Measuring Trust in Peruvian Shantytowns*

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Abstract

We propose a methodology to measure trust within a social network and apply it in a field experiment in shantytowns of Lima, Peru. We model trust as a transaction cost which an agent pays to gain permission to use someone else's asset. Social closeness reduces the transaction costs through two channels: (1) it reduces asymmetric information and makes it more likely that the asset's owner can identify the user as a 'good' (responsible) type; (2) it gives the owner the ability to control the agent's use of the asset and hence reduce moral hazard.

We have designed a microfinance program where we invite a subsample of the Shantytown community to become 'sponsors'. Sponsors receive a line of credit and can use a fixed share of it to obtain loans for their own household. The rest of their credit line (the 'asset') is allocated for 'sponsoring'. Any household in the community can get a low-interest rate loan from our microfinance partner by finding a sponsor who agrees to cosign the loan application. We randomize interest rates across all client-sponsor pairs: this allows us to measure the tradeoff between accessing a socially close sponsor with a high interest rate and a socially distant sponsor with a low interest rate. A second randomization varies the extent to which a sponsor is responsible for a borrower's default which allows us to separate our two trust channels. In this paper we report early results from two communities. We find that social distance up to length three reduces transaction costs by about 1 to 4 percent in terms on monthly interest rates. Moreover, geographic distance is also highly significant.

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1 Introduction

We propose a new methodology to measure trust in a social network and implement it through a field experiment in Lima, Peru. We start from the observation that social networks facilitate lending of 'assets' which can be both monetary and physical (tools, means of transportation such as a car or a bicycle, etc.). Social closeness reduces asymmetric information and makes it easier for the owner of an asset to identify the potential of a borrower to be a reliable type. Closeness also enables owners to control agents' use of assets such as avoiding excessively risky investments and hence reduce moral hazard.

We implement this methodology through a microfinance field experiment. We map the social network of a community and invite a subsample of residents to become 'sponsors'. Sponsors receive a credit line from our microfinance partner and can access part of it for self-loans at low interest rates. The rest is reserved for *sponsored loans*. Any resident in the community can obtain such a loan by finding a sponsor who agrees to cosign the loan and guarantee it. Lines of credit therefore serve as artificial assets which cannot be used by the asset owner herself. We randomize interest rates for all client/sponsor pairs which allows us to measure the tradeoff between accessing a socially close sponsor with a high interest rate and a socially distant sponsor with a low interest rate. A second randomization varies the extent to which a sponsor is responsible for a borrower's default which allows us to separate our two trust channels.

In this paper we report early results from two communities using the data collected between March and September 2005 and based on the interest rate randomization only.[1] This allows us to address the basic question question of how social distance affects trust (i.e. transaction costs between agents). We find that social distance up to length three reduces transaction costs by about 1 to 4 percent in terms on monthly interest rates. Moreover, geographic distance is also highly significant.

Our research program is related to a large literature in development economics and anthropology which studies the role of social networks in insuring against adverse income shocks. The poor in developing countries often lack savings to self-

[1] The full programm will be eventually implemented in 30 communities. Most of loans from the two pilot communities are still pending and were therefore cannot yet evaluate the outcome of randomization in sponsor responsibility.

insure against such shocks. Social networks then become the prime source of small credit as Lomnitz (1977) and Singerman (1995) have shown in two anthropological studies in Mexico and Egypt. Townsend (1994) provides strong indirect evidence that social networks can be very efficient for risk-sharing by showing that villagers in Southern India are remarkably successful in insuring each other against income shocks in the absence of formal institutions providing credit. A micro-model of trust in communities based on the ability of social networks to solve asymmetric information problems and reduce moral hazard is therefore useful in assessing the ability of networks to provide such insurance.

Our research also complements the large literature in experimental economics which has developed around the investment game (or trust game) due to Berg, Dickhaut, and McCabe (1995).[2] The investment game is well suited to study trust between strangers and requires further assumptions to explain observed behavior in the context of game theory. In contrast, our method is designed to study trust in a network of agents who interact frequently with each other and we can use the standard tools of game theory.

The paper is organized as follows. In section 2 we introduce a simple theoretical framework which motivates our experimental design in section 3. The preliminary results from the pilot are reported in section 4. Section 5 discusses future stages of our project.

