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by

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Ability and Agency Costs: Evidence from Polish Banking

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ABSTRACT

Theory and evidence suggest that performance-based pay can increase productive effort but may also give rise to distorted effort choices (multitasking or "gaming"). Performance-based pay is often coupled with delegation of broad decision-making authority. Much existing work assumes that the gains to delegation are increasing in the agent's (cognitive) ability. However, this work does not address the possibility that such ability may be correlated with agents' ability to game their incentive plans. In certain settings, agency losses from ability could outweigh the productivity gains. We investigate this possibility using data from a large Polish retail bank. We find that branch managers select the interest rate and size of consumer loans in a manner consistent with gaming of their incentive plan. Furthermore, evidence of this gaming behavior is stronger for managers with a better understanding of their incentive plan. Finally, we estimate that the bank loses between three and twelve percent of its profits from managers' pricing decisions and that the losses are greater for the more-knowledgeable managers. We estimate these agency costs through a novel empirical strategy, using managers' position in their incentive plan as a supply shifter to identify the bank's demand for loans.

Key words: agency costs, incentives, pay for performance, multitasking, worker ability, delegation

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

Strong financial incentives are often coupled with grants of wide decision making autonomy to employees (Foss & Laursen, 2005; Prendergast, 2002). Such autonomy may be justified if employees have superior information about the actions that are likely to maximize the principal's profits. The economics literature frequently assumes that the benefits from such delegation are increasing in the employee's skill – usually defined as cognitive ability (Bresnahan, Brynjolfsson, & Hitt, 2002; Caroli & Van Reenen, 2001; Ichniowski, Shaw, & Prennushi, 1997). However, a worker's skill affects more than her productivity. It also potentially affects her ability to game her incentives – to identify and exploit weaknesses in the system arising from imperfections in monitoring effort and performance. This link between ability and agency costs has not been studied theoretically or empirically.

A priori, it is not obvious which of the two effects of ability – productivity or agency costs – should dominate. In settings where the agent's private gains from

[1] For example, Lazear & 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 & Oyer (2007) for a recent review.

ability are relatively high, the principal's optimal response might be to weaken or eliminate explicit performance-based incentives.

In this paper, we study branch managers of a large Polish retail bank, observing their daily performance over a 13-month period. The managers' incentive plan features a "piece rate" bonus for new loans issued. Managers have discretion over the loan size and interest rate, which they can potentially manipulate to earn higher bonuses each month. Their calculations are complicated by an opaque "ratcheting" process in the bank's incentive plan (Baron & Besanko, 1984; Freixas, Guesnerie, & Tirole, 1985; Laffont & Tirole, 1988). The piece rate 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. Branch managers are not told how their target is determined, and their ability to infer this information – which we measure as accuracy in predicting their own target – varies greatly.

We have three key 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 piece rate bonus. Second, managers who are better able to predict their sales target (i.e., who have high "plan knowledge") have distinctly different behavior from managers with low plan knowledge. They give larger discounts on average, and they more heavily emphasize small loans above the highest bonus threshold. This latter result suggests that they better understand the dynamic aspect of their private optimization problem, since larger average loan sizes at this point serve only to raise future performance targets. Our third key 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 discounting behavior are between three and twelve percent of the theoretical maximum across all outlets. Furthermore, the profit loss is greatest for the managers with high plan knowledge – between four and thirteen percent.

We make several contributions with these results. First, we show that gaming responses to incentives are driven at least partly by a special type of cognitive ability. Nagin et al. (2002) find that a large fraction of employees under an output-contingent pay plan did not respond opportunistically to variations in monitoring output quality, and that this is explained to some degree by employees' feelings about their treatment by their employer. A further, unexplored, hypothesis is that employees varied in their ability to make correct inferences about how the monitoring rate was changing. Our results suggest that a similar type of cognitive ability – the ability to make correct inferences 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 final contribution is the empirical setting. Ours is one of a small number of detailed analyses of incentives in higher-skill, service sector jobs, and the only one we know of for the banking industry. In light of the ongoing credit crisis, and the prevalent belief that the crisis was fuelled by bankers' high-powered financial incentives, it is important to understand in greater detail the impact of these incentives and the magnitude of the possible agency costs.

The paper is structured as follows. In Section 2, we present the institutional background and the bank's incentives. In Section 3, we describe the data. In Section 4, we present preliminary evidence of agency problems. In Sections 5 and 6, we estimate the effects of gaming on discounting and loan size respectively. We calculate the magnitude of agency costs via demand estimation in Section 7. Finally, in Section 8, we investigate the time series of loan portfolio quality. Section 9 summarizes our conclusions.

2. INSTITUTIONAL SETUP AND INCENTIVE INSTRUMENTS

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 over 2000 people and serving loans to over 500,000 customers yearly. Its focus is on the sales of non-complex banking products, such as 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 some loans. Outlets are grouped into small regions, each supervised by a “micro-region manager”. At the country level, micro-regions 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

The pay of the outlet managers and salespeople is tightly linked to outlet performance. While the incentive regime is frequently changed, we report results from a 13-month period when all units were operating under the same incentive structure. The incentive system in the bank, compared to the banking industry in Poland, is extremely high-powered. While the percentage contribution of variable pay to total remuneration does not go as high as in, for example, the software industry (Larkin, 2007), throughout the period of our study it can easily reach 60 percent.

There are two main types of loans that outlets can sell. A primary loan, which is the bank’s focus at the time of our study, is a loan sold to first-time customers. Typically, first-time customers can borrow up to their monthly income (approximately 2000 zloty[3] at the time of the study) from the bank. The second type of loan – a secondary loan – is reserved for repeating clients and usually is conditional on their successful repayment history for the primary loan. As we focus on sales of primary loans, we report the detailed incentive structure for this product only.

