t} = \alpha_0 + \alpha_1 month_t^{\beta_0 + \beta_1 PK_u + \beta_2 AE_u} + \alpha_3 PK_u + \alpha_4 AE_u + \alpha_2 Z_u + \varepsilon_{u,t}$$

where $AC_{u,t}$ is agency costs for outlet u in month t , PK_u indicates whether outlet u 's manager has high plan knowledge, AE_u is the advanced education indicator and Z_u contains controls for outlet type. Agency costs are based on the conservative benchmark. Other than the intercept, the results for the other benchmark are virtually identical and so we do not report them.

 Insert Table 10 around here

We focus the discussion on column 4 of Table 10. The point estimates for both α_1 and β_0 are positive and significant, indicating that the increase observed in Figure 4 is significant. Column 4 gives no conclusive evidence that high-plan-knowledge managers have a higher rate of adverse learning. The point estimate of β_1 is positive, and we would reject the null hypothesis that $\beta_1 \leq 0$ (one-sided test). However, we would not reject the more conservative null hypothesis that the coefficient is zero at conventional levels. In contrast, the point estimate for the advanced education coefficient, β_2 , is negative. Figure 5 plots the curves corresponding to these estimates. As the coefficients β sum to less than one, the curves show diminishing learning effects over time, consistent with the general shape of Figure 4. Figure 5 shows an increase in agency costs from the first to the thirteenth month of the plan of 3.6 percentage points for low-plan-knowledge managers and 4.8 percentage points for high-plan-knowledge managers.

 Insert Figure 5 around here

Overall, these results strongly suggest that the costs of managers' adverse learning outweigh the benefits of any productive learning that is occurring. There is suggestive, but inconclusive, evidence that managers with higher plan knowledge have a higher rate of adverse learning.

10. PORTFOLIO QUALITY

One common theme in popular analyses of the 2008 global financial crisis is the belief that bankers' strong incentives destabilized the system by rewarding short-term profits without regard to longer-term risk. This suggests another possible source of agency costs – underperforming loans – in the bank we study. As discussed above, new loan applications enter one of two approval tracks depending on the applicant's credit score. Scores indicating higher risk trigger centralized approval, whereas outlet managers can approve lower-risk loans on the spot. At the margin, managers can avoid centralized controls by carefully shaping the information that they input into the bank's credit scoring system. The bank clearly provides no established procedures for doing this, so we might expect this behavior to be more widespread among the high-plan-knowledge managers. As we have shown, a variety of evidence indicates that these managers have a more sophisticated understanding of how the system works and how to “work the system”.

We analyze loan portfolio quality – the share of performing loans in an outlet's portfolio, measured at monthly intervals. Table 11 gives some preliminary evidence. High-plan-knowledge managers' share of performing loans is 0.7 percentage points lower than the corresponding figure for low-plan-knowledge managers. This is consistent with the hypothesis that high-plan-knowledge managers are more skilled at manipulating the bank's systems for their own benefit. Also, it suggests that the bank's lost profits from these managers are even greater than we have estimated above, although we cannot be certain.²⁴

²⁴ Since portfolio quality is a count-based measure, differences across ability types do not necessarily translate directly into differences in revenue. Conceivably, a value-weighted measure of portfolio quality would give a different result, but we do not have such data. Recall that high- and low-plan-knowledge managers issue

While Table 11 is consistent with the hypothesis that high-plan-knowledge managers are more likely to manipulate portfolio quality, there are multiple factors that might affect loan performance: (a) outlet managers' decisions, (b) bank-level decisions (i.e., centralized risk controls) and (c) random shocks (e.g., to applicant quality or borrowers' ability to pay).

As discussed above, our interviews indicate that the bank's centralized risk management procedures are independent of the outlet: its characteristics, its managers' characteristics and its current performance. Therefore, outlet-level variation in portfolio quality must be attributable either to (a) outlet-level variation in the quality of borrowers whose applications are submitted for central approval or (b) outlet-level variation in the quality of borrowers whose applications bypass central controls. In either case, these must arise from outlet managers' decisions or random shocks rather than from bank-level decisions.

If an outlet's portfolio quality depends only on random shocks to borrower quality, then, conditional on the general state of the economy, we should expect to see portfolio quality follow a random walk. In contrast, if portfolio quality also depends on outlet managers' decisions, we should expect a different time-series pattern.

