Birds of a feather indebted together
Peer-effects on mortgage decisions*

Ákos Aczél[1] – Lajos Tamás Szabó[1]

[1]Central Bank of Hungary

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Abstract

We examine peer-effects in mortgage borrowing decisions. We find that having a financially literate colleague improves the borrowing decision of the financially less literate co-workers. The interest rate of the mortgage loan of these co-workers is significantly lower than similar employees at other companies, who do not have such a colleague. The magnitude of the effect is economically significant, roughly one fourth of the standard deviation of mortgage loan interest rates. Placebo and robustness tests verify our results. Roughly one third of the effect is due to which bank is chosen by the borrower. The results are heterogeneous in the strength of competition among banks. In those districts, where the competition is lower the peer-effect is considerably higher.

Keywords: peer effects, skills, borrowing decisions, mortgage loan

JEL codes: J24, G21, G41

1 Introduction

Taking a mortgage loan is one of the largest decision of people from a financial perspective. It has long-lasting effects on individuals' financial obligations, and the total amount of money payed back accounts to a high share of total (life-long) savings. In the same time terms of mortgage loans look quite complex, especially for those whose financial knowledge is weak. Some people are more familiar with financial questions than others and an advice from an experienced friend can help in choosing among the offers of banks. In our research we show that such mechanism plays an important role in the borrowing decision.

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People spend the majority of their time in their workplaces and they discuss not just job related topics. We would like to know how does a borrowing decision of a colleague affects other colleagues' same decision. Our hypothesis is that employees whose financial knowledge is potentially low choose better loans if they have a financially literate colleague than similar employees who does not have such a colleague.

To study this question we use the Hungarian credit registry database between 2015-2019, which contains all information on mortgages. We merge this dataset with the administrative database of the Hungarian firms and employees. In this way we can establish a co-worker network and see borrowing decisions as well. We also use the skill sets for occupational categories from the O*NET database.

In our empirical approach we first define the group of financially literate employees. We start by identifying those basic skills that are strongly related to borrowing decisions. According to our results mathematics is the most relevant basic skill that explains the interest rate of a mortgage loan. Using this result we consider all employees who fulfill the following two criteria as financially literate: i) they have material experience in the mortgage loan market, i.e. they have taken a mortgage in the last one year, ii) the mathematical score based on their occupation is in the highest 10 percent. Similarly, we assign a borrower to the group of low financial literacy if mathematical skill related to the borrower's occupation is below the median. We consider the treatment as having a financially literate colleague. The treated group contains only borrowers from the low financial literacy group. We think that these borrowers can learn potentially from their colleague. We use only small firms since at large firms we do not know whether two co-workers know each other.

We derive the determinants of mortage loan interest rate by regression analysis. The dependent variable is the interest rate of the credit. We can control for every factor, which are relevant from the perspective of mortgage (e.g. wage, interest period, maturity, principal, payment-to-income ratio, age, place of residence etc.). The parameter of interest is an indicator variable, which shows whether there is a co-worker who is financially literate. The parameter of interest is significant and the magnitude is large. Those with low financial literacy, who have a high financial literacy colleague took mortgages with 0.3 percentage point lower interest rate than those who do not have such a peer. The average mortgage interest is 5.1 percentage point during the sample period, while the standard deviation of mortgage loan interest rates is 1.2 percentage point.

To rule out endogeneity problems we run placebo tests as well. We define placebo tests that challenge both criteria of financial literacy: having high mathematics skills and having experience in the mortgage loan market. First, we check whether borrowers with low financial literacy have an effect on the financially literates' mortgage interest. According to the expectations, we do not find any effect. Second, we flip timing and check whether having a colleague with high financial literacy who took her mortgage loan *after* that the low financial literacy borrower took her mortgage has any effect on the interest rate. In this case we also do not find any effect.

We also run several robustness checks. First, we increase the small firm employee threshold. If we enlarge our sample with higher number employee firms the parameter gradually decreases. This is intuitive because in our data the number of financially literate employees does not increase that much, therefore there is less chance for seeking advice of financially literate colleagues. Second, we change the definition of financially literate. We use a broader and a narrower definition as well. In the first case we use those, whose mathematical skill is above the 75$^{\text{th}}$ percentile, in the second we define financially literate who is above the 95$^{\text{th}}$ percentile. Using the broader definition, the parameter of interest is somewhat smaller, in the narrower, it is larger. This result shows that the more financially literate give smarter advice to their peers.