Each month, an outlet is assigned a sales target (in zloty) for primary loans. The sales targets are set centrally, with the macro and micro-region 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

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

increases in a stepwise fashion up until 130 percent of the sales target, after which it stays constant[4]. 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 can infer that the sales targets for primary loans are a function of:

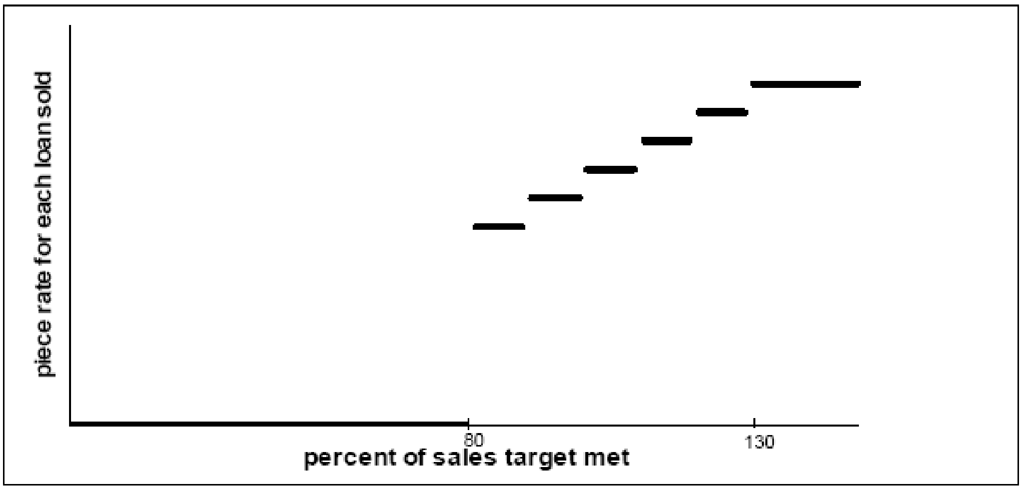
i) The outlet's performance in the past,

ii) Similar outlets' performance in the past,

iii) Headquarters' demand forecast,

iv) Headquarters' assessment of outlet and outlet manager potential.

FIGURE 1.
Graphical representation of the incentive plan for sales of primary loans[5]



3. DATA DESCRIPTION

In our analysis, we focus on the narrow "production" process of selling primary loans, and we observe outcomes for this process at a large number of sites over an extended time period. Our analysis draws on archival sales (panel) data, interviews with bank executives and managers (yielding detailed knowledge of the production process and incentive systems) and a large-scale survey of outlet managers. We

[4] For confidentiality reasons we can not reveal the exact specification of the incentive scheme.
[5] Y axis values are not reported for confidentiality reasons.

therefore see our study as in the tradition of "insider econometrics" described in Ichniowski and Shaw (2003). This section introduces our data. Further details, including the interviews and survey methodology, are presented in Appendix A.

3.1. Archival Data

The bank provided confidential archival data on sales, loan performance and incentives spanning 24 months. We restrict the study to primary loans issued over a period of 13 months when incentive systems remained unchanged. The restricted dataset covers over 500,000 individual loans. This set represents all loans granted by all outlets of the bank during the analyzed period and contains the following information.[6]

Loan-Level data

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

TABLE 1.
Typical structure of the loan-level data

Day	Interest rate	Loan size	Number of loans	Approval track	Loan type
1	5	5	1	Fast	Primary
1	3	2	2	Fast	Primary
1	4	2	3	Slow	Primary
2	4	4	2	Slow	Primary
2	3	4	2	Slow	Secondary

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

[6] 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 60 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.

appropriate.[7] We also observe the exact total value (in zloty) of sales of all primary loans by a unit on a particular day.

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

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.

Loan type: This field identifies the loan as primary or secondary, defined above. As mentioned there, we restrict the analysis to primary loans. The reason is that, because these customers have no prior transacting history with the bank, the product much more resembles a homogenous product, and there is a lower likelihood of

[7] 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.

unobserved customer heterogeneity.[8] This in turn allows us to reliably estimate the demand function for this product, which is central to our analysis.

Outlet-Level Data

Sales target: We observe the exact value (in zloty) of the sales target for each outlet each month. Because we know the exact value of loans issued (across all approval tracks), we observe 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. 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, 2004).[9] One of the bank's executives told us:

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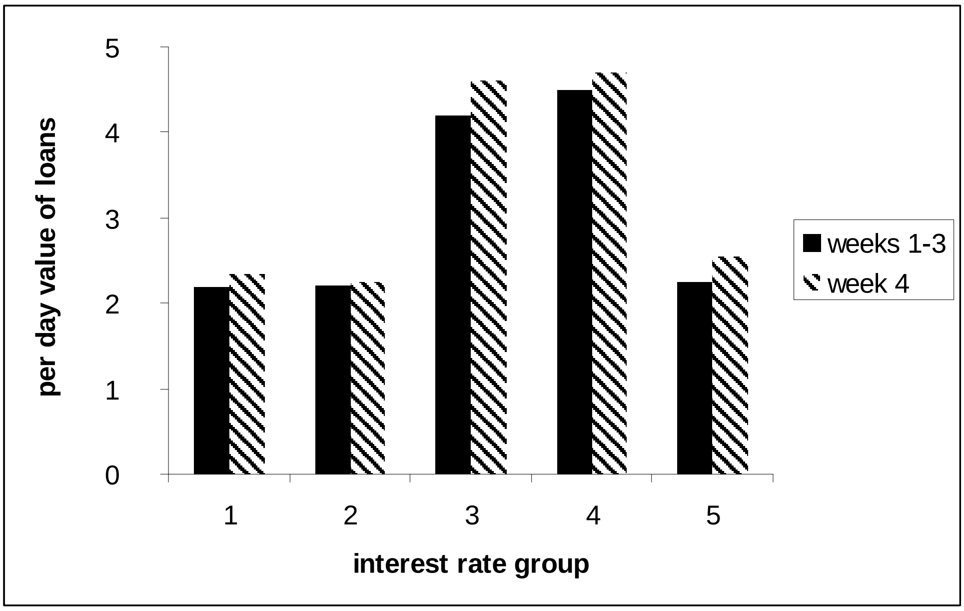
[8] One objection could be that, due to differences in loan sizes, we actually observe heterogeneous, not homogenous products. We acknowledge this as a potential limitation; however, due to the bank's specific customer profile we do not think this is the case. The bank targets low-end mass market customers, and all loans are relatively small consumption loans (no mortgages or investment loans).

[9] Credit cards are still unavailable to most of the mass-market customers in Poland.

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.[10] 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.

FIGURE 2
Daily loan sales (value) by interest rate group



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) than in the first three weeks.

[10] 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.

