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Financial technology in developing economies: A note on digital lending in Turkey

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A R T I C L E I N F O

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A B S T R A C T

We examine the differences in the loan performance of fintech and bank borrowers in Turkey. Using data of 5.5 million consumer loans by the fifth-largest private commercial bank in Turkey and its fintech subsidiary, we demonstrate that fintech borrowers are on average younger, better educated, have higher income and savings levels, pay less interest and have better credit history than traditional bank borrowers. Furthermore, fintech borrowers are less likely to default. Superior performance of fintech loans is driven by the fintech firm's ability to identify creditworthy borrowers among individuals with low-credit scores. These results contrast with the earlier evidence for developed markets where fintech borrowers are found to be more risky.

1. Introduction

Studies examining the differences between traditional and fintech borrowers mainly focus on developed economies. However, fintech industry is essential for emerging economies where access to financing is limited due to low levels of financial literacy (Cole et al., 2011), regulatory constraints (Zetsche et al., 2017; Philippon, 2016), and lack of proper physical infrastructure (Yermack, 2018).

In this study, we examine whether there are significant differences in the performance of consumer loans in fintech and traditional lending in an emerging market. We use consumer loan data from the fifth-largest private bank (henceforth, the bank) operating in Turkey and its fintech subsidiary. Although the fintech firm is owned by the bank, both firms are separate entities with a different customer base. The loan application process is significantly different for these two firms, where evaluations by the bank rely on information analysis conducted by the loan officer while fintech loan evaluations rely on information processed with data analysis tools. The fintech platform examined here is the *only* platform in Turkey where all transactions are conducted without the intermediation of a bank. Lending activities are strictly regulated in Turkey since the 2001 banking crisis. In contrast to developed countries such as US, tight regulation over the peer-to-peer land marketplace for lending activities resulted in the development of fintech firms under existing banking groups (Banking Regulation and Supervision Agency of Turkey, 2005).

We find that fintech borrowers in Turkey are younger, better educated, have higher income and savings levels, better credit history, and pay less interest than traditional borrowers. They are also less likely to default. In developed economies, fintech borrowers are more likely to default since fintech firms target risky underbanked individuals (Tang, 2019; Erel and Liebersohn, 2020; Di Maggio and Yao, 2020). In contrast, we show that in emerging economies where lending activities are strictly regulated, fintech firms target higher-quality borrowers. Thus, growth in the fintech market share can significantly differ across emerging and developed markets. We attribute these contrasting results to the differences in the regulation of lending activities across countries.

2. Data

We obtain a proprietary dataset of over 5.5 million consumer loans offered by the bank and fintech firm between 2014 and 2019. Approximately 4 million observations are bank loans while the rest are fintech loans. For each loan, we have data on the date, loan size, maturity, interest rate and information about the borrower such as income, savings, age, gender, education,

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Table 1
Individual characteristics of fintech borrowers — Credit attributes.

Variable	Credit attributes								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Deposit amount	0.035* (630.2)								0.032* (563.6)
Nu. accounts		0.080* (568.4)							– –
Loan size			−0.066* (−363.1)						−0.061* (−304.4)
Maturity				−0.005* (−373.0)					−0.002* (−137.6)
Low credit score					−0.066 (−138.1)				−0.024* (−51.7)
Mid credit score						−0.059* (−151.0)			– –
High credit score							0.171* (343.5)		0.104* (207.7)
Interest rate								−0.041* (−103.7)	−0.015* (−39.2)
Intercept	0.5487	0.5721	1.2737	0.8211	0.7016	0.7401	0.6594	0.7488	1.1373
City & Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	5,580,562	5,580,562	5,580,562	5,580,562	5,580,562	5,580,562	5,580,562	5,580,562	5,580,562
R^2	14.5%	13.4%	10.5%	10.7%	8.7%	8.8%	10.3%	8.6%	18.1%

Results of the following model : $Fintech_{i,c,t} = \beta X_{i,t} + \mu_c + \varphi_t + \varepsilon_{i,c,t}$. Values in parentheses are t-statistics of the coefficients.
*Indicates statistical significance at 1% level.

Table 2
Individual characteristics of fintech borrowers: Demographic attributes.

Variable	Demographic attributes													
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Income	0.028* (287.6)													0.016* (−168.0)
Primary school		−0.221* (−498.0)												– –
High school			−0.150* (−406.5)											0.044* (−100.9)
Undergraduate				0.275* (742.7)										0.289* (−590.1)
Graduate					0.341* (395.4)									0.437* (−499.9)
Private sector						0.674* (104.6)								−0.060* (−46.82)
Public sector							0.138* (250.4)							−0.012* (−9.31)
Self employed								0.019* (23.7)						−0.041* (−28.69)
Retired									−0.215* (−0.2)					−0.010* (−7.42)
Unemployed										−0.025* (−8.1)				– –
Male											0.048* (112.9)			0.084* (−214.7)
Age												−0.011* (−685.8)		−0.009* (−414.5)
Young													0.241* (594.9)	– –
Intercept	0.4602	0.7084	0.7435	0.5303	0.6656	0.3256	0.6703	0.6977	0.7365	0.6981	0.6621	1.1031	0.5175	0.6203
City & Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	5,580,562	5,580,562	5,580,562	5,580,562	5,580,562	5,580,562	5,580,562	5,580,562	5,580,562	5,580,563	5,580,564	5,580,565	5,580,566	5,580,567
R^2	9.8%	12.3%	11.1%	16.7%	10.9%	8.6%	9.4%	8.4%	11.1%	8.4%	8.6%	15.5%	13.9%	26.0%

Results of the following model : $Fintech_{i,c,t} = \beta X_{i,t} + \mu_c + \varphi_t + \varepsilon_{i,c,t}$. Values in parentheses are t-statistics of the coefficients.
*Indicates statistical significance at 1% level.

occupation, and credit performance. See Appendix A for a detailed description of the variables and the descriptive statistics of the loan and borrower characteristics.

3. Methodology and results

To examine the ex-ante heterogeneity among the bank and fintech borrowers, we employ the following model (Di Maggio and Yao, 2020):

$$Fintech_{i,c,t} = \beta X_{i,t} + \mu_c + \varphi_t + \varepsilon_{i,c,t} \quad (1)$$

The dependent variable takes the value one if the borrower i, in city c, obtains a fintech loan in year t and otherwise 0. The independent variables are loan and borrower characteristics, $X_{i,t}$. We control the impact of year- and city-specific characteristics using fixed effects.

Tables 1 and 2 provide the estimates of the model with the credit and demographic attributes as independent variables. Fintech borrowers have accounts with higher deposit levels and more accounts with a positive balance. Fintech loans are smaller in size, have shorter maturities and are more likely to obtain higher credit scores, resulting lower interest rates. Controlling for other factors, one basis point (bps) increase in borrowing costs reduces the likelihood obtaining loans from the fintech firm by almost 2%. The univariate regressions indicate that fintech borrowers have higher income levels, are more likely to be young and less likely to be unemployed (Table 2). An undergraduate (graduate) degree increases the probability of obtaining a fintech loan by 28% (33%) while being a retiree reduces the probability of getting a fintech loan by 22%.