We also check how does the peer-effect depend on the magnitude of competition among banks. We find that if the competition is among the lowest 10$^{\text{th}}$ percentile in the country the peer-effect is considerably larger. This means that in a lower competition market a good advice is more valuable than in a market with higher competition, where range of prices (interest rate) is generally narrower.

We also check what could be behind the peer-effect, i.e. what can be the advice, which is given to a financially unskilled peer. By including bank fixed effects the magnitude of the estimated parameter decreases by one third. This implies that a considerable part of the advice is about choosing a specific bank.

Policy implications are the following. We learn that the quality of borrowing decisions depend on the informal advice of peers. The existence (and significance) of peer-effects shows that in general non-optimal borrowing decisions are made (e.g. by borrowers in the control group in our analysis). It has potential effects on banks' behavior on the mortgage loan market (financial institutions may exploit that borrowers have low financial knowledge) as well. Taking into account the most relevant costs of banks (such as financing cost, operational cost, risk cost) regarding mortgage loans we find that the identified effect is as large as one fourth of the profit that banks can achieve on a mortgage loan. Finally, financial education may be an important factor in informing borrowers and support them making good decisions.

Peer-effects are examined in case of several economic decisions (see e.g. Carlsson and Reshid 2022 for parental leave take-up, Bailey et al. 2022 for new phone purchases, Pazzona 2022 for interaction between highly skilled workers' productivity, Serafinelli 2019 for knowledge spillovers from highly productive workers to less productive ones etc.). Financial decisions are not an exemption. Bursztyn et al. 2014 confirm peer-effects in investment decisions in an experimental design. They also find that financially unsophisticated investors learn more from their peers. Browne et al. 2021 find peer-effect in risk preferences. The closest research to our paper is Ouimet and Tate 2020, who find significant peer-effect in investment decisions through co-worker network. We examine peer-effects in borrowing decisions, which – according to our understanding – have not been studied before. Furthermore, we show that there is heterogeneity in peer-effect related to the strength of competition.

Our research has several contributions to the literature. First, we identify peer-effects in case of borrowing. There are studies, which deal with peer-effect in financial decisions but non of these focus on loans. Second, by identifying heterogeneity in peer-effects we also show that in case of lower competition information is more valuable. Our method can be used in other countries to figure out whether there are monopolistic behavior of the banking system. Third, we use very high quality administrative datasets. The possibility to examine not just credit data but the co-worker network of the debtors is extremely rare.

The study organised as follows. In Section 2 we present the databases and some descriptive statistics. In Section 3 we show the identification strategy. We carry out the estimation and discuss the results in Section 4. In Section 5 we conclude.

2 Database

We use three different datasources to test our research hypothesis. We merge these three databases using individual identifiers and the occupational codes.

2.1 Hungarian State Treasury (MÁK) Database

The database of the Hungarian State Treasury (MÁK) contains the full population, who had at least one day legal work between 1997-2019. The following variables are used in the study:

- district level place of residence,
- four digit occupational code (FEOR),
- firm identifier.

There are 198 districts in Hungary, with average population of 55 thousand. One district can be considered as a local labour market because according to the 2011 Census, except for Budapest and its surroundings, 80% of the residents live and work in the same district. This ratio is 72% for Budapest and its commuting area.

For every debtor we choose that firm as an employer, where he earns the most. Based on this definition we can identify the co-workers, which is an essential measure in our calculations.

2.2 ONET database

We define skills based on the ONET database. We can merge the American occupational categories (ISCO-08) with the four-digit Hungarian counterparts (FEOR-08) but there are cases, where we cannot find an exact match for some Hungarian occupational categories. The maching rate is 73%. I As a robustness checks we average the mathematical score for every three-digit occupational categories and use this average if the four-digit mathematical score is missing. In this case we have mathematical scores for 87% of the total observations. For the descriptive statistics of mathematical score see Table 1.

Table 1: Descriptive statistics of mathematics skills

Percentile					Min	Max	Mean	Nr. Of obs.
1%	25%	50%	75%	99%				
13	31	44	50	72	0	81	41	82,455

Source: ONET and MÁK

2.3 Credit Registry Database (KHR)

The Credit Registry database contains all loans taken by individuals. We use the 2015-2019 time period because this time span contains all relevant information.