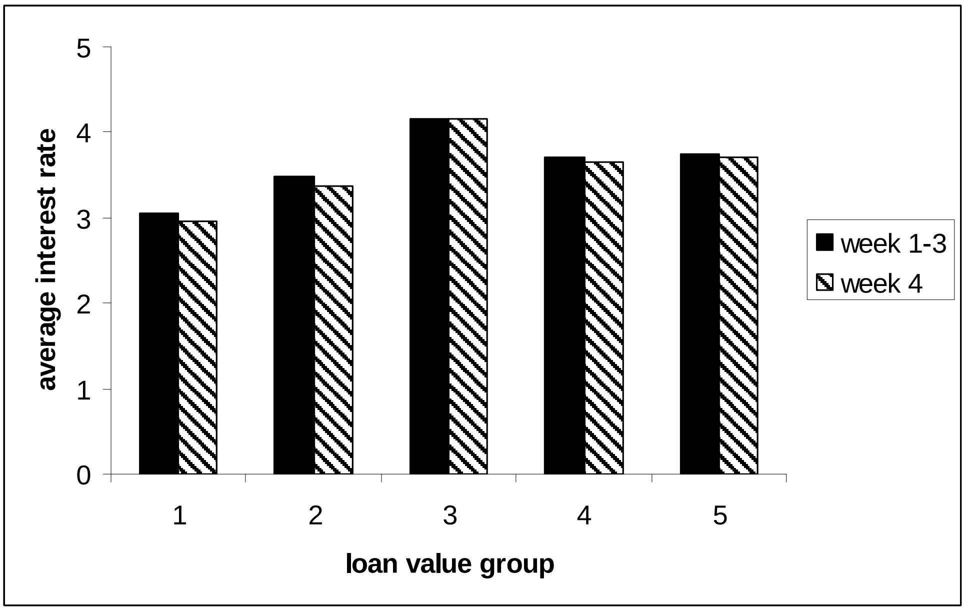
Although a simple supply and demand model predicts that prices will rise in periods of peak demand, this prediction is occasionally violated empirically. Chevalier et al. (2003) discuss and test three classes of models that predict falling prices in peak demand periods: (a) cyclical demand elasticities (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 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 7 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 et al. 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, Figures 2 and 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 Table 1 (because sales should be weakly lower in week four), and (b) is not consistent with Table 2 (because prices should be higher in week four). Below, we analyze this apparent gaming behavior in more depth.

FIGURE 3
Average interest rate by loan size group



5. DISCOUNTING BEHAVIOR

An obvious instrument that outlet managers can use to game the incentive system is the price 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 <u>when you need to sell</u>* <u>[loans]</u> *and the customer wants it, not just when the customer wants it* [emphasis ours].

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, 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 they 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 the cognitive abilities of managers affect these patterns.

5.1 Empirical Specification

The dependent variable, $D_{u,t}$, is the value-weighted average discount granted on loans sold by outlet *u* on day *t*.. The discount is measured with respect to the average interest rate across all units for the calendar month. The key independent variable, "plan deviation" ($PD_{u,t}$) measures 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.

$$PD_{u,t} = \frac{ST_{u,m}}{T} - \frac{(ST_{u,m} - CV_{u,t,m})}{T - t}, \qquad (1)$$

T denotes the number of days in month *m*, *ST* the sales target and *CV* is 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 of plan deviation signal below-expected outlet performance. When plan deviation equals zero, the outlet is performing exactly at the rate needed to meet the sales target. This measure is consistent with insights from interviews that managers follow a heuristic where their best approximation of end-of-month performance is their current rate of performance. Our approach is conceptually similar to the one used by Chevalier & 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 unit's average sales rate that month.

To analyze how managers' cognitive abilities affect their responses to their incentives, we focus on managers' understanding of the incentive system, or "plan knowledge". As noted above, the bank gives managers no information on how the sales plans for their units are constructed.[11] We measure plan knowledge as follows. We asked outlet managers to predict their sales targets in the month following the survey. We compare their predictions with the actual targets set by management. We construct a dummy variable equal to one if the manager's absolute prediction error is below the mean and zero otherwise[12]. We would expect the "plan knowledge" variable to indicate their skill and proficiency with organizational procedures and routines and, therefore, their ability to "work the system." [13]

To some extent, plan knowledge appears to be a measure of ability, as it is positively correlated with the probability of meeting sales targets and with the number of loans sold conditional on being above the bonus threshold. Additionally, managers

[11] 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."
[12] The raw prediction error varies from -190 percent to 540 percent. 90 percent of observations fall within the [-100%, 100%] range.
[13] Note this measurement is taken once after the sample time frame. Because of learning, prediction error regarding the sales plan is likely to change over time. This is not a problem as long as prediction error relative to the group at any time is negatively correlated with "ability", which we assume.

better able to predict their sales targets seem to be high performers in absolute terms. Table 2 presents mean comparisons across plan knowledge groups for four measures of performance: sales target, average daily number of loans sold, average volume of loans sold and average plan position at the end of the month. All point estimates are higher for mangers better able to predict their sales targets.[14] However, these differences are also relatively small and not statistically significant. This suggests that plan knowledge may be a good candidate for a form of ability that has a higher marginal impact on agency costs than on productivity.

Although plan knowledge is a measure of cognitive ability, it is a special type of ability, possibly distinct from ability as measured by education. We therefore control separately for an advanced education level (MSc or above) in our regressions.

TABLE 2.
Mean comparison of performance measures between high and low plan knowledge managers

Performance measure	Low Plan Knowledge	High Plan Knowledge
Plan position (last day of the month)	0.963	0.998
Sales plan (target)	3.987	4.123
Average daily volume of loans	0.181	0.185
Average daily number of loans	1.54	1.716

We estimate the following reduced-form equation:

$$D_{u,t} = \alpha_1 + \alpha_2 PD_{u,t} + \alpha_2 PD^2{}_{u,t} + \beta_1(X_{u,t}) + \beta_2(Z_u) + \chi(E_t) + \varepsilon_{u,t} \qquad (2)$$

We include the square of plan deviation to allow for a possible nonlinearity of its effect. In (2), *X* represents a vector of control variables. We include the total

[14] We observe similar differences when controlling for outlet characteristics.

number of loans sold and the average size of loans as controls to capture possible demand variations that might also affect discounting. *Z* is a vector of outlet type and outlet manager characteristics including the outlet manager's "plan knowledge", education, tenure, marital status, gender and age. Vector *E* contains controls for the base interest rate of the Bank of Poland, four week effects and year-quarter fixed effects. We also introduce interaction terms between manager characteristics and the plan deviation in some specifications. Further details of the construction of the variables are presented in Appendix B. Summary statistics are in Table 3.

