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The effect of fintech financing on firm performance: Evidence from emerging economies

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ABSTRACT

This paper rigorously examines the relationship between fintech financing and the financial and real performance of financially constrained firms in emerging countries. Using data from 45,770 firms across 20 countries for 2012–2020, we find that the performance of external-finance dependent firms is disproportionately higher when they operate in countries that receive more fintech funds. A host of robustness tests confirm our main finding. We further find that: (i) P2P lending and crowdfunding have greater implications on firm performance than balance sheet lending (ii) the relationship is particularly strong in young firms, and financially developed emerging countries with deeper disclosure of credit information, and (iii) specifically, in countries with greater banking penetration, there is evidence of a substitution effect between bank lending and fintech. Additionally, fintech finance increases capital investment, lowers borrowing costs, and boosts total factor productivity (TFP) to improve firm performance.

1. Introduction

Financial technology (fintech) has evolved alongside information and communications technology, offering a potential alternative to bank credit for firms needing external finance (Livshits et al., 2016; Sutherland, 2018). Studies have shown that a lack of access to funding impedes firms from reaching their full potential (Berger & Udell, 2006; Rahaman, 2011; Stiglitz & Weiss, 1981). This constraint is particularly severe in emerging market economies, where businesses have less access to financing than those in industrialized countries (Demirgüç -Kunt et al., 2018). Fintech firms, with innovative financial instruments, have revolutionized the financial sector and reduced the financing gap created by traditional banks. In recent years, fintech platforms have emerged as viable alternatives to conventional banks. These novel platforms integrate diverse benefits for users, including faster, more flexible, and cheaper access to credit. A distinctive advantage of fintech platforms is that they fuse algorithmic credit scoring mechanisms and other innovative techniques that decrease the need for collateral while lowering transaction costs. These features are particularly valuable in countries with underdeveloped financial systems.

However, there is limited insight into the firm-level impacts of fintech, especially in contexts where firms face financial constraints and banks remain the primary source of external funding. Despite the rapid rise in fintech adoption, there remains little evidence on

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how fintech influences performance at the firm level. Most existing studies tend to focus on a specific fintech platform, a single country, or narrow outcomes such as access to credit or innovation.

To address this gap, this study investigates whether firms in external-finance dependent industries perform disproportionately better in countries where fintech financing is more accessible than in countries where it is not. We examine how fintech impacts financial and real outcomes for firms across 20 emerging economies and highlight the role of mechanisms such as borrowing costs, capital investment, and firm productivity. In doing so, we contribute new evidence on whether fintech alleviates financing frictions and enhances firm performance.

Traditional banks have developed sophisticated credit risk assessment mechanisms based on extensive financial histories and regulatory frameworks, enabling precise pricing of borrower risk (Petersen & Rajan, 1994). The effectiveness of these mechanisms relies mainly on "hard" financial data that may exclude small firms without any credit history. In contrast, fintech firms rely on "soft" data sources such as digital footprints and e-commerce transactions and combine them with the latest algorithmic processing for assessing the creditworthiness of firms efficiently and inclusively (Buchak et al., 2018; Jagtiani & Lemieux, 2019). While fintech credit risk models may not match the depth of traditional banks' approaches, they have the potential to offer lower operational costs and expand credit access, especially for underserved borrowers (e.g., Fuster et al., 2019; Liberti & Petersen, 2019). Lower financing costs and better credit availability are expected to enhance firms' financial and real performance. In this study, drawing on the theories of financial constraints and cost of capital, we hypothesize that fintech financing relatively enhances both the real and financial performance of firms in industries that are more dependent on external finance.[2]

To test our hypotheses, we utilize a panel dataset comprising 45,770 manufacturing firms from 20 emerging market economies, spanning the years 2012–2020. Emerging markets provide an ideal setting for evaluating the degree to which fintech enhances firm performance.[3] We use the fixed effects approach to carry out our main analysis. To mitigate concerns about bias due to omitting confounding variables, we include a comprehensive set of firm, industry-year, and country-year fixed effects along with numerous controls capturing country and firm characteristics. We find strong support for our hypotheses; both financial performance, measured by return on assets and return on equity, and real performance, measured by value-added and employment growth, are relatively higher for firms in external-finance dependent industries in countries with higher fintech financing. These findings survive an array of robustness and sensitivity tests for omitted variables bias, reverse causality, and alternative measures of external finance dependency (EFD), fintech financing, and firm performance.

We further obtain several supplementary findings. Firstly, our results show that the impact of the interaction between fintech financing and EFD on firm performance is heterogeneous along several dimensions. In particular, in the disaggregated analysis of fintech financing, we find positive and statistically significant impacts of balance sheet lending, P2P lending, and crowdfunding, but no statistically significant effect of other forms of fintech financing.[4] Further, the impact of the interaction between fintech financing and EFD on firm performance is more pronounced for younger firms and firms located in emerging countries with greater financial development and a deeper credit information environment. Secondly, the results reveal a diminished effect of fintech lending in emerging countries with higher levels of banking activities, indicating that these two types of loans may substitute each other.

Finally, we identify and find empirical support for three mechanisms leading to the disproportionate impact of fintech financing on firm performance for financially constrained firms. Fintech enables firms to make capital expenditures that expand their production capacity; ease financial constraints and lower borrowing costs; and enhance total factor productivity (TFP) (Krishnan et al., 2015).

Our findings are novel and contribute to the relevant literature in several ways. Firstly, the study presents the first firm-level analysis of the impact of fintech financing in a cross-country context spanning 20 emerging markets. Existing research is typically limited to single-country settings and adopts a narrow focus on topics such as credit access, innovation, or investment (e.g., Ding et al., 2022; Frost et al., 2019; Huang, 2022). In contrast, we examine the broader effects of fintech financing by focusing on firm performance outcomes, namely return on equity (ROE), return on assets (ROA), employment growth, and value-added growth (ValG). To the best of our knowledge, this is the first empirical study that methodically links fintech financing to both financial and real performance using firm-level data from a diverse sample of emerging economies.

Secondly, we document evidence of the disproportionate benefits of fintech financing for financially constrained firms. This extends the literature that focuses on access to finance and firm performance under credit frictions (Bollaert et al., 2021; Colombo & Shafi, 2016; Cornelli et al., 2024) and links to the broader theories on growth and external finance dependence (e.g., Beck et al., 2005; Rajan & Zingales, 1998). Our findings show that fintech reduces borrowing costs and expands financing access for firms that may

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[2] We examine both financial and real performance. However, given a relatively low goodness of fit found in the empirical results, our focus in this paper is on the impact of fintech on financial performance.

[3] Fintech is regarded more important in emerging economies than in advanced economies. It has experienced exponential growth in emerging economies due to limited financial inclusion in traditional banking, where fintech is potentially able to bridge the funding gap, in particular, for SMEs (Da Silva, 2018). The lower cost of capital makes investment affordable for low-income countries. Digitized transactions tend to lead to transparency, which would reduce such behaviour as corruption and bribery. It is also found that fintech facilitates the economic integration of the informal sector into the formal financial system, contributing to equitable financial inclusion – see Hamidi (2021). In the case of developed countries, the advanced financial sector is well-structured with extensive financial inclusion, hence, the main benefit of fintech for these countries is likely to be its efficiency rather than access to credit. The overview of the fintech development in emerging economies is found in Fig. A1 in Appendix 1. The detailed comparative analyses for emerging and developed countries are also found in B, Appendix 1.