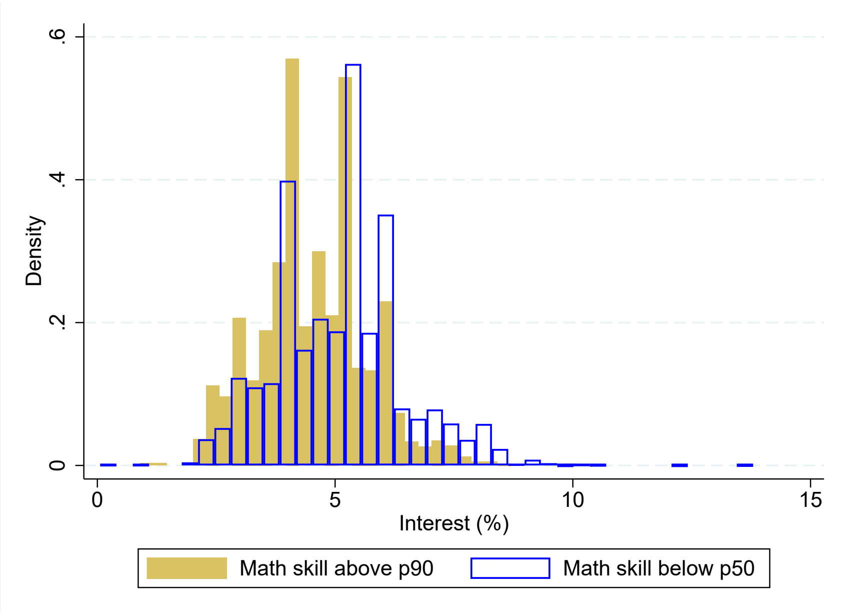
The distribution of interest rate based on mathematics score (see Figure 1) is somewhat different for those whose mathematics skill is above the 90^{th} percentile and below the 50^{th} percentile.

Table 2: Descriptive statistics for mortgage loans

variable	p10	p50	p90	mean
interest	3.12	4.79	6.17	4.78
period (month)	10	61	122	90
principal (mo. HUF)	3	7	17	9
maturity (years)	8	15	25	16
ln(wage)	12	13	14	13
age (years)	27	36	48	37

Note: for years 2015-2019. Source: Credit Registry

Figure 1: Mortgage interest rates based on math skills



Note: the graph show the distribution of mortgage interest rates for those who work at firms with less than 50 employees.

3 Empirical approach

When we identify the impact of having a financially literate colleague on the borrowing decision we follow a three step procedure. First, as we have no direct information on financial literacy we use a working definition of financial literacy that can be applied on our sample. Those who i) have taken a mortgage loan in the recent past and ii) have high mathematic skills are considered as financially literate. Second, we measure the direction and the strength of the relationship between having a financially literate colleague and the interest of the borrower's mortgage. We do that by regression analysis on the borrower level where the dependent variable is the interest rate and the key independent variable is an indicator variable that marks the borrower who has any financially literate colleague. To avoid omitted variable bias we use a large set of control variables including time and district (198 districts) fixed effects. As a final step we also show that the estimated effect comes from the two sources of high mathematic skills and experience on the mortgage loan market. We do that by running placebo tests that show that missing any of these two criteria results in non-significant effects. We flip timing and test if having a colleague with high mathematic skills who has taken a mortgage loan *after* that the borrower took her mortgage has any effect on the interest rate. Then we also test if having a colleague who has taken a mortgage loan in the last year and has low mathematic skills has any impact on the interest rate of the borrower.

3.1 Define financial literacy

As we do not have information on the financial knowledge of borrowers we create an own definition of financial literacy that can be applied on our dataset. This definition can be looked at as a proxy for true financial literacy. We consider a colleague being financially literate if the following two criteria is fulfilled:

i) the colleague has taken a mortgage loan in the last one year,

ii) the score of skill mathematics required by the occupation of the borrower is above the 90^{th} percentile.

The first point is supported by the idea that experience increases knowledge. Moreover, it is also important from the perspective of identifying peers that employees potentially know if a colleague of them has taken a loan in the recent past. As experience increases knowledge, the fact that someone has taken a loan already signals a certain level of financial knowledge. Therefore, we think that the chance that an experienced colleague is asked for advice is higher compared to that a non-experienced one is asked. Timing is also important as the experience should be relevant (considering that banks' offers change through time) and colleagues should also know about that their colleague has experience.