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TABLE 3.
Summary statistics

	Mean	Min	Max	S.D.	
Dependent variables					
Average daily discount	0.00	-3.60	3.69	0.75	*
Proportion of number of small loans to all loans	0.41	0.00	1.00	0.40	
Proportion of performing (good) loans	.92	0.09	1.00	.07	
Independent variables					
Plan deviation	0.04	-7.50	4.68	0.29	
Plan deviation squared	0.08	0.00	56.18	0.64	
$I_{plan\_position \le 0.5}$	0.58	0.00	1.00	0.49	
$I_{plan\_position \in (0.5,0.8]}$	0.24	0.00	1.00	0.43	
$I_{plan\_position \in (0.8,1.3]}$	0.16	0.00	1.00	0.36	
$I_{plan\_position > 1.3}$	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 plan	4.23	0.10	11.42	1.63	*
Plan position	0.48	0.00	3.31	0.35	
Interest rate	3.98	1.00	5.00	1.04	*
$I_{plan\_position \in (0.5,0.8]}$ *plan knowledge	0.18	0.00	1.00	0.38	
$I_{plan\_position \in (0.8,1.3]}$ *plan knowledge	0.12	0.00	1.00	0.32	
$I_{plan\_position > 1.3}$ *plan knowledge	0.02	0.00	1.00	0.13	
$I_{plan\_position \in (0.5,0.8]}$ *education	0.17	0.00	1.00	0.38	
$I_{plan\_position \in (0.8,1.3]}$ *education	0.11	0.00	1.00	0.31	
$I_{plan\_position > 1.3}$ *education	0.02	0.00	1.00	0.13	

Education*plan deviation	-0.03	-4.68	4.81	0.23
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	1.50	1.00	2.00	0.50
Tenure	2.82	1.00	5.00	1.26
High plan knowledge	0.53	0.00	1.00	0.44
High education	0.51	0.00	1.00	0.45

Note: * denotes data that has been transformed in order to protect confidentiality

We estimate equation (2) using fixed effects OLS, to control 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 hence use fixed effects at the level of the outlet type described in Section 3. 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 (2) 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). Using the test proposed by Wooldridge (2002, p. 282), we reject the hypothesis of serial correlation in our panel (F=0.43). Another potential concern is that the number of loans and average size of loans may also be endogenous in equation (2). Although their coefficients are only "nuisance" parameters, such endogeneity, if present, would bias all of our estimated coefficients (Greene, 2003, p. 149). To test the robustness of our estimation results to this possibility, we estimated the model instrumenting the number of loans and average size of loans at the outlet level with aggregate measures at the macro region level.[15] The Hausmann test cannot reject the hypothesis that the OLS estimates are consistent ($\chi^2 = 8.34$). We therefore report the OLS results only.

5.2 Results

Table 4 presents results of the estimation of equation 2. Columns 1 and 2 present specifications of the restricted models without the influence of cognitive abilities, with and without outlet fixed effects. The Hausmann test strongly favors the fixed effects over the random effects specification ($\chi^2 = 207.02$). Column 3 presents the specification with outlet type fixed effects. Note that the individual coefficient estimates barely change across the two specifications. We cannot reject the hypothesis of joint equality of coefficients 3 ($\chi^2 = 13.87$). Also, the R^2 does not decrease in going from column 2 to column 3, which makes us confident that the unobserved heterogeneity at the outlet level is well captured by the outlet type. The remaining specifications (columns 4 and 5) hence present fixed effects estimates pooled at the outlet type level. The specification in column 4 is the baseline model with individual characteristics variables and outlet type fixed effects. In column 5 we add interaction terms between individual characteristics and our main independent variable, plan deviation. The following discussion pertains to column 5.

[15] Using population level aggregate measures does not change the result. Note that the discount is calculated compared to the whole population so the instruments are at a lower aggregation level.

TABLE 4.
The pattern of discounting behavior across managers

Dependent variable: average daily discount

	(1)	(2)	(3)	(4)	(5)
Plan deviation	-0.186	-0.068	-0.075	-0.116	-0.237
	(6.69)***	(2.67)***	(2.98)***	(3.56)***	(4.23)***
Plan deviation-sq	0.048	0.018	0.021	0.036	0.038
	(3.96)***	(1.95)*	(2.20)**	(2.61)***	(2.94)***
Value of loans	0.019	-0.006	-0.000	-0.027	-0.025
	(0.75)	(0.22)	(0.01)	(0.94)	(0.87)
Number of loans	0.022	0.028	0.023	0.027	0.027
	(8.30)***	(10.30)***	(8.74)***	(8.91)***	(8.77)***
Bank of Poland	-0.169	0.424	0.417	0.410	0.409
	(11.35)***	(16.96)***	(16.78)***	(14.04)***	(14.03)***
Week2	0.038	0.038	0.038	0.046	0.046
	(2.75)***	(2.78)***	(2.71)***	(2.86)***	(2.87)***
Week3	0.070	0.064	0.064	0.078	0.078
	(5.03)***	(4.67)***	(4.71)***	(4.89)***	(4.89)***
week4	0.120	0.106	0.104	0.115	0.115
	(8.52)***	(7.68)***	(7.51)***	(7.06)***	(7.06)***
High education				0.006	0.004
				(0.44)	(0.29)
High plan knowledge				0.321	0.286
				(3.76)***	(2.71)***
Education*Plan deviation					0.042
					(1.02)
Plan knowledge*Plan deviation					0.110
					(2.31)**
Quarter f.e.	no	yes	yes	yes	yes
Outlet f.e.	no	yes	no	no	no

Outlet type f.e.	no	no	yes	yes	yes
Personal traits	no	no	no	no	yes
Observations	39609	39609	39609	28670	28670
R-squared	0.01	0.06	0.06	0.06	0.07