[4] Other forms of fintech include community share and pension-led funding (see Table A1 in the Appendix). These are estimated as, a separate category, along with balance sheet lending, P2P, and crowdfunding and presented as 'Others' in the tables.

otherwise be underserved by conventional banks.

Thirdly, our study presents a comparative analysis of fintech financing by disaggregating it into distinct business models, including P2P lending, balance-sheet lending, and crowdfunding. While previous studies have primarily focused on only one type of fintech (e.g., Tang, 2019), this study analyzes and compares the differential impact of these identified models on firm performance.

Fourthly, we contribute to the ongoing debate on whether fintech complements or substitutes conventional bank lending. Previous studies provide mixed evidence (e.g., De Roure et al., 2022; Gopal & Schnabl, 2022; Thakor, 2020). Our findings at the firm level provide a novel perspective. We find that the positive effect of fintech on the performance of firms that rely on external finance weakens in environments that have higher bank branch density. This suggests that fintech may serve as a substitute for bank lending, particularly in markets with underdeveloped banking systems. Finally, we provide new firm-level evidence that fintech strengthens total factor productivity (TFP), which is a vital indicator of resource allocation and firm efficiency. While prior studies indicate that access to finance and financial development improve productivity in emerging countries (Arizale et al., 2009; Bekaert et al., 2005; Fidrmuc et al., 2024; Gupta & Yuan, 2009; Tybout, 2000), we are among the first to show that access to fintech financing, particularly for firms facing financial constraints, leads to higher firm-level TFP.[5] We further identify two reinforcing mechanisms, namely lower borrowing costs and greater capital investment, which amplify fintech's impact on firm performance.

The remainder of the paper is structured as follows. Section 2 motivates the analysis by developing our main hypotheses. Section 3 presents the methodology and the data, followed by the main empirical results and sensitivity checks in Section 4. Section 5 demonstrates the channel from fintech to firm performance. Section 6 contains the conclusion.

2. Background and development of hypotheses

2.1. Background

Banks have resources for obtaining and processing information (Diamond, 1984; Berger et al., 2005) with the capacity for screening and monitoring (La Porta et al., 2006). However, there are certain limitations to these intermediation efforts, such as relatively high costs, complicated approval procedures, and limited loan availability for specific businesses. This has paved the way for new fintech innovations to cater to these inefficiencies. Investors who utilize a fintech-based lending strategy apply complex algorithms to check the creditworthiness of a borrower, which helps them decide whether or not a loan will be granted. The use of algorithms increases the efficiency of the loan process, reduces the cost of assessing loan applications, and increases loan availability. For instance, Fuster et al. (2019) argue that fintech lenders can process applications faster than banks due to an informational advantage created by algorithms. Buchak et al. (2018) note that fintech lenders utilize diverse information sources while making credit assessments, offering capital to firms that traditional banks might not effectively serve. The reliance of fintech on alternative data and automated decisions using numerical data, therefore, is an important characteristic that enables fintech firms to provide finance to a wider set of borrowers. (e.g., Buchak et al., 2018; Liberti & Petersen, 2019).

Fintech lending primarily consists of digital lending, which subsequently falls into two categories: balance sheet lending and marketplace (P2P) lending (Naceur et al., 2023; Bollaert et al., 2021; CCAF, 2021). Additionally, crowdfunding is typically categorized under digital capital raising (CCAF, 2021) rather than being classified as a lending model. While all fintech credit models leverage digital technology to enhance financing accessibility, their specific advantages may differ. For instance, some models may prioritize financial performance by improving access to financing at lower borrowing costs, while others may support real performance by facilitating investment in productive assets. We examine these differences in Section 4.4.1, where we decompose fintech financing into its main categories and analyze their distinct effects on firm performance.

By surpassing conventional financial intermediaries, P2P lending is a platform-based concept that directly integrates borrowers with individual or institutional investors (Naceur et al., 2023; Bollaert et al., 2021). P2P systems evaluate borrowers' creditworthiness, provide loans, and regulate repayments. Investors, not the platform, assume the default risk on the loan. P2P lending is currently one of the biggest categories of digital lending due to the exponential growth of the market and the substantial involvement of institutional investors (Bollaert et al., 2021). In contrast, balance sheet lending functions similarly to a traditional non-bank credit intermediary, where fintech platforms create loans and maintain them on their balance sheets (Naceur et al., 2023). Regardless of having similarities to traditional banking, this approach can be described as fintech credit since it incorporates advanced technology, including digital infrastructure, machine learning, and automated credit scoring (Bollaert et al., 2021; CCAF, 2021). These technology developments set balance sheet lenders apart from conventional non-bank lenders and enable them to optimize loan processing and enhance risk

[5] Cheng and Zhu (2024) investigate the impact of the liberalization of the Chinese stock market on TFP. Their regression results show that the implementation of the "Shanghai-Hong Kong Stock Connect" program significantly increases the TFP of target companies. Jin et al. (2024) examine the direct relationship between digital finance and the TFP of manufacturing enterprises using data collected from China's digital inclusive finance. Their findings suggest that digital finance has positive and significant impact on manufacturing TFP. See also Guo and Wang (2025), who extend this analysis by focusing on A-share listed companies in China from 2012 to 2022. However, these studies are limited to Chinese firms, do not take account for financial constraints, and are hard to generalize beyond China. For related work on the negative effects of resource misallocation on productivity, see Han and Shen (2015), Hsieh and Klenow (2007), and Restuccia and Rogerson (2007).

management.[6] Within the realm of digital capital raising, crowdfunding is a unique category that consists of lending, equity, and reward-based approaches (Bollaert et al., 2021; CCAF, 2021). Crowdfunding often involves raising relatively small amounts of capital from numerous individuals to support certain initiatives or endeavours. Even though loan-based crowdfunding shares some characteristics with marketplace lending (Cumming et al., 2022), other types of crowdfunding, such as equity crowdfunding, are not included in the fintech credit category. Therefore, while balance sheet lending involves platforms that develop and retain loans, P2P lending and crowdfunding link borrowers and investors directly.

2.2. Development of hypotheses

2.2.1. Fintech financing and firm real performance

Fintech technologies provide numerous advantages in emerging economies by serving as a valuable alternative financing source for firms that rely heavily on external financing to grow. This is crucial because conventional financial institutions in most emerging economies fail to meet the firms' financial needs due to fundamental issues such as underdeveloped financial infrastructures, inadequate collateral, and information asymmetry (e.g., Beck et al., 2005). In contrast, fintech platforms can reach widely dispersed firms and offer innovative financing solutions. For instance, when firms lack collateral assets, fintech companies can use big data and digital footprints to evaluate their credit risk (Holmström, 2018) and their financial conditions or other behavioral attributes (Berg et al., 2020; Jagtiani & Lemieux, 2019). This enables fintech platforms to provide credit to firms, including those without collateral assets or a long financial history (Cornée, 2019).

Drawing on the Theory of Financial Constraints, firms facing external financing constraints underinvest in physical and human capital, even when profitable opportunities exist (Fazzari et al., 1998; Hubbard, 1998). Firms' output is decreased when they are unable to take advantage of their growth potential due to a lack of funding. This constraint is inherently more prominent for firms operating in industries that depend heavily on external funding. By offering improvements in loan allocation through sophisticated credit assessment algorithms and data-driven decision-making, fintech platforms mitigate such acknowledged financing challenges (Bazarbash & Beaton, 2020). In this regard, fintech financing enables firms to take on investments that boost productivity and improve their real performance.