The second point requires high mathematics skill. We choose among skills based on how they are related to observed interest rates. The relationship is pinned down by regression analysis where the dependent variable is interest rate, the key independent variables are occupation related scores from the ONET database where a large set of controls are also included. We estimate Equation (1) to decide what are the relevant skills for borrowing decisions.

$$y_{it} = \alpha + \sum_{k=1}^{6} \beta_k S_{kit} + \gamma X_{it} + \theta_t + \varepsilon_{it} \tag{1}$$

where

- i - individual, t - year
- y the interest of the loan
- S_k - basic skill (active listening, mathematics, reading comprehension, science, speaking, writing)
- X - other variables (wage, age, age square, district FE, repricing period, maturity of the loan, pti, agent, age max)
- θ_t - time FE.

According to the results (Table 3) mathematics is the most relevant skill that is related to interest rates. Although there are some other variables that are negative and significant (therefore could proxy good financial decision making) we focus on mathematics in this paper as it is established well in the literature that numeric skills are strongly related to financial literacy (see eg. Lusardi and Mitchell 2007).

3.2 Estimation of peer-effects

In the next step we focus on only those, who are financially unskilled. We define this group as those for whom the mathematic skill is below the 50^{th} percentile. We check whether they have a colleague, who is financially skilled and took a mortgage at most one year before the financially unskilled took the mortgage. There are other colleagues, who took a mortgage in the recent past but are not skilled in mathematics. We define a dummy for those colleagues, who took a credit in the past year but their mathematical skill is below the 50^{th} percentile. We call these colleagues as financially unskilled. Since we do not know the mathematical skills for everyone we define a category (other) for them as well. In a robustness check we impute the missing mathematical scores based on the scores of similar occupations.

We estimate Equation (2) as our main regression.

$$y_{it} = \alpha + \beta_1 C_{FSit} + \beta_2 C_{FUit} + \beta_3 C_{Oit} + \gamma X_{it} + \theta_t + \varepsilon_{it} \tag{2}$$

where

Table 3: Basic skills and mortgage interest rate

	Interest rate
mathematics	-0.00678***
	(0.000336)
active_listening	0.00206*
	(0.00119)
reading_comprehension	-0.00163**
	(0.000806)
science	0.000912***
	(0.000219)
speaking	0.000233
	(0.000823)
writing	-0.00657***
	(0.000616)
Constant	4.947***
	(0.529)
Observations	116058
R^2	0.138
Other covariates	Yes
Time FE	Yes
District FE	Yes
Nr of colleagues	no limit

Standard errors in parentheses *** p<0.01, ** p<0.05, * p<0.1

- i - individual, t - year
- y - the interest of the loan
- C_{FSit} - financially literate colleague dummy (1 if have a financially skilled colleague, who took a credit in the past year)
- C_{FUit} - financially non-literate colleague dummy (1 if have a financially unskilled colleague, who took a credit in the past year)
- C_{Oit} - other colleague dummy (1 if a colleague took a credit in the past year and he is between the 50^{th} and 90^{th} or we cannot observe the mathematical skill)
- X_{it} - other variables (number of colleague, principal, repricing period, wage, age, age square, district FE, maturity of the loan, payment-to-income ratio)
- θ_t - time FE.

In this setup the parameter of interest is the coefficient of the financially literate colleague dummy (C_{FS}). We expect this coefficient to be significant and negative. The financially non-literate colleague dummy (C_{FU}) should be non-significant because we think that the mathematical skills and the mortgage experience together makes someone proficient enough to give a good advice. The expect the magnitude of the other colleague dummy (C_{FO}) to be between 0 and the parameter of C_{FS} variable.

Based on our specification the significance of the parameter of interest can be due to some firm related factors (e.g. some kind of special offers from banks for certain firms). To rule out this endogeneity issue we flip the timing of the variables. That is the colleague dummies are going to be one if the colleague take the mortgage *after* their co-worker, all other conditions are the same. If these variables are insignificant that means that not firm related factors are behind our results.