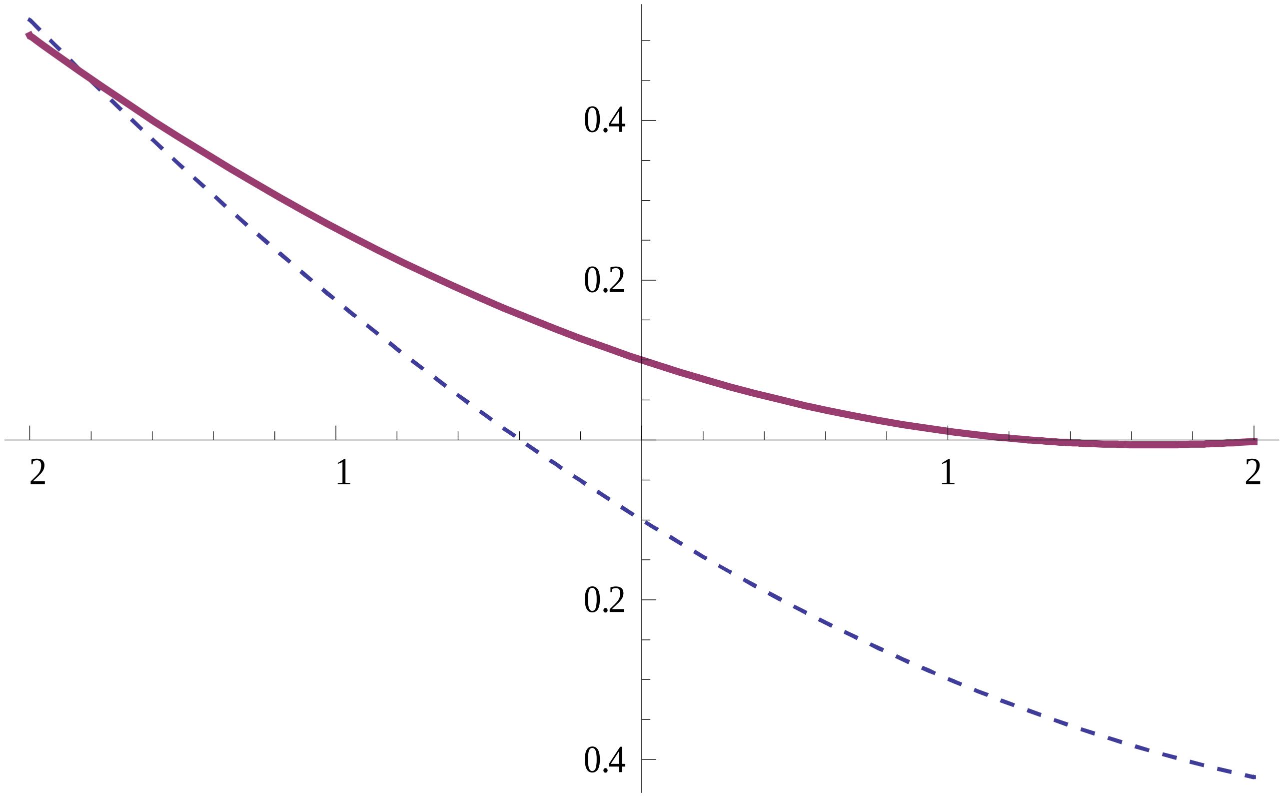
Ordinary Least Squares estimates. Robust t statistics in parentheses, constant included but not reported. * significant at 10%; ** significant at 5%; *** significant at 1%

Recall that positive values of the plan deviation mean that the outlet is performing ahead of plan. Column 5 shows that the coefficient on this variable is negative and highly significant, indicating that outlets further "ahead of schedule" give lower discounts. Furthermore, the coefficient on the squared term is positive and significant, indicating that the graph is convex. Unit managers decrease their use of discounting as they approach the expected level of performance.

The coefficients on both the education variable and its interaction with plan deviation are insignificant. At the same time, the coefficients on plan knowledge and its interaction with plan deviation are significant. This suggests that, as we suspected, these scales measure different constructs. Managers with high knowledge of the sales plan discount more heavily. The coefficient on the interaction term between plan knowledge and plan deviation indicates that managers with high plan knowledge are less sensitive to where they are in their sales plan.. Figure 4 presents discounts as a function of plan deviation for high- and low-plan-knowledge managers, using the coefficient estimates from column 5 of table 4, with the other variables held constant at their average values. The solid line represents the high-plan-knowledge managers and the dashed line the low-plan-knowledge managers. While the figure suggests that the discounts reach a minimum and then increase, the minima of the two graphs lie largely outside the range of the data (99.9 percent of observations are below the point where the high-plan-knowledge curve reaches its minimum). We believe the coefficient estimates rather indicate that discounts are asymptotically approaching a minimum value, and that managers of different "ability", as measured here, approach these minima at different rates. If this is so, the estimates suggest that high-plan-knowledge managers stop discounting at lower levels of plan performance. This possibly indicates a greater sensitivity to the dynamic penalty of overshooting their target, although this interpretation is difficult to reconcile with the fact that they give higher discounts throughout.

FIGURE 4.

Discounting behavior as a function of distance from expected performance: high (solid line) and low plan knowledge employees



6. 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 they 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].*

These preferences are driven by the incentive plan. Managers' incentives to reduce loan size vary depending on their current position relative to their sales plan. At low levels of sales, managers' incentives are to push larger loans, as these help them more quickly reach the threshold for the piece rate bonus. At intermediate levels of performance (80 to 130 percent of plan), managers' incentives are somewhat ambiguous. On the one hand, the piece rate is increasing in plan position in this range, as is the expected dynamic penalty (future ratcheting of sales targets due to "over performance"). Both of these favor substituting quantity for volume (aggregate loan value). On the other hand, larger average loan sizes more quickly get managers to higher performance thresholds, where they earn higher piece rates. However, above 130 percent of plan, managers' incentives are unambiguously toward smaller loans. In this range, the piece rate is constant, while the expected costs of ratcheting continue to increase.[1]

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

[1] If there is a limit – real or perceived by managers – to the amount by which sales targets are ratcheted each month, then the dynamic ratcheting penalty may be weakly increasing in current performance rather than strictly increasing.

loans (“slicing” in the managers’ jargon) or (b) by proposing a loan below the client’s borrowing capacity. Our interviews indicate that managers do game the incentives by manipulating loan size:

> *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.*

Therefore, we predict that the share of small loans in the manager’s daily sales will be increasing in her current plan level. Furthermore, we expect this effect to be stronger for managers with higher levels of plan knowledge.

6.1 Empirical Specification

We estimate variations of the following equation:

$$PS_{u,t} = \alpha D_{u,t,a-b} + \beta_1 PP_{u,t} + \beta_2 Z_u + \chi E_t + \varepsilon_{u,t} \qquad (3)$$

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.[2] $PP_{u,t}$ measures unit *u*’s “plan position”, or performance against plan, on day *t*: it is the ratio of cumulative sales to the sales target. $D_{u,t,a-b}$ is a vector of indicator variables for various plan position thresholds, where each element equals one if outlet *u* is between *a* and *b* percent of the sales target on day *t*. 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.[3]. *Z* is a vector of outlet type and outlet manager characteristics including manager’s “plan knowledge”,

[2] Our results are robust to alternative classifications of small and large loans.
[3] Interviews with managers suggested that 50 percent was an important psychological threshold. Our results are robust to other partitions of plan position.

education, marital status, tenure, gender and age. The vector E contains four week effects and year-quarter fixed effects. Some specifications include interaction terms between $D_{u,t,a-b}$ and outlet manager characteristics. Appendix B contains a further description of the variables. We estimate equation (3) using outlet fixed effects OLS.