The positive impact of fintech financing on real firm performance is supported by prior empirical evidence. For instance, Eca et al., (2022) found that fintech lending has the potential to impact real economic activity for small and medium enterprises and can boost the investment, growth, and employment of these firms. We propose the following hypothesis:

H1: Fintech financing relatively improves the real performance of firms in industries that are more dependent on external finance.

2.2.2. Fintech financing and firm financial performance

The provision of efficient and easy access to financing by fintech enables firms to leverage opportunities in the market more effectively, thus improving their revenues. Fintech financing helps firms, most preferably those operating in industries that rely highly on external sources of finance, by reducing financial constraints. Based on evidence from China, Chen et al. (2022) document that credit access via fintech platforms minimizes revenue volatility for small firms, supporting fintech's ability to mitigate financial limitations. Furthermore, the fintech platforms provide firms that heavily rely on external financing with potentially lower interest rates on loans. Several factors contribute to this cost discrepancy. For instance, as fintech firms operate online, they typically have a smaller workforce, which reduces their operating costs (Lu, 2018). In the case of P2P lending, investors, not the platforms, provide the funds. Hence, fintech platforms do not need significant capital to safeguard against loan defaults. Furthermore, fintech firms can leverage vast amounts of data to assess credit risk accurately and efficiently. Consequently, by lowering borrowing costs and facilitating access to external financing, fintech platforms help firms optimize working capital, invest in high-return projects, and eventually increase profitability.

The impact of fintech financing on firm financial performance can be explained through the Cost of Capital Theory (Modigliani & Miller, 1958). This theory suggests that firms seek to minimize their cost of capital, particularly the cost of debt, to enhance firm value and profitability. Fintech facilitates this by offering more accessible and lower-cost financing options. By offering lower-cost financing, fintech reduces the cost of debt and improves financial performance. Zhou and Li (2024) argue that fintech accelerates firms' financial adjustments by mitigating financing constraints and enhancing information transparency, further reinforcing its role in improving firm profitability. Because financially dependent firms are in constant need of accessing outside funding to support their operations and growth, the characteristics of cost reduction and credit availability are especially significant in externally dependent industries. This aligns with the broader implications of the Cost of Capital Theory, where firms strategically adjust their financing structures to optimize their capital costs in response to evolving financial market conditions (Girardone et al., 2024). Based on this, our second hypothesis is as follows:

H2: Fintech financing relatively increases the financial performance of firms in industries that are more dependent on external finance.

While fintech finance provides firms easier access to financing from outside sources, there are several mechanisms through which it affects firm performance. First, through capital investments, firms with easier access to external finance can invest in assets like

[6] It is important to note that balance sheet lending is a business model rather than a lending instrument, as it represents a method of credit origination. The main feature that makes fintech credit differ from traditional financial intermediation is the reliance on innovative technologies for loan origination, underwriting, and risk assessment (Fuster et al., 2019; Buchak et al., 2018).

technology, machinery, and human capital that increase production and enhance performance. Second, lower borrowing costs from fintech lenders enable firms to reallocate financial resources, lower financial burden, and boost profitability. Lastly, by increasing TFP, fintech platforms help businesses scale operations more efficiently and optimize their production processes. In section 5, we evaluate these channels and examine the relationship between fintech finance and firm performance in financial and real terms.

3. Methodology and data

3.1. Model specification

We examine whether firms more dependent on external finance perform relatively better when located in countries with higher fintech financing. To achieve this, we specify the following regression equation:

$$Performance_{ijct} = \Delta.EFD_j \times Fintech_{ct} + \gamma_m.Controls_{ijct} + \delta_i + \delta_{jt} + \delta_{ct} + \varepsilon_{ijct} \tag{1}$$

where $Performance_{ijct}$ refers to the performance of firm i belonging to industry j for country c in year t, EFD_j measures the degree to which industry j depends on external sources of finance, $Fintech_{ct}$ denotes fintech financing as a percentage of GDP for a country c in the year t, $Controls_{ijct}$ is a vector of firm-level variables that vary over time, and ε_{ijct} stands for the error term. A firm's financial constraint and its performance influence each other raising serious reverse causation concerns. External finance dependence is measured at the industry, rather than firm, level to mitigate this endogeneity issue. The dummy variables δ_i, δ_{jt} and δ_{ct} represent firm, industry (SIC 2 digit)-year, and country-year fixed effects, respectively. We construct four dependent variables to examine firms' (i) financial performance, measured by return on assets (*ROA*) or return on equity (*ROE*), and (ii) real performance, represented by value-added growth (*ValG*) or growth in the number of employees (*EmplG*). Following Laeven and Valencia (2013), we compute the firm's value-added as the sum of earnings before taxes, depreciation, and labor expenses. Using this information, we obtain the value-added growth, which is the difference between the ending and beginning values divided by the beginning value. Since a country's GDP growth is a function of the value added by its enterprises, greater economic performance is naturally associated with higher firm value added. Overall, the two real indicators demonstrate a firm's contribution to the economy, while the two financial indicators highlight a company's profitability as seen by investors and shareholders.[7]

The total fintech financing consists of balance sheet lending (*BSheet*), P2P lending (*P2P*), crowdfunding financing (*CrowdF*), and other types of fintech lending (*Others*). We use the total fintech financing (as % of GDP) in our main analysis and its four components in the ancillary analysis. The interaction term $EFD_j \times Fintech_{ct}$ is our variable of interest. The coefficient Δ measures the differences in firm performance in financially dependent industries between countries with high versus low fintech financing. A positive and statistically significant point estimate of Δ supports our hypothesis that firms in financially dependent industries perform better if located in countries with more fintech financing.

We follow the existing literature on the factors affecting business performance to take into consideration firm characteristics (e.g., Barbiero et al., 2020; Burns et al., 2017; Demirgüç-Kunt et al., 2020, Igan et al., 2023). Specifically, we include the following five variables. The natural logarithm of a firm's total assets is an indicator of its size (*Size*), and the ratio of shareholder's equity capital to total assets as a proxy for the firm solvency (*Solv*). The impact of size is an empirical question. Larger firms may attract more resources and take advantage of economies of scale but may experience diminishing returns on investments due to the scale and complexity of their operations. Solvent firms can perform better as they have more assets against which shareholders have a residual claim. We next calculate the firm's leverage ratio (*Leve*), which is a firm's total debt as a fraction of its total assets, and liquidity ratio (*Liqu*), which is current assets minus inventories divided by current liabilities. The liquidity ratio shows a firm's capacity to pay its debts, while the leverage ratio indicates how much debt a company has used to finance its assets. Hence, we expect the effects of leverage ratio and liquidity ratio on firm performance to be negative and positive, respectively. Finally, the firm's fixed assets ratio (*FixA*), measured as a ratio of a firm's fixed assets to its total assets, points to how much a firm's operations rely on its tangible assets to produce income. The relationship between fixed assets and firm performance is complex and can be either positive or negative (e.g., fixed assets are not actively contributing to generating income).