Table 3
Default characteristics of borrowers — Credit attributes.

Variable	Credit attributes								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Deposit amount	−0.003* (−124.1)								−0.002* (−68.1)
Nu. Accounts		−0.006* (−102.5)							– –
Loan size			0.004* (56.7)						0.002* (21.8)
Maturity				0.001* (183.7)					0.001* (142.4)
Low credit score					0.067* (339.5)				0.064* (315.1)
Mid credit score						−0.028 (−174.3)			– –
High credit score							−0.027* (−128.1)		−0.008* (−35.4)
Interest rate								0.012* (75.5)	0.013* (77.1)
Fintech	−0.016* (−46.6)	−0.010* (−55.0)	−0.013* (−71.7)	−0.009* (−51.8)	−0.011* (−62.1)	−0.016* (−92.4)	−0.011* (−62.1)	−0.014* (−77.9)	−0.001* (−6.5)
Intercept	−0.0146	−0.0177	−0.0637	−0.0537	−0.0306	−0.00311	−0.0208	−0.0403	−0.0824
City & Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	5,580,562	5,580,562	5,580,562	5,580,562	5,580,562	5,580,562	5,580,562	5,580,562	5,580,562
R^2	2.2%	2.1%	2.0%	2.5%	3.9%	2.5%	2.2%	2.1%	4.7%

Results of the following model : $Default_{i,c,t} = \beta X_{i,t} + \mu_c + \varphi_t + \gamma Fintech_{i,c,t} + \varepsilon_{i,c,t}$. Values in parentheses are t-statistics of the coefficients.
*Indicates statistical significance at 1% level.

Table 4
Default characteristics of borrowers — Demographic attributes.

Variable	Demographic attributes													
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Income	−0.0004* (−9.8)													0.0004* (10.8)
Primary school		0.012* (64.2)												– –
High school			0.007* (47.6)											−0.007* (−34.26)
Undergraduate				−0.015* (−91.8)										−0.024* (−102.6)
Graduate					−0.013* (−34.7)									−0.027* (−66.29)
Private sector						0.010* (64.0)								−0.027* (−46.03)
Public sector							−0.016* (−70.7)							−0.039* (−62.93)
Self employed								0.017 (51.3)						−0.015* (−22.18)
Retired									−0.017* (−76.0)					−0.038* (−59.14)
Unemployed										0.007* (5.3)				– –
Male											0.005* (27.5)			0.002* (−12.2)
Age												−0.001* (−74.3)		−0.0005* (−50.55)
Young													0.010* (56.2)	– –
Fintech	−0.014* (−79.4)	−0.012* (−66.3)	−0.013* (−72.0)	−0.009* (−50.0)	−0.013* (−74.4)	−0.015* (−84.0)	−0.013* (−73.3)	−0.014* (−81.7)	−0.017* (−93.1)	−0.014* (−81.2)	−0.014* (−82.4)	−0.018* (−98.8)	−0.017* (−92.5)	−0.010* (−51.86)
Intercept	−0.021	−0.027	−0.028	−0.019	−0.024	−0.030	−0.022	−0.025	−0.020	−0.025	−0.028	−0.002	−0.030	0.040
City & Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	5,580,562	5,580,562	5,580,562	5,580,562	5,580,562	5,580,562	5,580,562	5,580,562	5,580,562	5,580,562	5,580,562	5,580,562	5,580,562	5,580,562
R^2	2.0%	2.0%	2.0%	2.1%	2.0%	2.0%	2.0%	2.0%	2.1%	2.0%	2.0%	2.1%	2.0%	2.5%

Results of the following model : $Default_{i,c,t} = \beta X_{i,t} + \mu_c + \varphi_t + \gamma Fintech_{i,c,t} + \varepsilon_{i,c,t}$. Values in parentheses are t-statistics of the coefficients.

*Indicates statistical significance at 1% level.

To compare the loan performance of the bank and fintech firm, we use the following specification:

$$Default_{i,c,t} = \beta X_{i,t} + \mu_c + \varphi_t + \gamma Fintech_{i,c,t} + \varepsilon_{i,c,t} \quad (2)$$

The dependent variable takes the value one if the borrower i, in city c obtains a loan in year t, and defaults on his/her debt and zero else. Borrowers with high deposit levels are less likely to default (Table 3). As the number of accounts with a positive balance increases, default probability decreases. Borrowers are more likely to default as the loan size gets bigger and maturity gets longer. Borrowers in mid- and high-credit score groups are less likely to default than borrowers in low-credit score groups. A 1% increase in the interest rate on the loan is associated with a 1.3% increase in the default probability. Unlike their counterparts in developed markets, we document that fintech borrowers are *less* likely to default on their debt. We show that being a fintech borrower reduced default probability by 10 bps after controlling for credit attributes.

Table 4 controls for demographic attributes when examining the relationship between fintech lending and default probability. The univariate results indicate a negative relationship between income levels and default probability. Borrowers with under/graduate degrees are less likely to default than less educated borrowers. Retirees and those who work in the public sector are less likely to default on their debt than those who work in the private sector or are self-employed. These findings may be

Table A.1
Descriptive statistics of the full sample.