4 Results and discussion

4.1 Main results

Table 4: The main specification

Regression	Main	Robustness	
Financially literate	p90	p75	p95
d_finlit_one	-0.302**	-0.284***	-0.475*
	(0.139)	(0.0998)	(0.250)
d_nonfinlit_one	-0.00220	-0.00198	0.000334
	(0.0509)	(0.0509)	(0.0511)
d_ofinlit_one	-0.115**	-0.106**	-0.122***
	(0.0470)	(0.0486)	(0.0459)
finlit_col_additional	-0.0193**	-0.0197**	-0.0198**
	(0.00951)	(0.00932)	(0.00939)
Observations	9,905	9,905	9,905
R-squared	0.368	0.368	0.368
Other covariates	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
District FE	Yes	Yes	Yes
Mean of dependent variable	5.10	5.10	5.10

The table contains those mortgage loan takers, for whom the mathematical score is below the median and work at a firm, where the number of employees is less than 50. The parameter of interest is d_finlit_one, which shows is there a colleague, for whom the mathematical score is above the 90^{th}, 75^{th}, 95^{th} percentile respectively and took a mortgage at most 1 year before. The dependent variable is the mortgage loan interest rate. The d_nonfinlit_one means is there a colleague, for whom the mathematical score is below the 50^{th} percentile and took a mortgage at most 1 year before. The d_ofinlit_one shows those who are between the 50^{th} and 90^{th} or we cannot cathegorise the occupation based on mathematic skills. Standard errors are clustered on company level. *** p<0.01, ** p<0.05, * p<0.1

The main specification (Table 4, first column) shows that for those, who are not good in mathematics (the skill is below the 50^{th} percentile) and has a financially literate colleague (the math skill is above the 90^{th} percentile and took a credit in the past one year) the mortgage interest rate is 0.3 percentage point lower than without a financially literate colleague. This magnitude is considerable since the average mortgage loan interest rate was 5.1 percentage point. The results also show that those who are not good in maths (the skill is below the 50^{th} percentile) but took a credit in the past one year does not have any effect on the colleagues' interest rate (insignifcance of parameter d_nonfinlit_one). This means that not only mortgage loan taking but math skills are together important to give a good advice for someone who is not financially literate.

We also include a dummy for presence of a mortgage loan taker colleague, whose math score is between 50^{th} and 90^{th} percentile. The negative sign and significance of this coefficient shows that getting advice from less skilled peers also matters.

The negative and significant sign of the number of mathematically skilled colleagues shows that these people can also give a good advice to their colleagues but the impact is smaller.

All in all the mathematical skill and the mortgage loan taking together are important when someone seeks for advice from colleagues.

4.2 Placebos and robustness checks

In the second and third columns of Table 4 there are robustness checks for the definition of financially literate colleagues based on different thresholds for mathematic skills. In the two specifications we define a broader and a narrower group of people to be mathematically skilled. In the broader definition we use those whose mathematical skills above the 75^{th}, in the narrower those, who are above the 95^{th} percentile. In both categories we also use only those who took a mortgage in the past year. In both cases we got intuitive results. In the 75^{th} percentile case the coefficient is somewhat smaller than in the main specification. This is intuitive because we include more people to the financially literate, who are not so skilled in mathematics, therefore the coefficient is somewhat lower. The smaller standard error is due to the fact that more people have financially literate colleagues than in the main specification. In the second case the magnitude is larger, which is also intuitive because we define the financial literacy more strictly. The larger standard error is due to the change in the number of treated employees but now in the other direction. There is no large change in the coefficient and significance in the other three observed variables.

In the next robustness check we change the threshold for small firms (Table 5). If we increase the number of employees the parameter of interest decreases gradually. This is intuitive since at a larger firm the chance of knowing a financially literate is smaller because by increasing the firm size the number of financially literate colleagues does not increse that much (see Table 6).

Since we do not know the mathematical skill for all the occupations we change the financially unskilled definition. We selected those occupational categories, where only basic skills (only primary or vocational education) are needed. The results are similar to the main specification, the parameter of interest is somewhat larger (see Table 7).

Table 5: Robustness check with different employee threshold

Nr of colleagues	<60	<70	<80	<90	<100
d_finlit_one	-0.280**	-0.243**	-0.223**	-0.170*	-0.118
	(0.131)	(0.116)	(0.109)	(0.101)	(0.0980)
d_nonfinlit_one	-0.0154	-0.00736	-0.0281	-0.0281	-0.0428
	(0.0460)	(0.0424)	(0.0396)	(0.0377)	(0.0359)
d_ofinlit_one	-0.102**	-0.0885**	-0.0969***	-0.0980***	-0.0905***
	(0.0421)	(0.0390)	(0.0365)	(0.0343)	(0.0332)
finlit_col_additional	-0.0159*	-0.00491	-0.00151	-0.00662	-0.00467
	(0.00813)	(0.00630)	(0.00576)	(0.00565)	(0.00538)
Observations	10,639	11,277	11,777	12,265	12,668
R-squared	0.371	0.368	0.369	0.369	0.367
Other covariates	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes
Mean of dep. variable	5.09	5.08	5.08	5.08	5.08