Managers' incentives suggest what time period pattern we should see. Obviously, managers care little about borrower quality, since the bank's bonus purely rewards customer acquisition. Yet it is highly unlikely that the bank would allow managers to consistently sell nonperforming loans. Therefore, we assume that there is a lower limit to acceptable portfolio quality beyond which managers are sanctioned or fired. In the presence of random shocks, the optimal strategy from the manager's perspective is to try to maintain some minimum, "safe", steady-state level of portfolio quality. Therefore, if portfolio quality received a positive shock in the last period, the manager would relax lending standards in the current period. If the previous period's shock was negative, the opposite is true. Under such behavior, we would observe the outlet's portfolio quality following an autoregressive

roughly equal volumes (monetary value) of loans each month, but high-plan-knowledge managers issue a greater quantity of loans.

process where current-period quality is negatively correlated with previous-period quality.²⁵ Furthermore, we might expect this relationship to be stronger for high-plan-knowledge managers, since the strategy requires a relatively high degree of sophistication, both in assessing borrower risk and in acting on the margins of the bank’s own risk control procedures.

10.1. Empirical specification

We estimate the following equation:

$$PQ_{u,m} = \beta_0 + \beta_1 PQ_{u,m-1} + \varepsilon_{u,m} \tag{8}$$

where $PQ_{u,m}$ is outlet u ’s loan portfolio quality, measured as the proportion of good (performing) loans in the current portfolio, at the end of month m . Fixed effects OLS estimation of an AR(1) process will be biased by construction Nickell 1981. Therefore, we estimate (8) using the Arellano-Bond estimator (Arellano and Bond 1991), which uses lagged first differences as instruments to produce unbiased estimates of β_1 . Under the hypothesis of a random walk, β_1 will equal one. Under the hypothesis that outlet managers are actively managing their portfolio risk, β_1 will be negative.

10.2. Estimation results

Table 11, column 2, presents the results of the estimation for the full sample. The Arellano-Bond test for autocorrelation of residuals of order 2 is insignificant, which is necessary for Arellano-Bond to produce unbiased estimates (Arellano and Bond 1991). For comparison, we also report the OLS results with outlet fixed effects in column 1.

 Insert Table 12 around here

²⁵ We assume that the size and maturity distribution of new loans is stable from month to month.

The estimate of β_1 is negative and highly significant, consistent with a mean-reverting process and inconsistent with a random walk. These results are consistent with the hypothesis that managers tend to sell more risky loans if their profile is sufficiently secure.²⁶

Columns 3-4 and 5-6 present results for high and low plan knowledge managers, respectively. The estimate of β_1 is negative and highly significant for high-plan-knowledge managers while it is smaller in magnitude and statistically insignificant for low-plan-knowledge managers. The difference in the point estimates across columns 4 and 6 is statistically significant ($p < 0.05$).²⁷

These results are consistent with our predictions. Outlet managers appear to actively control their portfolio risk, and this behavior appears to be confined to the managers with high plan knowledge.

11. CONCLUSION

Theoretical and empirical research on performance-based incentives suggests that the optimal incentive strength depends on a tradeoff between productivity and agency costs. The effect of employee ability and learning on this tradeoff is *a priori* unclear. While both should increase the employee's productive output, they may also be associated with more sophisticated gaming responses. In some settings, the increase in agency costs may dominate the productivity impact.

We observe branch managers of a large Polish retail bank following the introduction of a new incentive plan. We use a novel empirical strategy to estimate the profits the bank loses through managers' manipulation of loan sizes and interest rates. We find that these agency costs are between three and twelve percent of profits on average. Managers' formal education ("book smarts") has no impact on agency costs, but their ability to infer undisclosed information about the incentive plan ("street smarts") does. More-able

²⁶ One potential caveat to this interpretation is the following: Because portfolio quality is bounded above and below, even if it is a random walk over short intervals, it will be observed as a mean-reverting process over a sufficiently long time period. We assume that our time horizon is shorter than that which would produce mean reversion for mechanical reasons.

