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Does FinTech credit affect firms' cost of capital and capital structure?

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ABSTRACT

This paper explores the effect of FinTech credit on firms' cost of capital and capital structure. Based on a sample of 3,491 non-financial firms operating in 38 OECD countries during the period 2015–2021, we estimate that the economic effect of FinTech credit is approximately 17% on the cost of debt, and 9.5% on the cost of equity. In terms of cost of capital and capital structure, we observe a smaller yet economically significant reduction by around 5.5% and 3%, respectively. We also find that FinTech credit affects especially firms with stakeholders' oriented corporate governance practices, which operate in countries with higher bank market power and in more innovative industries. Finally, using a Difference-in-Difference model built around the COVID-19 outbreak, our evidence suggests that these effects are robust and hold also in time of crisis when the cost of capital generally increases due to the greater economic uncertainty.

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1. Introduction

Over the last two decades or so, the financial industry has witnessed significant growth in new credit providers, known as FinTech credit companies or 'FinTechs'. These are online platforms offering a variety of financial services such as peer-to-peer (P2P) lending, balance sheet lending, invoice trading, and debt-based securities issuing facilities (Allen, Gu, and Jagtiani 2021; Boot et al. 2021; Cornelli et al. 2020; Gomber, Koch, and Siering 2017; McKinsey 2019). The flow of credit granted by FinTechs worldwide has grown from around USD 11 billion in 2003 to USD 572 billion in 2019 (Claessens et al. 2018; Cornelli et al. 2020). Furthermore, the burst of the COVID-19 pandemic has enhanced online transactions and the business digitalization processes, thus fostering further FinTechs expansion as well as their profit margins (+11%in 2020 and +25% during the period 2021–2023[1]) (Boot et al. 2021; Capgemini and Efma 2021).

Compared to traditional financial intermediaries, FinTechs represent an additional and/or alternative source of funds that benefit from significant competitive advantages associated with their lending activity. Specifically, they can gather and deal with vast amounts of data that allow for lower search costs, higher potential economies of scale and more precise risk estimations. They also lever on sophisticated algorithms that speed up the screening process of borrowers, thus reducing the transaction costs associated with creditworthiness assessment, as well as the time needed to accept/deny loan requests. Although there are several concerns among regulators about the impact of FinTech credit on financial stability, FinTechs have so far benefited from less stringent regulation (e.g. prudential requirements) and lower regulatory burden compared to traditional banks (Buchak et al. 2018; Fuster et al. 2019; Stultz 2019).

These advantages mean that FinTechs can be in the position to offer credit at lower rates compared to traditional intermediaries, as they overcome the typical asymmetric information problems associated with credit origination (Thakor 2020). Another channel through which lending rates may be pushed downward

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thanks to the proliferation of Fintechs is through the greater competitive pressure they exert on traditional intermediaries, particularly banks (Anagnostopoulos 2018; Stultz 2019). As observed by Allen, Gu, and Jagtiani (2021), FinTechs may also contribute to further reduce the cost of equity of the firms they finance, thanks to the greater transparency and data disclosure they require from the firms they fund. Ultimately this 'spillover' effect is likely to decrease the risk perceived by equity investors thereby lowering their required return. For non-financial firms, it is therefore reasonable to expect that the availability of FinTech credit will affect their cost of funds and, consequently, their internal decisions in terms of optimal capital structure.

Although FinTechs offer credit at lower rates, translating into lower cost of capital for firms, the literature has, to date, underestimated the investigation of the effects of FinTech credit expansion on non-financial firms. The current literature has mainly focused on the effects of Fintech on financial markets, the banking sector and financial stability. However, the investigation of its impact on non-financial firms is equally relevant as it contributes to identifying alternative ways firms can create value. Decisions about financial structure and firms' ability to minimize the cost of capital are, indeed, levers firms may use to maximize their value (with the same profitability). Furthermore, the availability of capital at lower cost allows firms to invest more, thereby creating value for themselves and for the real economy.

This paper makes several contributions to the relatively vast literature on firms' financing decisions as well as to the more recent literature on FinTech credit (Tantri 2021). Despite the growing interest in the FinTech credit phenomenon (e.g. Buchak et al. 2018), our study is the first to provide an in-depth empirical investigation of the relationship between FinTech credit on the cost of debt and cost of equity for non-financial firms worldwide.

Secondly, our paper is also related to the literature exploring the consequences of FinTech expansion on the financial system (e.g. Junarsin et al. 2023*)*, providing suggestive evidence of the overall impact of FinTech credit on firms' decisions in terms of financial structure – a relevant aspect for the firms' stability, profitability, and value creation (Easley and O'Hara 2005). Last but not least, we contribute to the literature focusing on the effect of the COVID-19 pandemic on capital markets and firms' financing choices (Hodula 2023).

We perform an empirical analysis using a relatively large sample of 3,491 non-financial firms operating in 38 OECD countries, including 14,756-year observations from 2015 to 2021. We collect country-level data on the total amount of credit provided by FinTech players normalized by country GDP; we also use firm-level data for the cost of debt, the cost of equity, the Weighted Average Cost of Capital (WACC) and the financial leverage. Furthermore, we include in the model a set of market-specific and firm-specific variables that we expect may affect the FinTech credit on firms' cost of capital. We conjecture the effect will likely be stronger for firms that: (1) are based in countries characterized by higher banking market power levels, as bank concentration has been found to be one of the most important obstacles to obtaining finance (Beck, Demirguc-Kunt, and Maksimovic 2004; Ornelas, Da Silva, and Van Doornik 2022) and could push more firms to opt for FinTech credit; (2) rely on stakeholders' oriented corporate governance practices, as these may generate goodwill from stakeholders (Chiaramonte et al. 2022); and (3) operating in highly innovative industries, where firms are more prone towards the technology. We estimate a cross-sectional panel regression and a Difference-in-Difference (DID) model built around the outbreak of the COVID-19 pandemic, i.e. an exogenous shock that has increased economic uncertainty and hence risk premia required by lenders and investors (Liu, Qiu, and Wang 2021).

Our main findings suggest that the increase in FinTech credit lowers both the cost of debt and the cost of equity and, in turn, impact significantly the WACC of non-financial firms included in our sample. We also find that the growth in FinTech credit affects firms' financing decisions, by increasing the weight of the equity component of capital and thus reducing the leverage. As expected, the effects of the provision of FinTech credit are stronger for firms operating in countries characterized by higher banking market power levels, with stakeholders' oriented corporate governance practices, and with more innovative industries. Finally, our results suggest that firms headquartered in countries with higher availability of FinTech credit are more prepared to weather the negative effects brought about by the increased level of economic uncertainty.

This paper is organized as follows: in Section 2, we survey the relevant literature and develop our main hypotheses. Data and methodology are detailed in Section 3. Section 4 presents and discusses the results. Section 5 reports additional tests and robustness checks. Section 6 concludes and offers some policy implications.

2. Selected literature review and hypotheses development

The topic of FinTech credit is attracting the attention of academics towards two main issues: the effectiveness and efficiency of Fintech lenders compared to traditional lending institutions, and their impact on the structure and functioning of the banking system (e.g. Allen, Gu, and Jagtiani 2021; Berg, Fuster, and Puri 2022; Branzoli and Supino 2020). In this context, an important aspect that increases the competition with traditional banks relates to the greater specialization of FinTech lenders in screening and monitoring activities that apparently leads to a higher number of eligible firms and a reduction in the cost of credit.

To date, several eminent scholars have addressed these issues through the lens of the traditional theories of financial intermediation, providing illuminating reviews and suggesting new frameworks (e.g. Carletti et al. 2020; Cecchetti and Schoenholtz 2021; Thakor 2020). Although FinTechs' behaviour and their impact on the real economy have not yet been theoretically modelled, the past few years have witnessed a proliferation of broad-scope empirical studies, mainly focusing on single countries, both developing and developed ones. To our knowledge, there are no studies measuring how the availability of Fintech credit may affect non-financial firms' cost of capital and capital structure, however, the findings provided by a variety of empirical papers support us in formulating our hypotheses, as discussed below.