6.2 Results

We report the results of our analysis in Table 5. The specification in column 1 reports OLS results of the estimation of 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 model (2), the estimated coefficients in column 2 and 3 do not statistically differ ($\chi^2 = 16.2$). The specification in column 4 reports outlet type fixed effects estimates with education and plan knowledge variables. In column 5 we add interaction terms between manager characteristics and the plan position thresholds.

TABLE 5.
Effect of Incentives on Loan Size

Dependent variable: daily proportion of number of small loans to all loans

	(1)	(2)	(3)	(4)	(5)
$I_{plan\_position \le 0.5}$	0.431	0.426	0.401	0.402	0.566
	(83.72)***	(32.75)***	(49.67)***	(18.60)***	(8.08)***
$I_{plan\_position \in (0.5,0.8]}$	0.448	0.443	0.427	0.421	0.586
	(38.48)***	(27.11)***	(31.55)***	(16.66)***	(8.15)***
$I_{plan\_position \in (0.8,1.3]}$	0.486	0.484	0.456	0.458	0.614
	(26.81)***	(22.83)***	(23.67)***	(14.74)***	(8.40)***
$I_{plan\_position > 1.3}$	0.590	0.592	0.564	0.575	0.666
	(19.25)***	(18.42)***	(17.88)***	(12.93)***	(7.89)***
Plan position	-0.019	-0.019	-0.020	-0.022	-0.022
	(9.37)***	(8.95)***	(9.24)***	(7.63)***	(7.69)***
Week2	0.037	0.035	0.037	0.044	0.044
	(5.52)***	(5.21)***	(5.37)***	(5.35)***	(5.35)***
Week3	0.088	0.083	0.087	0.098	0.098
	(10.94)***	(10.28)***	(10.78)***	(9.92)***	(9.95)***
Week4	0.110	0.103	0.110	0.123	0.123
	(12.20)***	(11.17)***	(12.03)***	(11.04)***	(11.05)***
High plan knowledge				0.001	0.001
				(0.09)	(0.03)
High education				-0.003	-0.005
				(0.67)	(1.06)
$I_{plan\_position \in (0.5,0.8]}$ *plan knowledge					0.010
					(0.85)

$I_{plan\_position \in (0.8,1.3]}$ *plan knowledge					-0.002
					(0.13)
$I_{plan\_position > 1.3}$ *plan knowledge					0.082
					(2.21)**
$I_{plan\_position \in (0.5,0.8]}$ *education					0.001
					(0.08)
$I_{plan\_position \in (0.8,1.3]}$ *education					0.011
					(0.82)
$I_{plan\_position > 1.3}$ *education					0.009
					(0.26)
Quarter f.e.	no	yes	yes	yes	yes
Unit f.e.	no	yes	no	no	no
Unit group f.e.	no	no	yes	yes	yes
Personal traits	no	no	No	no	yes
Observations	40890	40890	40890	29602	29602
R-squared	0.51	0.52	0.51	0.52	0.53

Robust t statistics in parentheses, constant suppressed.
*significant at 10%; ** significant at 5%; *** significant at 1%
Ordinary Least Squares estimates

The coefficients on the plan position thresholds are positive, significant, and monotonically increasing. Each consecutive coefficient is statistically significantly greater (F<2.16) than the former.[1] These results indicate that managers steadily 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 interaction of the plan knowledge indicator and the plan position thresholds. A positive coefficient indicates that knowledgeable managers substitute even more strongly to small loans as they progress in their plan position. Interestingly, there is a significant interaction between plan knowledge and the 130 percent threshold. 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.

7. ESTIMATION OF AGENCY COSTS VIA DEMAND ESTIMATION

The foregoing evidence clearly suggests an agency problem arising from managers' delegated authority to set prices and influence loan sizes. In this section, we establish bounds for the agency costs arising from discounting behavior. We do this by comparing actual profits on primary loans with the profits the bank would have earned under two different counterfactual scenarios described below. To

[1] Although the coefficient on the continuous plan position variable is negative and significant, its magnitude is small and not enough to overturn the monotonic pattern described.

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 margins on loans (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 analysis: (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.

As discussed above, bank executives expressly discourage price discounting in the fourth week of the month, because demand increases during that time. Therefore, a lower bound for the bank's agency costs can be estimated by comparing actual fourth-week profits with the profits the bank would have earned had managers maintained prices at their levels from the first three weeks of the month. This is a lower bound 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. If this is true, using these prices as the benchmark to compute week four agency costs underestimates these costs.

The argument for this lower bound 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 lower bound measure is valid.

An upper bound for the agency costs can be established by comparing actual bank profits in all weeks of the month with the profits the bank would have earned had managers priced at the profit-maximizing level. This is an upper bound because the bank's objectives are more complex than simple short-term profit maximization. New customers generate profits not only through the primary loans analyzed here, but also through the secondary loans discussed above. Also, one of the bank's strategic objectives is rapid growth and market share capture. Both of these imply that the price that maximizes long-run profits may be lower than the price that maximizes short-run profits from the sales of primary loans. Therefore, agency costs based on short-run profit maximization will overstate the extent of the problem.

7.1 Empirical specification

Computing agency costs via demand estimation is facilitated by the fact that the product we analyze is a highly homogenous good sold to mass-market consumers. We model an outlet's daily demand for primary loans as follows[2]:

$$Y = \alpha_0 + \alpha_1 P * I_{week4} + \alpha_2 P * I_{week1-3} + I_{region} + I_{month} + I_{unit\_type} + I_{week} + \varepsilon \,, \qquad (4)$$

where Y denotes the daily value of loans sold and P denotes the price (interest rate). [3] We include fixed effects for region (five regions), month (thirteen months), unit type (six dimensions defined above) as well as 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 vary across weeks one through three and the last week of the month. The summary statistics for our variables are incorporated into Table 3.

To consistently estimate (4), 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".

7.2 Results

Table 6 reports OLS and first- and second-stage estimates for the instrumental variables specification. The estimated slope of the demand function does not

[2] Subscripts are suppressed for clarity

[3] 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.

statistically differ in week four from that in the first three weeks of the month (F=1.87)[4]. We hence report results for pooled estimation.

TABLE 6.
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
Unit 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***

Robust t statistics in parentheses,
- significant at 10%; ** significant at 5%; *** significant at 1

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 6 only briefly. The Hausmann test rejects the null hypothesis of equality of coefficients obtained under OLS and 2SLS ($\chi^2 = 113.07$). 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

[4] 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.

test statistic is insignificant (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 unit's *own* demand function, conditional on whatever unobserved "game" the unit 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 unit, 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. 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 Bank of Poland's base interest rate.