²⁷ We find no significant difference when dividing the sample on education and so we do not report these results.

managers in the latter sense cost the bank an extra two percent of profits. An analysis of portfolio quality suggests that these managers may cost the bank an additional percent of profits by selling riskier loans. Finally, agency costs are increasing over time, suggesting that “adverse learning” dominates productive learning. There is suggestive, but inconclusive, evidence that higher levels of “street smarts” are associated with a higher rate of adverse learning.

There is a long literature suggesting that ability and strong financial incentives are complements. We do not attempt to dispute or overturn those results with our own. Rather, we wish to suggest that, while this complementarity may be a pervasive phenomenon, it is not a universal one. Our results raise the possibility that there are certain environments or production technologies for which the perverse effects of ability and learning outweigh the beneficial ones when strong financial incentives are in place. Future research might focus on clarifying the conditions under which the net benefits of ability and learning are negative.

Another possibility is that the difference between our results and past work is due not to differences in context or production technologies, but rather to the fact that our analysis includes a dimension of ability that other work has not considered. Our two ability measures correspond closely to the concepts of theoretical and practical intelligence, which research in cognitive psychology suggests are distinct capabilities. The practical, or “street smarts” dimension, is typically not addressed as a separate construct in economics research, but it is in this dimension that we find great differences in outcomes.

Finally, we believe that our results point to a new line of research in the theoretical foundations of contracts. We find that the bank earns higher profits from managers with lower levels of cognitive ability. These managers could be considered “boundedly rational” in that they appear not to perceive information relevant to choosing an optimal response to the bank’s incentive plan. Future research might consider the implications for optimal contracting when the principal faces boundedly rational agents, or an array of agents who differ in their degree of rationality.

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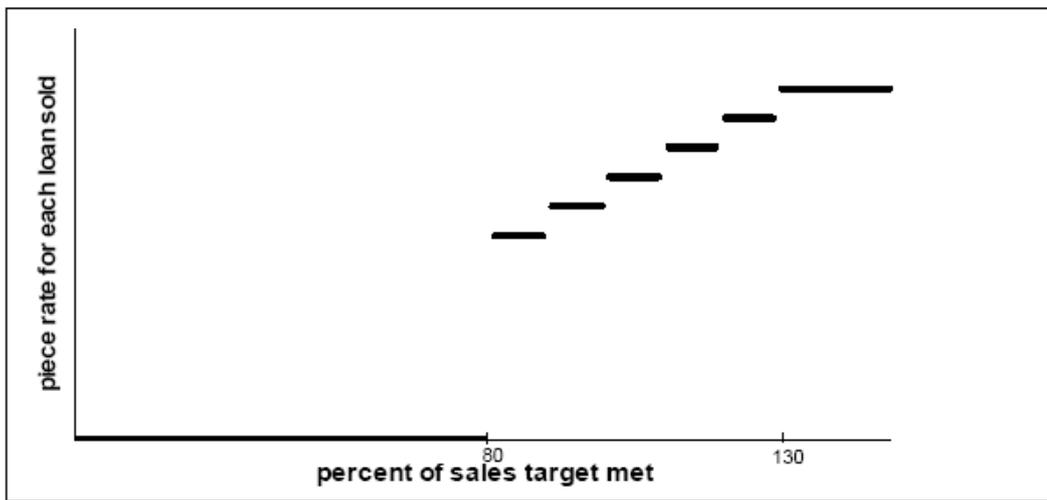
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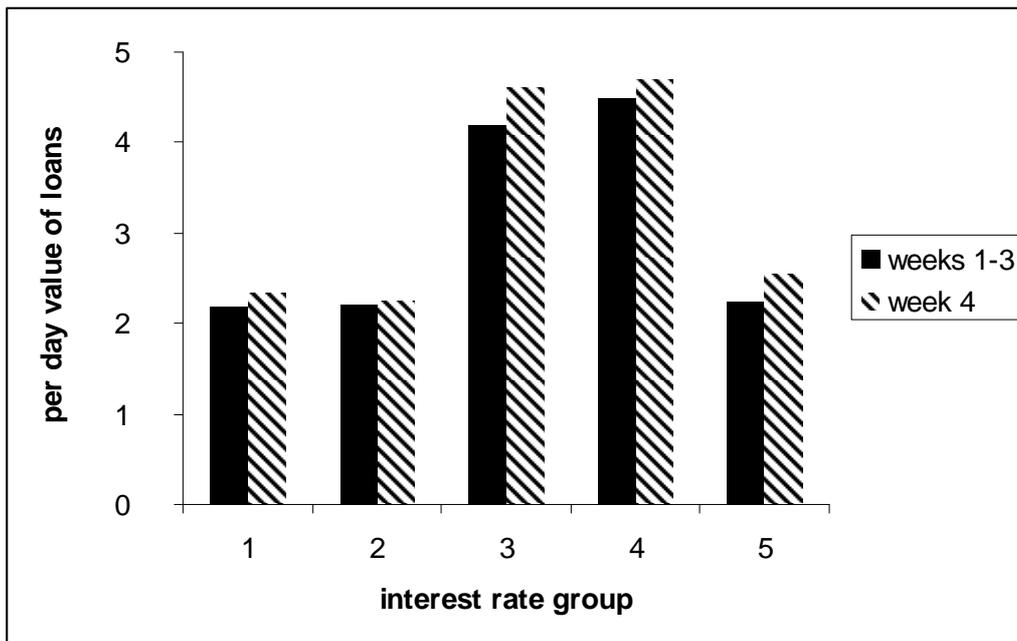
FIGURE 1.