2.1. The effect of FinTech credit on the cost of debt

A first strand of literature has addressed the efficiency of FinTech lenders in carrying out screening and risk estimation activities. Bartlett et al. (2018) suggest that the availability of big data, in conjunction with advances in artificial intelligence (AI) and machine learning (ML), allows FinTechs to achieve more precise risk estimations. Fuster et al. (2019) add that, thanks to sophisticated algorithms, FinTechs can speed up the borrower screening processes and reduce the time needed to accept/deny loan requests. These results are supported by Wang and Perkins (2019), which demonstrate that AI and ML methods used by FinTechs can produce more accurate out-of-sample predictions of default on future loans with respect to the estimation techniques adopted by traditional intermediaries. This translates into lower risk assessment and transaction costs and more generally into a greater efficiency of FinTech lenders compared to traditional financial intermediaries, which explains the lower rates charged to borrowers (Thakor 2020). For example, De Roure, Pelizzon, and Thakor (2022), by analyzing the credit market in Germany, find that for FinTechs borrowers the risk-adjusted interest rates are lower than for those borrowing through bank loans.

A second strand of literature investigates the relationship between FinTech lenders and banks from a competitive perspective. FinTechs may complement the traditional credit supply, by representing an opportunity for marginal and risky firms to obtain credit that they would not receive from traditional intermediaries. However, in line with the disruptive innovation theory, FinTech credit might also substitute traditional credit and create competition in the market (Christensen 2013). Studies carried out in developing countries broadly confirm the complementary role of FinTech lenders in the financial markets. Hau et al. (2019), for example, by analysing a comprehensive dataset of 28.67 million monthly credit offered by Alibaba's online trading platform in China, find that FinTech lenders finance riskier borrowers, often excluded from traditional bank credit. Focusing on the case of Argentina, Frost et al. (2019) reach similar results and find support for the hypothesis that BigTech lenders have an advantage in credit assessment relative to a traditional credit bureau and that typically they serve the financial needs of borrowers rejected by traditional lenders.

In developed countries, recent empirical evidence mainly focuses on the US and shows that FinTech credit has mostly substituted bank lending, implying that borrowers who obtained loans from FinTechs would otherwise have been able to obtain them from banks or other sources (Di Maggio and Yao 2021; Tang 2019). Focusing on a US consumer platform ('LendingClub'), Jagtiani and Lemieux (2018) find that the typical borrowers do not represent the lower end of creditworthy ones. Other US-based studies (e.g. Balyuk 2016; Buchak et al. 2018) find that non-financial firms recur to FinTech credit to refinance existing bank loans, suggesting that banks and FinTechs mainly target the same type of borrowers. Similarly, Fuster et al. (2019), by employing data on mortgage applications and originations in the US, reject the hypothesis that FinTech lenders 'lax-screen' borrowers, selecting risky or marginal ones.

Using a panel of 78 countries for 2013–2019, Hodula (2022) reveals that especially in less stable and highly concentrated banking sectors, FinTech credit may act as a direct substitute for bank credit and may enhance competition. In a more recent cross-country study, Hodula (2023) finds that the rise of FinTech credit flows reduces incumbent banks' interest rates, as traditional banks tend to respond defensively to the rising share of alternative credit lines, lowering lending rates. However, to what extent the supply of Fintech credit affects the cost of debt of non-financial firms is still an open question. Therefore, we formulate our first hypothesis, H1, as follows:

H1: The higher the FinTech credit the lower the cost of debt for non-financial firms

2.2. The effect of FinTech credit on the cost of equity

Another topic addressed by the literature on FinTech credit looks at the effect on transparency and disclosure (Allen, Gu, and Jagtiani 2021) as unlike banks, lending platforms and investors jointly produce and divulge hard and soft information. To access FinTech credit, in most cases borrowers must disclose not only financial and economic data but also how funds will be used and other soft information. Banks and other traditional lenders typically own these data and information but do not disclose them (Correia, Martins, and Waikel 2022; Iyer et al. 2016).

The positive impact of information disclosure on the cost of equity capital is extensively acknowledged in the finance literature (among others, Dhaliwal et al. 2014; Easley and O'Hara 2005; Lambert, Leuz, and Verrecchia 2007) also in relation to alternative finance (Farag and Johan 2021). Related empirical research mainly points to a significant negative relationship between financial and non-financial disclosure and the cost of equity (Reverte 2012). This occurs mainly for two reasons: (1) firms with less publicly available information are perceived as riskier as they are opaquer; and (2) investors need to spend resources on information gathering and analysis (Diamond 1985). The evidence is in line with the agency theory (Jensen and Meckling 1976) suggesting that, if investors find corporate transparency valuable, they could expect to reward firms by lowering their costs of capital because of reduced costs of contracting. Furthermore, the negative effect of disclosure on the cost of capital is also supported by the disclosure theory (Verrecchia 2001). According to this theoretical perspective, transparency and disclosure practice go through two channels to lower the cost of equity. First, by reducing asymmetric information and, thus, mitigating the adverse selection problem and increasing asset liquidity; second, by reducing estimation risk (Chiao, Lin, and Lai 2015), which is systematic in nature (Kumar et al. 2008).

It follows that along with the effects on the firms' cost of debt, the development of FinTechs may also benefit the cost of equity. To our knowledge, how FinTech credits affect firms' cost of equity has not yet been explored. Therefore, we formulate the following hypothesis (H2):

H2: The higher the FinTech credit the lower the cost of equity

2.3. The effect of FinTech credit on the capital structure and cost of capital (WACC)

The supply of FinTech credit and the reduction in the cost of debt and equity may also affect firms' financing decisions about capital structure and consequently their leverage. Indeed, financing decisions and the identification of an optimal capital structure have long been theoretically controversial issues. Since the seminal work by Modigliani and Miller (1958), several theories have succeeded. However, the advent and growth of FinTechs and their effect on the cost of capital urge us to further reflect on this issue.

To create more value, in line with the leverage effect hypothesis (Black 1976), given a reduction in the cost of debt, non-financial firms could decide to exploit the leverage effect and increase their degree of indebtedness, provided the profitability ratio (e.g. ROA) is higher than the cost of debt. Besides, the Pecking Order Theory (POT) posits that when firms cannot lever on internal finance, they prefer debt to equity, thus increasing their leverage (Myers 1984).

However, one of the key POT's assumptions, i.e. the presence of information asymmetry in capital markets, may not hold in the case of FinTechs. This is because, as described above for our second hypothesis (*H2*), they can generate greater firm transparency, thus reducing the return required by equity investors. It follows that firms will likely prefer to raise equity capital rather than debt. In this vein, the trade-off theory suggests that the costs of bankruptcy limit the increase of debt and outweigh the relevant fiscal benefits (Kraus and Litzenberger 1973; Miller 1977), thus providing a rationale for a decrease in the firm leverage. Based on these arguments, we formulate the following third hypothesis (*H3)*

H3 The higher the FinTech credit the lower the leverage

Given the expected reduction of both the cost of debt and the cost of equity, we conjecture that the expansion of FinTech credit may in turn reduce the weighted average cost of capital (WACC) of non-financial firms. In light of these arguments, we formulate the fourth hypothesis (*H4*) as follows:

H4: The higher the FinTech credit the lower the WACC

3. Data and methodology

3.1. Data sources and sample

To perform our empirical analysis, we construct a dataset for the period 2015–2021, containing both firm-level data, provided by Refinitiv, and country-level data, drawn from Bloomberg and the World Bank's Global Financial Development Database[2] (Table A2). The former provides details on the cost of debt, cost of equity, the weighted average cost of capital and debt-to-equity ratio, as well as data on firms' size, profitability, and liquidity. Country-level variables proxy the countries' capital market structure and their risk and return, and the amount of FinTech credit, which is our main variable of interest.

