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Legal enforcement and fintech credit: International evidence

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ABSTRACT

Previous studies have shown that the quality of legal institutions is negatively associated with the interest rates of business loans. Fintech lending, with improved *ex ante* risk-sharing practices that change the approach to credit provision, presents a challenge to the traditional relationship between law and finance. Compiling and studying over five million fintech loans from 24 countries, we show that, in comparison to traditional bank loans, the quality of legal enforcement matters less to the cost of fintech credit. Nonetheless, the impact of legal protection on the interest rates of fintech credit is more persistent when (1) the loans bear higher risk, (2) the fintech platforms have fewer risk-sharing tools, and (3) borrowers' jurisdictions have fewer information-sharing channels. Our study contributes to the debate on the role of legal protection in the fintech credit market.

1. Introduction

Previous studies have demonstrated that the quality of legal institutions is negatively associated with the interest rates of business loans because the collection and recovery efficiency of delinquent loans is fundamental to the credit market (e.g., Bae and Goyal, 2009; Calomiris et al., 2017; Liberti and Mian, 2010; Qian and Strahan, 2007). Given the axiom that better legal enforcement lowers the cost of borrowing, few people would doubt that a similarly negative relationship also holds for fintech credit, often referred to as peer-to-peer (P2P) lending. However, it is unclear *ex ante* whether legal enforcement matters to a lesser or greater extent when it comes to the price of fintech loans because fintech lending, thanks to various advances and innovations, diverges from the traditional way in which financial credit is provided.

On the one hand, the use in fintech credit risk analysis of alternative data sources (soft and nonstandard information), big data and machine learning (ML) technology, and other complex artificial intelligence (AI) algorithms can generate a more accurate prediction of an individual's likelihood of defaulting on a loan (Jagtiani and Lemieux, 2019; Berg et al., 2020; Iyer et al., 2016).[1] Because an effective credit rating model is a crucial factor in pre-screening borrowers' creditworthiness, the new business model in fintech lending helps to mitigate loan default risk *ex ante* by effectively gauging the riskiness of the borrowers. Further, because investors in fintech lending are encouraged to invest in a diversified portfolio by means of the digital facilities provided by the platform, the risk is shared among investors to a larger extent than when lending to just one or a few borrowers. From an investor's perspective, if one borrower in the diversified portfolio becomes insolvent, they experience only a limited proportion of the capital

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[1] In this context, soft information can include, for example, proximity information (Morse, 2015), social networks and friends (Freedman and Jin, 2017; Lin et al., 2013), and digital footprints (Berg et al., 2020).

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loss. Similarly, the default risk can also be shared between investors and platforms through a platform safeguarding service. In short, the better risk-sharing applications adopted by fintech platforms are more likely to alleviate investors' concerns about default risk. Because these innovative practices provide safety-enhancing measures for lenders, it is likely that the need for *ex post* legal enforcement is lowered in fintech loans.

On the other hand, although the use of new digital technologies and more granular customer data in fintech credit promises greater convenience, lower transaction costs, and better risk assessment (e.g., Berg et al., 2020; Fuster et al., 2019; Jagtiani and Lemieux, 2019; Tang, 2019), the declining credit quality of fintech loans is garnering increasing concern among practitioners, academics, and regulators. In particular, higher default rates and lower investor returns are being observed as fintech lending appears to have catered to more risky borrowers.[2] In light of this, the collection and recovery efficiency of delinquent loans is key to the new credit market because it is central to overcoming the default problem that plagues unsecured consumer lending.[3] Therefore, in comparison to traditional bank loans, court enforcement can be more important to fintech loans as a response to debt recovery, thus affecting their interest rates.

In this paper, we first examine how, compared to traditional bank loans, the relationship between the enforceability of contracts and the interest rates of fintech credit evolves by compiling and studying 5,540,449 loan-level fintech transactions across 24 countries between 2015 and 2018. We measure the quality of enforcement by the average score of three components of the resolution of a commercial dispute through a local first-instance court: resolution time, cost of claims, and judicial quality. We first test the relationship between the quality of legal institutions and the cost of credit by using country-level average interest rates for bank loans and for fintech loans. Our empirical results indicate that the negative association between the enforceability of contracts and interest rates is less pronounced for fintech loans than bank loans. This suggests that the quality of legal enforcement has less bearing on the cost of fintech credit.

Facilitated by our granular data on individual fintech loans, we next ask how this relationship is moderated by the risk level of individual loans. Fintech platforms provide low-cost information advancements in order to collect standardized information from dispersed individual borrowers on a large scale, pre-screen loans by means of a scalable algorithm that gauges the riskiness of the underlying loan applications, and allocate the qualified applications into risk buckets (Vallée and Zeng, 2019). It is intuitive to hypothesize that enforcement should be more important for high-risk loans than low-risk ones, given that high-risk loans are, by definition, more prone to default and therefore have a greater need for *ex post* enforcement. Our empirical results suggest that the negative relationship between the quality of legal enforcement and interest rates is more prevalent in relation to high-risk loans than low-risk ones, which is consistent with our conjecture. It is worth noting that the original fintech loan data describes four levels of risk: very low, low, medium, and high. To test our hypothesis, we categorize the medium- and high-risk loans into a high-risk group and the very low and low-risk ones into a low-risk group. For robustness, we also implement alternative definitions of loan risk levels and our results continue to hold.

As fintech platforms can be heterogeneous in the risk-sharing applications, we also test the interaction between legal enforcement and fintech risk-sharing innovations. We find that legal protection plays a lesser role in reducing interest rates when loans are issued by platforms with a higher risk management index (a weighted index manually constructed to include platform-level credit default risk, cash flow timing risk, platform risk, and regulatory and compliance risk) and by platforms that provide safeguarding services to investors, both of which are indicative of better risk-sharing tools.

Further, we conjecture that the implications of information sharing, as normally applied to credit information exchanges in bank loans, can be extended to fintech loans. Besides their own credit-rationing models, fintech platforms also need to draw on credit reporting systems to screen borrowers and monitor the risk profiles of existing loan portfolios. More information-sharing channels help online lenders to better avoid adverse selection problems (e.g., Brown et al., 2009; Jappelli and Pagano, 2002; Djankov et al., 2007). Given the heterogeneity in the degree of credit information sharing in different countries, we expect legal protection to play a lesser role in countries with more information-sharing channels. Empirically, we also find that the need of fintech loans for legal enforcement is less pressing if the borrower's jurisdiction has a higher availability of credit information in terms of both coverage and depth, which is consistent with the literature on traditional credit-information-sharing channels.

As additional robustness checks, we repeat our main analyses using alternative samples, additional sets of control variables in relation to legal institutions, additional controls of other country-level factors, and alternative model specifications. Our results are robust to all of these alternative specifications.

Our study makes several contributions to the literature. First, we contribute to the law-and-finance literature by examining how the role of legal enforcement evolves in fintech lending. Previous studies have shown that legal protection is a crucial element of bank loan enforcement (Bae and Goyal, 2009; Djankov et al., 2008; La Porta et al., 1997; Qian and Strahan, 2007; Qian et al., 2018), corporate bond covenants (Qi et al., 2011), capital structure (Cho et al., 2014; Ghoul et al., 2020), and corporate risk-taking (Acharya et al., 2011; Favara et al., 2017). To the best of our knowledge, we are one of the first to extend the discussion of legal protection and loan prices to the consumer finance market in the fintech context. Our evidence shows that compared to traditional bank loans, legal protection matters less in fintech loans because they provide better risk-sharing practices *ex ante*.

Second, our study of the fintech credit market is important because fintech innovations are presenting new challenges to the traditional law-and-finance relationship. These innovations in products, services, and the joint information production of the P2P

[2] Beioley, K., Megaw, N., 2009, March 22. Peer-to-peer pressure: Do the risks outweigh the rewards? *Financial Times*. https://www.ft.com/content/6bf2c806-4a6b-11e9-8b7f-d49067e0f50d.

[3] For instance, Bondora, a leading European fintech lending platform, reports that legal enforcement procedures, including bailiffs and the courts, are the most important recovery stages in the insolvent credit recovery process. See https://www.bondora.com/blog/category/collection-and-recovery/.

business model can, to some extent, substitute for the role of legal protection by performing risk-sharing functions (Berg et al., 2020; Fuster et al., 2019; Jagtiani and Lemieux, 2019; Tang, 2019). Our evidence of the heterogeneous effects of legal enforcement according to the risk-sharing innovations of the various fintech platforms uncovers a potential benefit of technological advancements in relation to debt enforcement.

Third, our cross-country study provides a comprehensive view of worldwide fintech lending markets and offers a key to future financial stability. Notwithstanding the risk-mitigating innovations referred to above, the declining credit quality of fintech loans is garnering increasing concern among practitioners, academics, and regulators that fintech credit may have already "hit the wall". In the long run, the resilience of this young market has not yet been tested over a full economic and credit cycle (Claessens et al., 2018; CGFS–FSB, 2017). Turning to broader systemic impacts, our study helps address the concern that legal protection is fundamental to its financial stability, especially when economic conditions deteriorate.

The rest of the paper proceeds as follows. In Section 2 we introduce the background to our study and develop our hypotheses; Section 3 describes our sample, the measurement of variables, and descriptive statistics; Section 4 presents our empirical results and we conclude the paper in Section 5.

2. Background and hypothesis development

2.1. The business model of fintech credit

Over the past decade, fintech credit markets have been experiencing exponential growth worldwide. As this new business model develops, platforms have evolved from agents that merely offered marketplaces to agencies that assist investors with pre-screening of loan applications and diversification of investment risk (e.g., Claessens et al., 2018; Vallée and Zeng, 2019; D'Acunto et al., 2019).

As such, the standard lending process for most fintech platforms now means that when a potential borrower registers on the platform and submits their loan application, the platform pre-screens it. Here, in contrast to traditional bank lending that utilizes standard credit scores and information, the innovation of fintech lending is that it uses "big data" technology to collect nonstandard information from disparate individual borrowers on a large scale (Iyer et al., 2016) and uses this to pre-screen loans using scalable algorithms to gauge the riskiness of the underlying loan applications. Verified applications are listed on the platform and allocated into risk buckets, called "grades" or "subgrades" (Vallée and Zeng, 2019), which in turn map to interest rates; that is, loan prices.