The table contains those mortgage loan takers, for whom the mathematical score is below the median and work at a small firm (with different employee thresholds). The parameter of interest is d_finlit_one, which shows is there a colleague, for whom the mathematical score is above the 90^{th} percentile and took a mortgage at most 1 year before. The dependent variable is the mortgage loan interest rate. The d_nonfinlit_one means is there a colleague, for whom the mathematical score is below the 50^{th} percentile and took a mortgage at most 1 year before. The d_ofinlit_one shows a colleague took a mortgage at most 1 year before and between the 50^{th} and 90^{th} percentile or we cannot cathegorise the occupation based on mathematic skills. Standard errors are clustered on company level. *** p<0.01, ** p<0.05, * p<0.1

To make sure that we indeed identified a peer-effect we make some placebo tests as well. In the first case we define those financially literate, who took a mortgage *after* the non-financially literate had taken. If this variable is significant that would mean that the peer-effect, which we estimate is some kind of firm specific effect, which is not related to the mechanism described in Section 3. This firm specific effect can be, for instance, if the employees of a firm get some special offer from a certain bank. In placebos (Table 8) the parameter of interest is not significant neither at the 50 employee threshold, nor for larger firms. The number of financially literate colleague, who did not take a mortgage is

Table 6: Number of financially literate colleagues by firm size (descriptive statistics)

Firm size	p90	mean	max
<50	0	0.007	4
<60	0	0.008	4
<70	0	0.011	6
<80	0	0.012	6
<90	0	0.013	6
<100	0	0.014	6

Table 7: Robustness check for occupational category 6-9

d_finlit_one	-0.434***
	(0.141)
d_nonfinlit_one	0.0167
	(0.0576)
d_ofinlit_one	-0.0559
	(0.0412)
finlit_col_additional	0.00785
	(0.00806)
Observations	10,732
R-squared	0.360
Sample	FEOR6-9
Other covariates	Yes
Time FE	Yes
District FE	Yes
Mean of dependent variable	5.2

The table contains those mortgage loan takers, who work in occupational category 6-9 (6 Agricultural and forestry occupations, 7 Industry and construction industry occupations, 8 Machine operators, assembly workers, drivers of vehicles, 9 Elementary occupations not requiring qualification) and work at a firm, where the number of employees is less than 50. For the parameter description see the previous table. The dependent variable is the mortgage loan interest rate. Standard errors are clustered on company level. *** p<0.01, ** p<0.05, * p<0.1

still significant. But it does not connect to the placebo test itself, it just shows that the number of financially literate colleagues still matters.

In the other placebo setup (Table 9) we test whether the financially non-literate have an effect on the financially literate. For this we define the "financially literate", who took a mortgage at most one year before and for whom the mathematical skill is below 25th. We define the"'financially non-literate" who are above the 90th, 75th and 50th percentile respectively. In our regression the dummy for the financially literate colleague is not significant. This means that the financially literate indeed has an effect on the non-literate.

Table 8: Placebo test: financially literate colleague, who took a mortgage *after*

Nr of coll.	<50	<60	<70	<80	<90	<100
d_finlit_one_after	-0.0903	0.0365	-0.0367	0.00324	0.0786	0.0552
	(0.144)	(0.133)	(0.139)	(0.139)	(0.137)	(0.135)
d_nonfinlit_one_after	-0.00421	2.77e-05	-0.00577	-0.0132	-0.0191	-0.0200
	(0.0546)	(0.0501)	(0.0473)	(0.0450)	(0.0434)	(0.0421)
d_ofinlit_one_after	-0.0165	-0.0254	-0.0278	-0.0312	-0.0217	-0.0332
	(0.0550)	(0.0504)	(0.0473)	(0.0451)	(0.0436)	(0.0425)
finlit_col_add	-0.0218**	-0.0196**	-0.0189**	-0.0123	-0.0165**	-0.0140*
	(0.0105)	(0.00945)	(0.00840)	(0.00818)	(0.00796)	(0.00761)
Observations	8,565	9,035	9,386	9,651	9,889	10,076
Other covariates	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes
Mean of dep. var.	5.10	5.09	5.09	5.09	5.08	5.08