2 Theory Framework

The first basic question we want to address is the following:

Question 1 *How do various measures of social distance affect trust?*

In the context of our field experiment this question can be restated as: how much harder will it be for a borrower to approach a distant rather than socially close sponsor to cosign a loan? There are two two basic ways to define social distance - the *path length* between two agents is defined as the shortest sequence of friends

[2]The trust game is a two player game where player 1 can decide to send some or all of his money to player 2. The experimenter triples the amount sent and player 2 then can send some or all of the money back to player 1. The amount sent by player 1 is usually interpreted as a proxy for trusting behavior while the degree to which player 2 reciprocates is interpreted as trustworthiness.

connecting two agents (such as being 'friend of a friend', for example). *Structural equivalence* is an alternative measures which captures the number of friends shared by two agents (Burt, 1995). Structural equivalence is closely related to the concept of 'weak' and 'strong' links (Granovetter, 1973).

In this section we sketch a simple model to inform the design of our field experiment as well as the empirical model we are estimating.

2.1 Relationships and Favors

Time is discrete ($t = 0, 1, 2, ..$) and agents discount utility at rate δ. Each time period is sub-divided into 3 sub-periods which we call $t.0$, $t.1$ and $t.2$. In each period $t.2$ two direct neighbors on the social network can either cooperate (action C) or defect (action D). If they both cooperate they get a payoff of 1 and otherwise 0. If one them cooperates and the other player defects the defector gets 2 and the cooperator gets 0. The value of a bilateral relationship is $\frac{1}{1-\delta}$ and we assume that $\delta > \frac{1}{2}$ such that a cooperative trigger-strategy equilibrium can be sustained.

Each agent can also take a continuous *transfer* action $x \in [0, 1]$ to transfer an amount x of resources to some other agent at cost x. While x could be simply money we prefer to think of it more generally as special 'favors' provided by the sender in a cash constrained economy.

2.2 Investment Opportunities

In each time period $t.0$ there is exactly one randomly chosen agent i in the social network who has an investment opportunity with return $U > 0$ but needs access to a resource A. There are two other random agents j_1 and j_2 who have access to resource A but who have no investment opportunity. For example, these agents might have savings which they do not need at the moment or access to a tool (such as a car or motorcycle) which they can lend out. In our design agent j will be a sponsor while agent i will be the client and the resource will be providing access to the sponsor's credit line by cosigning a loan.

There are two types of clients - high types H and low types L with equal probability. A high type will return the asset intact while a low type will destroy it for sure. We assume $U < A$ - it is therefore socially inefficient to lend the resource to low types.

The lender has some signal on the borrower's type which indicates the correct type with probability $p(d_{ij}) > \frac{1}{2}$ and its precision is decreasing with social distance. We assume that $(1-p(d_{ij}))A < U$ for all d_{ij}. This implies that it is always efficient to provide the asset to a borrower whose observed signal is high. However, the borrower will need to compensate the lender for the expected loss $(1-p(d_{ij}))A$ by transferring $x = (1-p(d_{ij}))A$ in period $t.1$.[3] To minimize his cost the borrower will try to borrow from the socially closest available sponsor. Furthermore, *social learning* about others' types will reduce the borrower's transaction cost.

2.3 Moral Hazard

As a final element to the model we add moral hazard. Any borrower can give an asset back on time which has a utility cost ϵ to her. Alternatively, she can give it back late which has zero cost to her but which causes a loss $E > \epsilon$ to the lender.

Agents' relationships can be leveraged in some equilibria to control the lender's behavior. For example, if the lender and borrower share a common friend D then the borrower can extract his damage E by forcing friend D to transfer $x = E$. This friend in return can extract his damage from the late-paying borrower and force him to also transfer $x = E$. The more common friends the borrower and lender share the more leverage the lender has over the borrower. While there are many other possible equilibria it is reasonable to expect that social distance reduces the ability of the lender to prevent moral hazard. Put differently, the lender can leverage the supergame (i.e. relationships) to control the borrower's moral hazard.

3 Experimental Design

We implement our micro-lending program in low-income communities where residents have few outside options to obtain loans.

3.1 Baseline Survey I

We conduct a *short* baseline survey which provides us with basic data on household income, occupations of adult household members, housing quality, names of local

[3]We assume that the lost asset can never be recovered due to limited liability of the borrower.

community leadership, tenure in the community and point of origin. Our two pilot communities have a size of about 250-300 households.