On the investor side, each verified loan application is first appended to a sub-loan market (a pool of loans with the same credit grade) and is then split into small-sized "notes" (the unit of a note is often ten U.S. dollars or ten Euros). Registered investors are encouraged to invest in a diversified portfolio of notes. Once an investor has set up their lending preferences, such as their acceptable credit risk grades and terms, their investment is automatically split into tranches to be matched with a number of notes. Given high volumes of loan applications, the platforms offer robot advisors (or automated portfolio optimizers) to investors, so that their lending becomes more diversified and subject to less portfolio volatility (D'Acunto et al., 2019). Through this matching process, platforms create highly dispersed and complex relationships between borrowers and lenders. To further share/diversify the default risk, a few platforms or their co-operating partners also provide a safeguarding service to investors. Under this service, if a borrower becomes insolvent, the platform or its co-operating partners seek to recover the losses of the investors first, and then make a claim for any amount outstanding under the loan on the investors' behalf.

2.2. Hypothesis development

Legal enforcement is a key element of legal protection for financial contracting. Even the best-designed law is useless if it is not enforced effectively, while powerful enforcement can supplement or even compensate for weak legal provisions (La Porta et al., 1997, 1998; Bhattacharya and Daouk, 2009; Qian et al., 2018). Bae and Goyal (2009) argue that variation in the enforceability of contracts matters a great deal more than how loans are structured and priced. Using loan data from 48 countries, they find that banks reduce loan sizes, shorten loan maturities, and increase interest rate spreads in response to poor law enforcement. Similarly, Renneboog et al. (2017) use a global sample of 1100 cross-border M&As and find that the bondholders of bidding firms respond more positively to deals that expose their firms to jurisdictions with stronger creditor rights and more efficient claims enforcement through the courts.

In fintech lending, an effective credit rating model is a crucial factor in pre-screening borrowers' creditworthiness. The use of alternative data sources (soft and nonstandard information), big data and ML technology, and other complex AI algorithms in fintech credit risk analysis can generate a more accurate prediction of an individual's likelihood of loan defaulting (Jagtiani and Lemieux, 2019; Berg et al., 2020; Iyer et al., 2016). As a consequence, the new business model of fintech lending helps to reduce the risk of loan default *ex ante* by gauging the riskiness of the borrowers more effectively. Further, because the digital facilities provided by the platform encourage investors to invest in a diversified portfolio, the risk is shared among a much larger pool of investors, rendering it much lower for the individual investor than when lending to just one or a few borrowers. Thus, if one borrower in their diversified portfolio becomes insolvent, the investor experiences a relatively limited proportion of the capital loss. Further, this risk of default can also be shared with the platform itself if it offers a platform safeguarding service. In short, the better risk-sharing services offered by fintech platforms are far more likely to alleviate investors' concerns about the risk of loan defaulting. Thus, we posit that compared to traditional bank loans, the demand for legal protection in relation to fintech loans will be less pressing if the fintech platform itself is effective in its deployment of risk-sharing tools:

Hypothesis 1. Compared to its effect on traditional bank loans, the role of legal enforcement in reducing interest rates is less pronounced for fintech loans.

Lenders are often unable to observe the characteristics of borrowers and this causes adverse selection problems, especially for high-risk borrowers. Lenders are also normally incapable of controlling the borrower's actions once the loan has been received. Consequently, lenders may ration credit or charge higher interest rates. From a lender's perspective, the most effective approach to overcoming this informational problem is to obtain information about the borrower (via screening and monitoring). As already described, fintech platforms provide low-cost information to would-be borrowers in order to collect standardized information from them on a large scale, enabling the platform to pre-screen loans through scalable ML algorithms that allocate the qualified applications into different buckets on the basis of their assessed risk (Vallée and Zeng, 2019). It is logical to expect that enforcement *ex post* will be more important for loans placed in high-risk buckets than low-risk ones because the former are, by definition, more likely to default:

Hypothesis 2. The negative relationship between the quality of legal enforcement and the cost of credit is more persistent for high-risk loans than low-risk ones.

3. Data and variables

3.1. Sample selection

For this study, we collect information on 5,540,449 fintech loan transactions between 2015 and 2018 across 24 countries from seven world-leading fintech platforms. Panel A in Table 1 provides a summary of these seven fintech platforms: Mintos, Bondora, Funding Circle U.K., Lending Club, RateSetter U.K., Renrendai, and Zopa. We focus on these particular platforms for four reasons. First, these platforms are representative of the largest fintech lenders by funding amount across the world.[4] By the end of 2019, Lending Club had the largest loan amount originated (around 59.29 billion U.S. dollars), followed by Renrendai with 15.65 billion U.S. dollars. Rate Setter U.K., Mintos, Zopa, and Funding Circle U.K. are comparable with one another in terms of loan amount originated, ranging from 4.88 to 7.61 billion U.S. dollars.

Second, all of these platforms are financed in a comparable way. Fintech platforms perform the intermediation role between investors and borrowers. To apply for a loan, the applicant reports their name, address, the purpose of the requested funds, and the amount to be borrowed. The platform uses the applicant's identity to acquire information on their credit status and proposes a menu of loans with different amounts, maturities, and interest rates to those who successfully negotiate this screening process. Once an applicant has selected a loan, the loan request is listed on the platform's website and is made accessible to investors, who can choose to invest in particular loans or a basket of loans via the platform's auto-investment tool.

Third, these platforms have made their loan-level data publicly available.[5] The last column of Panel A shows the data availability for each fintech platform. Lending Club, Zopa, Funding Circle U.K., RateSetter U.K., and Mintos provide loan books that can be downloaded for registered users; Bondora offers data access via an application programming interface (API); Renrendai allows investors to view historical loan transactions online but does not grant access to a loan book or API via which they can be downloaded directly. Thus, to obtain the loan-level data from Renrendai, we constructed a Python program to scrape loan transaction data from over one million historical web pages.

Last, our sample covers the main fintech lending markets worldwide, providing country-level diversity in relation to investor protection, legal environment, and economic development. For example, Mintos accepts borrowers from 23 countries and investors from 65 countries, while Bondora takes loan applications mainly from Estonia, Finland, and Spain, and accepts investors from EU countries and a further 12 non-EU countries. The other five platforms operate in single-country mode: Lending Club runs in the U.S.; Zopa, Funding Circle U.K., and Rate Setter U.K. focus on the U.K.; Renrendai is based in China.[6]

Panel B in Table 1 shows the sample distribution by country. The U.S., Georgia, China, and the U.K. are the four countries with the largest number of observations (more than 650,000 loans in each), accounting for 29%, 17%, 15%, and 13% of the overall sample, respectively. Kenya, the Czech Republic, Sweden, South Africa, and Mexico are the five countries with fewest observations, that is, less than 10,000 loans each. Some countries in our sample (Georgia, Latvia, and Moldova) are small in terms of population and economic size but account for a sizable proportion of all loans. This is because one of our data sources is the P2P lending platform Mintos, which mainly operates in Europe. Its headquarters are located in Latvia, and the majority of loans on the platform involve Latvia and neighboring countries such as Georgia and Moldova.

[4] We do not include Prosper, Funding Circle U.S., Sharestates, Assetz Capital, or ThinCats because U.S. and U.K. data are already covered by the inclusion of Lending Club, Funding Circle U.K., Zopa, and RateSetter U.K.

[5] A number of fintech platforms do not make their loan data available, including Twino, Fellow Finance, Exporo, CreditGate, and October.

[6] We are aware that our data can still be subject to selection bias as these platforms might not be representative to the overall fintech credit development in that country. To help the reader understand the representativeness of our sample, we supplement information about the comparison between fintech credit and alternative credit in Table A.4. According to the statistics, taking Georgia for example, total fintech lending in our sample makes up 89.72% of alternative credit, and 0.016% of total private credit.

Table 1
Sample distribution and descriptive statistics.

Panel A: Summary of Platforms

Platform	Head-quarters	Start Year	No. of Countries (on the investor side)	No. of Countries (on the borrower side)	Amount Originated (billions of U.S. dollars)	Loan Maturity (Months)	Safeguard	Data Availability
1 Mintos	Latvia	2015	65	23	5.84	1 - 240	Yes	Loan book
2 Bondora	Estonia	2009	EU & another 12	Estonia, Finland & Spain	0.41	3 - 60	No	API
3 Funding Circle U.K.	U.K.	2010	U.K.	U.K.	7.61	24 – 60	No	Loan book
4 Lending Club	U.S.	2006	U.S.	U.S.	59.28	24 – 60	No	Loan book
5 RateSetter U.K.	U.K.	2010	U.K.	U.K.	4.88	12 – 60	Yes	Loan book
6 Renrendai	China	2010	China	China	15.65	3 – 48	Yes	Scraping
7 Zopa	U.K.	2005	U.K.	U.K.	6.54	12 – 60	Yes	Loan book

Panel B: Sample Distribution by Country

Country	Obs.	Percent	Platform(s)	Country	Obs.	Percent	Platform(s)
Albania	43,888	0.79	1	Lithuania	91,253	1.65	1
Botswana	10,890	0.20	1	Mexico	429	0.01	1
Bulgaria	63,101	1.14	1	Moldova	291,879	5.27	1
China	843,418	15.22	6	Poland	106,880	1.93	1
Czech Republic	6,319	0.11	1	Romania	17,461	0.32	1
Denmark	11,524	0.21	1	Russian Federation	70,167	1.27	1
Estonia	45,554	0.82	1, 2	South Africa	1,672	0.03	1
Finland	21,556	0.39	1, 2	Spain	52,046	0.94	1, 2
Georgia	958,407	17.30	1	Sweden	6,831	0.12	1
Kazakhstan	17,721	0.32	1	United Kingdom	668,796	12.07	1, 3, 5, 7
Kenya	9,819	0.18	1	United States	1,608,221	29.03	4
Latvia	530,239	9.57	1	Zambia	62,378	1.12	1