Our empirical strategy consists of four parts. In the first part, we estimate Equation (1) using the fixed-effects estimator. The

[7] ROA indicates how effectively a company uses its total assets to generate profit. Since it accounts for all assets, it demonstrates a broad view of operational efficiency or financial performance. A declining ROA may indicate operational inefficiencies or an excess of investment not generating yields. ROA can compare firms in the same industry, as low-capital industries typically have higher ROAs and vice versa. The indicator of ROE demonstrates how well a firm's equity is used to generate profit. A high ROE suggests that firms are performing with a high efficiency in the use of equity funds. Hence, it is seen as a key indicator of a firm's financial performance (Martinez, 2023), together with ROA. Real performance can be effectively measured by the value-added variable. The value-added variable measures the increase in value generated by firms, focusing on the firm's contribution (e.g., labour, capital, and R&D) and removing external factors (e.g., the cost of inputs, cost volatility, or inflation). The cost of intermediate goods and services used in production is not considered. Therefore, value-added revenue provides a precise measure of profitability by concentrating on the value created within the establishment (Dunlap, 2024). Since real performance refers to productivity, the value added is a key indicator by showing the value of additional output derived from per unit of resources. Employment is defined as the number of hours of labour input per unit of output. Economic performance is measured by how these measures change over time since they reflect the capacity of job creation in an economy, indicating the level of economic activity. Since a high level of employment implies increased production, it is closely related to real GDP. It serves as a useful measure of real performance together with the value-added variable.

multidimensional (firm-industry-country-year) nature of our panel data allows us to control for a wide range of omitted variables through the use of interacted fixed effects (Hsu et al., 2014). In our baseline specification, the firm fixed effects, δ_i, control for all characteristics that are specific to a firm and do not vary across other dimensions of our panel data, such as a firm's risk-taking culture and its status as public or private.[8] δ_{jt} account for time-varying and industry-specific features that might drive cross-industry differences in financial/real performance, such as the technology content of production. Finally, the country-year fixed effects,δ_{ct}, are added to control for time-varying and country-specific determinants, such as macroeconomic and financial structure and development. Our fixed-effects specification absorbs all *industry* (δ_j) and *country* (δ_c) characteristics that do not change over time, such as the institutional, cultural, and legal environment, and all time-specific shocks (δ_t) common across industries and countries, such as a global crisis. Therefore, we can only estimate those variables that simultaneously vary across either firms and years or industry, country, and years – such as our main variable of interest ($EFD_j \times Fintech_{ct}$). Consequently, the direct impact of *Fintech*, which varies over country-year, and *EFD*, which changes only across industries, are eliminated by the fixed effects. Regression errors may be correlated within clusters, potentially biasing statistical inferences. We, therefore, cluster standard errors at a country-year level to account for the correlation of errors and regressors across industries within a given country and year. Our key identification strategy relies on the assumption that, after controlling for a rich set of covariates and fixed effects, any remaining unobserved factors are uncorrelated with our main variable of interest. Assuming no endogeneity related to reverse causality, measurement error, or omitted variables, and given that our variable of interest has sufficient within-variation, the coefficient for the interaction term represents a change in firm's performance attributed solely to the change in the interaction term, holding everything else constant.

In the second part, we conduct several robustness checks to address potential endogeneity. First, the relationship between fintech financing and firm performance might be influenced by factors omitted from our model. Our interacted fixed effects approach mitigates but does not fully eliminate the omitted variables bias. For example, businesses in countries with low penetration of traditional banks might require more alternative financing and thus perform better. The country-year fixed effects account for these variables if the impact of financial development, which varies over time, is uniform across industries. Otherwise, the results could be biased. Therefore, we control for other potential channels that affect firm performance by including variables that could influence it, particularly at the country and industry levels. Then, based on these observable variables, we assess the likelihood that our estimates are influenced by unobserved heterogeneity across countries and industries (Altonji et al., 2005). Second, the financial performance of large firms may drive the emergence of alternative finance, such as P2P lending, in a country, leading to reverse causality. Although we doubt that the financial constraint of a firm affects the supply of fintech lending, we conduct a series of sensitivity tests for reverse causality in Section 4.2 to confirm our results.

In the third part, we implement additional tests. First, we assess the sensitivity of our results to alternative measurements of our variables of interest. Second, we decompose total fintech financing into four components and evaluate their impacts. We further perform a host of additional regressions to explore the possible heterogeneous effects of firm maturity and the characteristics of the financial sector. We then investigate the substitution or complementary effects of fintech financing.

In the final part, we explore the potential mechanism that explains our observed relationships by examining the impact of fintech financing on capital investments, borrowing costs, and total factor productivity.

3.2. Data

We obtain data for our variables from multiple sources and merge them to construct a panel dataset. Firm performance data are sourced from the ORBIS database by Bureau Van Dijk, which is one of the most comprehensive firm databases and has been increasingly used in academic research (e.g., Demirgüç-Kunt et al., 2020; Barbiero et al., 2020; Cathcart et al., 2020; Igan et al., 2020). We include firms that belong to the 22 manufacturing industries as classified by U.S. SIC codes for the period 2012–2020. The time frame is chosen based on the fintech data availability. We exclude microfirms (firms with fewer than 10 employees) and those that do not report total assets for the last 5 years during the sample period. We include all emerging countries with adequate fintech data, resulting in 20 emerging economies.[9] Consequently, 45,770 firms for the 20 selected emerging economies survive the filtering criteria. The number of firms in our dataset varies by country; on average, each sample country has about 2,288 firms.

Fintech data are collected from the Cambridge Center for Alternative Finance (CCAF)-hosted by the Global Alternative Finance data repository. This project ended in 2020, making it impossible to extend our data beyond this year. The Fintech transactions include digital lending and online capital-raising activities at the country level that have evolved outside of established banking institutions and traditional capital markets. CCAF (2021) reports 20 variables under alternative finance measured in dollars. For each country-year, we aggregate the values of these variables to determine the total annual amount of fintech financing. For our main measure of fintech financing, we compute the total fintech financing as a percentage of GDP. We also group the 20 variables into four categories – balance sheet lending (*BSheet*), P2P lending (*P2P*), crowdfunding (*CrowdF*), and *Others*– and analyze each category. Tables 2 and 3 present the summary statistics of the fintech financing, which are discussed in the next section.

The degree of financial dependence of each industry is based on Duygan-Bump et al. (2015), in the spirit of Rajan and Zingales (1998), which is constructed using data on U.S. firms. The Rajan and Zingales's (1998) approach is followed, for example, by Igan et al. (2020) and Wang (2022). The external financial dependence of each industry is computed by using the share of investment not

[8] It should be noted that since country-industry fixed effects are saturated by firm fixed effects, we do not need to include them.

[9] Table 2 (Panel A) lists these countries.

financed with internal cash flows, where industries are categorized using the U.S. SIC system. The underlying assumption is that financial markets in the United States are relatively frictionless and informative and, consequently, industry characteristics based on U. S. firm data reflect solely technological features rather than U.S. industry attributes. Appendix Table A1 describes all variables, including other country-level measures used in this study, along with data sources. The variables are winsorised at the top and bottom one percentile.

3.3. Summary statistics

Table 1 presents the fintech financing in absolute terms (Panel A) and as a percentage of GDP (Panel B). We observe significant annual fluctuations in fintech financing. In particular, fintech financing experienced a dramatic increase in 2016 and 2017, followed by a sharp decline starting in 2018. It is also noteworthy that fintech financing is predominantly driven by P2P lending, exhibiting the highest value and percentage of GDP among other forms of fintech financing, indicating the popularity of this platform.