3.2 Selecting Sponsors

Based on income data we randomly invite about 10 percent of all households above the median income to become sponsors. Our microfinance partner screens sponsors for past default and eligible sponsors are allocated a credit line which is based on their economic circumstances. The goal is to recruit about 10 percent of households to become sponsors.

Credit lines can be used both for personal use and for sponsoring loans of other households in the community subject to the following conditions:

- up to 30 percent of the credit line is available to the sponsor himself and members of the sponsor's household
- up to 35 percent can be used to sponsor relatives who live in the community but not in the sponsor's household

3.3 Baseline Survey II

Before starting the lending program we conduct a second, more detailed survey on social interactions with each adult household member of a sponsor household.

The survey asks participants to name relatives, work colleagues, friends, compadres, and neighbors inside and outside the community. We measure the strength of connection between friends and acquaintances in three ways:

1. Time spent together per week.[4]
2. Ranking of friends and compadres by degree to which they are trusted

For each such social contact we collect information on past economics transactions:

- Did the subject borrow or lend money from that friend, compadre or acquaintance?

[4] In a social network survey conducted in November 2003 at Harvard University we asked 600 subjects to name their friends and to report the time they spend together. For friends who named each other the reports on time spent agreed by half an hour in 80 percent of the time.

- Did the subject borrow or lend objects from that friend, compadre or acquaintance (such as tools, TV and other consumer products)?
- Did the subjects participate with that friend or compadre in a village bank or rotating savings group?
  - the type of co-parent chosen (e.g., family, employer, friend) and place of residence
  - the event for which the co-parent was chosen (e.g., baptism of a child)
  - the frequency and type of interaction with the co-parent

This same social network survey is also conducted with each of the friends, compadres and acquaintances of sponsors who are listed by sponsor households. For the pilot study we restricted the social network survey initially to sponsor households and their friends to reduce the amount of survey work necessary and later expanded the survey to non-surveyed clients who had taken loans.[5] In future iterations we will conduct baseline II surveys with every household to address concerns about endogeneity of networks.[6]

The social network survey allows us to classify relationships between borrowers and all potential sponsors. From this data we ca calculate path length between any potential client-sponsor pair as well as the number of common friends.

3.4 Getting a Loan

The program is presented to *all* households in the community as a new microfinance program which requires clients to match up with one of the sponsors to obtain a loan. A sponsor is responsible for repaying a loan if the client defaults. Each adult household member receives a card which outlines the rules of the program and includes a list of all sponsors in the community as well as a map of the community showing the location of sponsors. Both spouses of a sponsoring household and borrowing household must act as co-signers.

[5] Baseline I surveys take about 30 minutes while the social network survey takes about 60 minutes for each adult household member.

[6] For example, a client might list a sponsor as an acquaintance after the sponsor agrees to cosign the loan. In our empirical analysis we use both networks before the start of the program and after the start of the program and the results are very similar.

Crucially, the client's card also clearly lists interest rates for each different sponsor and indicates the location of each sponsor on a map of the community. It is important for our field experiment that all agents know the owner of an asset (i.e. credit line) and the return they can derive from that asset (i.e. interest rate). We constrain all interest rates to lie between 3 and 5 percent per month.

We choose an interest rate randomization which is geared to estimate the tradeoff between choosing a socially close sponsor and a more distant sponsor with lower interest rate. Every client is randomly assigned one of 4 'slopes': slope 1 decreases the interest rate by 0.125 percent per month for 1-step increase in social distance. Slopes 2 to 4 imply 0.25, 0.5 and 0.75 decrements. Therefore, close friends generally provide the highest interest rate and distant acquaintances the lowest but the decrease depends on SLOPE. The interest rate offset for close friends is either 4.5 percent with 75 percent probability (DEMAND=0) or 5 percent (DEMAND=1) with 25 percent probability and DEMAND is a i.i.d. draw across clients. Finally, we add a random 'wobble' to each interest rate of 0.125 percent and then round to the one or two closest quarter percentage points.

SLOPE identifies the interest rate/social distance tradeoff. DEMAND allows us to test whether interest rates also influence the demand for loans in addition to affecting the choice of sponsors.