Panel C: Descriptive Statistics

	Mean	SD	Min	P25	P50	P75	Max
Dependent variable							
Median *Interest Rate (%)*	11.270	1.470	8.730	10.100	12.000	12.130	16.000
Average Interest Rate (%) of Bank Credit	6.500	4.630	0.050	4.300	6.500	9.120	23.920
Average Interest Rate (%) of Fintech Loans	12.010	1.979	9.133	10.672	11.198	12.430	17.500
Independent variables							
Median *Enforcement*	74.187	6.257	49.990	71.660	75.970	79.060	79.060
Other loan features							
Median *Loan Maturity (Month)*	22.419	13.814	1.000	11.000	24.000	36.000	52.000
Median *Loan Size ($)*	5,726.323	5,473.828	15.916	255.256	3,240.428	12,300.000	12,300.000
Collateral (%)	7.440	14.175	0.000	0.000	0.016	6.823	45.308
Risk Rating A-Very Low (%)	18.209	30.823	0.000	0.000	0.396	29.351	99.571
Risk Rating B-Low (%)	69.769	39.517	0.000	30.227	92.995	100.000	100.000
Risk Rating C-Medium (%)	10.609	26.969	0.000	0.000	0.000	6.010	100.000
Risk Rating D-High (%)	1.413	4.326	0.000	0.000	0.000	0.580	20.590
High Risk (%)	16.834	30.785	0.000	0.000	0.000	23.832	100.000
Safeguard (%)	92.535	22.851	0.000	99.547	100.000	100.000	100.000
Other country-level factors							
Median *Coverage of Credit Information*	0.883	0.228	0.074	0.911	0.957	1.000	1.000
Median *Depth of Credit Information*	7.787	0.617	5.000	8.000	8.000	8.000	8.000
Median *Property Rights*	65.085	15.819	33.350	54.575	62.125	76.500	91.100
Median *Rule of Law*	0.521	0.901	−0.794	−0.364	0.430	1.199	2.027
Median *Bank Competition*	63.199	16.850	37.935	51.230	60.462	78.661	91.470
Median *Digital Financial Inclusion*	58.703	29.447	13.329	30.925	57.315	88.936	98.307
Median *Fintech Credit Development*	0.227	0.705	0.000	0.000	0.000	0.061	3.379
Median *Sovereign Risk*	6.356	4.686	1.000	2.000	5.000	10.000	16.000
Median *Log(GDP)*	27.493	3.052	23.149	24.009	28.609	30.560	30.560
Median *GDP Growth*	3.786	1.698	0.787	2.217	4.000	4.770	6.737
Median *Credit to Private Sector*	119.866	60.946	11.177	62.529	134.256	192.165	192.165

Panel A provides a brief summary of the fintech platforms in our sample. Information is originally collected from the fintech platforms and then double-checked with data on the website P2PMarketData (https://p2pmarketdata.com/) as of 30th April 2020. Panel B reports the distribution of 5,540,449 fintech loans by country, with their corresponding fintech platform(s) indicated (as per Panel A). Panel C presents summary statistics for variables used in the empirical analysis. It displays the medians of loan characteristics, legal enforcement, and other factors related to development of the fintech sector at the country level. The variables are defined in Table A.1

The types of fintech loans include personal loans, pawnbroking loans, car loans, business loans, mortgage loans, and agricultural loans, of which personal loans are the majority, accounting for 93.78% of our sample.[7] Most loans on the platforms involve terms of 60 months or less; only Mintos accepts longer loans, and these account for only 0.25% of its sample.

3.2. Measuring interest rates

To compare the differential effects of enforcement on fintech credit vs. bank credit, we obtain the *Average Interest Rate of Fintech Loans* per country-year from our fintech loan data, and we use the *Average Interest Rate of Consumer Loans* provided by Oxford Economics (http://www.oxfordeconomics.com) via Refinitiv Datastream as a proxy for the average bank lending rates because it provides the greatest coverage for our sample by including 23 countries (exclusive of Moldova).[8]

In terms of individual fintech loan, our primary dependent variable is *Interest Rate*, defined as the natural logarithm of the flat annual percentage rate charged by the lenders after excluding any fee charged by the platform (Bae and Goyal, 2009; Qian et al., 2018). The interest rate is the critical characteristic of the fintech loan contract, indicating the investor's required rate of return.

[7] Pawnshop loans and auto loans account, respectively, for 3.83% and 1.86% of all loans; all other types of loan account for less than 0.5% each. We conducted subsample analysis in the robustness test described in Section 4.4.2.

[8] https://www.refinitiv.com/en/products/datastream-macroeconomic-analysis

Because the size and maturity of each loan is repackaged by the platform via the diversification strategy described in Section 2.1, they are less obvious to investors as structural features of the loan by comparison with traditional bank loans. Therefore, in our primary analysis, we focus only on loan prices, that is, interest rates.

3.3. Measuring enforcement

The proxy we use to measure country-level enforceability of contracts was initially developed by Djankov et al. (2003), and afterwards maintained, adjusted, and updated in the World Bank's *Doing Business* database.[9] Specifically, *Enforcement* is a score for the enforcement of contracts, calculated by averaging the scores of three component aspects: the time and the cost required to resolve a commercial dispute through a local first-instance court, and a quality of judicial processes index.[10]

3.4. Loan-level control variables

Loan characteristics, such as *Loan Maturity*, *Loan Size*, *Collateral*, and *Risk Rating*, as determinants of the structure of a loan contract, have significant effects on interest rates. *Loan Maturity* is the duration of the loan, reported in months. Fintech platforms place restrictions on the maximum loan maturity; while most platforms provide loans with terms of 60 months or less, Mintos has longer loan maturities because it supports mortgage loans. *Loan Size* is the loan amount granted to the borrower. We convert all amounts into U.S. dollars based on the currency exchange rate at the time each loan was contracted, and then convert this loan size into 2018 equivalents using a deflator based on the value of the Consumer Price Index (CPI) for the respective country. *Collateral* is a dummy variable that takes a value of 1 if the loan is secured against assets (cars, houses, etc.), and 0 otherwise.

Risk Rating is defined as the credit grade for each loan. This is a crucial determinant of the interest rate of the loan. Platforms usually follow a two-step process to decide the pricing of a loan: (i) assigning a loan grade; (ii) calculating an interest rate based on the platform's base rate (for that grade) plus an upward adjustment to reflect the quoted factors.[11] The platforms in our sample show variation in the rules and categories used to define borrowers' credit ratings. To render them comparable across platforms, we standardize the variable *Risk Rating* into four universal categories indicative of increasing risk: A (very low), B (low), C (medium), and D (high).[12] Because Zopa and RateSetter U.K. (11.58% of the overall sample) do not disclose credit grades for borrowers, we assign all of these "unrated" loans an average risk (B).[13]

3.5. Country-level control variables

We also include a number of country-level variables to control for the impact on loan contracting of heterogeneity among different countries' economic development and institutions, following the previous literature (e.g., Bae and Goyal, 2009; Guérineau and Léon, 2019; Houston et al., 2010; Qian and Strahan, 2007).

Thus, *Sovereign Risk* denotes country-level credit ratings, representing the likelihood that a government might be unable or unwilling to meet its debt obligations in the future. Previous research demonstrates that sovereign ratings provide information about country risk that is absent from other macro-level factors. Ratings are obtained from S&P Global Ratings (New York), and we follow Bae and Goyal (2009) by converting them to a numerical score ranging from 1 to 16, with higher numbers reflecting poorer ratings. *Log(GDP)* is the natural logarithm of real GDP, in U.S. dollars, and *GDP Growth* is the annual percentage growth rate of GDP at market prices based on constant local currency (aggregates are based on constant 2010 U.S. dollars).

Likewise, we control for a country's degree of financial development of the private sector by incorporating the control variable *Log(Credit to Private Sector)*. *Credit to Private Sector* is defined as the domestic credit extended to the private sector by financial corporations relative to GDP, referring to financial resources provided to the private sector, such as through loans, purchases of non-equity securities, and trade credits and other accounts receivable, that establish a claim for repayment. To control for economic development, we use *Log(GDP)* and *GDP Growth*.

3.6. Descriptive statistics

We combine the data on fintech loans with the legal enforcement measures and other macro-level factors from multiple sources. To minimize the effect of extreme values, we winsorize all continuous loan variables at the top and bottom 1% of each variable's distribution. Panel C of Table 1 shows the medians of the loan characteristics, measures of legal enforcement, and other factors related to the development of the fintech sector at the country level.

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[9] The *Enforcement* score has been widely employed in recent studies on how cross-country differences in judicial efficiency affect various corporate outcomes, for example, investment and risk (Favara et al., 2017), capital structure (Shah et al., 2017), and bond performance in M&As (Renneboog et al., 2017).

[10] The data are collected by the World Bank through the study of the codes of civil procedure and other court regulations as well as analysis of questionnaires completed by local litigation lawyers and judges: *Resolution Time* is the time taken to enforce contracts, originally recorded in days, counted from the moment a plaintiff decides to file the lawsuit in court until payment; *Cost of Claim* is the cost of enforcing contracts, recorded as a percentage of the claim value; *Judicial Quality* is a quality of judicial processes index, measuring whether each economy has adopted a series of good practices in its court system in four areas: court structure and proceedings, case management, court automation, and alternative dispute resolution.

[11] For more detail, see, as an example, Lending Club's loan pricing process (Tang, 2019).

[12] Appendix Table A.2 presents the mapping and distribution of the variable *Risk Rating* using credit grades provided by fintech platforms.

[13] We also assign Zopa and RateSetter U.K. loans risk level C, and the results are unaltered.