Table 7 compares the average observed daily price with the profit-maximizing price, 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 profit-maximizing level, at about 83 percent of the theoretical 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.

TABLE 7.
Profit maximizing price (p-max) estimation

All outlets		High knowledge of sales targets		Low knowledge of sales targets	
p-max*	**p-observed**	**p-max**	**p-observed**	**p-max**	**p-observed**
4.86	**4.03**	**4.84**	**3.98**	**4.89**	**4.08**

Calculated based on estimated demand parameters

To estimate the upper bound to agency costs, we compare the bank's actual profits with the profits it would have earned had managers chosen the price that maximizes short-term profits. Because the absolute values have no economic meaning due to the bank's variable transformation, we report the actual profits as a percentage of the theoretical maximum. Table 8 reports the comparison, first pooled for all outlets, then separately for high- and low-plan-knowledge managers.

TABLE 8.
Profit comparison. Upper bound to gaming costs

All outlets		High knowledge of sales targets		Low knowledge of sales targets**	
Total		Per outlet		Per outlet	
Π-max*	**Π -observed**	**Π-max**	**Π –observed**	**Π-max**	**Π -observed**
100	88	100	87	100	89

* Benchmark assumes profit maximization based on estimated demand parameters.
** Difference in Π–observed between high and low plan knowledge managers significant at better than 0.01 level. Bootstrapped standard errors. See Appendix C for details of bootstrapping procedure.

Table 8 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. This difference is significant at better than the 0.01 level.

To estimate the lower bound to gaming costs, 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. Table 9 presents this comparison. 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.

TABLE 9.
Profit comparison. Lower bound to gaming costs

All outlets		High knowledge of sales targets		Low knowledge of sales targets**	
Total		Per outlet		Per outlet	
Π-hypothetical*	**Π-observed**	**Π – hypothetical**	**Π –observed**	**Π - hypothetical**	**Π -observed**
100	97	100	96	100	98

* Benchmark assumes that managers maintain loan prices in week 4 at the level of weeks 1-3.
** Difference in Π–observed between high and low plan knowledge managers significant at better than 0.01 level. Bootstrapped standard errors. See Appendix C for details of bootstrapping procedure.

Table 9 shows that the bank loses at least three percent of its profits due to managers' pricing decisions. As for the upper bound estimated above, this lower bound is also higher 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.

The upper bound estimate must be treated with some caution. As noted, 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 lower-bound estimate. Bank executives explicitly discourage fourth-week discounting, and so price reductions in this period cannot be construed as in the bank's interests.

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.

8. PORTFOLIO QUALITY

An obvious question to ask, especially in light of the recent credit crisis, is whether the bank's incentives cause managers to sell more risky loans and hence endanger the institution. While our data unfortunately do not permit a detailed analysis of this question, they do allow us to shed some light.

Outlets' loan portfolio quality could be affected by (a) outlet managers' decisions, (b) the bank's risk management policy and (c) random shocks. If neither outlet managers nor risk managers adjust their probability of approving a risky loan according to the outlet's current portfolio quality, then controlling for the state of the economy, we should expect outlets' portfolio quality to evolve as a random walk.

As discussed above, our interviews suggest that the risk management procedures are independent of outlet or manager characteristics, and independent of outlet performance. In other words, the probability that a loan is approved does not depend on the outlet's current portfolio quality. Therefore, if we observe outlet portfolio quality evolving as something other than a random walk, this suggests that it is due to outlet managers' loan approval choices.

Obviously, managers could try to boost their sales and hence benefit from increased bonuses by selling riskier loans.[5] Yet it is highly unlikely that the bank would allow managers to consistently sell loans that are under-performing. 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 point of view of the manager 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 push riskier loans in the current period. If the previous period's shock was negative, the opposite is true. In the presence of such behavior, we would observe the portfolio quality following an

[5] Although the bank imposes risk controls, our interviews indicate that managers can manipulate the information contained in loan applications at the margin to avoid higher approval levels.

autoregressive process where current-period quality is negatively correlated with previous-period quality.[6]

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

8.1. Empirical specification

We estimate the following equation:

$$Q_{u,m} = \alpha Q_{u,m-1} + \varepsilon \ , \qquad (5)$$

where $Q_{u,m}$ is unit *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). In order to efficiently estimate our model (5) we use the Arellano-Bond estimator (Arellano and Bond, 1991). This estimation technique uses lagged first differences as instruments to produce unbiased estimates of α. Under the hypothesis of a random walk, α will equal one. Under the hypothesis that outlet managers are actively managing their portfolio risk, α will be negative.

8.2. Estimation results

Table 10 presents the results of the estimation. The Arellano-Bond test for autocorrelation of residuals of order 2 is insignificant, which is necessary for Arellano-Bond to produce unbiased estimates (Arellano & Bond, 1991). For comparison, we also report the unit fixed effects OLS results.

TABLE 10.
Evolution of loan portfolio quality

Dependent variable: proportion of performing loans in the outlet's portfolio

	OLS	Arellano-Bond
Lag(1)loan quality	-.105(4.45)***	-.0567(2.07)**
Constant	1.014(46.63)***	-.001(3.88)***
Observations	1992	1826
A-B test for autocorrelation of residuals of order 1		-26.25***

A-B test for autocorrelation of residuals of order 2	-0.68

Robust t statistics in parentheses,
* significant at 10%; ** significant at 5%; *** significant at 1%

The estimate of α 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.[7]

9. CONCLUSION

The economics literature on incentives has long recognized and, recently, increasingly documented the propensity of agents to game their incentive systems. The human capital stream of the literature highlights the relationship between cognitive ability and productivity. Work on technical and organizational change has often assumed that returns to delegation are increasing in employees' ability, but has typically not analyzed the potentially confounding effects of agency costs.

In this paper, we propose that agency costs may be increasing in a special type of cognitive ability – knowledge of how the incentive plan is constructed – and that in some settings these costs might outweigh the benefits to delegation. Our results are consistent with this initial intuition. We find that bank managers in a large Polish retail bank manipulate loan prices and sizes, apparently to maximize their private benefits from their incentive system. We further find evidence suggesting that more "able" employees are more costly to the bank. The bank earns between 87 and 96 percent of its theoretical maximum profits in branches managed by employees with higher ability to predict their performance targets, while it earns between 89 and 98

7 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.

percent of its theoretical maximum profits in branches managed by employees with low plan knowledge.