3.5 Empirical Model

Based on our model we estimate the following discrete choice model. Each client i who applies for a loan can approach any sponsor j who participates in the program. Client i's utility from being sponsored by j can be written as:

$$U_{ij} = \alpha r_{ij} + \beta S_{ij} + \eta_i + \epsilon_{ij} \tag{1}$$

where

$$\begin{aligned} r_{ij} &= \text{interest rate for client } i\text{/sponsor } j \text{ combination} \\ S_{ij} &= \text{social distance between } i \text{ and } j \\ \eta_{ij} &= \text{client } i\text{'s private rate of return to the loan} \\ \epsilon_{ij} &= \text{i.i.d. error term} \end{aligned}$$

We expect that the interest rate enters negatively. The second term captures the social learning and moral hazard channels - i.e. the transaction cost. We expect that socially close neighbors have lower transaction costs. By comparing α and β we can measure trust in monetary terms.

The client fixed effect η_i captures the client-specific private return to investment which is equal across all client/sponsor combinations. The client will maximize over all sponsors:

$$U_i = \max_{j \in S} U_{ij} \tag{2}$$

By assuming a type 1 extreme value distribution for the i.i.d. error term ϵ_{ij} we obtain a standard discrete choice logit model with fixed effects.

We also run an auxiliary regression to check whether variations in interest rates additionally induce variations in the demand for loans. For that purpose we regress takeup T_i of *any* loan by client i on our experimental DEMAND variable D_i:

$$T_i = \alpha D_i + \epsilon_i \tag{3}$$

4 Preliminary Results from Two Pilot Communities

Our two pilot communities consist of 282 households and 26 sponsors and 371 households and 25 sponsors respectively. The program was started in March 2005 in the first community and July 2005 in the second community and both programs are ongoing as of September 2005. There are 26 client-sponsor loans with unique clients in the first community and 50 such loans in the second community. Moreover, over time there are repeat loans by some clients. These usually (but not always) involve the same sponsors as for the first loan. There are 4 such repeat loans in the first community and 14 in the second one. We restrict attention to first loans only because second loans are usually granted after the sponsor could assure herself of the reliability of the client. 65 of the 76 loans are between unrelated parties and 11 loans involve a relative.

The estimated coefficients of the discrete choice model are presented in table 1. We estimate a slightly more flexible functional form than proposed in equation 1. We introduce the dummy variables SOCIALDISTi ($i = 1, 2, 3, 4$) which equal 1 if social distance has value i.[7] We also include geographic distance as a competing measure for social distance as well as a dummy for pilot community 2.[8]

Our two pilot communities were quite different. The second community was slightly poorer, was younger and had a better community organization than the first community. There was ample anecdotal evidence that suggested that 'social capital' was higher in the second community.

The tradeoff between interest rates and social distance is captured by the ratio of the estimated coefficient on social distance and interest rates. It is encouraging that the estimated coefficients on social distance across both communities are similar for both fixed and random effects (columns RE and FE). Furthermore, the results do not change much when we only use social network data collected before the start of the program (which alleviates endogeneity concerns). The estimates suggest that a close neighbor is worth as much as 3-4 interest rate points. The significance of connectedness decreases with social distance but is still about 1 percentage point for contacts at distance 3.

Columns RE-1 and RE-2 suggest that clients in the first (low social capital) community are much less responsive to interest rates because the coefficient on INTEREST is negative but no longer significant. This is consistent with the idea in a low social capital community access to credit is mainly determined by close friends.[9] It also means, however, that our simple geodesic network distance measures do not fully capture social capital. If social capital is just a function of lower average path length within a community (due to a denser network, for example) then the ratio of the coefficients on SOCIALDIST and INTEREST should be similar.[10] However, we also have much less data on our first community which could explain the imprecise estimates on INTEREST for that community. Nevertheless, it would be interesting with more data to decompose social network links by type and also include further measures of network structure (such as number of shared friends).

A quite surprising result is the significance of geographic distance. If a client

[7]Social distance greater than 4 is the omitted category.

[8]The random effects regressions include the outside option of not getting a loan while the fixed effects regressions effectively only include data from client households which took out loans.

[9]Interestingly, 6 out of 26 unique loans in the first community are between related households while only 5 out of 50 loans in the second community are between relatives.