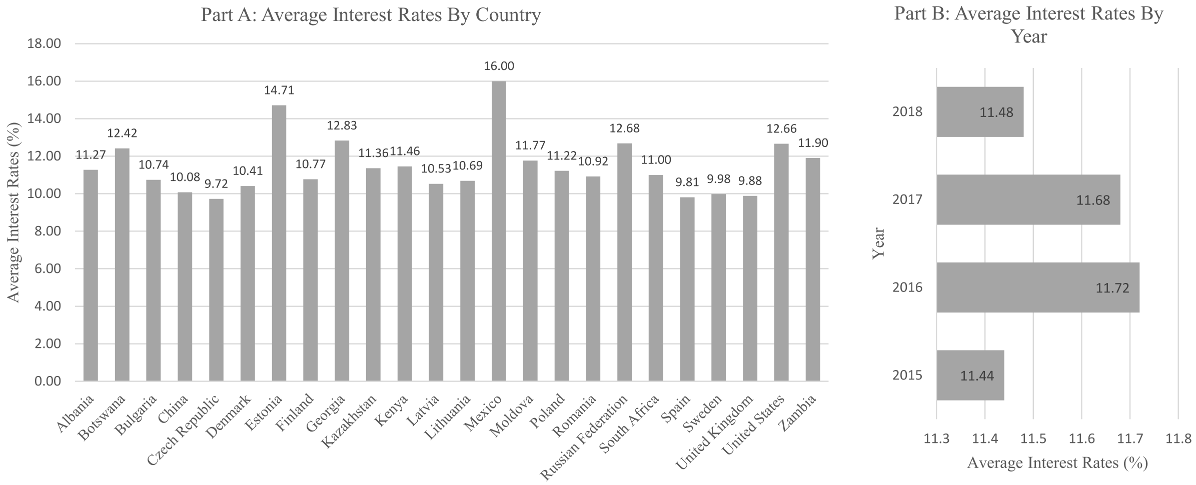

Fig. 1. Average interest rates by country and by year.
This figure shows the average interest rates across 24 countries (Part A), and the average interest rates by year from 2015 to 2018 (Part B).
Source: Seven fintech platforms: Mintos, Bondora, Funding Circle U.K., Lending Club, RateSetter U.K., Renrendai, and Zopa

The median interest rates of fintech loans by country range from 8.73% to 16.00%, with a standard deviation of 1.47%, suggesting a large variation in the loan prices across countries. The average interest rates of fintech loans by country have a similar distribution. The mean of the country-averaged interest rate for bank credit is 6.5%, with a standard deviation of 4.64%, which is lower than that for fintech loans. As for our key independent variable, *Enforcement*, our sample shows wide variation, from countries with high enforcement scores, such as the U.S. (79.1) and Lithuania (78.6), to those with low enforcement scores, such as Botswana (50.0) and Zambia (51.7) (see Fig. 1).

In terms of loan-level features, the country-level medians of loan maturity and loan size are, on average, about 22 months and 5726 U.S. dollars, respectively. Across the sample countries, 7.44% of loans are secured with collateral, and most loans are classified as either very low (18.21%) or low (69.77%) in terms of risk rating. This is consistent with most platforms' policies of only accepting loans with a low risk level; for example, Zopa only posts 20% of the loan applications received to its investors. In addition, most of the loans (92.54%) are safeguarded by the platform or a third party. In short, the country-level variables reflect substantial differences in credit information, legal protections, financial development, country-level credit risk, economic scale and growth, and the banking sector's financing of the private sector.

4. Empirical results

4.1. The differential effects of enforcement on fintech credit vs. bank credit

To examine whether fintech credit rates respond to the quality of legal enforcement to a greater or lesser extent than do bank credit rates, we set up the following economic model:

$$\textit{Average Interest Rate} = \beta_0\, \textit{Enforcement} + \beta_1\, \textit{Fintech Dummy} + \beta_2\, \textit{Enforcement} \times \textit{Fintech Dummy} + Controls + \varepsilon \tag{1}$$

where the dependent variable *Average Interest Rate* denotes the average interest rate of fintech or consumer bank credit at the country-year level. Our key independent variables include the *Enforcement* score from the World Bank, a *Fintech Dummy*, and the interaction term between the two. *Fintech Dummy* is a dummy variable that takes a value of 1 if the average interest rate belongs to the fintech loan category, and 0 otherwise (basically bank loan category). The coefficient β_2 is our primary interest. We expect β_2 to be positive if fintech loans are less affected by legal enforcement than bank credits. The control variables are country-level variables, including *Sovereign Risk*, *Log(GDP)*, *GDP Growth*, and *Log(Credit to Private Sector)*. We also include country fixed effects and year fixed effects to control for country- and time-based heterogeneity.

Table 2 reports the regression results of comparing the differential effect of legal enforcement on fintech vs. bank credit. We use country-level *Average Interest Rate* to run the regressions, so the total observations in the regressions amount to 122. In terms of enforcement, all columns show that the coefficients on *Enforcement* are negatively correlated with *Average Interest Rate* at the one-percent level. This result is consistent with the law and finance literature. The variable *Fintech Dummy* is also positively and significantly correlated with the dependent variable, indicating that fintech loans have higher average interest rates than consumer credits. More importantly, the coefficient on the interaction term between legal enforcement and fintech loans *(Enforcement × Fintech Dummy)* is positively related to *Average Interest Rate*. This suggests that fintech credit rates are less affected by legal enforcement

Table 2
Comparing the differential effect of enforcement on Fintech credit vs. Bank credit.

	Average Interest Rate			
	(1)	(2)	(3)	(4)
Enforcement	−0.1071***	−0.1252***	−0.1252***	−0.1378***
	(0.0168)	(0.0155)	(0.0156)	(0.0145)
Fintech Dummy			0.7961***	−0.9550
			(0.1366)	(0.4744)
Enforcement × *Fintech Dummy*				0.0254***
				(0.0043)
Sovereign Risk		0.6063	0.6063	0.6063
		(0.2632)	(0.2646)	(0.2661)
Log(Credit to Private Sector)		0.840**	0.840**	0.840**
		(0.237)	(0.239)	(0.240)
GDP Growth		−0.0124	−0.0124	−0.0124
		(0.0174)	(0.0174)	(0.0175)
Log(GDP)		−0.1636	−0.1636	−0.1636
		(0.3160)	(0.3177)	(0.3195)
Country FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Obs.	122	122	122	122
Adj. R^2	0.225	0.236	0.446	0.476

This table shows the results of the differential effects of enforcement on fintech credit vs. bank credit. The dependent variable is the *Average Interest Rate* of a country, either the *Average Interest Rate of Fintech Loans* or the *Average Interest Rate of Consumer Loans* in that country. The *Average Interest Rate of Fintech Loans* is calculated from our sample and the *Average Interest Rate of Consumer Loans* is obtained from *Oxford Economics*. *Enforcement* is the score for enforcing contracts at the country level from the World Bank's *Doing Business* database. *Fintech Dummy* is a dummy variable that takes a value of 1 if the average interest rate belongs to the fintech loan category, and 0 otherwise. The interaction term between *Enforcement* and *Fintech Dummy* is presented in column (4). Other variable definitions are provided in Table A.1. Country and year fixed effects are included in all regressions. Heteroskedasticity-robust standard errors are reported in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

protection than are bank credit rates. In a test of robustness, we instead use the median of fintech loan interest rates per country-year, and the results are unaltered.

Among the country-level controls, *Sovereign Risk* has a positive but insignificant relationship with interest rates, which could be because country effects are constant across all loans to borrowers within the same country. Financial development, as measured by *Log(Credit to Private Sector)* – a country's total private credit relative to GDP, is associated with higher interest rates. This may be driven by loan demand, because a higher ratio of private credit extended would imply a higher demand for loans and thus a higher price, consistent with Qian and Strahan (2007). Other country-level controls are consistent with previous studies (e.g., Qian and Strahan, 2007; Bae and Goyal, 2009; Houston et al., 2010; Guérineau and Léon, 2019).

4.2. The effect of enforcement on fintech credit: Low risk vs. high risk

To examine whether legal enforcement matters more for high-risk loans than low-risk loans, we estimate the following:

$$Interest\ Rate = \beta_0\, Enforcement + \beta_1\, High\ Risk + \beta_2\, Enforcement \times High\ Risk + Controls + \varepsilon \quad (2)$$

where *Interest Rate* is the natural logarithm of the annual interest rate of the fintech loan in question, and *Enforcement* is a continuous variable that measures the judicial efficiency of the enforcement of contracts at the country level. At the outset, all fintech loans were mapped into four risk-rating categories – Very Low Risk (A), Low Risk (B), Medium Risk (C) and High Risk (D) – using credit grades provided by the fintech platforms (see Table A.2 for the mapping and distributions of the variable *Risk Rating*). To test Hypothesis 2, we re-categorized the high-risk group as (C) and (D), and the low-risk group as (A) and (B). In other words, we set up a dummy variable *High Risk* for the regressions that takes a value of 1 if a loan belongs to categories (C) or (D). *Controls* is a vector of loan-level (*Collateral*, *Risk Rating*, *Log(Loan Size)* and *Log(Maturity)*) and country-level (*Sovereign Risk*, *Log(GDP)*, *GDP Growth*, and *Log(Credit to Private Sector)*) control variables, as defined in the previous sections. We include country fixed effects to control for unobserved time-invariant country features, and year fixed effects to account for intertemporal variations such as market-wide shocks. We further control interacted country-year fixed effects to account for a host of potentially confounding unobservable time-varying factors. Because Mintos and Bondora operate internationally, we also include platform fixed effects to control for unobserved time-invariant platform characteristics.

Table 3 shows the results of testing whether high-risk loan pricing shows more dependence than low-risk loans on enforcement. In columns (1), (2), and (3), the coefficients on *Enforcement* are negatively and significantly associated with interest rate at the one-percent level. This suggests that the quality of legal enforcement in the borrower's jurisdiction is negatively associated with fintech loan prices. In columns (2) and (3), the coefficients on *High Risk* are significantly positive, suggesting that high-risk loans have higher interest rates than low-risk loans. This is consistent with the results in column (1) and previous fintech lending literature

Table 3
The effect of enforcement on Fintech credit: Low risk vs. high risk.