A further contribution of our study is that our estimates of gaming costs derive from a novel empirical strategy. We use managers' performance relative to the incentive plan as an instrument for their supply of loans in order to estimate the bank's demand function. We can therefore compare actual profits against the benchmark of profit maximization – an entirely new approach and an appealing alternative to the current state of the art.

Finally, a minor contribution of our results is to highlight the multidimensional nature of "ability". In our results, the effects of our ability measure differ in sign and significance from the effects of a standard education measure.

We should acknowledge one important limitation of our study. We work with data that is partially aggregated and transformed by the bank due to its confidentiality concerns. Although the key variables – loan size and interest rate – are technically provided as categorical data, we use standard linear techniques. We feel justified in doing so because we took steps during data collection to ensure that the categories were equidistant, meaning the values form a cardinal scale. While the use of standard techniques facilitates the analysis and the interpretation of our results, the significance of our estimates is perhaps a bit overstated due to a lack of precision arising from the compression of continuous into categorical data.

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Appendix A. Data collection procedure and survey methodology

The data collection procedure comprised four phases. In phase one, we conducted interviews with the top management team of the bank and outlet managers. The CEO, Sales Director, HR Director and Risk and Accounting Director were interviewed. We have then conducted 17 semi-structured interviews with bank outlet directors in different regions of Poland. Most of the interviews were recorded. However, due to delicate subject of interviews, some managers did not approve of recording. In such cases, the notes from an interview were taken by two researchers and compared directly after the interview. Each interview lasted from 40 minutes to 1.5 hours. In phase two we have developed the measurement scales for a survey instrument based on interviews and literature review. We then pre-tested the scales with academics and executives to ensure clarity and unidimensionality of the measures. These pre-tests lead to several revisions in our questionnaire. In phase three, we administered an online survey to *all* outlet managers in the bank. Following the TDM guidelines by Dillman (Dillman, 1978) we mailed two follow-up letters to all non-respondents. Considerable effort was expanded to ensure reliability of the survey data. In total, we have achieved the response rate of over 86%. Out of non-respondents, 43% were caused by vacant position rather than non-response on the side of managers. In total over 200 usable surveys were returned. Non-response bias was analyzed with regard to outlet type, outlet size, outlet performance and manager gender. No significant bias in responses was found. We also compared the early respondents and late (second and third mailing) respondents and found no significant differences in distribution of answers.

The survey contains, among others, the following classes of information

1. Personal traits such as gender, tenure, age, marital status
2. Cognitive abilities measures – education (measured on a five point Likert scale) and sales target knowledge.
3. Sales targets evaluation and construction

Appendix B. Variable construction

While we do not have data on the interest rate for each of the loans granted on a particular day, we make use of more fine grain structure of our data than daily aggregation. The loans granted by a unit on a particular day are divided into groups based on size of the loan as well as the interest rate at which it was granted. As the base interest rate could be dependent on the size of the loan (compare with Figure 3), it would be inaccurate to calculate absolute day average without taking into account the loan size. For each of the loan size groups we hence calculate the average interest rate in a given month based on data from all units. The difference between this average and the daily interest granted represents the discounting behaviour on the side of the unit from the norm established by all outlets. We adjust this difference by the total number of loans granted in each of the size groups. Formally:

$$D_{u,t} = Average\_discount_{u,t} = \frac{\sum_{v}((ir_{v,t,u} - \overline{ir}_{v,m}) \times (number_{u,t,v}))}{\sum_{v} number_{u,t,v}}, \ \forall_{t \in m}$$

$$\overline{ir}_{v,m} = \frac{\sum_u \frac{(ir_{u,v,m})}{n_{u,v,m}}}{U}$$, where U is the total number of units

Independent variables used in estimation of equation (2) and (3):
We define the percentage meeting of the sales plan on a particular day in a given month as the ratio of cumulative value of loans given this month and the value of the sales plan. Throughout the analysis we always use the first lag of this variable as it represents the information that outlet managers have on a given day[8]. Formally:

$$Plan\_position_{u,t,m} = \frac{(\sum_{t=\min(t\in m)}^{t-1} volume\_zloty_{t,u})}{plan_{u,m}}, \ \forall_{t\in m}$$

We calculate the average size of a loan granted on a particular day as the ratio of daily value of loans and the total number of loans granted on a particular day:

$$Avg\_value_{u,t} = \frac{\sum_v volume\_cat_{u,t,v}}{\sum_v number\_ofloans_{u,t,v}}$$

Where V denotes the volume group of the loan.

Personal traits vector contains controls for:
1. gender (binary)
2. tenure (in years)
3. age (in years)
4. marital status (binary)

We define the indicator variables used in estimation of equation (3) in the following manner:

$$I_{plan\_position\in(0.5,0.8]} = \begin{matrix} 1 \ if \ \ plan\_position_{u,t,m} \in (0, 0.5) \\ 0 \qquad\qquad\qquad otherwise \end{matrix}$$

$$I_{plan\_position\in(0.5,0.8]} = \begin{matrix} 1 \ if \ \ plan\_position_{u,t,m} \in (0.5, 0.8) \\ 0 \qquad\qquad\qquad otherwise \end{matrix}$$

$$I_{plan\_position\in(0.8,1.3]} = \begin{matrix} 1 \ if \ \ plan\_position_{u,t,m} \in (0.8, 1.3) \\ 0 \qquad\qquad\qquad otherwise \end{matrix}$$

$$I_{plan\_position>1.3} = \begin{matrix} 1 \ if \ \ plan\_position_{u,t,m} \in (1.3, \infty) \\ 0 \qquad\qquad\qquad otherwise \end{matrix}$$

[8] Using non-lagged values did not change the results

Appendix C. Bootstrapping Procedure

The theoretical basis for bootstrapping is described in Efron and Tibshirani (1993). Our procedure consists of the following steps. From the population of size n of daily sales of loans, we draw with replacement to construct a new random sample of size n, from which we estimate the coefficient of interest, β. In our case, β represents the difference in profits between managers of low and high plan knowledge, respectively.

We repeat this procedure 1000 times to obtain a vector of 1000 estimates of β. Since our point estimate from the baseline analysis is negative, inference consists of computing what fraction (α) of the empirical distribution of β is weakly greater than zero. We report hypothesis tests based on a "two-tailed" test, i.e., 2α. We recognize that this is not a perfect analogue of the classical two-tailed test, since bootstrapping is a Bayesian procedure, but we choose it because it is more conservative.

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