Figure 1: Graphical Representation of Primary Loan Incentive Plan*



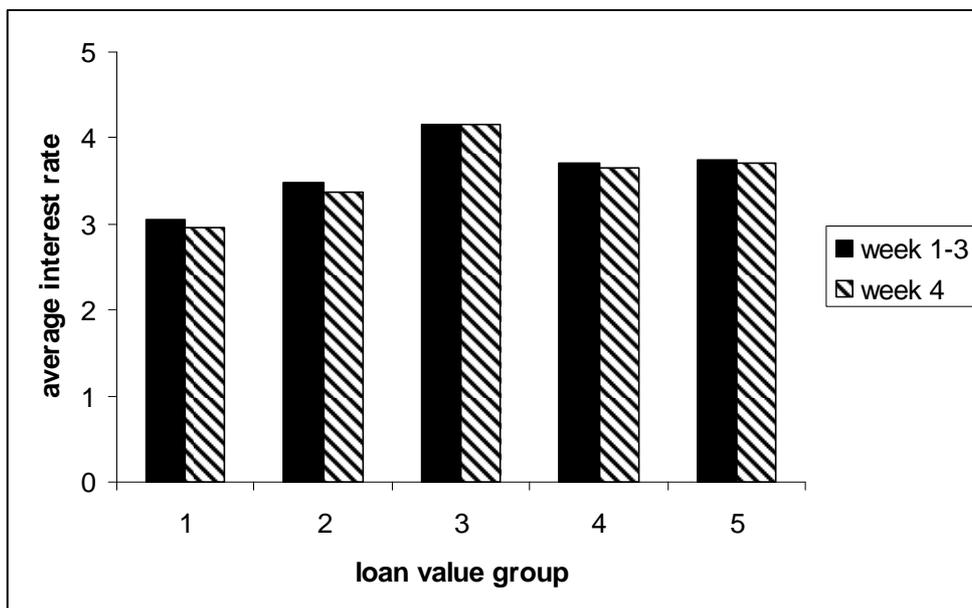
*Y-axis values suppressed for confidentiality reasons.

Figure 2: Daily Loan Sales (Value) by Interest Rate Group*



*Average daily value of sales across all outlets

Figure 3: Average Interest Rate by Loan Value Group*



*Average interest rate on loans across all outlets

Table 1: Sample Structure of Loan-Level Data

Day	Interest Rate	Loan Size	Number of Loans	Approval Track
1	5	5	1	Fast
1	5	2	2	Fast
1	4	2	3	Slow
2	4	4	2	Slow
2	3	4	2	Slow

Table 2: Conditional Correlations – Ability Measures, Tenure and Age

	High Plan Knowledge	Advanced Education	Tenure (years)
High Plan Knowledge	---		
Advanced Education	0.0507*	---	
Tenure (years)	0.0460*	0.1267*	---
Age	0.2462*	0.2660*	0.2204*

*Significant at 10%; ** significant at 5%; *** significant at 1%.