[10]A lot of empirical work on social capital essentially counts links within a community and relates these measures to varous outcomesPutnam (2000); Fukuyama (1995).

and sponsor household are located one standard deviation of geographic distance closer to each other this is worth almost as much as a one point decrease in the interest rate. There are two possible explanations: (1) our social distance measure does not fully capture social networks; or (2) a decrease in social distance makes monitoring of the client easier for the sponsor. We hope to distinguish between both hypothesis in the future with the help of our second randomization.

In table 2 we exploit the feature of the randomization that interest rates are uniformly higher by half a percentage point for 25 percent of our clients where DEMAND equals 1. For both communities the coefficient is indeed negative but not significant. At least for the second community the effects of the interest on the takeup of *any* loan seems to be less strong that the effects of the interest rate on the choice of sponsor conditional on applying for a loan. This is consistent with the hypothesis that clients who take out loans are severely credit constrained and therefore do not greatly reduce their demand for credit if they are faced with a higher interest rate. However, they do attempt to optimize on the interest rate/social distance tradeoff when choosing a sponsor.

5 Future Work

5.1 Decomposing Links

Question 2 *What type of links are most effective in lowering transaction costs?*

We want to decompose the social distance effect further by distinguishing between different types of links. In our basic regression we say that two agents are linked if one of them lists the other as a financial, trust or other link. A proper decomposition will require more data than we have collected in the pilot so far.

5.2 Decomposing Trust Channels

Question 3 *Which channels give rise to trust along a given link?*

While the model distinguishes between social learning and the ability to control moral hazard as two sources of trust we only estimated a reduced form which combines both effects. At the end of the program when we can observe loan performance we want to use the second randomization on the extent of sponsor responsibility to distinguish both channels.

5.3 Trust Intermediaries

Question 4 *What type of agents are effective trust intermediaries?*

For example, if I have a friend B who is trusted by C will I have the same cost of lending from C as B? Are there such trust intermediaries as described in Coleman (1990) and how efficient is trust intermediation?

5.4 Risk Sharing

Question 5 *How much risk sharing within a community can be explained by trust?*

Assume, for example, a fixed distribution of rates of return across households which is determined by investment opportunities in the wider economy. We expect that trust enables efficient risk-sharing by facilitating the transfer of resources from low-return to high-return households (Townsend, 1994).

5.5 Efficient Resource Allocation

Question 6 *Do social networks allocate resources efficiently?*

Our methodology also allows us to test how *efficient* social networks are in allocating resources. Existing research has primarily focused on the positive effects of social capital and trust on well-being (Putnam, 2000; Fukuyama, 1995). However, recent papers such as Khwaja and Mian (2004) have demonstrated that social networks can give rise to cronyism and inefficient allocation of resources.[11] A priori, it is difficult to define and distinguish inefficient cronyism from efficient discrimination against borrowers whose type is less well known because they are more socially distant. By varying the average client/sponsor interest rate level *across* communities we can interpret an increase in the share of sponsored loans provided

[11] Khwaja and Mian (2004) show that politically connected firms in Pakistan both borrow double as much *and* default 50 percent more often than other firms.

to ‘insiders’ versus ‘outsiders’ in response to a decrease in the interest rate as evidence for true cronyism. We describe details of this methodology in appendix A.

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A Measuring Cronyism

We develop the following test for cronyism. Each community generates investment opportunities $U_1 > U_2 > U_3$... according to some known distribution. For simplicity we start with the assumption that all client/sponsor pairs carry the same community interest rate r_C. The social planner would allocate the credit lines of sponsors as follows:

- She would start to fund the most profitable investment opportunity U_1 and continue to fund the second-highest, third-highest etc. until (1) all credit lines have been exhausted *or* (2) the marginal investment opportunity has value r_C.
- We assume that credit lines are sufficiently small such that the marginal investment opportunity satisfies $U \gg r_C$ (e.g. the total loan volume is determined by available credit lines rather than the community interest rate).[12]

We next take into account that each sponsor j receives transaction cost T_{ij} from client i to compensate for the risk of default. Taking this constraint into account the efficient solution of the social planner is as follows:

- For each investment opportunity U of agent i find the lowest transaction cost $T(U) = \min_{j \in J} T_{ij}$ over the set of sponsors J. Rank all investment opportunities by $\tilde{U} = U - T(U)$ and fund the most profitable investment opportunity $\tilde{U}$ first.
- Allocate the residual credit lines to the next highest investment opportunity, then the third-highest etc. until all credit lines are exhausted.
- For insiders and outsiders there will be marginal cutoff values U_I^* and U_O^* such that all investment opportunities above those cutoff values are funded. The precise cutoffs will depend on the distributions of investment opportunities amongst insiders and outsiders, the total amount of credit available and the extent to which sponsors trust insiders more than outsiders.