	Interest Rate		
	(1)	(2)	(3)
Enforcement	−0.1253***	−0.1076***	−0.0969***
	(0.0021)	(0.0137)	(0.0150)
High Risk		0.3386***	0.6371***
		(0.0006)	(0.0061)
Enforcement × *High Risk*			−0.0077***
			(0.0001)
Collateral	−0.0340***	−0.1213***	−0.1133***
	(0.0006)	(0.0004)	(0.0004)
Risk Rating: B (Low)	0.3230***		
	(0.0004)		
Risk Rating: C (Medium)	0.5500***		
	(0.0004)		
Risk Rating: D (High)	0.8952***		
	(0.0006)		
Log(Loan Size)	−0.0268***	−0.0387***	−0.0388***
	(0.0002)	(0.0002)	(0.0002)
Log(Maturity)	0.0813***	0.0952***	0.0966***
	(0.0002)	(0.0002)	(0.0002)
Sovereign Risk	1.6318***	0.4336***	0.5689***
	(0.1563)	(0.0329)	(0.0332)
Log(GDP)	0.3964***	−0.7513**	−0.9681**
	(0.0255)	(0.3533)	(0.3791)
GDP Growth	−0.0129***	0.0274	0.0563*
	(0.0041)	(0.0288)	(0.0308)
Log(Credit to Private Sector)	3.3769***	0.5186***	0.6422***
	(0.3013)	(0.1925)	(0.2145)
Country FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Country-Year FE	Yes	Yes	Yes
Platform FE	Yes	Yes	Yes
Obs.	5,540,449	5,540,449	5,540,449
Adj. R2	0.493	0.230	0.213

This table shows the results of testing whether enforcement has a different impact on low-risk and high-risk fintech loans. All fintech loans have been mapped into four risk-rating categories – Very Low Risk (A), Low Risk (B), Medium Risk (C), and High Risk (D) – by using credit grades provided by the fintech platforms (see Appendix Table A.2 for the mapping and distributions of the variable *Risk Rating*). To test the hypothesis, we set up a dummy variable *High Risk* that takes a value of 1 if a loan belongs to Medium Risk (C) or High Risk (D). The dependent variable is *Interest Rate*. The interaction term between *Enforcement* and *High Risk* is presented in column (3). Variable definitions are provided in Table A.1. Country, year, interacted country-year, and platform fixed effects are included in all regressions. Heteroskedasticity-robust standard errors are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

(e.g., Hildebrand et al., 2017). More importantly, in column (3), the interaction term *Enforcement* × *High Risk* is negative and significant, implying that legal enforcement matters more in high-risk loans than low-risk ones, and supporting Hypothesis 2.

Turning to the loan-level control variables, *Loan Size* and *Collateral* are negatively associated with interest rates, while *Loan Maturity* is positively related to interest rates, consistent with the prior literature on bank credit (e.g., Bae and Goyal, 2009). Loan credit risk is also positively associated with interest rates, consistent with previous fintech lending literature (e.g., Hildebrand et al., 2017). In particular, loans with the highest level of risk (D) exhibit much higher interest charges than those with the lowest level of risk (A), which is the benchmark group.

4.3. The moderating role of risk sharing and information sharing

4.3.1. Impact of enforcement on interest rates: Risk sharing

In this section, we examine whether platforms' risk-sharing applications alter the impact of legal enforcement on interest rates. We use two proxies, *Risk Sharing Index* and *Platform Safeguard,* as indicators of the risk-sharing functions of fintech platforms.

Risk Sharing Index. From an investor's perspective, the risks of investing in fintech loans include credit default risk, cash flow timing risk, platform risk, and regulatory and compliance risk. To handle the heterogeneity of platforms' risk-sharing tools, we create an index based on their specific risk management methods. We collect information for this index by exploring ten questions that cover five risk dimensions of risks. If a platform can answer in the affirmative it scores 1, and otherwise 0. The *Risk Sharing Index* is the sum of scores from these ten questions, and ranges from 5 to 9 for the platforms in our sample. Appendix A.1 provides a more detailed description of the index and the procedures used to construct it.

Table 4
The impact of enforcement on interest rates: Risk sharing.

	Interest Rate			
	Risk Sharing Index		Platform Safeguard	
	(1)	(2)	(3)	(4)
Enforcement	−0.0277***	−0.0449***	−0.1151***	−0.0896***
	(0.0007)	(0.0027)	(0.0117)	(0.0121)
Risk Sharing Index	−0.0042***	−0.2277***	−0.0177***	−0.3362***
	(0.0007)	(0.0354)	(0.0022)	(0.0388)
Enforcement × Log(Risk Sharing Index)		0.0032***		0.0042***
		(0.0005)		(0.0005)
Platform Safeguard	−0.0360***	−0.0353***	−0.0340***	−0.0345***
	(0.0005)	(0.0006)	(0.0006)	(0.0006)
Enforcement × Platform Safeguard	0.3156***	0.3154***	0.3228***	0.3228***
	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Collateral	0.5465***	0.5462***	0.5498***	0.5498***
	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Risk Rating: B (Low)	0.8927***	0.8924***	0.8950***	0.8950***
	(0.0006)	(0.0006)	(0.0006)	(0.0006)
Risk Rating: C (Medium)	−0.0269***	−0.0269***	−0.0269***	−0.0268***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Risk Rating: D (High)	0.0780***	0.0780***	0.0815***	0.0813***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Log(Loan Size)	−0.2235***	−0.2144***	0.9487***	1.0002***
	(0.0075)	(0.0076)	(0.0327)	(0.0334)
Log(Maturity)	0.7474***	0.7358***	1.7105***	1.0437***
	(0.0174)	(0.0174)	(0.3077)	(0.3187)
Sovereign Risk	−0.0014***	−0.0011**	−0.2341***	−0.1809***
	(0.0005)	(0.0005)	(0.0252)	(0.0260)
Log(GDP)	−0.0279***	−0.0213**	2.8368***	2.5164***
	(0.0106)	(0.0106)	(0.1537)	(0.1586)
GDP Growth	−0.0277***	−0.0449***	−0.1151***	−0.0896***
	(0.0007)	(0.0027)	(0.0117)	(0.0121)
Log(Credit to Private Sector)	−0.0042***	−0.2277***	−0.0177***	−0.3362***
	(0.0007)	(0.0354)	(0.0022)	(0.0388)
Country FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Country-Year FE	Yes	Yes	Yes	Yes
Platform FE	No	No	Yes	Yes
Obs.	5,540,449	5,540,449	5,540,449	5,540,449
Adj. R^2	0.490	0.490	0.493	0.493

This table shows the results of how platform-level risk-sharing applications interact with legal enforcement. The dependent variable is *Interest Rate*. The interaction term between *Enforcement* and *Risk Sharing Index* is presented in column (2). The interaction term between *Enforcement* and *Platform Safeguard* is presented in column (4). The construction of the *Risk Sharing Index* is described in Appendix A.1. Variable definitions are provided in Table A.1. Country, year, interacted country-year, and platform fixed effects are included in all regressions. Heteroskedasticity-robust standard errors are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

Platform Safeguard. Some fintech platforms provide a safeguarding service that ensures that lenders get their full principal back if a borrower should default. We create a dummy variable, *Platform Safeguard*, that takes a value of 1 if a fintech platform provides such a service, and 0 otherwise.[14]

Table 4 shows the results of the interaction between platform-level risk-sharing applications and legal enforcement. Because the *Risk Sharing Index* for each platform is time-invariant during our sample period, and will be dropped off when we control for platform fixed effects, we did not control for platform fixed effects in columns (1) and (2). Columns (1) and (3) show that the coefficients on *Risk Sharing Index* and *Platform Safeguard* are both negative and significant, indicating that a platform's risk-sharing applications can lower interest rates. More importantly, columns (2) and (4) show that the coefficients on the interaction terms between legal enforcement and risk-sharing measures are significantly positive, suggesting that the role of legal enforcement in reducing interest rates is less pronounced when the platform has more effective risk-sharing applications, such as functional credit-screening and safeguarding services.

[14] Of our seven platforms, Zopa, RateSetter U.K., and Renrendai provide safeguarding schemes that cover the lender for the principal loan amount should a loan default. For loans from those platforms, we assign *Platform Safeguard* a value of 1. Mintos also provides a similar scheme ("buyback guarantee") whereby, if the loan repayment is delayed by more than 60 days, the originator company will repurchase the loan for the nominal value of the principal and accrued interest. Mintos' buyback guarantee scheme covers most of its loans (99%), and we assign a value of 1 to the variable *Platform Safeguard* for all such loans. All loans from LendingClub, Funding Circle U.K., Bondora, and the remaining 1% of Mintos' loans do not provide any compensation if a loan defaults, and we assign a value of 0 to the variable *Platform Safeguard* accordingly.

Table 5
The impact of enforcement on interest rates: Information sharing.

	Interest Rate			
	Information Coverage		Information Depth	
	(1)	(2)	(3)	(4)
Enforcement	−0.0422***	−0.0567***	−0.0447***	−0.0533***
	(0.0017)	(0.0025)	(0.0009)	(0.0016)
Information Coverage	−0.0183***	−0.6712***		
	(0.0069)	(0.0645)		
Enforcement × Information Coverage		0.0106***		
		(0.0009)		
Information Depth			−0.0031***	−0.1345***
			(0.0004)	(0.0164)
Enforcement × Information Depth				0.0017***
				(0.0002)
Collateral	−0.0326***	−0.0352***	−0.0326***	−0.0268***
	(0.0005)	(0.0005)	(0.0005)	(0.0005)
Risk Rating: B (Low)	0.3213***	0.3166***	0.3213***	0.3213***
	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Risk Rating: C (Medium)	0.5491***	0.5471***	0.5491***	0.5489***
	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Risk Rating: D (High)	0.8941***	0.8932***	0.8942***	0.8937***
	(0.0006)	(0.0006)	(0.0006)	(0.0005)
Log(Loan Size)	−0.0266***	−0.0276***	−0.0266***	−0.0263***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Log(Maturity)	0.0812***	0.0782***	0.0812***	0.0825***
	(0.0002)	(0.0002)	(0.0002)	(0.0002)
Sovereign Risk	0.1227***	−0.3286***	0.0850***	0.5260***
	(0.0091)	(0.0157)	(0.0073)	(0.0076)
Log(GDP)	−0.1650***	0.5142***	−0.1456***	−0.6842***
	(0.0125)	(0.0156)	(0.0129)	(0.0063)
GDP Growth	−0.0122***	−0.0210***	−0.0127***	−0.0182***
	(0.0003)	(0.0003)	(0.0003)	(0.0006)
Log(Credit to Private Sector)	0.1534***	−0.2537***	0.0861***	0.5239***
	(0.0121)	(0.0145)	(0.0127)	(0.0228)
Country FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Country-Year FE	Yes	Yes	Yes	Yes
Platform FE	Yes	Yes	Yes	Yes
Obs.	5,540,449	5,540,449	5,540,449	5,540,449
Adj. R^2	0.491	0.491	0.491	0.491

This table shows the results of testing how country-level information-sharing quality interacts with legal enforcement. The dependent variable is *Interest Rate*. The interaction term between *Enforcement* and *Information Coverage* is presented in column (2), and that between *Enforcement* and *Information Depth* in column (4). Variable definitions are provided in Table A.1. Country, year, interacted country-year, and platform fixed effects are included in all regressions. Heteroskedasticity-robust standard errors are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

4.3.2. Impact of enforcement on interest rates: Information sharing

Further, we examine whether information-sharing channels can mitigate the impact of legal enforcement on the interest rates of fintech loans. Following recent literature (e.g., Guérineau and Léon, 2019), we use *Information Coverage* and *Information Depth* to measure the country-level degree of information sharing.