	Panel A: Bank					
	Observations	Mean	Std. Dev.	Min	Median	Max
Age	4059986	39.95	11.55	18.00	38.00	96.00
Loan size †	4059986	8.60	0.99	3.60	8.70	15.88
Maturity	4059986	26.80	13.55	1.00	24.00	120.00
Male	4059986	0.76	0.43	0.00	1.00	1.00
Young	4059986	0.68	0.47	0.00	1.00	1.00
Income †	4059986	7.04	2.23	−5.26	7.55	25.36
Private sector	4059986	0.64	0.48	0.00	1.00	1.00
Public sector	4059986	0.11	0.31	0.00	0.00	1.00
Self employed	4059986	0.06	0.23	0.00	0.00	1.00
Retired	4059986	0.18	0.38	0.00	0.00	1.00
Unemployed	4059986	0.00	0.06	0.00	0.00	1.00
Primary school	4059986	0.26	0.44	0.00	0.00	1.00
High school	4059986	0.43	0.50	0.00	0.00	1.00
Undergraduate	4059986	0.24	0.43	0.00	0.00	1.00
Graduate	4059986	0.02	0.15	0.00	0.00	1.00
High-credit score	4059986	0.12	0.32	0.00	0.00	1.00
Mid-credit score	4059986	0.67	0.47	0.00	1.00	1.00
Low-credit score	4059986	0.21	0.41	0.00	0.00	1.00
Default	4059986	0.04	0.20	0.00	0.00	1.00
Nu. Accounts	4059986	0.81	1.00	0.00	1.00	56.00
Deposit amount †	4059986	2.26	3.00	−5.26	0.35	18.12
Interest rate	4059986	1.64	0.44	1.00	1.54	3.60
Variable	Panel B: Fintech					
	Observations	Mean	Std. Dev.	Min	Median	Max
Age	1520576	32.88	7.41	18.00	31.00	74.00
Loan size †	1520576	8.38	1.01	2.57	8.44	10.90
Maturity	1520576	22.17	15.87	1.00	18.00	72.00
Male	1520576	0.79	0.41	0.00	1.00	1.00
Young	1520576	0.93	0.26	0.00	1.00	1.00
Income †	1520576	7.92	0.60	−0.36	7.86	21.54
Private sector	1520576	0.72	0.45	.00	1.00	1.00
Public sector	1520576	0.18	0.38	0.00	0.00	1.00
Self employed	1520576	0.05	0.23	0.00	0.00	1.00
Retired	1520576	0.03	0.17	0.00	0.00	1.00
Unemployed	1520576	0.00	0.05	0.00	0.00	1.00
Primary school	1520576	0.05	0.23	0.00	0.00	1.00
High school	1520576	0.24	0.42	0.00	0.00	1.00
Undergraduate	1520576	0.60	0.49	0.00	1.00	1.00
Graduate	1520576	0.11	0.31	0.00	0.00	1.00
High-credit score	1520576	0.24	0.43	0.00	0.00	1.00
Mid-credit score	1520576	0.65	0.48	0.00	1.00	1.00
Low-credit score	1520576	0.11	0.31	0.00	0.00	1.00
Default	1520576	0.01	0.11	0.00	0.00	1.00
Nu. Accounts	1520576	1.62	1.70	0.00	1.00	133.00
Deposit amount †	1520576	4.53	3.42	−5.26	4.98	15.46
Interest rate	1520576	1.59	0.45	1.01	1.44	2.93

In this table, we present the descriptive statistics for loan and borrower characteristics. Panel A provides the descriptive statistics for the bank. Panel B provides the descriptive statistics for the fintech firm. The first column in each panel corresponds to variable names. The second column presents the number of observations. The third and fourth columns respectively show the sample mean and standard deviation. Columns five, six, and seven present minimum, median and maximum values for a given variable, respectively. We adjust the variables that are denoted by † to changes in the inflation and use logarithmic transformations.

attributable to the uncertainties associated with working in the private sector or running a business in an emerging economy, affecting debt repayment.

Being a male increases the probability of default by five bps. Also, older people are less likely to default. Similar to findings in Table 3, fintech borrowers are less likely to default even after controlling for all other demographic attributes. Being a fintech borrower reduces the probability of default by one percentage point. Since our sample's average probability of default is around 3%, we argue that our results are both statistically and economically significant.

To check whether our results are affected by unobserved heterogeneity between fintech and bank loans or fintech and bank borrowers, we apply the propensity score matching (PSM) methodology and repeat our analysis using two subsamples; one that has similar fintech and bank loans with respect to loan size, maturity and month of loan initiation, and another that has similar borrower characteristics such as income, age and credit score. We provide the details of our PSM analyses in Appendix B. We observe that even after controlling for unobserved heterogeneity in loans and borrowers along with all other credit and demographic characteristics, fintech loans have lower probability of default unlike their counterparts in the developed markets.

Similarly, we present the results of the interaction terms in our regression analysis in Appendix C. In line with our findings for PSM analysis, we see that the default rate for low-credit score borrowers of the fintech firm is significantly lower compared to the performance of the bank borrowers with similar credit scores. Moreover, the superior performance of a fintech firm seems to be driven by its ability to identify individuals that are in a neglected subsample of the market. Specifically, our results indicate that using sophisticated machine learning and data analysis tools,

Table B.1
Propensity score matching (Matched loans).

Panel A: Logistic propensity score model results				
Variable	Coefficient	Standard error	Wald Chi-Square	p-value
Intercept	−2.883	0.022	17555.72	0.00
Maturity	0.032	0.000	33490.32	0.00
Loan size	−0.159	0.003	3496.31	0.00
Month Of Initiation	−0.005	0.001	55.46	0.00
Panel B: Propensity score characteristics				
Average propensity score of data				3.30%
Standard deviation of propensity score of data				1.47%

Results of the following logistic propensity-score model : $Pr(Default) = \alpha + \beta_1 LoanSize_i + \beta_2 Maturity_i + \beta_3 MonthOfInitiation_i + \epsilon_i$. Panel A provides the results of the logistic propensity-score model. Details on the Loan size and maturity are provided in Appendix A. We control for the month of initiation to capture any seasonal effect in loan characteristics for both fintech and bank loans. Panel B provides the mean and standard deviation of the predicted propensity scores in our full sample.

Table B.2
Descriptive statistics of the matched sample (Matched loans).

Variable	Observations	Fintech		Bank		Difference	
		Mean	Std. Dev.	Mean	Std. Dev.	Bank–Fintech	t-statistic
Age	1,176,529	33.81	7.82	40.83	11.34	7.02	257.59
Loan size †	1,176,529	8.64	0.85	8.58	0.99	−0.06	−14.64
Income †	1,176,529	7.84	0.59	6.54	2.67	−1.31	−211.88
Maturity	1,176,529	34.33	4.30	33.59	5.03	−0.73	−39.43
Deposit amount †	1,176,529	3.83	3.38	1.70	2.59	−2.13	−310.09
Male	1,176,529	0.78	0.41	0.77	0.42	−0.02	−15.77
Private sector	1,176,529	0.69	0.46	0.63	0.48	−0.07	−55.42
Public sector	1,176,529	0.19	0.39	0.10	0.30	−0.09	−110.24
Self employed	1,176,529	0.06	0.23	0.05	0.22	0.00	−8.31
Retired	1,176,529	0.04	0.20	0.20	0.40	0.16	164.95
Unemployed	1,176,529	0.00	0.06	0.01	0.07	0.00	11.42
Primary school	1,176,529	0.07	0.26	0.29	0.45	0.22	203.77
High school	1,176,529	0.28	0.45	0.44	0.50	0.16	132.93
Undergraduate	1,176,529	0.57	0.50	0.18	0.39	−0.38	−375.83
Graduate	1,176,529	0.09	0.28	0.01	0.12	−0.07	−189.98
High credit score	1,176,529	0.17	0.37	0.09	0.29	−0.08	−97.82
Mid credit score	1,176,529	0.69	0.46	0.65	0.48	−0.03	−28.46
Low credit score	1,176,529	0.14	0.35	0.25	0.44	0.11	102.80
Interest rate	1,176,529	1.51	0.45	1.31	0.71	−0.21	−122.18
Young	1,176,529	0.90	0.29	0.65	0.48	−0.25	−223.85
Nu. Accounts	1,176,529	1.36	1.47	0.63	0.81	−0.72	−303.01
Default	1,176,529	0.03	0.18	0.06	0.24	0.03	53.23

In this table, we present the descriptive statistics for loan and borrower characteristics of our subsample where the observations are matched with respect to loan characteristics. Second column presents the number of observations for a given variable. Third and fourth columns present the mean and standard deviation of a given variable for the fintech loans, respectively. Fifth and sixth columns respectively present the mean and standard deviation of a given variable for the bank loans. Column seven shows the mean difference. The last column corresponds to the t-statistic of a test that has a null hypothesis that bank and fintech loans have the same mean for a given variable. We adjust the variables that are denoted by † to changes in the inflation and use logarithmic transformations.

fintech firms can identify creditworthy individuals among the group of borrowers who are less educated and who have low-credit scores. This, in turn, reduces the quality of the pool of borrowers in those subsegments of the market for the bank.