In Table 2 , Panel A, we show the total number of firms, the average values for firm performance, and fintech financing, including its components, across emerging countries. Depending on the measure of firm performance, high-growth countries vary. For instance, firms in Poland have shown the highest performance at 7.5 % using *ROA*, whereas those in Chile stand out at 18.18 % using *ValG*. It appears that China, the largest emerging economy, has the highest use of fintech financing at 0.92 % among the selected countries. For each industry, the averages of firm performance, fintech financing, and external financial dependence are presented in Panel B, Table 2. On average, *ROA* is around 5 % for these industries, and most achieve more than 11 % *ROE*. Note also that the highest need for external finance is found in the Chemical & Allied Products industry at 0.28, whereas Leather & Leather Products industry shows the least need.

The descriptive statistics of the main variables are shown in Table 3. As expected for emerging countries, these variables are, in general, volatile with a relatively high standard deviation. *ValG* exhibits the highest fluctuation among firm performance indicators, whereas P2P lending reveals high volatility among fintech measures.

The firm performance is plotted together with fintech financing over the sample period in Fig. 1. *ValG* broadly traces the rise and decline of fintech financing, peaking in 2017. *ROA* is also in line with fintech, *albeit*, to a lesser degree. *ROE* is rather constant over the period, irrespective of fintech development. Similarly, the movement of *EmplG* appears to be independent of fintech, in particular, with a sharp upward shift in 2013. It remains to be seen how fintech financing and firm performance behave based on the statistical analyses.

Table 4 compares the firm performance of industries in low fintech lending countries and those in high fintech financing, conditional on the degree of finance dependence. For instance, when high external-finance dependent industries (75^{th} percentile) move from countries with low fintech financing (25^{th} percentile) to countries with high fintech financing (75^{th} percentile), *ROA* increases from 0.048 to 0.049. However, for less external-finance dependent industries, a similar shift leads to a decrease in firm performance from 0.052 to 0.050. The net, 'difference-in-difference', value is positive at 0.003. This supports our conjecture that if fintech financing can help industries perform better, this should be more pronounced for industries more dependent on external finance. The conclusion holds for other measures of performance, except for *ValG* where the difference-in-difference effect is negative at −0.004.

4. Empirical results

4.1. Baseline results

Table 5 reports the baseline results. The key variable of interest is the interaction between EFD and Fintech (*EFD* × *Fintech*), which allows us to explore whether the firms in external-finance dependent industries benefit more from fintech financing. In all models, we add Firm, SIC x Year and Country x Year fixed effects. Columns 1–4 do not contain any other control variables. In columns 5–8, firm-specific variables – size (*Size*), solvency (*Solv*), leverage (*Leve*), liquidity (*Liqu*) and fixed assets ratio (*FixA*) – are included to control for firm characteristics.

The important finding is that the effect of the interaction term, *EFD* × *Fintech*, is positive and statistically significant across all specifications. Hence, firms with a higher level of external-finance dependency demonstrate stronger financial and real performance if they are located in a country with a high level of fintech financing. These results support both of our hypotheses. Note that the firm-specific control variables in columns 5–8 are well-determined; the coefficients are mostly highly significant at the 1 % level with expected signs. The magnitude of the interaction effect varies depending on the firm performance measure used. For financial performance, the effect ranges from 0.005 (*ROA*) to 0.028 (*ROE*), while for real performance, the impact ranges from 0.025 (*EmpG*) to 0.441 (*ValG*). Furthermore, the size of corresponding coefficients slightly decreases as we add firm-specific controls, which may indicate that some unobserved factors are correlated with the main variable of interest.[10]

Our results align with the existing literature that highlights a positive effect of fintech on finance (e.g., Colombo & Shafi, 2016;

[10] The focus of our study is on the interaction between fintech and EFD. The partial effect of fintech on firm performance is the sum of its direct effect and the interaction effect at a given value of EFD. We cannot estimate the partial effect as the independent impact of fintech is washed out by the fixed effects. To estimate the direct impacts of fintech and EFD, we performed a regression analysis by removing all fixed effects except for the year-specific effects. As expected, the impacts of fintech and EFD are positive and negative, respectively. However, the interaction term is not statistically significant, underscoring the importance of controlling for unobserved heterogeneities (available upon request).

Table 1
Fintech financing in 20 emerging market economies.

	2012	2013	2014	2015	2016	2017	2018	2019	2020
Panel A. Value (million dollars)									
Fintech financing (Total)	0.76	1307.71	6057.28	25592.39	64897.82	97400.22	58476.23	23626.33	930.43
BSheet	0.00	0.49	43.69	186.59	9948.02	6142.67	1779.79	324.83	415.63
P2P	0.74	1299.21	5933.10	24414.51	53507.54	89049.00	56351.65	23175.10	411.84
CrowF	0.02	1.11	9.49	591.43	753.55	404.29	68.21	57.04	73.92
Others	0.00	6.91	71.00	399.86	688.70	1804.26	276.58	69.36	29.03
Panel B. In percentage of GDP									
	2012	2013	2014	2015	2016	2017	2018	2019	2020
Fintech financing (Total)	0.0003	0.015	0.061	0.240	0.604	0.840	0.493	0.277	0.088
BSheet	0	0	0.0004	0.002	0.089	0.050	0.014	0.008	0.013
P2P	0.0003	0.015	0.060	0.228	0.500	0.763	0.467	0.254	0.056
CrowF	0	0.0001	0.0002	0.006	0.008	0.009	0.005	0.007	0.009
Others	0	0.0001	0.001	0.004	0.007	0.018	0.006	0.008	0.010

Butticè et al., 2017; Balyuk, 2022; Beaumont et al., 2022). Fintech finance generally fills the gap in the financing cycle and is viewed as a new form of finance for entrepreneurial startups with significant financial constraints (Bollaert et al., 2021). Studies show that reward-based crowdfunding helps firms obtain venture capital (Colombo & Shafi, 2016), and the use of pooled investment through equity crowdfunding, as opposed to a direct shareholder structure, facilitates venture capital fundraising (Butticè et al., 2017). Furthermore, Chemla and Tinn (2020) argue that crowdfunding offers significant visibility and helps firms advertise and sell their products, while Belleflame et al. (2015) point out that it reduces startups' operating costs, supporting the close association between fintech lending and firms' profitability. There is also evidence that in the peer-to-peer lending platform in Germany, the fintech lenders' risk-adjusted interest rates are lower than those of traditional banks (De Roure et al., 2022). Balyuk (2022) find that a large portion of fintech lending goes to small businesses, which is crucial given their vulnerability to fundraising. Therefore, the development of fintech lending would mitigate financial constraints, improving firm performance, an implication consistent with our empirical findings.

The estimated relationships also carry economic significance, as shown in the *Differential in firm performance*[11] at the bottom of Table 5. These are the estimated values for the difference in firm performance between industries that depend more and those that depend less on external financing. Focusing on the coefficient of the interaction term ($EFD_j \times Fintech_{ct}$) in column 1, we find that when moving from a country with fintech financing level at the 25th percentile to a country in the 75th percentile of fintech lending distribution, *ROA* for a firm in an industry at the 75th percentile of the external finance dependence distribution is nearly 1.8 % higher than the one in an industry at the 25th percentile of the same distribution. When *ROE* in column 2 is taken into account, the difference is approximately 8.4 %. These numbers are economically significant, given the sample mean of 6 % (13 %) and standard deviation of 12 % (36 %) for *ROA* (*ROE*).