Table 3: Performance vs. Ability

Performance Measure	Low Plan Knowledge	High Plan Knowledge	Basic Education	Advanced Education
Plan Position (last day of the month)	0.963	0.998	0.976	0.979
Sales Target	3.987	4.123	3.948	4.058
Daily Loan Sales (value)	0.181	0.185	0.179	0.183
Daily Loan Sales (quantity)	1.54	1.716**	1.691	1.562

Stars indicate statistically significant difference between high and low levels of the ability measure.

*Significant at 10%; ** significant at 5%; *** significant at 1%.

Table 4: Summary Statistics

	Mean	Min	Max	S.D.	
Dependent variables					
Value-weighted daily interest rate	3.67	1	5	1.07	*
Proportion of number of small loans to all loans	0.41	0.00	1.00	0.40	
Proportion of performing (good) loans to all loans	.92	0.09	1.00	.07	
Agency costs	0.033	-0.74	0.71	0.11	
Independent variables					
Plan deviation	0.04	-7.50	4.68	0.29	
Plan deviation squared	0.08	0.00	56.18	0.64	
Plan Position ≤ 0.5	0.58	0.00	1.00	0.49	
Plan Position $\in (0.5,0.8]$	0.24	0.00	1.00	0.43	
Plan Position $\in (0.8,1.3]$	0.16	0.00	1.00	0.36	
Plan Position > 1.3	0.02	0.00	1.00	0.15	
Number of loans	1.66	0	19.00	1.72	
Loan size (zloty)	0.18	0.01	3.25	0.19	*
Loan size (category)	3.02	1.00	5.00	1.16	
Monthly sales target	4.23	0.10	11.42	1.63	*
Plan position	0.48	0.00	3.31	0.35	
Plan Position $\in (0.5,0.8]$ *High Plan Knowledge	0.18	0.00	1.00	0.38	
Plan Position $\in (0.8,1.3]$ *High Plan Knowledge	0.12	0.00	1.00	0.32	
Plan Position > 1.3 *High Plan Knowledge	0.02	0.00	1.00	0.13	
Plan Position $\in (0.5,0.8]$ *Advanced Education	0.17	0.00	1.00	0.38	
Plan Position $\in (0.8,1.3]$ *Advanced Education	0.11	0.00	1.00	0.31	
Plan Position > 1.3 *Advanced Education	0.02	0.00	1.00	0.13	
Advanced education * Plan deviation	-0.03	-4.68	4.81	0.23	
High plan knowledge * Plan deviation	-0.03	-3.79	7.50	0.25	
National bank of Poland interest rate	4.20	4.00	4.75	0.25	
Personal traits					
Age	26.90	23.00	33.00	2.27	
Marital status	1.50	1.00	2.00	0.50	
Tenure (in years)	2.82	1.00	5.00	1.26	
High plan knowledge	0.53	0.00	1.00	0.44	
Advanced education	0.51	0.00	1.00	0.45	

* Data transformed by the bank to protect confidentiality.

Table 5: Loan Pricing as a Function of Deviation from Sales Plan

Dependent Variable: Value-Weighted Daily Interest Rate

	(1)	(2)	(3)	(4)	(5)	(6)
Plan Deviation	0.074 (2.57)**	0.092 (3.07)***	0.076 (2.63)***	0.158 (5.00)***	0.156 (4.92)***	0.181 (3.60)***
Plan Deviation Squared	-0.030 (2.73)***	-0.034 (2.66)***	-0.031 (2.78)***	-0.045 (4.07)***	-0.044 (4.01)***	-0.046 (4.58)***
High Plan Knowledge					-0.028 (2.32)**	-0.026 (2.10)**
Advanced Education					-0.021 (1.49)	-0.023 (1.63)
High Plan Knowledge*Plan Deviation						0.069 (2.01)**
Advanced Education*Plan Deviation						-0.067 (1.44)
Bank of Poland Rate				1.07 (3.82)***	1.07 (3.77)***	1.07 (3.76)***
Outlet f.e.	no	yes	no	no	no	no
Outlet type f.e.	no	no	yes	yes	yes	yes
Quarter f.e.	no	no	no	yes	yes	yes
Region f.e.	no	no	no	yes	yes	yes
Outlet type f.e. * Quarter f.e.	no	no	no	yes	yes	yes
Region f.e. * Quarter f.e.	no	no	no	yes	yes	yes
Personal traits	no	no	no	yes	yes	yes
Observations	39609	39609	39609	30807	30807	30807
R-squared	0.004	0.01	0.01	0.09	0.09	0.1