Although the PSM analysis indicates that our results are robust to unobserved heterogeneity we also acknowledge that it is difficult to claim strict causality. We attribute the difference between Turkish and US fintech borrowers to the strict restrictions on (non-bank) lending activities in Turkey.

4. Conclusion

We provide new evidence on fintech lending by documenting that in an emerging market where lending is strictly regulated, fintech companies tend to grow their market share by identifying high-quality borrowers. Specifically, we document that fintech borrowers in Turkey are on average younger, better educated, have higher income and savings, pay less interest, and have better credit scores than borrowers of the bank. In turn, fintech borrowers are less likely to default even after controlling for borrower and loan characteristics.

These results are in contrast with the findings in developed markets where fintech firms target risky borrowers. Our results suggest that fintech firms' growth in consumer loan markets can take alternative paths in emerging economies with different regulatory environments.

Appendix A. Data

We obtain a proprietary dataset of over 5.5 million consumer loans offered by the bank and fintech firm between 2014 and 2019. Our sample is skewed towards loans provided by the bank, with approximately 4 million observations attributed to the bank

Table B.3
Default characteristics of borrowers — Credit attributes (Matched loans)

Variable	Credit attributes								
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Deposit amount	−0.00378*								−0.0025*
	(−47.36)								(−31.04)
Nu. Accounts		−0.0105*							–
		(−45.51)							–
Loan size			0.00792*						0.0122*
			(34.30)						(23.48)
Maturity				0.00154*					−0.00129*
				(33.97)					(−11.95)
Low credit score					0.0821*				0.0804*
					(160.62)				(153.15)
Mid credit score						−0.0443*			–
						(−96.82)			–
High credit score							−0.0475*		−0.0229*
							(−68.29)		(−32.14)
Interest rate								0.0237*	0.0216*
								(59.63)	(40.81)
Fintech	−0.00796*	−0.00845*	−0.0141*	−0.0148*	−0.0100*	−0.0156*	−0.0111*	−0.0156*	−0.00368*
	(−12.97)	(−13.79)	(−23.55)	(−24.80)	(−16.89)	(−26.13)	(−18.48)	(−26.21)	(−6.04)
Intercept	−0.0319	−0.0322	−0.1143	−0.0973	−0.0494	−0.00693	−0.0361	−0.0733	−0.1336
City & Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1,176,529	1,176,529	1,176,529	1,176,529	1,176,529	1,176,529	1,176,529	1,176,529	1,176,529
R^2	2.0%	2.0%	1.9%	1.9%	4.0%	2.6%	2.2%	2.1%	4.6%

Results of the following model : $Default_{i,c,t} = \beta X_{i,t} + \mu_c + \varphi_t + \gamma Fintech_{i,c,t} + \varepsilon_{i,c,t}$. Values in parentheses are t-statistics of the coefficients.
*Indicates statistical significance at 1% level.

loans and the remaining 1.5 million to fintech loans.[1] Each entry in our sample contains information regarding the loan, such as the date, loan size, maturity, interest rate, and information about the borrower, such as income, savings, age, gender, education, occupation, and credit performance. A detailed description of the variables is provided below. We provide the descriptive statistics about the loan and borrower characteristics of both the bank and the fintech firm in Table A.1. We observe that fintech borrowers are younger compared to borrowers of the bank. Specifically, the average age of a bank borrower is around 40, whereas fintech borrower's average age is around 33. People under the age of 45 use 93% of the fintech loans in our sample.

Fintech borrowers, on average have higher savings levels compared to bank borrowers. The number of accounts with a positive balance is also higher for fintech borrowers. We also observe that an average fintech borrower has a larger income than an average bank borrower. 24% (12%) of the fintech (bank) borrowers had a high credit score at loan initiation. 11% of fintech borrowers in our sample had a low credit score at loan initiation, whereas 21% of the bank borrowers had a low credit score. We observe that 72% (64%) of the fintech (bank) borrowers work in the private sector. The difference in terms of borrowers' occupation is most significant when we examine the retirees. The percentage of retirees borrowing from the bank is around 18%, whereas only 3% of the fintech borrowers are retirees. In terms of borrowers' education, 60% of the fintech borrowers have an undergraduate degree. On the other hand, most of the bank borrowers (43%) only have a high-school degree.

Loan specific variables

- **Loan Size**† : Loan size is the TL denominated amount borrowed from the bank or from the fintech firm.
- **Interest Rate**: Interest Rate is the monthly interest rate on the loan.
- **Maturity**: Maturity of the loan.

Savings and income

- **Income**† : Borrower's monthly income at the initiation of the loan.
- **Deposit Amount**†: Borrower's deposit levels in the bank or in the fintech firm.at the initiation of the loan.
- **Nu. Accounts:** Number of accounts of the borrower (with positive balance) in the bank or in the fintech firm at the loan initiation.

Past credit performance

- **High-credit score**‡: A dummy variable that takes one if the borrower is in the high-credit score group.
- **Mid-credit score**‡: A dummy variable that takes one if the borrower is in the mid-credit score group.
- **Low-credit score**‡: A dummy variable that takes one if the borrower is in the low-credit score group.

Borrower's personal characteristics

- **Male**: A dummy variable that takes one if the borrower is male.
- **Age**: Age of the borrower at the initiation of the loan.
- **Young**: A dummy variable that takes one if the borrower's age is less than 45.
- **Primary School**: A dummy variable that takes one if the borrower's education ends after obtaining a primary school degree.
- **High School**: A dummy variable that takes one if the borrower's education ends after obtaining a high school degree.
- **Undergraduate**: A dummy variable that takes one if the borrower's education ends after obtaining an undergraduate degree.

[1] Our sample consists 2,567,333 million unique individuals; 366,975 of which are obtained consumer loans only from fintech firm, 55,589 of which obtained both traditional and fintech loans and the remaining 2.2 million obtained loans only from the bank. Therefore, our sample is skewed towards traditional banking channels in terms of number of borrowers, as well.

Table B.4
Default characteristics of borrowers — Demographic attributes (Matched loans).