Similarly, based on the coefficient of the interaction term in Column 3 (4), the value-added growth (employment growth) for a firm in an industry at the 75th percentile of the external finance dependence distribution is about 1.3 % (0.1 %) higher than that of a firm at the 25th percentile of the same distribution, when moving from a country with fintech financing at the 25th percentile to a country with fintech credit at the 75th percentile. Comparing these magnitudes to the sample mean of 10 % (7 %) and the corresponding standard deviation of 70 % (38 %), they are economically marginal, yet proves the benefit of fintech is more pronounced among external-finance dependent firms. The differential in firm performance values shown in columns 5–8 reveals similar findings.

4.2. Addressing the endogeneity issues

The key challenges to our empirical analysis are the potential endogeneity problems associated with omitted variable bias and reverse causality. In this section, we conduct several tests to address them.

4.2.1. Omitted variable bias

The interaction between fintech and EFD may capture the effects of some industry-level and/or country-level latent variables that could also affect firm performance. Failing to account for such variables could result in a potentially spurious positive association between firm performance and the interaction variable. In Table 5, we have incorporated an array of interactive fixed effects into our models to control for unobserved heterogeneity. However, to further mitigate any omitted variable bias that could arise from unaccounted factors, we control for additional variables that may affect firm performance. We consider five types of observable characteristics.

Tang (2019) argues that in the presence of a negative shock to bank credit supply, the quality of P2P borrowers worsens or improves

[11] We compute values as $\Delta\left[\left(EFD^{75th} - EFD^{25th}\right)\left(Fintech^{75th} - Fintech^{25th}\right)\right]$. See Eq. (1) for further elaboration on the variables and the coefficients.

Table 2
Descriptive statistics. Number of firms and the average firm performance, fintech financing and external financial dependence over the period 2012–2020.

Panel A: Average by country

			Financial performance (%)		Real performance (%)		Fintech financing (%)				
Code	Country	No. of firms	ROA	ROE	ValG	EmpG	Total	BSheet	P2P	CrowF	Others
1	Brazil	868	2.31	6.15	−17.55	0.39	0.054	0.046	0.005	0.002	0.002
2	Chile	31	3.49	8.44	18.18	1.20	0.092	0.001	0.016	0.001	0.073
3	China	12,414	4.57	11.43	6.44	9.25	0.921	0.064	0.840	0.006	0.011
4	Colombia	1380	6.52	28.00	9.53	9.66	0.051	0.005	0.011	0.000	0.034
5	Czech Rep.	3557	−0.63	1.71	5.32	3.59	0.016	0.000	0.004	0.001	0.011
6	Estonia	1308	6.70	13.14	12.39	8.68	0.288	0.000	0.248	0.025	0.015
7	India	1552	3.32	10.25	7.82	5.59	0.027	0.011	0.012	0.001	0.003
8	Indonesia	188	3.23	8.57	5.61	3.11	0.046	0.017	0.028	0.001	0.001
9	Kenya	13	4.87	17.20	11.97	−7.13	0.033	0.007	0.013	0.004	0.009
10	Latvia	1494	6.26	21.95	8.91	11.73	0.286	0.000	0.277	0.006	0.002
11	Lithuania	1231	7.35	18.89	6.12	8.38	0.126	0.022	0.091	0.003	0.011
12	Malaysia	199	5.04	10.93	3.86	4.59	0.012	0.001	0.007	0.002	0.001
13	Mexico	146	6.79	24.49		7.83	0.015	0.011	0.002	0.001	0.002
14	Nigeria	37	3.36	10.35	−6.41	1.06	0.002	0.000	0.001	0.001	0.000
15	Philippines	40	4.23	9.40	3.35	8.75	0.014	0.003	0.009	0.000	0.002
16	Poland	9284	7.50	18.47	11.74	6.52	0.028	0.000	0.024	0.003	0.001
17	Rep.of Korea	11,854	4.26	11.45	11.53	5.32	0.035	0.000	0.030	0.006	0.000
18	Singapore	90	0.47	1.79	0.57	5.84	0.076	0.024	0.022	0.022	0.009
19	South Africa	41	3.49	10.24	4.89	2.07	0.004	0.000	0.001	0.003	0.000
20	Thailand	43	5.58	13.41	12.84	21.56	0.001	0.000	0.000	0.001	0.000

Panel B: Average by industry

			Financial performance (%)		Real performance (%)		
SIC	Industry	No. of firms	ROA	ROE	ValG	EmpG	EFD
20	Food & Kindred Products	5095	5.19	15.20	10.59	7.18	−0.24
21	Tobacco Products	28	7.81	25.98	2.85	3.31	−0.92
22	Textile Mill Products	1216	3.32	9.76	8.08	3.78	0.10
23	Apparel & Other Textile Products	1365	5.00	16.70	5.18	5.59	−0.61
24	Lumber & Wood Products	1637	4.78	13.83	11.77	8.55	0.04
25	Furniture & Fixtures	1083	6.40	17.49	13.85	8.37	−0.23
26	Paper & Allied Products	1650	5.42	15.16	11.66	7.84	0.06
27	Printing & Publishing	771	4.91	14.45	8.96	6.43	−0.07
28	Chemical & Allied Products	4323	5.50	12.80	13.14	8.24	0.28
29	Petroleum & Coal Products	262	5.21	13.88	8.60	7.97	0.09
30	Rubber & Miscellaneous Plastics Products	2915	5.50	14.41	12.08	7.01	0.04
31	Leather & Leather Products	306	4.74	14.56	6.12	0.94	−0.96
32	Stone, Clay, & Glass Products	1834	4.74	11.67	10.29	6.54	−0.20
33	Primary Metal Industries	2262	3.64	9.89	7.03	5.03	0.03
34	Fabricated Metal Products	5273	4.98	13.73	8.98	6.88	−0.24
35	Industrial Machinery & Equipment	4812	4.57	11.66	10.98	6.92	0.01
36	Electronic & Other Electric Equipment	5169	4.40	11.38	10.75	8.78	0.22
37	Transportation Equipment	3318	3.86	11.30	5.68	6.75	0.00
38	Instruments & Related Products	1404	5.74	12.35	11.78	8.81	−0.04
39	Miscellaneous Manufacturing Industries	1047	4.99	12.66	11.54	8.07	−0.20

depending on whether P2P and bank credit are complements or substitutes. In the U.S., P2P financing is found to be a substitute for bank lending and a complement for small loans. Cornelli et al. (2020) find that the new credit entrants complement the existing traditional banking sector at a macro level and across the fintech lending space. Given that bank credit is an important determinant of firm performance, we, firstly, control for bank lending at the country level using the domestic credit to the private sector by banks. Secondly, the digitalization of finance could increase financial inclusion (Tantri, 2021). During the financial crisis, small businesses were disproportionately cut off from the credit market, making them more likely to face financial exclusion (Headd & Saade 2008). Fintech lending could fill the funding gap. Therefore, we add the number of commercial bank branches per 100,000 adults as a proxy for financial inclusion. The use of the number of branches is instrumental since bank service is likely to reach out to smaller start-up firms. Thirdly, the inclusion of the number of secure Internet servers (per 1 million people) at the country level permits us to control the quality of an IT infrastructure that is unique to each country. Lastly, we capture the general macroeconomic growth and the stability of

Table 3
Summary statistics of main variables, 2012–2020.