Ordinary Least Squares estimates. "Plan Deviation" = distance from constant sales rate needed to meet sales target exactly. See text for details. Robust *t* statistics in parentheses, constant included but not reported. * significant at 10%; ** significant at 5%; *** significant at 1%

Table 6: Loan Size as a Function of Position in Sales Plan

Dependent Variable: Daily Proportion of Number of Small Loans to All Loans

	(1)	(2)	(3)	(4)	(5)	(6)
Plan Position ≤ 0.5	0.449 (103.03)***	0.439 (39.67)***	0.419 (64.30)***	0.291 (8.77)***	0.274 (7.23)***	0.272 (6.66)***
Plan Position $\in (0.5,0.8]$	0.476 (48.16)***	0.467 (33.15)***	0.446 (40.30)***	0.321 (9.08)***	0.300 (7.60)***	0.308 (7.50)***
Plan Position $\in (0.8,1.3]$	0.499 (33.71)***	0.492 (27.66)***	0.469 (29.91)***	0.341 (9.06)***	0.329 (7.77)***	0.339 (7.69)***
Plan Position > 1.3	0.545 (22.34)***	0.542 (20.79)***	0.515 (20.59)***	0.393 (8.86)***	0.385 (7.62)***	0.379 (5.85)***
Plan Position	-0.010 (6.98)***	-0.009 (6.88)***	-0.010 (6.95)***	-0.012 (6.45)***	-0.013 (6.17)***	-0.013 (6.24)***
High Plan Knowledge					0.005 (1.61)	0.005 (1.82)*
Advanced Education					-0.001 (0.14)	-0.002 (0.20)
Plan Position $\in (0.5,0.8]$ *High Plan Knowledge						-0.008 (0.82)
Plan Position $\in (0.8,1.3]$ *High Plan Knowledge						-0.026 (2.01)**
Plan Position > 1.3 *High Plan Knowledge						0.063 (2.15)**
Plan Position $\in (0.5,0.8]$ *Advanced Education						-0.004 (0.41)
Plan Position $\in (0.8,1.3]$ *Advanced Education						0.009 (0.73)
Plan Position > 1.3 *Advanced Education						0.041 (0.13)
Outlet f.e.	no	yes	no	no	no	no
Outlet type f.e.	no	no	yes	yes	yes	yes

Quarter f.e.	no	no	no	yes	yes	yes
Region f.e.	no	no	no	yes	yes	yes
Outlet type f.e. * Quarter f.e.	no	no	no	yes	yes	yes
Region f.e. * Quarter f.e.	no	no	no	yes	yes	yes
Personal traits	no	no	no	yes	yes	yes
Observations	40890	40890	40890	30925	29602	29602
R-squared	0.51	0.54	0.54	0.56	0.56	0.56

Ordinary Least Squares estimates. “Plan Position” = Fraction of sales plan met at the start of the day. Robust t statistics in parentheses, constant suppressed. *significant at 10%; ** significant at 5%; *** significant at 1%

Table 7: Demand Estimation

	OLS	Stage 1	2SLS with Instruments
Dependent variable	Daily demand	Interest rate	Daily demand
Interest Rate	.16(54.81)***		-.86(8.02)***
Constant	2.53(25.47)***		6.97(12.45)***
Plan Position		-.176(11.31)***	
Plan Deviation		-.075(5.28)***	
Region fixed effects	Yes	Yes	Yes
Outlet type fixed effects	Yes	Yes	Yes
Month fixed effects	Yes	Yes	Yes
Week fixed effects	Yes	Yes	Yes
R-squared	0.04	0.28	
F-stat	181.93***	1388.19***	40.78***

“Plan Position” = Fraction of sales plan met at the start of the day. “Plan Deviation” = distance from constant sales rate needed to meet sales target exactly. See text for details. Robust t statistics in parentheses, * significant at 10%; ** significant at 5%; *** significant at 1%.