We follow previous studies (see e.g. Cornelli et al. 2023; Kowalewski and Pisany 2022) which use the new and unique database built by Cornelli et al. (2020) accounting for FinTech credit as the country-level sum of small-tech and big-tech credit scaled by domestic GDP. According to the authors, FinTech credit may be defined as a technology-driven and loan-based business model, using the peer-to-peer (P2P) and marketplace lending platforms. Our proxy of FinTech credit captures the most comprehensive FinTech lending operations in a country. Cornelli et al. (2020)'s data are drawn from multiple sources, including the Global Alternative Finance Database (2013–2018) of the Cambridge Centre for Alternative Finance (CCAF) and annual surveys provided by the CCAF and academic researchers (Kowalewski and Pisany 2022). Specifically, firms are requested to provide details on their annual alternative finance volumes through an online survey. The questionnaire consists of 11 essential time-series questions designed to elicit precise transaction values, the involvement of stakeholders, and related information. Within this assessment, all loan-centered business models are categorized as Fintech credit. This classification encompasses peer-to-peer (P2P) or marketplace lending directed at consumers, businesses, or property; balance sheet lending targeting consumers, businesses, or property; invoice trading; debt-based securities like debentures and bonds; and mini-bonds. However, equity-based, donation-based, and reward-based crowdfunding are not classified under Fintech credit. Notably excluded are profit-sharing crowdfunding, community shares, pension-led funding, and real estate crowdfunding. Therefore, the main recipients of such credit are firms participating in the survey, and their responses have been used to create the country-level index of FinTech credit.

For our purposes, FinTech credit data were directly retrieved by the publicly available World Bank's Global Financial Development Database and are available until 2019.[3]

Our sample includes all listed non-financial firms, as defined by the Global Industry Classification Standards (GICS), without missing values for our firm-specific variables, headquartered in OECD countries (38). Our sample focuses on OECD countries to ensure that the data used in our econometric analysis are highly reliable and complete, as in Naeem and Li (2019). After collecting firm-level data from Refinitiv, we merge it with the Global Financial Development Database, ultimately obtaining a sample of 3,491 listed firms, including 14,756 firm-year data for 38 OECD countries as shown in Table A1.

Table 1. Sample description.

Variable	Mean	Median	Standard Deviation	p25	p75
Cost of debt (KD)	0.015	0.010	0.017	0.003	0.190
Cost of equity (KE)	0.081	0.076	0.036	0.056	0.100
D/E	0.285	0.268	0.207	0.143	0.394
WACC	0.066	0.063	0.029	0.046	0.082
FinTech Credit	0.185	0.191	0.171	0	0.284
Size (Natural logarithm)	22.041	22.066	1.675	2.100	23.146
ROA	0.048	0.050	0.091	0.025	0.084
MTB	0.035	0.020	0.061	0.011	0.038
LIQ	0.138	0.089	0.157	0.035	0.178
ATO	0.081	0.068	0.060	0.040	0.103
SM_Size	0.248	0.134	0.021	0.1201	0.288
SM_Return	0.062	0.072	0.085	0.013	0.126
SM_Volatility	0.162	0.154	0.051	0.123	0.191
Eco_Dev	1.033	1	0.180	1	1.4

Notes: This table reports the summary statistics of our variables in the sample expressed as percentages (except for *Size*). Variable definitions are provided in Table A.2.

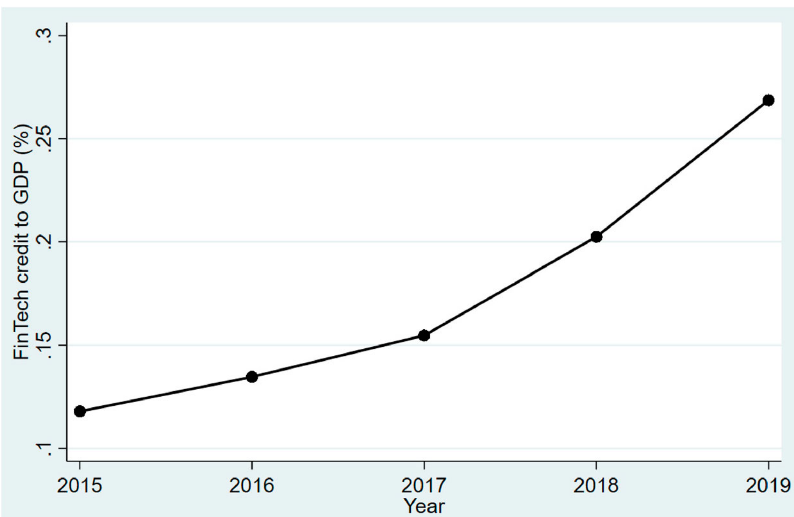

Figure 1. FinTech Credit to GDP in OECD countries. This figure illustrates the aggregate level of FinTech credit scaled by the countries' GDP (%) for OECD countries (2015–2019, averages). Source: World Bank database (2022).

3.2. Descriptive statistics

Table 1 reports the descriptive statistics for all the variables used in the empirical analysis. The measures of the cost of debt (KD), cost of equity (KE), debt-to-equity ratio (D/E) and weighted average cost of capital (WACC) are broadly in line with those found in recent literature (see e.g. Drobetz et al. 2018). Our target variable, the FinTech credit, accounts on average for 18.5%of GDP, ranging between 0% and 36%, thus highlighting a significant variability and polarization in the adoption of such alternative sources of financing among OECD countries.

Figure 1 plots the yearly trend of FinTech credit in our sample and confirms that overall, the FinTech credit adoption is rapidly increasing, especially in the most recent years (2017–2019). In line with Cornelli et al. (2020), FinTech credit reaches 35% and 36%of GDP for Korea and Japan, respectively, and about 30%of GDP for the UK and 25%for the US. In contrast, France, Cost Rica, Norway and Mexico show a FinTech credit score below 5%, with many EU countries showing very small or insignificant amounts for the period of interest.

3.3. Empirical strategy

To empirically explore the relationship between FinTech credit and firms' cost of capital and capital structure, we run the following OLS regression:

$$Y_{i,t} = c + \beta_1 FintechCredit_{i,t-1} + \beta_2 \mathbf{X}_{i,t-1} + \; Industry_i + Time_t + Country_i + \varepsilon_{i,t} \qquad (1)$$

where our dependent variable (*Y)* is, alternatively, the cost of debt (*KD*), cost of equity (*KE*), leverage D/E and WACC of firm *i* at year *t*. Our explanatory variable of interest *(FintechCredit*) is a proxy of the size of the Fin-tech sector (Cornelli et al. 2020) that measures the total amount of credit provided by FinTech players scaled by GDP. Additionally, we include several firm- and country-level variables that are typically found to be correlated with firm-level cost of capital (see e.g. Liu and Wang 2022), namely: asset size (*Size*), return on assets (*ROA*), market-to book ratio (*MTB*), liquidity ratio (*LIQ*), asset turnover (*ATO*). To account for the structure and efficiency of the countries' financial system we add a country-level measure of financial market size (*SM_Size*), stock market return (*SM_Return*), stock market volatility (*SM_Volatility*) as well as a proxy of the country economic development (*Eco_dev*) (Table A2). Finally, in Equation (1) we also include industry, time and country fixed effects.

4. Results

Table 2 reports the results of our baseline model. It shows that the amount of credit provided by FinTech players (*FinTech credit*) is negatively and statistically significantly correlated to the cost of debt (KD), cost of equity (KE), the leverage ratio (D/E) and the WACC in all models.

The magnitude of the coefficients of FinTech credit span from −0.0183 to −0.0223 for the KD, from −0.0381 to −0.0453 for the KE, from −0.0504 to −0.0671 for the D/E, and from −0.0220 to −0.0185 for the WACC, suggesting a strong negative and significant correlation with all our dependent variables. We economically estimate that an increase of one standard deviation of FinTech credit is associated with a decrease by 17%of the cost of debt and by 9.5%of the cost of equity, 3%on the D/E, and about 5.5%on WACC, hence supporting all our hypotheses *H1–H4*.