The table contains those mortgage loan takers, for whom the mathematical score is below the median and work at a small firm. The parameter of interest is d_finlit_one_after , which shows is there a colleague, for whom the mathematical score is above the 90th percentile and took a mortgage at most 1 year after. The dependent variable is the mortgage loan interest rate. The d_nonfinlit_one_after means is there a colleague, for whom the mathematical score is below the 50th percentile and took a mortgage at most 1 year after. The d_ofinlit_one_after shows a colleague took a mortgage at most 1 year after and between the 50th and 90th or we cannot categorise the occupation based on mathematic skills. Standard errors are clustered on company level. *** p<0.01, ** p<0.05, * p<0.1

The existence of the peer-effect shows that the Hungarian banking system is not competitive enough and a large part of the consumer surplus stays at the banks. To estimate this loss of consumer surplus we make a simple back-of-the-envelope calculation. The number of financially non-literate, who took a mortgage between 2015-2019 is more than 38 thousand. The average principal is HUF 7.4 million (€ 18500), the estimated peer-effect

Table 9: Placebo test: "financially literate" are below p25, treated group is above p90, p75 and p50 respectively

Sample	math>p90	math>p75	math>p50
d_finlit_one	-0.0749	-0.0721	-0.0638
	(0.135)	(0.0554)	(0.0471)
d_nonfinlit_one	0.0757	-0.0736	-0.0626
	(0.0909)	(0.0631)	(0.0540)
d_ofinlit_one	-0.0306	-0.0785***	-0.0877***
	(0.0672)	(0.0228)	(0.0194)
finlit_col_additional	-0.00623	-0.0149***	-0.0144***
	(0.00447)	(0.00363)	(0.00345)
Observations	2,017	19,103	26,900
R-squared	0.423	0.319	0.318
Other covariates	Yes	Yes	Yes
Time FE	Yes	Yes	Yes
District FE	Yes	Yes	Yes
Mean of dependent variable	4.53	4.78	4.80

The table contains those mortgage loan takers, for whom the mathematical score is above the 90^{th}, 75^{th} and 50^{th} percentile and work at a firm, where the number of employees is less than 50. The parameter of interest is d_finlit_one, which shows is there a colleague, for whom the mathematical score is below the 25^{th} percentile and took a mortgage at most 1 year before. The dependent variable is the mortgage loan interest rate. The d_nonfinlit_one means is there a colleague, for whom the mathematical score is above the 90^{th} percentile and took a mortgage at most 1 year before. The d_ofinlit_one shows a colleague took a mortgage at most 1 year before and between the 50^{th} and 90^{th} or we cannot categorise the occupation based on mathematic skills. Standard errors are clustered on company level. *** p<0.01, ** p<0.05, * p<0.1

is -0.302 percentage point. This means that the financially non-literate households payed at least HUF 85.3 billion (€ 213 million) more due to they did not choose the loan with the best conditions. This amount of money is 46% of the one year payroll of these people.

Subtracting the cost related to mortgage lending (based on The Report on Financial Stability 2019 May: financing costs 2.4, operational cost 1.1, risk cost 0.4 percentage point) from the total interest (5.1 percentage point) we get 1.2 percentage point profit on each loan[1]. The estimated impact of 0.3 percentage point is roughly one quarter of the banks' markup.

[1]One should keep in mind that this profit should cover the required rate of return on capital

4.3 Heterogenous effects based on the strength of competition between banks

In this subsection we focus on two bank related issues to better understand the mechanism behind the identified peer-effect. Firstly, we test how our results related to presence of banks in districts. We think that bank presence is related to competition among banks, i.e. the more the number of different financial institutions in a district the higher the competition. It is unclear how peer-effect is related to competition. On the one hand, low competition may lead to more relevance of good advice suggesting higher effect compared to highly competitive markets. On the other hand if competition is low then the number of choices for the borrowers are limited, therefore advice may have lower impact. Secondly, we test how the inclusion of bank fixed effects change our results. Intuitively, if the estimated coefficients decrease (in absolute terms) that indicates that the advice of peers includes which bank to choose. However if the coefficients do not change considerably that is a sign that advice is not related to the choice of banks. These two tests are feasible due to the fact that we run the related regressions on a larger sample. We enlarge our sample by assigning the average mathematics score of those observations that share the same three digit occupational code (FEOR) and the mathematics score is missing. Moreover, we alter our original specification and do not exclude borrowers with mathematics score above the median. We control for own mathematics skill by including an indicator variable that takes the value of 0 if the mathematics score is below the median, the value of 1 if it is above the median but below the 90^{th} percentile, and 2 if it is above.