Variable	Demographic attributes													
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Income	0.00209* (22.55)													0.00316* (32.88)
Primary school		0.0136* (27.20)												– –
High school			0.0103* (23.44)											−0.00759* (−14.34)
Undergraduate				−0.0224* (−42.38)										−0.0328* (−49.55)
Graduate					−0.0225* (−16.36)									−0.0408* (−28.15)
Private sector						0.0175* (38.79)								−0.0364* (−24.18)
Public sector							−0.0276* (−40.26)							−0.0573* (−35.38)
Self employed								0.0288* (29.95)						−0.0149* (−8.5)
Retired									−0.0251* (−43.85)					−0.048* (−29.19)
Unemployed										0.0126* (4.10)				– –
Male											0.00305* (5.98)			−0.00018 (−0.35)
Age												−0.00101* (−51.16)		−0.00095* (−34.93)
Young													0.0174* (36.71)	– –
Fintech	−0.0165* (−27.39)	−0.0118* (−19.53)	−0.0130* −21.58	−0.00676* (−10.79)	−0.0131* (−21.68)	−0.0153* (−25.67)	−0.0120* (−19.98)	−0.0150* (−25.14)	−0.0184* (−30.49)	−0.0147* (−24.60)	−0.0148* (−24.76)	−0.0219* (−35.76)	−0.0192* (−31.42)	−0.0109* (−16.73)
Intercept	−0.0586	−0.0449	−0.0464	−0.0335	−0.0412	−0.0509	−0.0386	−0.0425	−0.0337	−0.0419	−0.0441	0.00179	−0.0511	0.0319
City & Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1,176,529	1,176,529	1,176,529	1,176,529	1,176,529	1,176,529	1,176,529	1,176,529	1,176,529	1,176,529	1,176,529	1,176,529	1,176,529	1,176,529
R^2	1.9%	1.9%	1.9%	2.0%	1.9%	2.0%	2.0%	1.9%	2.0%	1.9%	1.9%	2.1%	2.0%	2.6%

Results of the following model : $Default_{i,c,t} = \beta X_{i,t} + \mu_c + \varphi_t + \gamma Fintech_{i,c,t} + \varepsilon_{i,c,t}$. Values in parentheses are t-statistics of the coefficients.

*Indicates statistical significance at 1% level.

Table B.5
Propensity score matching (Matched borrowers).

Panel A: Logistic propensity score model results				
Variable	Coefficient	Standard error	Wald Chi-Square	p-value
Intercept	−2.108	0.011	37777.89	0.00
Age	0.005	0.0002	587.66	0.00
Income	−0.047	0.001	2362.45	0.00
High credit score	0.015	0.001	38097.09	0.00
Mid credit score	0.005	0.001	97957.90	0.00
Panel B: Propensity score characteristics				
Average propensity score of data				3.29%
Standard deviation of propensity score of data				3.18%

Results of the following logistic propensity-score model : $Pr(Default) = \alpha + \beta_1 Age_i + \beta_2 Income_i + \beta_3 HighCreditScore_i + \beta_4 MidCreditScore_i + \epsilon_i$. Panel A provides the results of the logistic propensity-score model. Details on the age, income, mid-credit score and high-credit score are provided in Appendix A. Panel B provides the mean and standard deviation of the predicted propensity scores in our full sample.

- **Graduate**: A dummy variable that takes one if the borrower's education ends after obtaining a master's degree.
- **Private Sector**: A dummy variable that takes one if the borrower works in a private firm at the loan initiation.
- **Public Sector**: A dummy variable that takes one if the borrower works in public service at the loan initiation.
- **Self Employed**: A dummy variable that takes one if the borrower is self-employed at the loan initiation.
- **Retired**: A dummy variable that takes one if the borrower is retired at the loan initiation.
- **Unemployed:** A dummy variable that takes one if the borrower is unemployed at the initiation of the loan.

We use the logarithmic transformations of the variables that are indicated by †. Variables that are indicated by ‡ capture the past credit performance of the borrower. We label a borrower as high credit score if the probability of default for that borrower (delinquency rate) at the loan initiation is less than 1%. Any borrower who has a probability of default between 1% and 3% is labelled a mid-credit score. Finally, we label a borrower as low credit score if the probability of default is greater than 3% at the loan initiation. Each observation in our sample has information about the probability of default of the borrower at the loan initiation. The bank and the fintech firm have proprietary techniques to assess the probability of default of an individual.

Appendix B. Propensity score matching

Matching observations with respect to loan characteristics

To check whether our results contain any bias due to unobserved heterogeneity in fintech and bank loans, we apply propensity score matching approach (PSM) to make fintech and bank loans more comparable. Specifically, we match the loans in three dimensions, loan size, maturity and month of loan initiation. To that end, we estimate the following logistic propensity-score model for all loans in our sample:

$$Pr(Default) = \alpha + \beta_1 LoanSize_i + \beta_2 Maturity_i + \beta_3 MonthOfInitiation_i + \epsilon_i \quad (3)$$

Table B.6
Descriptive statistics of the matched sample (Matched borrowers).

Variable	Observations	Fintech		Bank		Difference	
		Mean	Std. Dev.	Mean	Std. Dev	Bank–Fintech	t-statistic
Age	603,813	29.52	4.97	29.96	5.89	0.45	25.91
Loan size †	603,813	8.10	0.88	8.38	0.84	0.28	108.92
Income †	603,813	7.64	0.50	7.55	0.56	−0.09	−92.29
Maturity	603,813	25.28	15.26	26.24	13.03	0.96	23.26
Deposit amount †	603,813	2.77	3.07	1.66	2.44	−1.11	−141.48
Male	603,813	0.82	0.38	0.79	0.41	−0.04	−30.34
Private sector	603,813	0.73	0.44	0.81	0.39	0.08	64.19
Public sector	603,813	0.17	0.38	0.08	0.28	−0.09	−94.30
Self employed	603,813	0.08	0.27	0.08	0.27	0.00	5.03
Retired	603,813	0.00	0.05	0.01	0.07	0.00	14.60
Unemployed	603,813	0.00	0.06	0.00	0.06	0.00	−2.82
Primary school	603,813	0.07	0.26	0.23	0.42	0.16	135.24
High school	603,813	0.32	0.47	0.52	0.50	0.19	128.26
Undergraduate	603,813	0.53	0.50	0.24	0.43	−0.29	−219.70
Graduate	603,813	0.07	0.26	0.02	0.12	−0.06	−110.03
High credit score	603,813	0.00	–	0.00	–	0.00	–
Mid credit score	603,813	0.00	–	0.00	–	0.00	–
Low credit score	603,813	1.00	–	1.00	–	0.00	–
Interest rate	603,813	1.50	0.31	1.52	0.46	0.03	19.58
Young	603,813	0.99	0.08	0.98	0.12	−0.01	−27.22
Nu. Accounts	603,813	1.05	1.19	0.63	0.76	−0.43	−160.17
Default	603,813	0.05	0.21	0.10	0.30	0.05	61.93

In this table, we present the descriptive statistics for loan and borrower characteristics of our subsample where the observations are matched with respect to borrower characteristics. Second column presents the number of observations for a given variable. Third and fourth columns present the mean and standard deviation of a given variable for the fintech loans, respectively. Fifth and sixth columns respectively present the mean and standard deviation of a given variable for the bank loans. Column seven shows the mean difference. The last column corresponds to the t-statistic of a test that has a null hypothesis that bank and fintech loans have the same mean for a given variable. We adjust the variables that are denoted by † to changes in the inflation and use logarithmic transformations.