Information Coverage. This denotes the number of individuals or firms listed by a private credit bureau (or a state's credit registry) – and offering current information on repayment history, unpaid debts, or credit outstanding – as a percentage of the adult population. If a country has both a private credit bureau and a public credit registry, we take whichever provides the larger coverage.

Information Depth. This measures rules and practices that affect the coverage, scope, and accessibility of credit information, available through either a credit bureau or a credit registry, based on surveys and questionnaires. The index ranges from 0 to 8, with higher values indicating the availability of greater amounts of credit information to facilitate lending decisions.

Table 5 shows the results of testing the interaction between the quality of country-level information sharing and legal enforcement. Columns (1) and (3) show that the coefficients on both *Information Coverage* and *Information Depth* are negative and significant, indicating that higher country-level information-sharing quality could lower interest rates, which is consistent with studies on business loans (Brown et al., 2009). Furthermore, columns (2) and (4) show that the interaction terms between legal enforcement and both the coverage and the depth of credit information are significantly positive. This implies that the role of legal enforcement in reducing interest rates is less pronounced when borrowers' jurisdictions have more channels for information sharing.

Table 6
Robustness test: Additional controls for legal rights.

	Average Interest Rate		
	(1)	(2)	(3)
Enforcement	−0.1406***	−0.1516**	−0.1510**
	(0.0187)	(0.0314)	(0.0324)
Fintech Dummy	−5.5602***	−5.5602***	−5.5602***
	(0.3765)	(0.3765)	(0.3786)
Enforcement × Fintech Dummy	0.0254**	0.0254**	0.0254**
	(0.0044)	(0.0044)	(0.0044)
Property Rights	0.0014		0.0012
	(0.0012)		(0.0010)
Rule of Law		0.2321	0.1815
		(0.2887)	(0.2450)
Sovereign Risk	0.3456***	0.5125***	−0.1426***
	(0.0047)	(0.0041)	(0.0034)
Log(GDP)	−1.1036***	−0.8813***	−0.9509***
	(0.0073)	(0.0047)	(0.0037)
GDP Growth	−0.0348***	−0.0316***	−0.0267***
	(0.0004)	(0.0004)	(0.0004)
Log(Credit to Private Sector)	−0.0126	0.3907***	0.3541***
	(0.0109)	(0.0087)	(0.0109)
Country FE	Yes	Yes	No
Year FE	Yes	Yes	Yes
Obs.	122	122	122
Adj. R^2	0.124	0.126	0.127

This table presents the test of robustness using additional controls for legal protection. The dependent variable is *Average Interest Rate*. The main independent variables are *Enforcement* in columns (1)–(3), *Property Rights* in columns (1) and (2), and *Rule of Law* in columns (2) and (3). Variable definitions are provided in Table A.1. Country and year fixed effects are included in all regressions. Heteroskedasticity-robust standard errors are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

4.4. Robustness tests

4.4.1. Additional controls for legal rights

Legal enforcement is a critical component of legal protection. Following law and finance literature, we incorporate into our estimations two alternative proxies for legal rights to check the robustness of our results, as described below.[15]

Property Rights. This index is a qualitative assessment of the extent to which a country's legal framework allows individuals to freely accumulate private property, secured by clear laws that are enforced effectively by the government. It measures the degree to which a country's laws protect private property rights, and the extent to which those laws are respected. It also assesses the likelihood that private property will be expropriated by the state, and analyzes the independence of the judiciary, the existence of corruption within the judiciary, and the ability of individuals and businesses to enforce contracts.

Rule of Law. This captures perceptions of the extent to which agents have confidence in and abide by the rules of society, and in particular the quality of contract enforcement, property rights, the police, and the courts, as well as the likelihood of crime and violence. It ranges from −2.5 (low) to 2.5 (high).

Table 6 shows the results of the robustness tests conducted by incorporating these alternative measures of legal protection: *Property Rights* in column (1), and *Rule of Law* in column (2). The coefficients on both proxies are not significant, but the coefficients on enforcement are still negatively significant. Our results are consistent with the argument that, within the set of formal institutions, law enforcement is more important than legal protection (Bae and Goyal, 2009; Qian et al., 2018).

4.4.2. Subsample analyses

To provide additional insights, we also conduct a number of tests to examine whether the impact of enforcement on interest rates is sensitive to various subsample analyses, and Table 7 shows the results. First, we are aware that the U.S., Georgia, China, and the U.K. account for the largest four fintech markets in our sample: 29%, 17%, 15%, and 13% of the overall sample, respectively, giving them far more loans than other countries. Thus, we cumulatively exclude the loans in these markets from our regression tests: column (1) excludes the U.S. sample; column (2) excludes the U.S. and Georgia samples; column (3) excludes the U.S., Georgia, and U.K. samples; column (4) excludes all four of these most prominent countries. Second, some countries in our sample, namely Georgia, Latvia and Moldova, are small in terms of population and economic size but account for a sizable proportion of all loans; column (5) excludes these countries' samples. Two platforms, both in the U.K., have unrated loans, Zopa and RateSetter U.K., accounting

[15] We also considered *Creditor Rights* as an alternative measure of legal protection (e.g., La Porta et al. (1998)). However, this index has been constructed for every year from 1978 to 2003, placing it outside the date range of our sample (2015–2018).

Table 7
Robustness test: Subsample analysis.

	Interest Rate						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Enforcement	−0.0596***	−0.0672***	−0.0368***	−0.1398***	−0.0490***	−0.0260***	−0.1116***
	(0.0007)	(0.0007)	(0.0025)	(0.0092)	(0.0009)	(0.0035)	(0.0158)
Collateral	−0.1191***	−0.1171***	−0.1176***	−0.0928***	0.1351***	−0.0149***	−0.1365***
	(0.0005)	(0.0005)	(0.0005)	(0.0004)	(0.0019)	(0.0004)	(0.0303)
Risk Rating: B (Low)	0.0926***	0.0862***	0.0970***	0.1245***	0.3263***	0.3313***	0.3778***
	(0.0007)	(0.0008)	(0.0008)	(0.0007)	(0.0004)	(0.0004)	(0.0004)
Risk Rating: C (Medium)	0.0777***	0.2920***	0.3444***	0.3289***	0.6305***	0.5668***	0.6072***
	(0.0009)	(0.0016)	(0.0016)	(0.0018)	(0.0004)	(0.0004)	(0.0004)
Risk Rating: D (High)	0.1716***	0.1874***	0.4802***	0.3879***	0.9266***	0.9023***	0.9397***
	(0.0016)	(0.0018)	(0.0040)	(0.0039)	(0.0006)	(0.0005)	(0.0006)
Log(Loan Size)	−0.0464***	−0.0581***	−0.0772***	0.0158***	−0.0516***	0.0158***	−0.0332***
	(0.0002)	(0.0002)	(0.0003)	(0.0002)	(0.0002)	(0.0001)	(0.0002)
Log(Maturity)	0.0772***	0.0941***	0.1012***	0.0564***	0.0911***	0.0681***	0.0574***
	(0.0002)	(0.0003)	(0.0003)	(0.0002)	(0.0004)	(0.0002)	(0.0002)
Sovereign Risk	0.0208***	0.2727***	0.2439***	0.3690***	0.3604***	−0.0918	−0.1183
	(0.0065)	(0.0134)	(0.0149)	(0.0122)	(0.0225)	(0.2692)	(2.8241)
Log(GDP)	0.0358***	0.0534***	−0.2965***	−0.1754***	−0.0981***	0.7036***	0.2150***
	(0.0113)	(0.0113)	(0.0219)	(0.0457)	(0.0134)	(0.0251)	(0.0277)
GDP Growth	−0.0037***	0.0198***	0.0030***	0.0208***	−0.0037***	0.0344***	−0.0283***
	(0.0005)	(0.0012)	(0.0009)	(0.0012)	(0.0005)	(0.0041)	(0.0047)
Log(Credit to Private Sector)	0.1026***	0.5806***	0.2867***	0.7639***	0.6300***	−0.0663	0.0420
	(0.0106)	(0.0249)	(0.0204)	(0.0189)	(0.0431)	(0.3389)	(5.1911)
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Platform FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Obs.	3,932,228	2,973,821	2,130,403	1,461,607	3,759,924	4,899,025	5,195,558
Adj. R^2	0.395	0.424	0.428	0.411	0.509	0.493	0.711

This table shows the results of examining the effect of enforcement on interest rates for country-level subsamples. The U.S., Georgia, China, and the U.K. account for the four largest fintech markets in our sample: 29%, 17%, 15%, and 13% of the overall sample, respectively. Column (1) excludes the U.S. sample; column (2) excludes the U.S. and Georgia samples; column (3) excludes the U.S., Georgia, and U.K. samples; column (4) excludes the samples of all four of these countries. Some countries in our sample, namely Georgia, Latvia, and Moldova, are minor in terms of population and economic size but account for a sizable proportion of all loans; column (5) excludes these countries' samples. There are unrated loans from two platforms in the U.K., Zopa and RateSetter U.K., which account for 11.58% of the overall sample; column (6) excludes these unrated loans. Column (7) only contains personal loans. The dependent variable is *Interest Rate*. The main independent variable is *Enforcement*. Country, year, interacted country-year, and platform fixed effects are included in all regressions. Variable definitions are provided in Table A.1. Heteroskedasticity-robust standard errors are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

for 11.58% of the overall sample; column (6) excludes these unrated loans. Finally, we check the loan types in our sample and find that personal loans account for 93.78% of all loans in our sample; column (7) excludes all other loan types. In each of these subsamples, the coefficients on enforcement are qualitatively equivalent to those of our initial results.