If the distribution of investment opportunities are similar for insiders and outsiders we would expect that $U_I^* > U_O^* > r_C$: in other words, more insider projects are funded because sponsors trust insiders more. It is important to note, that simply observing $U_I^* > U_O^*$ is *not sufficient* to claim that there is cronyism.

[12]This is likely to be true in heavily credit constrained communities.

What are the effects of decreasing the community interest rate r_C? In this model there are none: the share of loans going to insiders would remain the same because the cutoff values U_I^* and U_O^* would not change.[13]

Under cronyism, however, we would expect the share of loans to insiders to *increase* as the community interest rate r_C decreases. The reason is that sponsors will first fund projects of insiders as long as these projects have positive return and $U > r_C + T$. As the interest rate decreases sponsors can fund more marginal projects of insiders at the expense of providing funds for outsiders' investment opportunities with high social value.

The share of insider loans to total loans therefore provides a sharp prediction which distinguishes inefficient cronyism and favoritism from constrained efficient trust.

[13] This would remain true even if clients start to compete for sponsors and have to pay sponsors for access. As long as sponsors charge every client identical access fees the cutoff values would not change as r_C decreases.

Table 1: The tradeoff between interest rate and social distance.

Variable	RE (1)	RE-1 (2)	RE-2 (3)	RE-Start (4)	FE (5)
INTEREST	-0.862**	-0.178	-1.107**	-0.700*	-1.454**
	(0.266)	(0.601)	(0.301)	(0.273)	(0.441)
SOCIALDIST1	3.780**	4.111**	3.420**	2.746**	3.875**
	(0.514)	(1.159)	(0.588)	(0.437)	(1.217)
SOCIALDIST2	1.565**	1.396	1.624**	1.025*	1.587
	(0.499)	(1.141)	(0.555)	(0.414)	(1.146)
SOCIALDIST3	1.090*	0.595	1.255*	0.706†	1.011
	(0.482)	(1.158)	(0.528)	(0.392)	(1.060)
SOCIALDIST4	-0.519	-12.408	-0.238	-0.101	-0.728
	(0.819)	(550.550)	(0.839)	(0.547)	(1.155)
GEOGRAPHICDIST	-0.002**	-0.001	-0.002**	-0.002**	-0.002**
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)
COMMUNITY2	0.938**			1.080**	
	(0.259)			(0.257)	
N	16556	7306	9250	16556	1913
Log-Likelihood	-400.134	-132.375	-261.982	-423.259	-188.211

Significance levels: † : 10% $*$: 5% $**$: 1%

INTEREST is the client/sponsor specific interest rate which is printed on each client card. SOCIALDIST1, SOCIALDIST2, SOCIALDIST3, SOCIALDIST4 are dummy variables which indicate a client-sponsor distance of 1 to 4. The omitted social distance category includes any distance greater than 4. The mean value of geographic distance GEOGRAPHICDIST is 643 with standard error 382. The social network is always calculated using all surveys except for column (4) which only uses data collected before the start of the program. COMMUNITY2 is 1 if the client and sponsor live in the second (high social capital) community. Regressions (2) and (3) only include loans from the first and second community, respectively. Standard errors are shown in paranthesis. Regressions (1) to (4) use client random effects and (5) uses client fixed effects logit. The constant term is omitted when reporting the random effects estimation.

Table 2: The effect of interest rates on takeup of loans.

	Both communities	Community 1	Community 2
Variable	(1)	(2)	(3)
DEMAND	-0.040	-0.033	-0.045
	(0.029)	(0.039)	(0.041)
Intercept	0.128**	0.101**	0.149**
	(0.015)	(0.020)	(0.021)
N	653	282	371
R^2	0.003	0.003	0.003

Significance levels: † : 10% ∗ : 5% ∗∗ : 1%

DEMAND was an i.i.d. dummy variable and set to 1 if interest rates are uniformly higher by half a percentage point. This was the case for 25 percent of the sample.