Table B.7
Default characteristics of borrowers — Credit attributes (Matched borrowers).

Variable	Credit attributes					
	(1)	(2)	(3)	(4)	(5)	(6)
Deposit amount	−0.00856* (−61.59)					−0.00768* (−55.5)
Nu. Accounts		−0.0239* (−58.28)				– –
Loan size			0.0233* (54.68)			0.00159* (3.28)
Maturity				0.00253* (95.45)		0.00235* (78.97)
Interest rate					0.0416* (41.14)	0.0385* (37.79)
Fintech	−0.0277* (−31.42)	−0.0273* (−30.95)	−0.0289* (−32.89)	−0.0331* (−38.28)	−0.0300* (−33.87)	−0.0188* (−21.03)
Intercept	−0.0382	−0.0315	−0.2395	−0.1163	−0.1014	−0.1821
City & Year FE	Yes	Yes	Yes	Yes	Yes	Yes
R2	2.6%	2.6%	2.5%	3.5%	2.3%	4.2%

Results of the following model : $Default_{i,c,t} = \beta X_{i,t} + \mu_c + \varphi_t + \gamma Fintech_{i,c,t} + \varepsilon_{i,c,t}$. Values in parentheses are t-statistics of the coefficients.
*Indicates statistical significance at 1% level.

The independent variables loan size and maturity are defined in Appendix A. We provide the results of logistic propensity-score model along with the sample mean and standard deviation of estimated propensity scores in Table B.1. In Table B.1, we observe that the probability of default is higher on average for loans that are smaller in size and that have longer maturities. We control for the month of initiation to capture any seasonal effect in loan characteristics for both fintech and bank loans. Table B.1 Panel B shows that the mean and standard deviation of the estimated propensity scores are 3.30% and 1.47%, respectively.

Instead of examining the exactly matched propensity score subsamples, we round the propensity scores to second digit after the decimal to obtain subsamples where there are enough observations for statistical inference. We observe that even after aggregating subsamples by rounding the propensity scores, some subsamples have a limited number (if any) of fintech loans. This indicates that fintech loans may have specific characteristics that can lead to selection bias in our initial analysis. In our propensity score matching analysis, we use a subsample that has over 1.1 million loans, 16% of which are fintech loans and the percentage of defaults is around 6%. We provide the descriptive statistics for the variables in Table B.2. We observe that difference in the loan size and the maturity of the bank and fintech loans are smaller compared to our original sample, as expected from the matching procedure. In our full sample, bank loans are larger in size. However in the matched sample, the average fintech loan is larger in size compared to the average bank loan. Even though statistically significant, the difference in loan size between fintech and bank loans in our subsample corresponds to 330 Turkish Lira (TL) [approximately 40 USD] which is economically insignificant. The difference in the full sample is more than 1000 TL which is approximately the 20% of the average loan in our sample.

Table B.8
Default characteristics of borrowers – Demographic attributes (Matched borrowers).

Variable	Demographic attributes													
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Income	0.00740* (11.07)													0.00591* (6.96)
Primary school		0.0341* (36.95)												– –
High school			0.0157* (21.54)											−0.0174* (−17.82)
Undergraduate				−0.0407* (−50.33)										−0.0543* (−48.47)
Graduate					−0.0351* (−16.24)									−0.0668* (−28.62)
Private sector						−0.00319* (−3.58)								−0.058* (−23.97)
Public sector							−0.0357* (−29.63)							−0.0816* (−30.76)
Self employed								0.0321* (24.20)						−0.0359* (−13.11)
Retired									0.00826 (1.52)					−0.0598* (−10.09)
Unemployed										0.00229 (0.37)				– –
Male											0.00862* (9.65)			0.000499 (0.55)
Age												0.00118* (18.54)		0.000476* (6.19)
Young													−0.0268* (−8.49)	– –
Fintech	−0.0375* (−42.81)	−0.0314* (−35.63)	−0.0336* (−38.20)	−0.0251* (−27.97)	−0.0346* (−39.42)	−0.0368* (−42.09)	−0.0333* (−37.91)	−0.0365* (−41.89)	−0.0365* (−41.91)	−0.0365* (−41.94)	−0.0369* (−42.34)	−0.0358* (−41.12)	−0.0362* (−41.56)	−0.0194* (−21.11)
Intercept	−0.0951	−0.0452	−0.0457	−0.0253	−0.0374	−0.0364	−0.0327	−0.0397	−0.0389	−0.0388	−0.0453	−0.0758	−0.0129	−0.0111
City & Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	603,813	603,813	603,813	603,813	603,813	603,813	603,813	603,813	603,813	603,813	603,813	603,813	603,813	603,813
R^2	2.1%	2.3%	2.1%	2.4%	2.1%	2.0%	2.2%	2.1%	2.0%	2.0%	2.0%	2.1%	2.0%	2.9%

Results of the following model : $Default_{i,c,t} = \beta X_{i,t} + \mu_c + \varphi_t + \gamma Fintech_{i,c,t} + \varepsilon_{i,c,t}$. Values in parentheses are t-statistics of the coefficients.

*Indicates statistical significance at 1% level.

Similarly the difference in maturities between bank and fintech loans are less than 1 month in the matched subsample whereas in the original subsample the difference is around 4.5 months. Thus, our propensity matching procedure yields satisfactory matched results in that the matched set of loans are more similar in terms of loan size, maturity and initiation date characteristics as compared to the original full sample.

We then repeat our analysis in the original manuscript with the matched subsample. Specifically, we run the following model to compare loan performance of the bank and the fintech firm:

$$Default_{i,c,t} = \beta X_{i,t} + \mu_c + \varphi_t + \gamma Fintech_{i,c,t} + \varepsilon_{i,c,t} \quad (4)$$

Tables B.3 and B.4 provide the estimates of the model with the credit and demographic attributes as independent variables from the matched subsample. We observe that our baseline results are robust when we use the subsample where fintech and bank loan characteristics are similar. Specifically, in Table B.3, we document that borrowers with high deposit levels are less likely to default. Similarly, as the number of accounts with a positive balance increases, the default probability decreases. In line with our baseline results, we show that the borrowers are more likely to default as the loan size gets bigger and the maturity gets longer. Borrowers with mid- and high- credit scores are less likely to default than borrowers with low-credit score. In the matched subsample, we observe that a 1% increase in the interest rate on the loan is associated with 2.1% increase in the default probability. Finally, similar to our baseline findings, we document that in the subsample where the characteristics of fintech and bank loans are similar, fintech loans are *less* likely to default even after controlling for all borrower and loan characteristics. The coefficient that measures the effect of being a fintech borrower on default probability varies between −156 basis points (bps) and -80bps. We show that being a fintech borrower reduces default probability by almost 37 bps, after controlling for all credit attributes.