Regarding the control variables included in our main models, as shown in Table 2, our results are in line with the relevant literature (e.g. Liu and Wang 2022). Specifically, the coefficients for firms' profitability (measured as ROA), and market-tobook value (MTB) are negative and statistically significant. In contrast, the variables for liquidity, countries' stock market size and return appear positively associated to both cost of debt and cost of equity. One possible explanation is that the size of the internal capital market has a direct effect on firms' costs and efficiency (Tan et al. 2023). As for the stock market return, it is in line with the effects predicted by the corporate finance literature, which by being implicitly accounted in the CAPM function; it is expected to be positively associated with firms' cost of equity.

Since we can only observe the total cost of debt, we are unable to disentangle any direct and indirect effects of FinTechs, i.e. to verify empirically whether the reduction in the cost of debt is due to the lower cost of FinTech credit and/or also to a competitive effect on banks' interest rates. However, taken together our findings demonstrate that the expansion of FinTech lenders allows firms to borrow funds at lower interest rates and confirm the existence of an overall positive effect of FinTech credit on the cost of debt.

As for the relationship between Fintech credit and the cost of equity, it is possible that a 'spillover effect' could be at play, induced by the greater transparency and data availability generated by FinTechs. Such an effect would be in line with the agency and disclosure theory and consistent with the relevant empirical literature (see e.g. Reverte 2012) and may also explain why the expansion of FinTech credit determines a reduction in the leverage of non-financial firms. The lower cost of equity makes it more convenient for non-financial firms to strengthen their financial structure and at the same time, the lower interest paid on debts decreases the advantages associated with debt financing.

Last but not least, despite the decrease in financial leverage, the cost reduction of both funding sources prevails and translates into a lower overall cost of capital (WACC). Overall, our evidence confirms that Fintech credit

Table 2. The effect of FinTech credit on KD, KE, D/E and WACC.

	KD		KE		D/E		WACC	
Variables	(I)	(II)	(III)	(IV)	(VII)	(VIII)	(V)	(VI)
Fintech Credit (−1)	−0.0183***	−0.0223***	−0.0381***	−0.0453***	−0.0504***	−0.0671***	−0.0220***	−0.0185***
	(0.00218)	(0.00232)	(0.00398)	(0.00477)	(0.0169)	(0.0144)	(0.00358)	(0.00280)
Size (−1)		0.00173***		0.00104***		0.0101***		−0.000901***
		(0.000160)		(0.000304)		(0.00229)		(0.000233)
ROA (−1)		−0.0354***		−0.0514***		−0.353***		−0.0206***
		(0.00295)		(0.00562)		(0.0557)		(0.00490)
MTB (−1)		−0.0259***		−0.0156**		0.0550		0.00948*
		(0.00356)		(0.00645)		(0.0882)		(0.00505)
LIQ (−1)		−0.0128***		0.0112***		−0.327***		0.0231***
		(0.00189)		(0.00361)		(0.0269)		(0.00304)
ATO (−1)		0.0868*		0.0194		−3.138***		−0.0610
		(0.0495)		(0.0846)		(0.865)		(0.0618)
D/E (−1)		0.0277***		0.00953***				−0.0164***
		(0.00363)		(0.00328)				(0.00207)
SM_Size (−1)		0.0004***		0.00108***		−0.00101		0.000679***
		(0.00001)		(0.000188)		(0.000928)		(0.000152)
SM_Return (−1)		0.000118***		0.000294***		−0.00005		0.000178***
		(0.00001)		(0.00001)		(0.000145)		(0.00001)
SM_Volatility (−1)		0.000257***		0.000159		−0.00283***		−0.000157*
		(0.00001)		(0.000120)		(0.000499)		(0.00001)
Eco_Dev (−1)		0.0522***		0.128***		0.0569		0.0795***
		(0.00777)		(0.0145)		(0.0743)		(0.0117)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster S.E. Firm	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	14,756	14,756	14,756	14,756	14,657	14,657	14,756	14,756
R-squared	0.147	0.344	0.289	0.316	0.121	0.193	0.336	0.384

Notes: This table reports the results derived from the estimation of Equation 1 using an OLS model over the period 2015–2019. The dependent variables are KD, KE, D/E and WACC. The target variables are the total amount of credit provided by the FinTech industry scaled by country GDP (FinTech Credit). Variable definitions are provided in Table A.2. Columns (I), (III), (V), (VII) do not include control variables, while in Column (II), (IV), (VI), (VIII) are included. Time, industry and country fixed-effects (FE) are included in all specifications. Firm clustered standard errors (S.E.) are reported in parentheses. The superscripts ***, **, and * denote coefficients statistically different from zero at 1%. 5%. and 10% levels, respectively, in two-tailed tests.

have the potential to improve the financing conditions of non- financial companies, which can raise funds at a lower cost and curtail their indebtedness.

5. Additional tests and robustness checks

To strengthen our baseline results and provide further evidence, we perform the following set of additional tests and robustness checks; (1) a quasi-natural experiment analysis built around the COVID-19 pandemic outbreak; (2) an assessment of a possible moderating role of bank market power and firms' stakeholder engagement; (3) an industry subsample analysis; (4) a set of endogeneity checks.

5.1. Evidence from the COVID-19 pandemic

The COVID-19 pandemic can be considered the first exogenous shock (Cornelli et al. 2020) that, among other effects on the economic systems, has increased uncertainty and led financial institutions and investors to require higher risk premiums (Liu, Qiu, and Wang 2021). As shown by Ke (2022), US firms experienced an unprecedented increase of cost of equity capital due to the COVID-19 outbreak. Specifically, the induced (or voluntary) social distancing and lockdown to reduce the COVID-19 spread, lead to an economic downturn which pushed from 8%to about the 11%in the first semester of 2020 in US (Ke 2022).

We use a difference-in-difference (DID) regression setting, built around the outbreak of the COVID-19 pandemic (2015–2021) that represents an ideal setting for testing if the amount of credit provided to non-financial

Table 3. Difference-in-difference regression.

	KD		KE		D/E		WACC	
Variables / Models	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
Treated∗Covid-19	−0.0064***	−0.00395***	−0.0163***	−0.0127***	−0.0295***	−0.0194*	−0.00937***	−0.00820***
	(0.0012)	(0.00122)	(0.00227)	(0.00242)	(0.0104)	(0.0112)	(0.00174)	(0.00185)
COVID-19	0.0071***	0.00394***	0.00420**	−0.00361	0.0486***	0.0357***	−0.00260**	−0.00697***
	(0.0009)	(0.00114)	(0.00166)	(0.00222)	(0.00780)	(0.0100)	(0.00127)	(0.00170)
Treated	0.0028	−0.0107	0.00379	−0.0384*	0.135***	−0.000794	0.00331	−0.0172
	(0.0019)	(0.0106)	(0.00312)	(0.0218)	(0.0195)	(0.0996)	(0.00255)	(0.0158)
Controls (−1)	No	Yes	No	Yes	No	Yes	No	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster S.E. Firm	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,600	3,600	3,600	3,600	3,677	3,677	3,600	3,600
R-squared	0.229	0.459	0.398	3,600	0.137	0.233	0.381	0.446

Notes: In this table, we report the results of the differences-in-differences (DID) regression models exploring the impact of 2020 COVID-19 as an exogenous shock on our main variables of interest during the period 2015–2021. The dependent variables are KD, KE, D/E and WACC. The target variables are: *Covid-19*, that takes the value of 1 for years 2020–2021and 0 otherwise; *Treated*, that takes value of 1 for firms above mean values of FinTech credit to GDP in the years before of the shock (2018–2019), and 0 otherwise; the interaction term *Treated∗Covid-19*. All non-binary independent variables are lagged by one year with respect to the dependent variable. Columns (I), (III), (V), (VII) do not include control variables, while in Columns (II), (IV), (VI), (VIII) are included. Time, industry and country fixed effects (FE) are included in all specifications. Firm clustered standard errors (S.E.) are reported in parentheses. The superscripts ***, **, and * denote coefficients statistically different from zero at 1%, 5%, and 10% levels, respectively, in two-tailed tests.

firms by the FinTech industry affected firms' capital structure and financing costs. In detail, we test the following empirical specification:

$$Y_{i,t} = c + \beta_1 Treated^{*} Covid - 19 + \beta_2 Treated_{i,t} + \beta_2 Covid - 19_{i,t} + \gamma' X_{i,t-1} + Industry_i + Time_t + Country_i + \varepsilon_{i,t} \quad (2)$$

where all variables are defined as in Equation (1) and the dummy *Covid-19* represents the outbreak of the pandemic and takes the value of 1 for the years 2020 and 2021 and 0 otherwise.[4] The dummy *Treated* takes the value of 1 for firms operating in a country with a FinTech to GDP ratio above-average values for and 0 otherwise and *Treated∗Covid-19* is their interaction. Consistently, the variable of interest is the coefficient of *Treated∗Covid-19* which measures the causal and marginal effect of FinTech credit on firms' cost of capital after the unprecedented outbreak of COVID-19. Moreover, we test the difference-in-difference regression with and without the set of firm and country control variables, as well as industry, time, and country fixed effects. Subsequently, we estimate a propensity score matching (PSM) differences-in-differences regression using 2020–2021 as the years of the COVID-19 shock.