4.4.3. Additional country-level factors

The size of the fintech market varies significantly between countries, and its drivers are still the subject of debate. Recent studies (e.g., Claessens et al., 2018; Rau, 2019) find that economic development, financial market structure, and bank concentration, which also affect more traditional forms of credit, could explain the differences in fintech market size. Notably, legal enforcement is one of the mechanisms that facilitate economic and financial development. To partially address omitted-variable bias and provide further information on how other country-level drivers of fintech markets impact loan contracts, we also include proxies for bank competition, digital financial inclusion, and fintech credit development in our analysis, as described below.

Bank Competition. We adopt bank concentration as a measure of bank competition, calculated as the fraction of assets held by the three largest banks in each country. The structure–conduct–performance (SCP) paradigm assumes that there is a stable, causal relationship between the structure of the banking industry, firm conduct, and firm performance. It suggests that the fewer and larger firms are, the more likely they are to engage in anticompetitive behavior. In this framework, competition is negatively related to measures of concentration. Thus, as the proportion of assets held by the three largest banks increases, bank competition decreases. Previous literature (Beck et al., 2006; Van Leuvensteijn et al., 2013) suggests that stronger bank competition produces both lower bank interest rates and a stronger pass-through of market rate changes to bank rates.

Digital Financial Inclusion. Digital payment refers to payment services operated under financial regulations and performed from or via a digital device. Digital payments are becoming an essential instrument for payment service providers and market participants as a means to achieve new growth opportunities. The European Payments Council (2019) states that "new technology solutions provide a direct improvement to the operation's efficiency, ultimately resulting in cost savings and an increase in business volume". For banking, digital payments provide a new channel with which to improve financial services, with more security and convenience

Table 8
Robustness test: Additional country-level factors.

	Interest Rate		
	(1)	(2)	(3)
Enforcement	−0.2526***	−0.1101***	−0.0416***
	(0.0046)	(0.0015)	(0.0009)
Bank Competition	−0.0139***		
	(0.0005)		
Digital Financial Inclusion		−0.0155***	
		(0.0019)	
Fintech Credit Development			−0.0097***
			(0.0004)
Collateral	−0.0340***	−0.0340***	−0.0328***
	(0.0006)	(0.0006)	(0.0005)
Risk Rating: B (Low)	0.3230***	0.3230***	0.3212***
	(0.0004)	(0.0004)	(0.0004)
Risk Rating: C (Medium)	0.5500***	0.5500***	0.5490***
	(0.0004)	(0.0004)	(0.0004)
Risk Rating: D (High)	0.8952***	0.8952***	0.8941***
	(0.0006)	(0.0006)	(0.0006)
Log(Loan Size)	−0.0268***	−0.0268***	−0.0266***
	(0.0002)	(0.0002)	(0.0002)
Log(Maturity)	0.0813***	0.0813***	0.0812***
	(0.0002)	(0.0002)	(0.0002)
Sovereign Risk	8.7235***	0.5263***	0.1513***
	(0.2499)	(0.0371)	(0.0083)
Log(GDP)	2.0460***	0.3963***	−0.2174***
	(0.0573)	(0.0255)	(0.0131)
GDP Growth	0.1706***	−0.0129***	−0.0113***
	(0.0063)	(0.0041)	(0.0003)
Log(Credit to Private Sector)	17.8311***	1.0448***	0.1695***
	(0.5058)	(0.0592)	(0.0110)
Country FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Country-Year FE	Yes	Yes	Yes
Platform FE	Yes	Yes	Yes
Obs.	5,540,449	5,540,449	5,540,449
Adj. R^2	0.493	0.493	0.493

This table shows the results of how country-level bank competition, digital financial inclusion, and financial credit development affect fintech loan interest rates. The dependent variable is *Interest Rate*. The independent variables are *Bank Competition* in column (1), *Digital Financial Inclusion* in column (2), and *Fintech Credit Development* in column (3). Variable definitions are provided in Table A.1. Country, year, interacted country-year, and platform fixed effects are included in all regressions. Heteroskedasticity-robust standard errors are in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

(Mallat et al., 2004). Fintech platforms offer digital applications to investors and borrowers to manage their accounts. To measure digital financial inclusion, we use the proportion of the population in each year that used digital payments to pay bills or make purchases using money from their accounts.

Fintech Credit Development. Besides technology innovation, the growth of fintech credit within a country also relies on various economic and institutional factors, both demand- and supply-side, such as GDP per capita, regulation, the traditional credit market, the business environment, investor protection disclosure, and the judicial system (Cornelli et al., 2020; Rau, 2019). The development of fintech credit in a country indicates the overall acceptance and readiness of that country for fintech credit. Thus we define *Fintech Credit Development* as credit flows from fintech and the so-called Big Tech (e.g., Amazon, Apple, Google, Microsoft, and Meta) companies relative to GDP (%).

Table 8 shows the results for how country-level bank competition, digital financial inclusion, and the development of fintech credit affect fintech loan interest rates. The coefficients on *Enforcement* are still significant and negative after incorporation of these new control variables. The results also show that *Digital Financial Inclusion* and *Fintech Credit Development* are negatively related to interest rate, which is consistent with the fintech literature that describes how a good financial and technical environment can support the development of the fintech market (Haddad and Hornuf, 2019; Rau, 2019). Surprisingly, we find that *Bank Competition* is also negatively related to interest rate, that is, interest rates increase as bank competition increases. This may be because fintech loans act as a supplement to bank loans for high-risk consumers, providing an alternative channel for special financial needs (Claessens et al., 2018). Thus when bank competition increases, it becomes more difficult for fintech platforms to compete with traditional banks, and the platforms attract higher-risk consumers and charge higher interest rates accordingly.

5. Conclusion

The fintech lending market has grown dramatically in the last decade, and technology innovations in fintech lending are posing challenges to legal institutions with regards to contract enforcement between lenders and borrowers. Our study tests whether

Table A.1
Variable definitions.

Variable	Definition	Source
Dependent variables		
Interest Rate	The natural logarithm of the interest rate: flat annual percentage rate charged by lender after excluding any fee incurred by the platform.	Platforms
Average Interest Rate of Consumer Loans	The natural logarithm of the interest rate of consumer loans provided by Oxford Economics (oxfordeconomics.com) via Refinitiv Datastream.	Oxford Economics
Average Interest Rate of Fintech Loans	The mean value of fintech loan interest rates per country-year from our fintech loan data.	Platforms
Independent variables		
Enforcement	The score for enforcing contracts at the country level, defined as the average of the scores for each of three component indicators: the time and the cost of resolving a commercial dispute through a local first-instance court, and the quality of judicial processes that promote quality and efficiency in the court system. See World Bank's *Doing Business* database (DB).	DB
Other loan features		
Loan Maturity	The duration of the loan, in months.	Platforms
Loan Size	The loan amount provided to the borrower, in U.S. dollars.	Platforms
Log(Loan Size)	The natural logarithm of *Loan Size*.	
Collateral (1=Yes)	A dummy variable that takes a value of 1 if the loan is secured against assets (e.g., cars and houses), and 0 otherwise.	Platforms
Risk Sharing Index	The sum of scores from ten questions. See Appendix A.1 for more details.	Platforms
Platform Safeguard	A dummy variable that takes a value of 1 if a fintech platform provides a safeguard to ensure the lenders can get the full principal back if a loan defaults, and 0 otherwise.	Platforms
Other country-level factors		
Information Coverage	The number of individuals or firms listed by a private credit bureau (or a state credit registry) with current information on repayment history, unpaid debts, or credit outstanding. The number is expressed as a percentage of the adult population.	DB
Information Depth	A dummy variable that takes a value of 1 if the country's *depth of credit information index* is higher than the yearly median across countries, and zero otherwise. The *depth of credit information index* measure rules and practices affecting the coverage, scope, and accessibility of credit information available through either a credit bureau or a credit registry. The index ranges from 0 to 8, with higher values indicating the availability of more credit information, from either a credit bureau or a credit registry, to facilitate lending decisions.	DB
Property Rights	A qualitative assessment of the extent to which a country's legal framework allows individuals to freely accumulate private property, secured by clear laws that are enforced effectively by the government. It measures the degree to which a country's laws protect private property rights and the extent to which those laws are respected. It also assesses the likelihood that private property will be expropriated by the state and analyzes the independence of the judiciary, the existence of corruption within the judiciary, and the ability of individuals and businesses to enforce contracts. See the World Bank's *World Governance Indicators* (WGI).	WGI
Rule of Law	This captures perceptions of the extent to which agents have confidence in and abide by the rules of society, and in particular the quality of contract enforcement, property rights, the police, and the courts, as well as the likelihood of crime and violence. It ranges from −2.5 (low) to 2.5 (high).	WGI
Bank Competition	Negative bank concentration is adopted as the measure of bank competition, which is calculated as the negative value of the fraction of assets held by the five largest banks in each country.	WB
Digital Financial Inclusion	The percentage of respondents who used electronic payments (payments that one makes or that are made automatically, including wire transfers or payments made online) in the past 12 months to make payments on bills or to buy things using money from their accounts (% age 15+). See the Global Findex.	Global Findex
Fintech Credit Development	New lending provided by fintech and Big Tech companies over a calendar year, normalized by nominal GDP.	Cornelli et al. (2020)
Sovereign Risk	Country-level credit ratings, representing the likelihood that a government might be unable or unwilling to meet its debt obligations in the future. Original ratings are obtained from *S&P Global Rating* and we follow Bae and Goyal (2009) by converting them to a numerical score, with higher numbers reflecting poorer ratings.	S&P Global Rating
Log(GDP)	The natural logarithm of the real GDP, in U.S. dollars.	WDI
GDP Growth	Annual percentage growth rate of GDP at market prices based on constant local currency. Aggregates are based on constant 2010 U.S. dollars.	WDI
Log(Credit to Private Sector)	The natural logarithm of *Credit to Private Sector*. *Credit to Private Sector* refers to financial resources provided to the private sector by financial corporations through loans, purchases of non-equity securities, and trade credit and other accounts receivable that establish a claim for repayment, as a percentage of GDP.	WDI

contract enforcement affects the pricing of fintech loans in a different way to traditional bank loans, over a cross section of countries. Our findings show that compared to traditional bank loans, legal protection matters less in the context of fintech loans because they provide better risk-sharing practices *ex ante*.