Variable	N	Mean	Std.	P25	Mdn.	P75	Min.	Max.
Firm performance (%)								
ROA	326,079	5.64	12.04	1.04	4.41	9.91	−66.97	48.14
ROE	326,079	12.93	35.86	3.28	11.84	24.42	−184.93	126.93
ValG	117,278	10.46	69.69	−14.04	3.98	26.2	−272.4	376.89
EmpG	182,196	7.05	37.88	−4.55	0	8.66	−61	276.94
Fintech financing (%)								
Total	180	0.29	0.65	0	0.03	0.10	0	2.91
BSheet	180	0.02	0.06	0	0	0	0	0.33
P2P	180	0.26	0.59	0	0.02	0.09	0	2.66
CrowF	180	0.01	0.01	0	0	0.01	0	0.09
Others	180	0.01	0.02	0	0	0	0	0.36
External financial dep.								
EFD	20	−0.03	0.22	−0.24	0.01	0.06	−0.96	0.28
Firm variables								
Size (log)	326,077	9.32	2.06	7.97	9.28	10.53	3.9	14.71
Solv	325,795	0.50	0.24	0.31	0.49	0.69	0	0.97
Leve	310,953	0.84	0.21	0.78	0.92	0.98	−0.16	1.00
Liqu	310,564	1.84	2.33	0.65	1.09	1.99	0.09	15.29
FixA	317,586	0.42	0.23	0.24	0.42	0.59	0	0.96

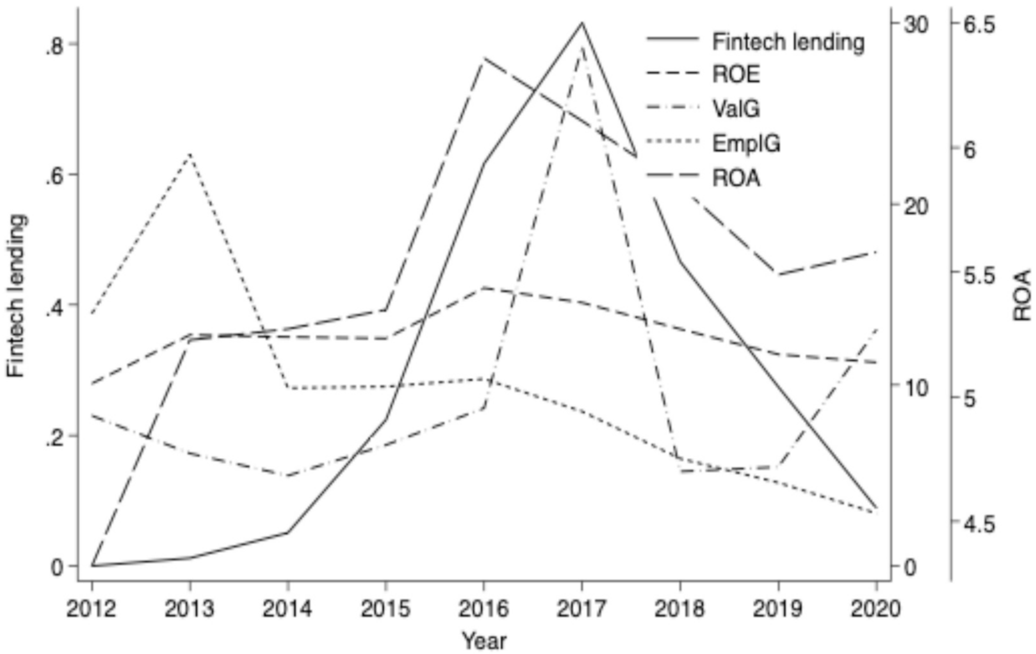

Fig. 1. Fintech financing and fir performance, 2012–2020.

a country by including GDP growth and inflation. All these control variables are specified by interacting with EFD in Table 6.[12]

Consistent with the baseline findings (Table 5), the effect of the interaction term on firm performance is positive and statistically significant with its magnitude remaining largely unchanged. The impacts of firm-specific variables also hold, though none of the country-level control variables are statistically significant at the 5 % level.

[12] Other possible control variables, like institutional quality (interacted with EFD), might be taken into account. However, we rule out these other potential control variables due to the multicollinearity issue, which is indicated by a large variance inflation factor (VIF). Nevertheless, we control for institutional quality index interacted with EFD as a robustness check and the results hold (see Appendix Table A2).

Table 4
Firm performance in countries with low vs high fintech financing.

	Countries with low fintech lending (25th p.)	Countries with high fintech lending (75th p.)	Difference
	Panel A: ROA		
(1) High dependent industries (75th p.)	0.048	0.049	0.001
(2) Less dependent industries (25th p.)	0.052	0.05	−0.002
Difference-in-difference	−0.004	−0.001	**0.003 (t = 0.83)**
	Panel B: ROE		
(1) High dependent industries (75th p.)	0.128	0.113	−0.015
(2) Less dependent industries (25th p.)	0.182	0.145	−0.037
Difference-in-difference	−0.054	−0.032	**0.022 (t = 2.20)**
	Panel C: ValG		
(1) High dependent industries (75th p.)	0.087	0.128	0.041
(2) Less dependent industries (25th p.)	0.047	0.092	0.045
Difference-in-difference	0.04	0.036	**−0.004 (t = -0.10)**
	Panel D: EmpG		
(1) High dependent industries (75th p.)	0.092	0.094	0.002
(2) Less dependent industries (25th p.)	0.081	0.067	−0.014
Difference-in-difference	0.011	0.027	**0.016 (t = 0.83)**

Table 5
Fintech financing and firm performance – Baseline results. This table reports the results estimating $Performance_{ijct} = \Delta.EFD_j \times Fintech_{ct} + \gamma.Controls_{ijct} + \delta_i + \delta_{jc} + \delta_{ct} + \varepsilon_{ijct}$ where $Performance_{ijct}$ refers to the performance of firm i belonging to industry j for country c in year t, EFD_j measures the degree to which industry j depends on external sources of financing, $Fintech_{ct}$ denotes fintech lending as a percentage of GDP for country c in year t, and $Controls_{ijct}$ is a vector of firm-level control variables. For detailed definition of variables, see Appendix, Table A1. All specifications contain a full set of firm (δ_i), industry-year (δ_{jt}) and country-year (δ_{ct}) fixed effects. The statistical inferences are based on robust standard errors (associated t-values reported in parentheses) clustered at the country-year level. ***, **, and * denote statistical significance at the 1 %, 5 %, and 10 % levels, respectively. Our sample includes 22 industries with two-digit SIC for 20 emerging economies over the period 2012–2020. Sample size varies across regression specifications because not all variables are available for all firms or years.