Table 3 reveals the result of the quasi-natural experiment, with and without control variables, confirming that firms headquartered in countries with a higher level of credit provided by FinTech firms have a marginally lower cost of debt, cost of equity, debt-to-equity ratio and cost of capital. Figure 2 shows that the results of the parallel trend assumptions hold thereby supporting the validity of our results.

5.2. The moderating role of bank market power

A well-established shred of literature has proven the negative effects of bank market power on the financial system, as well as on firms' cost of financing (see e.g. Mudd 2013). Similarly, in line with the *market power view* Beck, Demirguc-Kunt, and Maksimovic (2004) demonstrate that bank market power should be considered as one of the most important obstacles to obtaining finance, especially for firms' operating in countries with weak institutional environments and lower economic development. The market power view is also supported by Chong, Lu, and Ongena (2013), and Leone (2015), who empirically find that bank market concentration leads to lower access to credit also in developing countries. Yet, to what extent FinTech credits may affect the prediction of the market power view, is still an open question. We argue that the reduction effect of a FinTech

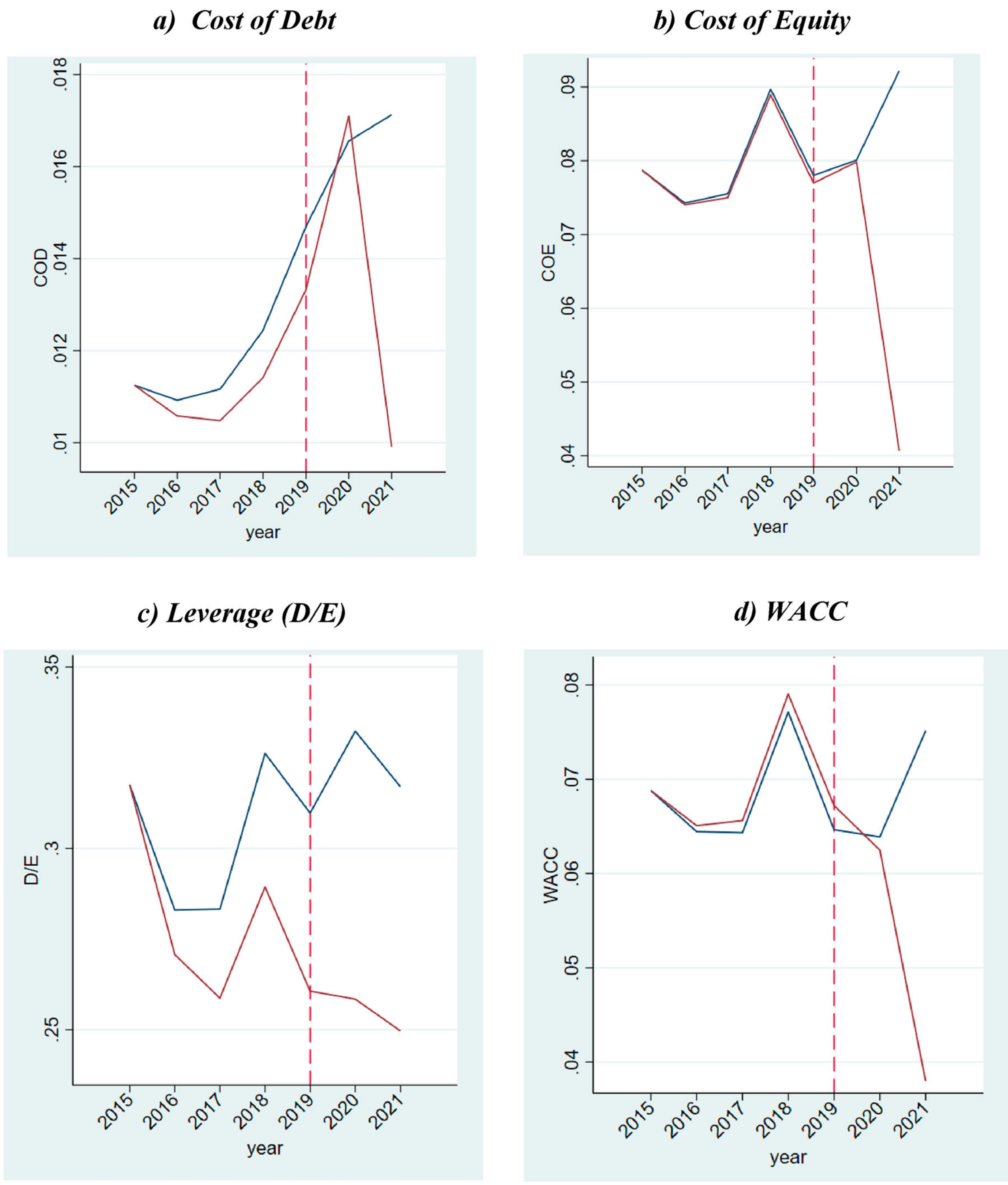

Figure 2. Parallel trend assumptions. (a) Cost of Debt, (b) Cost of Equity, (c) Leverage (D/E), (d) WACC. These figures illustrate that the parallel trend assumptions hold across all variables of interest (Cost of debt, Cost of equity, WACC and D/E) for firms headquartered in countries with FinTechs credit above the mean value before the outbreak of the COVID-19 pandemic (Target) versus firms headquartered in countries with FinTechs credit below the mean value before the COVID-19 (Controls). The pre-COVID-19 period is identified as 2015–2019; and COVID-19 period (2020–2021).

Table 4. The moderating role of bank market power.

	KD	KE	D/E	WACC
Variables	(I)	(II)	(III)	(IV)
FinTechs Credit (−1) ∗ High Bank Market Power	−0.0136***	−0.0398***	0.0229	−0.0269***
	(0.00307)	(0.00611)	(0.0242)	(0.00451)
Fintechs Credit (−1)	−0.0109***	−0.0117*	−0.0501*	0.000803
	(0.00266)	(0.00611)	(0.0274)	(0.00492)
High Bank Market Power	0.00164***	0.00283***	0.0152***	0.00112
	(0.000440)	(0.000951)	(0.00525)	(0.000802)
Controls (−1)	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Cluster S.E Firm	Yes	Yes	Yes	Yes
Observations	14,756	14,756	14,756	14,756
R-squared	0.345	0.318	0.194	0.386

Notes: This table shows the result of estimating an OLS model during the period 2015–2019, exploring the mediating effect of bank market power on the FinTechs credit-KD, KE, WACC and D/E relationship. The target variable is the total amount of credit provided by FinTechs industry scaled by country GDP (*FinTechs Credit*) interacted with Shareholders engagement (*FinTechs Credit∗High Bank Market Power*). Variable definitions are provided in Table A.2.Time, industry and country fixed effects (FE) are included in all specifications. Firm-clustered standard errors (SE) are reported in parentheses. The superscripts ***, **, and * denote coefficients statistically different from zero at 1%, 5%, and 10% levels, respectively, in two-tailed tests.

credit expansion on firms' cost of debt is stronger in countries where banks have significant market power. In those countries, FinTechs represent and even cheaper and more convenient source of financing compared to countries with low bank market power. The effect is attributable to the competition between Fintech and traditional banking institutions. The mechanism is explained as follows: when banks have significant market power, they can influence interest rates and on loan terms, leading to higher borrowing costs for firms. The entrance and expansion of FinTechs lead to two different, but not mutually exclusive, scenarios: (1) a reduction in the interest rate applied by banks, converging towards the price of Fintech credit; and (2) a substitution of bank loans with Fintech credit. In both case, the final result is the reduction of the overall cost of capital for firms.