Table 8: Profit-Maximizing vs. Observed Prices

All Outlets		High Plan Knowledge		Low Plan Knowledge	
p-max	p-observed	p-max	p-observed	p-max	p-observed
4.86	4.03	4.84	3.98	4.89	4.08

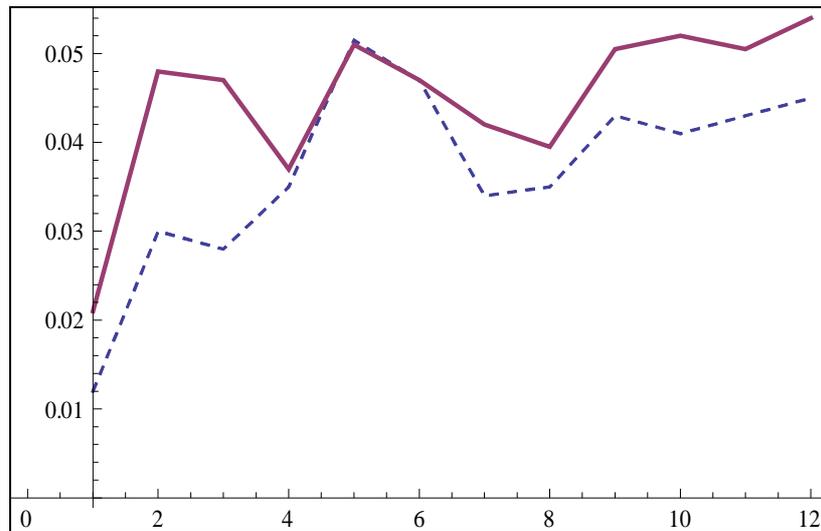
Profit-maximizing price = theoretical value computed from estimated demand parameters.

Table 9: Actual vs. Theoretical Profits (Ratio)

Theoretical Benchmark	All Outlets (Aggregate)	High Plan Knowledge (Per Outlet)	Low Plan Knowledge (Per Outlet)	Difference High-Low
1	0.88	0.87	0.89	-0.02***
2	0.97	0.96	0.98	-0.02***

Benchmark 1 assumes profit maximization based on estimated demand parameters. Benchmark 2 assumes that managers maintain loan prices in week 4 at the level of weeks 1-3. *Significant at 0.01; ** significant at 0.05; *** significant at 0.01.

Figure 4: Agency Costs - Time Trend



Solid line = high plan knowledge; dashed line = low plan knowledge. Agency costs (vertical axis) are defined as 1-(actual profits/theoretical profits), where theoretical profits are based on the conservative benchmark (Benchmark 2). The horizontal axis is in months since the introduction of the incentive plan.

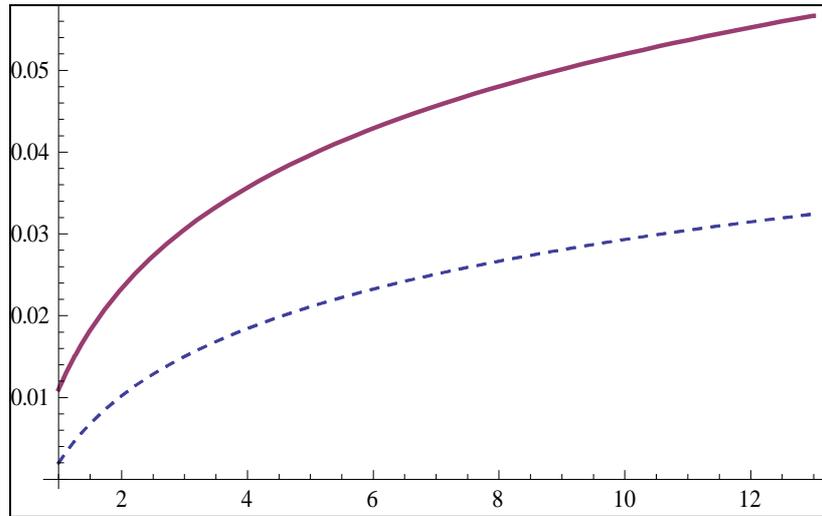
Table 10: Agency Costs - Learning Effects

Dependent Variable: 1-(Actual profits/Theoretical Profits)

	(1)	(2)	(3)	(4)
Learning constant (α_1)	13.44 (1760)***	15.07 (1703)***	15.02 (1677)***	14.82 (846.62)***
Learning elasticity (β_0)	0.001 (3.33)***	0.001 (3.74)***	0.001 (3.73)***	0.001 (2.41)***
High plan knowledge			0.014 (2.04)**	0.012 (1.92)*
Advanced education			0.008 (1.23)	0.021 (1.34)
High plan knowledge elasticity (β_1)				0.0005 (1.47)
Advanced education elasticity (β_2)				-0.0006 (1.09)
Outlet type f.e.	No	Yes	Yes	Yes

Non-linear least squares estimates. Constant included, not reported. Robust t statistics in parentheses, * significant at 10%; ** significant at 5%; *** significant at 1%.