Further, because the platforms play a risk-reducing role for investors, including *ex ante* loan pre-screening and *ex post* loan monitoring and default recovery, we find that the platform's risk-sharing mechanisms, fintech innovations, and fund safeguarding can all lessen investors' dependence on legal protection. In addition, fintech loans' sensitivity to legal enforcement is further reduced

Table A.2
Mapping and distribution of the variable risk rating.

Platform grade	*Risk*					
	Very Low Risk (A)	Low Risk (B)	Medium Risk (C)	High Risk (D)	Platform(s)	Obs.
A	1,259,428				1, 2, 4, 6	1,259,428
A	3,458				3	3,458
A+ (Very low risk)	2,672				3	2,672
A-	547,430				1	547,430
AA	5,371				2, 6	5,371
B		772,907			1, 2, 4, 6	772,907
B (Below average risk)		2,981			3	2,981
B+		96,390			1	96,390
B-		494,116			1	494,116
C			501,938		1, 2, 4, 6	501,938
C (Average risk)			2,251		3	2,251
C+			859,269		1	859,269
D				238,508	1, 2, 3, 4, 6	238,508
E				90,241	2, 3, 4 ,6	90,241
F				15,411	2, 4	15,411
G				888	4	888
HR				5,592	6	5,592
Uncategorized		641,598			5, 7	641,598
Total	1,818,359	2,007,992	1,363,458	350,640		5,540,449

This table presents the mapping and distribution of the variable *Risk Rating*, using credit grades provided by the fintech platforms. These platforms exhibit variation in the rules and categories used to define borrowers' credit ratings. To render them comparable across different platforms, we standardize the variable *Risk Rating* in four universal categories. Because Zopa and RateSetter U.K. do not disclose credit grades for borrowers, we assign all their "Uncategorized" loans as having average risk. Platform references are as follows: (1) Mintos, (2) Bondora, (3) Funding Circle U.K., (4) Lending Club, (5) RateSetter U.K., (6) Renrendai, and (7) Zopa.

if the borrower's jurisdiction offers higher availability of credit information, in terms of both coverage and depth, which is consistent with the literature on law and finance.

We contribute to this literature by extending the discussion of the relationship between law and finance to the fintech credit context. This interdisciplinary synergy is essential given that fintech innovations pose many challenges for the traditional law-and-finance framework. Moreover, this is among only a few studies that connect the fintech lending market to considerations of international dimensions. Our study also offers up the policy implication that legal protection remains fundamental to the financial stability of fintech credit markets, especially if and when economic conditions deteriorate.

CRediT authorship contribution statement

Hongfeng Peng: Conceptualization, Writing – review & editing, Supervision. **Jiao Ji:** Conceptualization, Writing – original draft, Writing – review & editing, Visualization. **Hanwen Sun:** Conceptualization, Writing – original draft, Writing – review & editing, Visualization, Project Administration. **Haofeng Xu:** Software, Conceptualization, Methodology, Investigation, Data curation, Writing – original draft.

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Appendix. Tables A.1–A.3

See Tables A.1–A.3.

A.1. Risk Sharing Index construction

From an investor's perspective, the risks of investing include credit default risk, cash flow timing risk, platform risk, and regulatory and compliance risk. We create an index (*Risk Sharing Index*) to capture the heterogeneity of platforms' risk-sharing tools according to their risk management methods. These methods have been disclosed publicly on each platform's website; for example, in *Investment Strategies*, *Security Methods*, *Statistics*, and/or annual reports.

We assess platforms' risk-sharing tools by asking the following ten questions of each platform: (1) does it have an auto-invest tool; (2) does it have a secondary market; (3) does it provide detailed information about the risk-rating model for a loan; (4) do its users have access to advanced statistics that reveal information about the loans on the platform (e.g., via an application programming interface (API)); (5) does it publish audited annual reports on the website; (6) does it present its risk management process on its website/in its annual reports; (7) is it a listed firm; (8) is it regulated by a financial regulator; (9) does it have an E-money license

Table A.3
Attribution of risk sharing index by platform.

		Mintos	Bondora	Lending Club	Funding Circle U.K.	RateSetter U.K.	Renrendai	Zopa
1	Does the platform have an auto-investment tool?	1	1	1	1	1	1	1
2	Does the platform have a secondary market?	1	1	0	0	1	1	1
3	Does the platform provide detailed information about its risk-rating model for a loan?	1	0	1	0	0	0	0
4	Do users have access to advanced statistics that reveal information about the loans on the platform (e.g., via an Application Programming Interface (API))?	0	1	1	1	0	0	0
5	Does the platform publish audited annual reports on its website?	1	1	1	1	0	1	1
6	Does the platform present its risk management process on its website or in its annual reports?	1	1	1	1	1	0	1
7	Is the platform a listed firm?	0	0	1	1	0	0	0
8	Is the platform regulated by a financial regulator?	0	1	1	1	1	1	1
9	Does the platform have an E-money license or an investment brokerage license?	0	0	1	1	0	0	1
10	Are all investors' funds stored in segregated bank accounts (with the platform not having the right to use them without agreement from investors)?	1	1	1	1	1	1	1
	Sum (*Risk Sharing Index*)	6	7	9	8	5	5	7

Table A.4
The volume comparison between Fintech credit and Alternative credit, as of GDP and Private credit respectively (%).
Source: Authors' calculations; Cambridge Centre for Alternative Finance; World Bank.

Country	Lending volume (% GDP) (1)	Lending volume (% private) (2)	Alternative credit (% GDP) (3)	Alternative credit (% private) (4)
Albania	0.1098	0.0033	0.0000	0.0000
Botswana	0.0584	0.0018	–	–
Bulgaria	0.0454	0.0009	0.0000	0.0000
China	0.1865	0.0012	4.1620	0.0264
Czech Republic	0.0132	0.0003	0.0000	0.0000
Denmark	0.0024	0.0000	0.0000	0.0000
Estonia	0.1603	0.0026	0.0000	0.0000
Finland	0.0054	0.0001	0.0000	0.0000
Georgia	0.9837	0.0157	1.0964	0.0175
Kazakhstan	0.8661	0.0334	0.0000	0.0000
Kenya	0.0087	0.0003	1.1763	0.0359
Latvia	0.3410	0.0093	0.0000	0.0000
Lithuania	0.1532	0.0038	0.0000	0.0000
Mexico	0.0001	0.0000	0.0187	0.0005
Moldova	0.5180	0.0223	–	–
Poland	0.0114	0.0002	0.0000	0.0000
Romania	0.0067	0.0003	–	–
Russian Federation	0.0175	0.0003	0.1298	0.0025
South Africa	0.0005	0.0000	0.0047	0.0000
Spain	0.0015	0.0000	0.0000	0.0000
Sweden	0.0040	0.0000	0.0000	0.0000
United Kingdom	0.0043	0.0000	0.3292	0.0024
United States	0.0250	0.0001	0.2848	0.0016
Zambia	0.1078	0.0072	0.0000	0.0000

This table shows the volume comparison between fintech credit and alternative credit as of GDP and private credit, respectively (%). *Lending volume* is the total fintech loan volume of each country based on our sample in 2018. *Alternative credit* is defined as the sum of fintech and big tech credit from the Global Alternative Finance Database at the Cambridge Centre for Alternative Finance (CCAF), which has been introduced by Cornelli et al. (2020). *Lending volume* and *Alternative credit* have been standardized by each country's GDP in columns (1) and (3), and total private credit in columns (2) and (4).

or investment brokerage license; (10) are all of its investors' funds stored in segregated bank accounts (and the platform does not have the right to use them without the agreement of investors)?

These ten questions capture the risk-sharing function of fintech platforms from five perspectives:

1. Automatic investing tool: Question 1. Fintech platforms provide investment tools to help investors diversify the risk of their investment portfolio. Jiang et al. (2018) find that these automatic investing tools are more effective in assisting investors to diversify their portfolio and mitigating herding effects.

2. Secondary market function: Question 2. Secondary markets in peer-to-peer lending are marketplaces that allow investors to buy and sell already funded loans after the repayment period has begun. They enable lenders to exit loans early or start lending instantly instead of waiting for new loans to become available for funding based on their liquidity needs. When a platform provides a secondary market, investors can mitigate cash flow timing risks.

3. Statistical transparency: Questions 3 and 4. Detailed information on loan pricing mechanisms in fintech platforms helps investors have a better understanding of the default risk (disclosure of default/estimated rates for the loans at each risk level). Furthermore, detailed information about loan applications can benefit investors by enhancing the screening process and reducing investment risk and improving investment reward. For example, Vallée and Zeng (2019) find that some sophisticated investors can take advantage of such detailed information to systematically outperform general investors.

4. Platform risk management: Questions 5 and 6. Fintech ventures are frequently new startups, which are more likely to face operational breakdowns. The disclosure of audited annual reports could build confidence in financial statements and give credibility to a platform and reassurance to its investors. The disclosure of risk management processes in its website or annual report indicates that a platform is less likely to have a problem in its operation. In addition, if a fintech platform is a listed firm, it must disclose more detailed information and should exhibit better management processes.

5. Regulatory and compliance risk management: Questions 7, 8, 9, and 10. Effective financial regulation is crucial to innovation and the future success of the fintech industry (Treleaven, 2015). Lack of supervision of financial intermediaries may lead to excessive risk-taking, and eventually damage financial stability (Di Tella, 2019). Fintech platforms in different countries face different regulations and compliance, which may affect their risk management strategies, and thereby affect investment risk.

A platform scores 1 if its answer to a specific question is 'Yes', and 0 otherwise. The *Risk Sharing Index* is the sum of scores from these ten questions, and ranges from 5 to 9 for the platforms in our sample, as shown in Appendix Table A.3.

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