Since our dataset includes a list of firms operating in many different countries' worldwide, it is interesting to understand how and to what extent bank market power affect the relationship between FinTech credit and non-financial firms cost of capital and financing decisions. We follow Wang et al. (2022), by measuring bank market power with a more accurate measure compared to bank concentration, which is represented by the Lerner index (data are provided by the World Bank Database).

Then, we test again our relationship as a mean of an interaction term between the dummy variable *High Bank Market Power* (equal to 1 for firms operating in countries with a level of Lerner index above the mean value of the sample and 0 otherwise) and our target variable (FinTech credit). Finally, in Table 4 we run our baseline model, testing the statistical significance of coefficients.

Table 4 shows that the effect of FinTech credit on the cost of debt, cost of equity and the cost of capital increases for higher levels of bank market power, supporting the existence of a moderating indirect effect of FinTechs on the cost of debt. Therefore, in financial systems where banks enjoy high market power and apply higher rates, the entry of FinTechs seem to represent a useful mechanism to mitigate the negative effect of concentration of the credit market, which ultimately reduce firms' cost of capital.

5.3. The moderating role of stakeholders' engagement

Corporate governance practices may generate goodwill from stakeholders which ultimately may lower the expected return on investments. Specifically, a stakeholder orientation signals to investors that managers are more in line with firms' best interest and long-term value, ultimately reducing potential agency problems (Lys, Naughton, and Wang 2015) that otherwise could delay corporate investment decisions and increase the cost of capital (Favara et al. 2017).

Table 5. The moderating role of stakeholders' engagement.

Variables	Cost of debt (I)	Cost of equity (II)	D/E (III)	WACC (IV)
FinTechs Credit ∗ Stakeholder engagement (−1)	−0.00351*	−0.0166***	0.0136	−0.0129***
	(0.00191)	(0.00383)	(0.0232)	(0.00292)
Fintechs Credit (−1)	−0.0205***	−0.0364***	−0.0611***	−0.0149***
	(0.00256)	(0.00523)	(0.0216)	(0.00400)
Stakeholder engagement (−1)	0.000156	0.00396***	−0.0200***	0.00376***
	(0.000559)	(0.00120)	(0.00706)	(0.000935)
Controls (−1)	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Cluster S.E Firm	Yes	Yes	Yes	Yes
Observations	14,756	14,756	14,657	14,756
R-squared	0.344	0.317	0.195	0.386

Notes: This table shows the result of OLS model during the period 2015–2019, exploring the mediating effect of stakeholder's engagement on the FinTechs credit-KD, KE, WACC and D/E relationship. The target variable is the total amount of credit provided by FinTechs industry scaled by country GDP (*FinTechs Credit*) interacted with Shareholders engagement (*FinTechs Credit∗Stakeholders engagement*). Variable definitions are provided in Table A.2.Time, industry and country fixed effects (FE) are included in all specifications. Firm-clustered standard errors (SE) are reported in parentheses. The superscripts ***, **, and * denote coefficients statistically different from zero at 1%, 5%, and 10% levels, respectively, in two-tailed tests.

Drawing on the stakeholder theory (Friedman and Miles 2002), we expect that in firms with higher stakeholder engagement, the reducing effect of FinTech credit expansion on cost of capital is even stronger as such firms are more prone to be open, inclusive and transparent (to support Hp2 we argue about the positive effects of transparency on cost of capital). Furthermore, stakeholder engaged in a firm's operations may support diversifying funding sources and push for the adoption of FinTech credit, leading to adjustments in their capital structure towards more efficient and diversified funding strategies.

To test these assumptions, we select a measure of firms' stakeholders' orientation drawn from the Refinitiv database and defined as a time-varying dummy variable equal to 1 if the company has a specific policy to facilitate stakeholder engagement, resolutions, or proposals to be consistent with stakeholders' objectives, and zero otherwise.

Similarly to Cuomo et al. (2022), we test the moderating effect of such policy by interacting the stakeholder's engagement variable with FinTech credit (*Stakeholders engagement∗FinTech credit*) testing our Equation (1). Results are reported in Table 5 and show that the measure of firms' stakeholders' engagement interacting with FinTech credit is negatively and significantly correlated with most selected dependent variables.

Consistently with the theory supporting the negative effects of agency conflicts on the cost of capital, our results suggest that the documented FinTech credit-cost of debt, cost of equity, and the cost of capital correlation is stronger for firms that are more oriented to stakeholders' interests and thus to long-term economic value creation.

5.4. *Fintech credit effects across industries*

Since firms' capital structure changes according to the industry in which firms operate (Li and Islam 2019), it is possible that the relationship FinTech credit-KD, KE, D/E and WACC follows a similar pattern. Moreover, as argued by Demirgüç-Kunt, Peria, and Tressel (2020), firms' capital structure also depends on the development of a country's financial and regulatory systems, as well as the firms' ability to reduce information asymmetry, which may change according to the industry type.

Evidence about firms' capital structure heterogeneity seems to be also supported by e.g. He et al. (2021), that show how firms' leverage structures change across industries and country-specific institutional environments.

Therefore, we re-run our baseline model in Equation (1) by splitting the sample according to their operating Global Industry Classification Standards (GICS).

Table 6 shows that firms operating in the Energy, IT, Materials, Industrials, Health Care, and Consumer discretionary are those most affected by the FinTech credit-cost of debt, cost of equity and WACC relationship, thus confirming the importance of the industry sector for the firms' cost of funding.

These results underline the importance of alternative finance credit for the cost of capital especially for firms operating in highly intensive innovative industries (e.g. Energy, IT, Materials, etc.), suggesting useful policy implications for firms operating in such industries.

Notwithstanding the decrease in the overall cost of capital for all the industries, looking at the coefficient for the variable D/E, we do not find a statistically significant effect on the capital structure, except for the Industrial and Utilities industries, and a positive correlation for Health Care. These results suggest that with only a few exceptions, FinTech credit acts similarly on the cost of debt and cost of equity side of firms' cost of financing, leaving the firms' capital structure preference unchanged for other sectors.

5.5. Robustness tests

Following previous studies (e.g. Kowalewski and Pisany 2022), in this paper, FinTech credit was proxied by the amount of credit provided by FinTech players (Cornelli et al. 2020) hence, our results might be biased by measurement errors and sample selection risks. In Table 7 we address this issue by re-estimating our baseline model (Equation 1) after replacing our main variable, the FinTech credit to GDP ratio, with a measure of FinTech operations, i.e. total payments made by mobile phones to pay bills. Recent studies such as Demir et al. (2022), consider this as reliable measure of FinTech market size and usage, which for our sample it is on average 15%with a range spanning from 0% to 30%. The variable *Mobile bill payments* was drawn from the World Bank's Global Financial Inclusion Database (Findex). The data is provided every three years and it allows us to strengthen the validity of our inference by extending the baseline regression in Equation (1) to 2021. Table 7 confirms that our results hold: we find that the Mobile bills payment is always negatively and statistically significantly correlated with all our variables of interests, hence confirming our baseline results.

A second concern is related to the fact that, unlike controlled experiments, our study is developed based on a public available database where countries are not randomly selected. Therefore, our empirical analysis may be affected by a sample selection bias. We reduce this concern by performing the Heckman two-step without exclusion restrictions regression methodology (1978), a common approach used in the finance literature (see e.g. Chiaramonte et al. 2022). The rationale behind the use of the Heckman two-step approach without exclusion restrictions lies in the impossibility of finding a truly exogenous variable to be used in the exclusion restriction model.