Figure 5: Agency Costs over Time - Estimated Regression Curves



Solid line = high plan knowledge; dashed line = low plan knowledge. Agency costs (vertical axis) are defined as 1-(actual profits/theoretical profits), where theoretical profits are based on the conservative benchmark (Benchmark 2). The horizontal axis is in months since the introduction of the incentive plan.

Table 11: Loan Portfolio Quality

Proportion of Performing Loans in the Outlet's Portfolio			
	High Plan Knowledge	Low Plan Knowledge	Difference High-Low
Mean	0.913	0.920	-0.007**
Standard Deviation	0.073	0.070	0.003*

*Significant at 0.10; ** significant at 0.05; *** significant at 0.01.

Table 12: Evolution of Loan Portfolio Quality

Dependent Variable: Proportion of Performing Loans in the Outlet's Portfolio

Estimator:	Full sample		High Plan Knowledge		Low Plan Knowledge	
	OLS (1)	Arellano-Bond GMM (2)	OLS (3)	Arellano-Bond GMM (4)	OLS (5)	Arellano-Bond GMM (6)
Lag(1) Loan Quality	-0.091 (3.95)***	-0.063 (2.30)**	-0.15 (4.17)***	-0.102 (2.50)**	-0.08 (1.89)*	-0.049 (1.07)
Constant	1.015 (46.72)***	-0.001 (3.57)***	1.05 (31.24)***	-0.001 (2.40)**	1.00 (27.39)***	-0.002 (2.75)**
Outlet f.e.	Yes	Yes	Yes	Yes	Yes	Yes
A-B test for autocorrelation of residuals of order 1		-26.39***		-16.81***		-16.10***
A-B test for autocorrelation of residuals of order 2		-0.70		-1.48		-0.58

Robust t statistics in parentheses,

* significant at 10%; ** significant at 5%; *** significant at 1%

A. Data Collection Methodology

The data collection procedure comprised three phases: preliminary interview phase, survey phase, and archival data collection. Data collected in phase three is discussed in detail in section 4 of the paper. Below we briefly discuss phases one and two.

In phase one, we conducted interviews with the top executive team of the bank (CEO, Sales Director, HR Director and Risk and Accounting Director), followed by semi-structured interviews with 17 outlet managers in different regions of Poland. Most of the interviews were recorded. In cases where managers objected to being recorded, two researchers took notes and compared them immediately after the interview. Each interview lasted from 40 minutes to 1.5 hours.

In phase two, we administered an online survey to all outlet managers in the bank. Our choice of questions and measurement scales was guided by the interviews from phase one and by a review of existing literature. Before administering the survey, we pre-tested it with academics and bank executives to ensure clarity and unidimensionality of the measures, which led to several revisions of the questionnaire. Following the TDM guidelines by Dillman (1978) we mailed two follow-up letters to all non-respondents.

Over 200 usable surveys were returned, for a response rate of over 86%.¹ Among non-responding outlets, 43% were due to a vacant manager position rather than non-response by the manager. We found no significant non-response bias with regard to outlet type, outlet size, outlet performance or outlet managers' personal traits. No significant bias in responses was found. Nor did we find any significant differences in the responses across the different waves of the survey (initial mailing, first follow up, second follow up).

¹ "Usable" is according to the criteria in Dillman (1978). Only one survey was excluded for not meeting the criteria.

Europe Campus

Boulevard de Constance

77305 Fontainebleau Cedex, France

Tel: +33 (0)1 60 72 40 00

Fax: +33 (0)1 60 74 55 00/01

Asia Campus

1 Ayer Rajah Avenue, Singapore 138676

Tel: +65 67 99 53 88

Fax: +65 67 99 53 99

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