The first column of Table 10 shows the estimated peer effect if all borrowers and districts are included in the sample and no bank fixed effects are estimated. We can look at this as a counterpart of the original estimations, though on the full sample. According to the results peer-effect accounts to -14 basis points, while the direct effect related to skills is -16 (-31) basis points in case of borrowers with mathematics skill between the 50^{th} and 90^{th} percentile (above the 90^{th} percentile). Next, we restrict our sample to that decile of districts where the number of financial institutions is the lowest, i.e where competition is presumably the lowest. Peer-effect is almost triple as high as in the baseline, while direct effects halved. We suspect that the reason is that in districts where the competition is low it is more difficult to find the good offer than in other districts, therefore advice of peers can be more valuable. The estimated peer effect in the third column is -10 basis point. The only difference between this regression compared to the first one is that here bank fixed effects are also included. The comparison of the estimated parameter in the first and

Table 10: Heterogeneity based on competition between banks

	(1)	(2)	(3)	(4)
d_finlit_one	-0.138***	-0.367***	-0.0995**	-0.239*
	(0.0403)	(0.136)	(0.0415)	(0.129)
d_nonfinlit_one	0.00354	0.0719	0.0162	0.0683
	(0.0224)	(0.0677)	(0.0193)	(0.0557)
d_less_finlit_one	-0.108***	-0.189***	-0.0602***	-0.109*
	(0.0215)	(0.0702)	(0.0188)	(0.0612)
maths:>90%	-0.314***	-0.169**	-0.202***	-0.0814
	(0.0246)	(0.0811)	(0.0222)	(0.0692)
maths:50-90%	-0.164***	-0.0743*	-0.106***	-0.0778**
	(0.0132)	(0.0416)	(0.0114)	(0.0350)
Constant	3.892***	4.290***	3.769***	4.003***
	(0.202)	(0.379)	(0.164)	(0.324)
Observations	33,161	3,833	33,161	3,833
R^2	0.347	0.357	0.509	0.556
Other covariates	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes
Bank FE	No	No	Yes	Yes
Competition proxy	No	Yes	No	Yes

The table contains all mortgage loan takers, who work at a firm, where the number of employees is less than 50 (the missing mathematical skills were imputed). The d_finlit_one shows is there a colleague, for whom the mathematical score is above the 90^{th} percentile and took a mortgage at most 1 year before. The dependent variable is the mortgage loan interest rate. The d_nonfinlit_one means is there a colleague, for whom the mathematical score is below the 50^{th} percentile and took a mortgage at most 1 year before. The d_less_finlit_one shows those colleagues, whose math score is between the 90^{th} and the 50^{th} percentile and took a mortgage at most 1 year before. Column (2) and (4) are restricted to those districts, where the number of banks is less than the country 10^{th} percentile. Standard errors are clustered on company level. *** p<0.01, ** p<0.05, * p<0.1

the third regressions suggest that the choice of bank is likely to be a relevant part of the peer advice as if we control for the bank then the effect considerably decreases. Moreover, the estimated direct effect decreases similarly. Finally, if we both restrict the sample and include bank fixed effects then the estimated peer effect will be between the first and the second regression. This result highlights that although the choice of bank is an important part of the peer-effect it is not the only channel through which colleagues help each other.

5 Conclusion

In our paper we used the whole universe of mortgage loans between 2015-2019 in Hungary for identifying peer-effect of co-workers. We find that if a mortgage loan-taker is financially unskilled than a co-worker, who has high mathematical skills and took a mortgage in the recent past has a significant negative effect on the loan-taker's interest rate. We also showed that mathematical skills and experience in mortgage loan taking are both important to be able to give a valuable advice. We showed that there are heterogeneity in peer-effects depending on the strength of competition among banks. If the magnitude of the competition is lower than the peer-effect is considerably higher. This result is intuitive since with a higher competition the price of a product (the interest rate in our case) is lower. In this case there is less room for bargain. In case of lower competition the value of a good advice is larger.

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