In Table 8 we estimate the Heckman model as follows: we firstly estimate the decision equation using a probit model to calculate the Inverse Mills Ratio (IMR), where the dependent variable is a dummy (*High_FinTech*) equal to 1 if the firm is headquartered in a country with a higher level of FinTech credit to GDP and 0 otherwise (Table 8, Column I); secondly, (Table 8 Columns II, III, IV and V) we run the Heckman model, by including the IMR among the regressors, confirming the negatively and statistically significant correlation between FinTech credit and firms' cost of debt, cost of equity, D/E and WACC.

A third robustness test addresses the potential issues due to the composition of our sample. As mentioned in Section 3.2, our sample is composed of firms headquartered in countries featuring large differences in FinTech credit adoption, with values ranging from 0% (some EU country) to 32% (Japan)of credit/GDP. Therefore, we re-estimate our baseline model by considering only countries with a value of FinTech credit greater than 0, trying to reduce biases stemming from such cross-country heterogeneity. Table 9 shows the results of this additional test, confirming the strength of the negative correlation between FinTech credit and firms' costs of capital and capital structure, except for the D/E ratio which is still negatively correlated but statistically insignificant.

To check for additional robustness, we re-run our baseline model (Equation 1) first excluding US firms from the sample, as they account for about 45%of the total; and then excluding the country (Japan) with the highest level of FinTech credit to GDP ratio. Finally, we run our baseline model (Equation 1) weighted for the Propensity Score Matching (PSM) without replacement with a Caliper distance of 1%, to control for unobserved differences between firms with higher and lower FinTech credit to GDP. All these tests confirm the negative and statistically significant correlation between FinTech credit to GDP and firms' cost of debt, cost of equity, D/E and WACC.

Table 6. Clustering by GICS industry.

	KD								
	Consumer discretionary	Industrials	IT	Materials	Real Estate	Utilities	Health Care	Energy	Communication services
Variables	(I)	(II)	III	IV	V	VI	VII	VIII	IX
FinTechs Credit (−1)	−0.0197***	−0.0289***	−0.0116***	−0.0252***	−0.0211	−0.0503***	−0.00770*	−0.0503**	−0.00929**
	(0.00401)	(0.00567)	(0.00331)	(0.00673)	(0.0132)	(0.0141)	(0.00401)	(0.0209)	(0.00389)
	KE								
FinTechs Credit (−1)	−0.0402***	−0.0577***	−0.0620***	−0.0589***	−0.0416*	−0.0608***	−0.0392***	−0.150***	−0.0232*
	(0.00917)	(0.00899)	(0.0117)	(0.0150)	(0.0215)	(0.0177)	(0.0150)	(0.0358)	(0.0137)
	D/E								
FinTechs Credit (−1)	−0.0277	−0.105***	0.0960*	−0.0736	−0.0430	0.0419	0.0367	0.0430	−0.0464
	(0.0457)	(0.0313)	(0.0507)	(0.0489)	(0.0946)	(0.0445)	(0.0968)	(0.0759)	(0.0605)
	WACC								
FinTechs Credit (−1)	−0.0196**	−0.0286***	−0.0546***	−0.0333***	−0.0121	−0.00605	−0.0251*	−0.0842***	−0.0156
	(0.00767)	(0.00588)	(0.0106)	(0.0123)	(0.0109)	(0.00769)	(0.0140)	(0.0183)	(0.0112)
Controls (−1)	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FE	No	No	No	No	No	No	No	No	No
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster S.E Firm	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	2,362	3,186	1,698	1,504	1,033	634	1,621	754	849

Notes: This table shows the result of OLS model during the period 2015–2019 for different subsample of Global Industry Classification Sector (GICS) clusters. The dependent variables are KD, KE, D/E and WACC. The target variable is the total amount of credit provided by FinTechs industry scaled by country GDP (FinTechs Credit). Variable definitions are provided in Table A.2.Time and country fixed effects (FE) are included in all specifications. Firm-clustered standard errors (SE) are reported in parentheses. The superscripts ***, **, and * denote coefficients statistically different from zero at 1%, 5%, and 10% levels, respectively, in two-tailed tests.

Table 7. Alternative measure of FinTechs Credit: Digital bills payments.

	KD	KE	D/E	WACC
Variables	(I)	(II)	(III)	(IV)
Digital Bills Payment (−1)	−0.0104***	−0.0328***	−0.0232***	−0.0346***
	(0.00125)	(0.00363)	(0.00305)	(0.0110)
Controls (−1)	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes
Cluster S.E Firm	Yes	Yes	Yes	Yes
Observations	14,756	14,756	14,756	14,657
R-squared	0.340	0.314	0.385	0.193

Notes: This table shows the result of OLS model during the period 2015–2021, using an alternative measure of FinTechs credit: the Digital Bills Payment data. The dependent variables are KD, KE, D/E and WACC. The target variable is the total amount of bills' payments using mobile phones (*Digital Bills Payments*). Variable definitions are provided in Table A.2.Time, industry and country fixed effects (FE) are included in all specifications. Firm-clustered standard errors (SE) are reported in parentheses. The superscripts ***, **, and * denote coefficients statistically different from zero at 1%, 5%, and 10%, levels, respectively, in two-tailed tests.

Table 8. Heckman two-step method regression.

	High FinTechs	KD	KE	D/E	WACC
	First-step				
Variables	(I)	(II)	(III)	(IV)	(V)
FinTechs Credit (−1)		−0.0223***	−0.0453***	−0.0343**	−0.0220***
		(0.00232)	(0.00477)	(0.0173)	(0.00358)
Size (−1)	0.0517***	0.00173***	0.00108***	0.00941***	−0.000884***
	(0.00753)	(0.000162)	(0.000312)	(0.00221)	(0.000239)
ROA (−1)	−0.105	−0.0354***	−0.0514***	−0.342***	−0.0206***
	(0.140)	(0.00295)	(0.00562)	(0.0514)	(0.00490)
MTB (−1)	0.205	−0.0259***	−0.0156**	0.0735	0.00946*
	(0.217)	(0.00356)	(0.00645)	(0.0831)	(0.00505)
LIQ (−1)	0.656***	−0.0128***	0.0114***	−0.333***	0.0232***
	(0.0885)	(0.00193)	(0.00363)	(0.0253)	(0.00303)
ATO (−1)	−2.174	0.0869*	0.0227	−3.075***	−0.0591
	−1.800	(0.0500)	(0.0851)	(0.813)	(0.0619)
Lev (−1)	−0.131**	0.0277***	0.00958***		−0.0164***
	(0.0579)	(0.00363)	(0.00329)		(0.00207)
SM_Size (−1)	−0.00396***	0.000447***	0.00106***	−0.00136	0.000669***
	(0.000602)	(9.09e-05)	(0.000186)	(0.000869)	(0.000150)
SM_Return (−1)	−0.0316***	0.000118***	0.000295***	−6.22e-05	0.000178***
	(0.00109)	(1.73e-05)	(3.93e-05)	(0.000145)	(3.15e-05)
SM_Volatility (−1)	−0.154***	0.000257***	0.000151	−0.00246***	−0.000162*
	(0.00273)	(5.52e-05)	(0.000120)	(0.000473)	(9.22e-05)
Eco_Dev (−1)	0.318***	0.0522***	0.127***	0.0164	0.0790***
	(0.0651)	(0.00780)	(0.0144)	(0.0702)	(0.0116)
IMR		1.77e-06	6.43e-05	−0.000969	3.67e-05
		(4.74e-05)	(0.000131)	(0.000714)	(0.000110)
Industry FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes
Cluster S.E Firm	Yes	Yes	Yes	Yes	Yes
Observations	19,319	19,319	19,319	19,319	19,319

Notes: This table reports the results of the first and second stages obtained from the Heckman two-stage model. Column (I) shows the result for the first step of the Heckman model (probit model), where the dependent variable is the *High FinTechs* dummy variable taking value of 1 for firms headquartered in countries with a higher level of FinTechs credit to GDP and 0 otherwise. Columns (II), (III), (IV), (V) show the results for the second step of the Heckman model, which includes the Inverse Mills Ratio (IMR) obtained from the first step. The dependent variables are KD, KE, D/E and WACC. The target variable is the amount of credit provided by FinTechs firms (*FinTechs Credit*). Variable definitions are provided in Table A.2. Time, industry and country fixed effects (FE) are included in all specifications. Firm-clustered standard errors (SE) are reported in parentheses. The superscripts ***, **, and * denote coefficients statistically different from zero at 1%, 5%, and 10% levels, respectively, in two-tailed tests.