Finally, in Table B.4, we control for demographic attributes when examining the relationship between fintech lending and default probability. In line with our baseline multivariate analysis, we document a positive relationship between income and default probability, which is unexpected. This relationship is possibly due to borrowers tendency to overstate their income. In this subsample, an educated individual is less likely to default, in line with our baseline findings. Similarly, we again document that individuals who work in the public sector or retirees are less likely to default compared to individuals who work in the private sector or are self-employed. Furthermore, we document a negative correlation between age and default probability, which again is in line with our original findings even though the coefficient is much smaller. Similarly, we observe that being a male increases the probability of default, even though the statistical significance disappears in multivariate setting. Finally, we document that fintech borrowers are less likely to default even after controlling for all other demographic attributes. Consistent with our baseline results, being a fintech borrower reduces the probability of default by 109 bps. Therefore, our baseline results are robust to potential unobserved heterogeneity across fintech and bank loans.

Matching observations with respect to borrower characteristics

Next, we match the observations with respect to three borrower characteristics; namely, income, age and credit score. To that end, we estimate the following logistic propensity-score model for all loans in our sample:

$$Pr(Default) = \alpha + \beta_1 Age_i + \beta_2 Income_i + \beta_3 HighCreditScore_i + \beta_4 MidCreditScore_i + \epsilon_i \quad (5)$$

The independent variables, income, age, mid-credit score and high-credit score, are defined in Appendix A. We provide the results of the logistic propensity-score model along with the sample mean and standard deviation of estimated propensity scores in Table B.5. In Table B.5, we observe that the probability of default decreases with the increases in the income and credit score and decreases with age. Table B.5 Panel B shows that the mean and standard deviation of the estimated propensity scores are 3.29% and 3.18%, respectively.

For proper statistical inference, we again round the propensity scores to second digit after the decimal to obtain subsamples with sufficient observations of default rates and fintech loans.

Table B.9
Default characteristics of borrowers — Credit attributes (Full sample).

Variable	Credit attributes									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Deposit amount	−0.003* (−124.1)								−0.002* (−68.1)	−0.007* (−71.4)
Nu. Accounts		−0.006* (−102.5)							– –	– –
Loan size			0.004* (56.7)						0.002* (21.8)	0.001* (12.6)
Maturity				0.001* (183.7)					0.001* (142.4)	0.015* (150.5)
Low credit score					0.067* (339.5)				0.064* (315.1)	0.072* (319.7)
Mid credit score						−0.028* (−174.3)			– –	– –
High credit score							−0.027* (−128.1)		−0.008* (−35.4)	−0.012* (−43.4)
Interest rate								0.012* (75.5)	0.013* (77.1)	0.006* (77.3)
Fintech	−0.016* (−46.6)	−0.010* (−55.0)	−0.013* (−71.7)	−0.009* (−51.8)	−0.011* (−62.1)	−0.016* (−92.4)	−0.011* (−62.1)	−0.014* (−77.9)	−0.001* (−6.5)	−0.006* (−29.4)
Deposit amount ∗ Fintech										0.005* (26.0)
Loan size ∗ Fintech										0.001* (6.7)
Maturity ∗ Fintech										−0.009* (−49.8)
Low credit score ∗ Fintech										−0.044* (−83.8)
High credit score ∗ Fintech										0.007* (16.0)
Interest rate ∗ Fintech										−0.004* (−24.1)
Intercept	−0.0146	−0.0177	−0.0637	−0.0537	−0.0306	−0.00311	−0.0208	−0.0403	−0.0824	−0.0277
City & Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	5,580,562	5,580,562	5,580,562	5,580,562	5,580,562	5,580,562	5,580,562	5,580,562	5,580,562	5,580,562
R^2	2.2%	2.1%	2.0%	2.5%	3.9%	2.5%	2.2%	2.1%	4.7%	5.0%

Results of the following model : $Default_{i,c,t} = \beta X_{i,t} + \mu_c + \varphi_t + \gamma Fintech_{i,c,t} + \varepsilon_{i,c,t}$. Values in parentheses are t-statistics of the coefficients.
*Indicates statistical significance at 1% level.

Our matched sample this time has around 600,000 observations. 24% of the loans in our matched subsample are fintech loans and the overall default rate is around 9%. We provide the descriptive statistics for the variables in the matched subsample in Table B.6. In Table B.6, we observe that all borrowers in the matched sample are coming from low credit score groups. As we matched observations across age, the difference between the age of fintech and bank borrowers (less than six months) is significantly lower than the full sample where the age difference between fintech borrowers and bank borrowers is around 7 years. Similarly, the average monthly income between bank and fintech borrowers is around 180 TL which is 10% of the minimum wage in 2019[2] To that end, we argue that in our matched subsamples, fintech borrowers are similar in terms of their age and income and identical in terms of their credit history.

Once again, we repeat our baseline analysis with the matched subsample. Specifically, we run the model presented in Eq. (5) to compare loan performance of the bank and the fintech firm over similar borrowers. Tables B.7 and B.8 provide the estimates of the model with the credit and demographic attributes as independent variables from the matched subsample. We again observe that our baseline results are robust using the subsample where fintech and bank borrower characteristics are similar. Specifically, in Table B.7, we document that as the borrowers' deposit amount and the number of accounts with a positive balance increase the probability of default decreases. Similar to our previous findings, we observe that loans that are larger in size, loans with longer maturities and loans with higher interest rates are more likely to default. Since all of the borrowers in the matched sample are low credit borrowers, we do not control for credit score in Table B.7. In line with our baseline findings, we observe that in the subsample where the characteristics of fintech and bank borrowers are similar, fintech borrowers are *less* likely to default even after controlling for all credit attributes. The coefficient that measures the effect of being a fintech borrower on default probability varies between −3.6 and −2.7 percentage points (pp). We also document that being a fintech borrower reduces the default probability by almost 1.8 pp, even after controlling for all credit attributes.

In Table B.8, we control for the demographic attributes of borrowers when examining the relationship between fintech lending and the default probability. Similar to our baseline results, we observe a positive relationship between borrowers' income and the default probability. We again observe that more educated borrowers are less likely to default. The coefficients for some borrower occupations are different from our baseline analysis. Specifically, under the matched subsample, we observe that borrowers who work in the private sector are less likely to default and the coefficient of being a retiree turns to positive even though it is statistically insignificant. The coefficient of age also switches sign. Therefore after addressing the unobserved heterogeneity in fintech and bank borrowers, we find that default rate increases with age. More importantly, we observe that fintech borrowers are less likely to default even after controlling for all demographic attributes. In line with our baseline results, we show that being a fintech borrower reduces the probability of default by almost 2 pp. Therefore, our baseline results are robust to potential unobserved heterogeneity across fintech and bank borrowers.

2 See Turkstat, www.tuik.gov.tr.

Table B.10
Default characteristics of borrowers — Demographic attributes (Full sample).

Variable	Demographic attributes														
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
Income	−0.0004*													0.0004*	0.0013*
	(−9.8)													(10.8)	(13.5)
Primary school		0.012*												–	–
		(64.2)												–	–
High school			0.007*											−0.007*	−0.006*
			(47.6)											(−34.26)	(−27.9)
Undergraduate				−0.015*										−0.024*	−0.025*
				(−91.8)										(−102.6)	(−97.2)
Graduate					−0.013*									−0.027*	−0.030*
					(−34.7)									(−66.29)	(−47.1)
Private sector						0.010*								−0.027*	−0.041*
						(64.0)								(−46.03)	(−57.0)
Public sector							−0.016*							−0.039*	−0.056*
							(−70.7)							(−62.93)	(−74.0)
Self employed								0.017*						−0.015*	−0.025*
								(51.3)						(−22.18)	(−31.0)
Retired									−0.017*					−0.038*	−0.051*
									(−76.0)					(−59.14)	(−67.0)
Unemployed										0.007*				–	–
										(5.3)				–	–
Male											0.005*			0.002*	0.003*
											(27.5)			(−12.2)	(13.0)
Age												−0.001*		−0.0005*	−0.006*
												(−74.3)		(−50.55)	(−50.5)
Young													0.010*	–	–
													(56.2)	–	–
Fintech	−0.014*	−0.012*	−0.013*	−0.009*	−0.013*	−0.015*	−0.013*	−0.014*	−0.017*	−0.014*	−0.014*	−0.018*	−0.017*	−0.010*	−0.042*
	(−79.4)	(−66.3)	(−72.0)	(−50.0)	(−74.4)	(−84.0)	(−73.3)	(−81.7)	(−93.1)	(−81.2)	(−82.4)	(−98.8)	(−92.5)	(−51.86)	(−27.8)
Income ∗ Fintech															−0.001*
															(−6.8)
High school ∗ Fintech															−0.003*
															(−4.1)
Undergraduate ∗ Fintech															0.007*
															(9.9)
Private sector ∗ Fintech															0.035*
															(25.1)
Public sector ∗ Fintech															0.044*
															(30.5)
Self employed ∗ Fintech															0.025*
															(16.0)
Retired ∗ Fintech															0.040*
															(23.8)
Male ∗ Fintech															−0.003*
															(−8.0)
Age ∗ Fintech															0.005*
															(25.4)
Intercept	−0.021	−0.027	−0.028	−0.019	−0.024	−0.030	−0.022	−0.025	−0.020	−0.025	−0.028	−0.002	−0.030	0.040	0.033
City & Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	5,580,562	5,580,562	5,580,562	5,580,562	5,580,562	5,580,562	5,580,562	5,580,562	5,580,562	5,580,562	5,580,562	5,580,562	5,580,562	5,580,562	5,580,562
R^2	2.0%	2.0%	2.0%	2.1%	2.0%	2.0%	2.0%	2.0%	2.1%	2.0%	2.0%	2.1%	2.0%	2.5%	2.6%

Results of the following model : $Default_{i,c,t} = \beta X_{i,t} + \mu_c + \varphi_t + \gamma Fintech_{i,c,t} + \varepsilon_{i,c,t}$. Values in parentheses are t-statistics of the coefficients.

*Indicates statistical significance at 1% level.

Appendix C. Interactions

In this section, we explore the interactions between being a fintech borrower and all borrower and loan characteristics. For our baseline regressions, we added interaction terms and present the results in Tables B.9 and B.10. In Table B.9, all of the interaction terms are statistically significant at 1% level. Similar to our baseline results, we observe that among fintech borrowers, as the deposit amount of the borrower increases, the default rate decreases. Similarly, as the maturity and the size of a fintech loan increases, the default probability increases. Fintech borrowers who have higher credit scores are less likely to default compared to borrowers with low- and mid-credit scores. Similar to our PSM analysis, the interaction between credit score and fintech signals a potential mechanism for the superior performance of the fintech firm. Specifically, we observe that low-credit individuals who borrow from the fintech firm have significantly lower default rates compared to bank borrowers with comparable credit score. The coefficient for the interaction term "Low-credit score * Fintech" is around -4pp and statistically significant at 1% level. Thus, our results suggest that fintech firm has a significant competitive advantage compared to the bank in identifying creditworthy individuals among borrowers who have low-credit score. On the other hand, high-credit score individuals who borrow from the fintech firm perform worse compared to high-credit score bank borrowers. The coefficient for the interaction term "High-credit score * Fintech" is around 70bps, indicating that the difference between the default rate of bank loans and fintech loans in that subsegment is small in magnitude. That is, the competitive advantage of the fintech firm over low-credit score individuals is much larger compared to its disadvantage over high-credit score individuals.

Moreover, the relationship between the default rate and the demographic attributes of the fintech borrowers is in line with our baseline results. Specifically, in Table B.10, we observe that fintech borrowers with higher incomes are less likely to default. In addition, fintech borrowers with graduate degrees are less likely to default compared to individuals with lower education levels. Among the fintech borrowers, individuals that are working in the private sector or are self-employed are more likely to default compared to individuals that work in public sector or are retirees. We observe that as fintech borrowers gets older, the default rate decreases. Finally, we observe that among the fintech borrowers, male borrowers are more likely to default compared to female borrowers. In terms of demographic attributes, we observe that all of the interaction terms for the occupations are positive. This would further imply that the loans that are offered to unemployed borrowers by the fintech firm have significantly *lower* default rate. Similarly, we observe that for the fintech firm, borrowers with high school degrees have significantly less default rates compared to bank borrowers who only have high school degree.

Taken together with our baseline findings and the findings from the PSM analysis, the extended regression analysis in this section further supports our conclusion that fintech loans have significantly lower levels of default compared to bank borrowers. Moreover, the mechanism for the superior performance of fintech firm seems to be driven from identifying individuals that are in a neglected subsample of the market. Specifically, our results indicate that through sophisticated machine learning and data analysis tools, fintech firm can successfully identify creditworthy individuals among the group of borrowers who are less educated and who have low-credit scores. This reduces the quality of the pool of borrowers in those subsegments of the market for the bank, decreasing the overall performance of the bank loans as the ratio of borrowers who are unemployed, less educated or who have low credit score in the portfolio of the bank is much larger compared to the portfolio of the fintech firm.

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