Table 9. Baseline model excluding countries with FinTech credit equal to 0.

	KD		KE		D/E		WACC	
Variables	(I)	(II)	(III)	(IV)	(V)	(VI)	(VII)	(VIII)
Fintech Credit (−1)	−0.0264***	−0.0283***	−0.0544***	−0.0556***	−0.0160	−0.0239	−0.0254***	−0.0266***
	(0.00353)	(0.00316)	(0.00985)	(0.00570)	(0.0244)	(0.0183)	(0.00390)	(0.00798)
Controls (−1)	No	Yes	No	Yes	No	Yes	No	Yes
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Cluster S.E. Firm	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	10336	10336	10336	10336	14,657	14,657	10,336	10,336
R-squared	0.147	0.344	0.289	0.316	0.121	0.193	0.353	0.411

Notes: This table reports the results derived from the estimation of Equation (1) using an OLS model over the period 2015–2019 only for countries with FinTech credit values > than 0. The dependent variables are KD, KE, D/E and WACC. The target variables are the total amount of credit provided by FinTech industry scaled by country GDP (FinTech Credit). Variable definitions are provided in Table A.2. Columns (I), (III), (V), (VII) do not include control variables, while in Columns (II), (IV), (VI), (VIII) are included. Time, industry and country fixed effects (FE) are included in all specifications. Firm clustered standard errors (S.E.) are reported in parentheses. The superscripts ***, **, and * denote coefficients statistically different from zero at 1%, 5%, and 10% levels, respectively, in two-tailed tests.

6. Conclusions

We investigate the effects of the increasing availability of FinTech credit on firms' cost of capital and financial structure. By using a cross-country dataset of 14,756 firm-year observations related to 3491 listed companies from 38 OECD countries, during a relatively long period which includes the outbreak of the COVID-19 shock, we find that FinTech credit leads to a lower cost of debt, cost of equity, WACC and D/E. Specifically, our evidence suggests that an increase of one standard deviation of FinTech credit is associated with an average decrease of 17%of the cost of debt, of 9.5%of the cost of equity, about 3%of the leverage and 5.5% of WACC.

Using a DID regression model, we also show that the negative relationship between FinTech credit-cost of financing and capital structure relationship holds especially during financial turmoil periods, such as after the outbreak of the exogenous shock of COVID-19, supporting the relationship documented during normal periods. Our evidence indicates that the negative relationship is particularly important for firms operating in countries with high bank market power, stakeholders' oriented corporate governance practices and operating in highly innovative industries (i.e. Energy, IT, Materials, etc.).

In a context where the relative importance of Fintech credit is still relatively small even in the most developed countries, overall, our paper suggests that the benefits for non-financial firms from these disruptive innovators are indeed quite significant. This is especially true when considering the effects they have on reducing the firms' cost of funding, so they represent a potentially serious challenge for the more traditional banking sector. However, how and to what extent FinTech credit players represent a risk for regulators and possibly for global financial stability in the longer run is an open question that will need to be addressed in future research.

Notes

1. Source: Statista (Accessed June 2024) https://www.statista.com/outlook/dmo/fintech/worldwide#revenue.
2. The World Bank Global Financial Development Database is a unique dataset including more than 214 countries, with more than 106 economic indicators during the period 1960–2021.
3. Although the latest available data for FinTech credit end in 2019, we can still perform a DID analysis built around the COVID-19 outbreak in 2020 because our treated (control) group is constructed with data pre-COVID-19 shock (Section 5.1).
4. Results are consistent also setting the COVID-19 period equal to 1 only for 2020, and thus checking the consistency during only the most acute phase of the pandemic.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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Appendix

Table A1. Country distribution.

Country	No. of Obs.	%
Australia	1295	8.78
Austria	129	0.87
Belgium	30	0.20
Chile	154	1.04
Colombia	51	0.35
Czech Republic	3	0.02
France	375	2.54
Germany	876	5.94
Ireland	136	0.92
Israel	56	0.38
Italy	18	0.12
Japan	2162	14.65
Korea, Rep.	689	4.67
Mexico	219	1.48
Netherlands	170	1.15
New Zealand	249	1.69
Norway	150	1.02
Poland	137	0.93
Portugal	36	0.24
Slovenia	3	0.02
Spain	211	1.43
Switzerland	554	3.75
Turkey	227	1.54
United Kingdom	147	1.00
United States	6679	45.26
Total	14, 756	100

Table A2. Variable description.

Variable	Definition	Data provider
KD	Cost of Debt	Refinitiv
KE	Cost of Equity	Refinitiv
D/E	Total debt-to-equity ratio	
WACC	Weighted Average Cost of Capital	Refinitiv
FinTechs Credit	New lending provided by FinTechs and big tech companies over a calendar year, scaled by country GDP	World Bank Database
Size	Natural logarithm of total assets	
ROA	Net income available to common shareholder deflated by total assets	
MTB	The ratio of the market value of assets to book value of assets	
LIQ	Cash from operations to total assets	
ATO	Total revenues to total assets	
SM_Size	Total value of all listed shares in a stock market as a percentage of GDP	
SM_Return	Stock market return is the growth rate of annual national average stock market index	
SM_Risk	Stock price volatility is the average of the 360-day volatility of the national stock market index	Bloomberg
Eco_Dev	Dummy variable equal to 1 for countries classified as middle-upper income and 2 high income	World Bank Database

Table A3. Correlation Matrix.

	Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1	KD	1													
2	KE	0.4999*	1												
3	D/E	0.0777*	0.0104	1											
4	WACC	0.1402*	0.5627*	−0.0075	1										
5	FinTechs Credit	0.0101	0.0357*	0.0051	0.0446*	1									
6	Size	0.2728*	−0.0099	−0.0732*	−0.1054*	0.1070*	1								
7	ROA	−0.1083*	−0.1121*	−0.0872*	−0.0567*	−0.0246*	0.1613*	1							
8	MTB	−0.1890*	−0.0274*	−0.0294*	0.0261*	0.0067	−0.1209*	0.0551*	1						
9	LIQ	−0.2576*	0.0466*	−0.0214*	0.1134*	0.0712*	−0.4060*	−0.3304*	0.2159*	1					
10	ATO	−0.0435*	−0.0225*	−0.0269*	−0.0089	−0.0148*	−0.0492*	0.2668*	0.0457*	−0.1422*	1				
11	SM_Size	−0.0480*	−0.0757*	−0.0147*	−0.0643*	−0.1888*	−0.0932*	0.0172*	−0.0041	−0.0325*	−0.0496*	1			
12	SM_Return	−0.0506*	0.0751*	0.0072	0.0970*	−0.1724*	−0.0526*	0.0228*	0.0320*	0.0478*	0.0265*	−0.1913*	1		
13	SM_Volatility	0.1084*	−0.0766*	−0.0064	−0.1354*	−0.1009*	0.0825*	−0.0157*	−0.0245*	−0.0175*	0.0010	−0.0770*	−0.0436*	1	
14	Eco_dev	0.1614*	0.1620*	−0.0013	0.0863*	−0.1316*	0.0482*	0.0287*	−0.0232*	−0.0478*	−0.0050	−0.1584*	−0.0040	0.0638*	1

Note: $*$ Denotes coefficients statistically different from zero at the 5% level.