	Financial performance		Real performance		Financial performance		Real performance	
	ROA	ROE	ValG	EmpG	ROA	ROE	ValG	EmpG
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
EFD_j x $Fintech_{ct}$	0.006**	0.028***	0.441***	0.029***	0.005**	0.021***	0.372**	0.025**
	(2.111)	(3.909)	(2.879)	(3.116)	(1.997)	(2.812)	(2.002)	(2.084)
$Controls_{ijct}$								
Size					0.009***	0.017***	0.106***	0.040***
					(3.800)	(2.854)	(4.501)	(2.809)
Solv					0.236***	0.449***	0.142***	−0.010
					(31.012)	(16.404)	(2.865)	(−0.631)
Leve					0.198***	0.503***	0.117	0.125***
					(22.394)	(17.681)	(1.271)	(3.236)
Liqu					−0.004***	−0.012***	−0.026***	−0.006***
					(−14.466)	(−17.048)	(−7.983)	(−5.182)
FixA					−0.124***	−0.339***	−0.645***	−0.018
					(−24.956)	(−24.180)	(−8.194)	(−1.106)
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y
SIC × Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Country × Year FE	Y	Y	Y	Y	Y	Y	Y	Y
# Countries	20	20	20	20	20	20	20	20
# Industries	22	22	22	22	22	22	22	22
*N (Firm*Year)*	325,724	325,724	117,586	193,531	304,917	304,917	116,856	173,079
Adj. R^2	0.438	0.330	0.049	0.033	0.509	0.370	0.055	0.059
Differential in firm performance	0.018	0.084	0.013	0.001	0.015	0.063	0.011	0.001

To assess the relative significance of omitted variable bias, we test the degree to which the inclusion of additional regressors (unobservable factors) modifies the coefficients of interest. This aligns with the method developed by Altonji et al. (2005) and its application by recent studies (e.g., Bellows & Miguel 2009; Fenske 2015; Igan et al., 2020; Nunn & Wantchekon 2011). Specifically, we use selection on observables to estimate the likely bias from unobservable variables and test whether adding predictor variables affects the coefficient estimates on fintech financing. If this change is significant, including more controls would likely reduce the estimated effect further. In the absence of evidence that these controls significantly impact the sizes of our coefficient estimates, a causal

Table 6

Addressing omitted variable bias. This table reports the results estimating $Performance_{ijct} = \Delta.EFD_j \times Fintech_{ct} + \gamma.Controls_{ijct} + \vartheta.EFD_j \times X_{ct} + \delta_i + \delta_{jt} + \delta_{ct} + \varepsilon_{ijct}$ where $Performance_{ijct}$ refers to the performance of firm *i* belonging to industry *j* for country *c* in year *t*, EFD_j measures the degree to which industry *j* depends on external sources of financing, $Fintech_{ct}$ denotes fintech lending as a percentage of GDP for country *c* in year *t*, and $Controls_{icjt}$ is a vector of firm-level control variables. X_{ct} is a vector of country-level variables. For detailed definition of variables, see Appendix, Table A1. All specifications contain a full set of firm (δ_i), industry-year (δ_{jt}) and country-year (δ_{ct}) fixed effects. The statistical inferences are based on robust standard errors (associated t-values reported in parentheses) clustered at the country-year level. ***, **, and * denote statistical significance at the 1 %, 5 %, and 10 % levels, respectively. Our sample includes 22 industries with two-digit SIC for 20 emerging economies over the period 2012–2020. Sample size varies across regression specifications because not all variables are available for all firms, countries or years.

	Financial performance		Real performance	
	ROA	ROE	ValG	EmpG
	[1]	[2]	[3]	[4]
EFD_j x $Fintech_{ct}$	0.007**	0.025***	0.366**	0.028**
	(2.484)	(2.858)	(1.999)	(2.002)
$Controls_{ijct}$				
Size	0.009***	0.017***	0.106***	0.040***
	(3.797)	(2.862)	(4.507)	(2.816)
Solv	0.236***	0.449***	0.140***	−0.009
	(30.963)	(16.383)	(2.823)	(−0.610)
Leve	0.198***	0.502***	0.114	0.125***
	(22.356)	(17.608)	(1.229)	(3.234)
Liqu	−0.004***	−0.012***	−0.026***	−0.006***
	(−14.502)	(−17.011)	(−7.960)	(−5.186)
FixA	−0.124***	−0.339***	−0.645***	−0.018
	(−24.933)	(−24.196)	(−8.194)	(−1.107)
$Controls2_{j*ct}$				
EFD_j x Bank $Credit_{ct}$	−0.0002	−0.0001	0.004	−0.0001
	(−0.748)	(−0.059)	(1.256)	(−0.027)
EFD_j x $Branch_{ct}$	−0.001	0.004	−0.018	−0.000
	(−0.529)	(0.807)	(−1.016)	(−0.076)
EFD_j x $Internet_{ct}$	−0.000	0.000	−0.000*	0.000
	(−0.903)	(0.023)	(−1.711)	(0.576)
EFD_j x GDP $Growth_{ct}$	−0.000	0.003	−0.001	−0.002
	(−0.410)	(0.833)	(−0.108)	(−0.538)
EFD_j x $Inflation_{ct}$	−0.002*	−0.003	0.011	−0.005*
	(−1.722)	(−1.134)	(1.239)	(−1.761)
Firm FE	Y	Y	Y	Y
SIC × Year FE	Y	Y	Y	Y
Country × Year FE	Y	Y	Y	Y
# Countries	20	20	20	20
# Industries	22	22	22	22
*N (Firm*Year)*	304,806	304,806	116,745	173,012
Adj. R^2	0.509	0.370	0.055	0.059

explanation is well grounded.

To account for the entire estimated effect, we calculate a ratio that measures how strong the selection on unobservables must be relative to the selection on observables to threaten the validity of results. Two regressions are required for this setup: a restricted regression, which uses no or a limited set of control variables, and a full regression, which uses the entire set of controls. We evaluate the coefficient's stability by calculating a ratio that compares the estimated coefficient without a restricted set of controls $\widehat{\Delta}^R$ to the estimated coefficient with a full set of controls $\widehat{\Delta}^F$ as $\frac{\widehat{\Delta}^F}{\widehat{\Delta}^R - \widehat{\Delta}^F}$. The higher the ratio, the greater the impact of unobservable variables on Δ must be relative to the observed controls to explain away the result.

To implement the test, we use a restricted regression with no control variables from baseline Table 5 (columns 1–4) and two full regressions, one with a full set of firm controls from Table 5 (columns 5–8) and another with a full set of firm and country controls from Table 6 (columns 1–4). The findings demonstrate that, except for one case, all calculated ratios are greater than unity. Their range is from 3 to 28, with an average of 8.7 and a median ratio of 5.4. Hence, to fully assign the OLS estimates to selection effects, the selection on unobservables needs to be at least three times greater than the selection on observables. We conclude that it is unlikely that entirely unobservable factors drive the estimated effect of fintech financing on firm performance.

4.2.2. Reverse causality

Reverse causality is another source of endogeneity concerns. To address this concern, we apply three strategies, as shown in Table 7. Firstly, if large firms accrue high *ROA* or *ROE*, they may be the ones to play a dominant role in receiving more fintech finance. To account for this, we exclude large firms with total assets exceeding $5 billion in columns 1–4. Secondly, it is conceivable that a highly technical industry with a relatively high external-finance dependence has a close relationship with fintech, potentially

Table 7
Addressing reverse causality.

	Excluding large firms (total assets > $5b)				Excluding the most high-tech intensive sector (SIC 36)				Excluding top 3 countries with highest share of EFD to GDP			
	Financial perf.		Real performance		Financial perf.		Real performance		Financial perf.		Real performance	
	ROA	ROE	ValG	EmpG	ROA	ROE	ValG	EmpG	ROA	ROE	ValG	EmpG
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]
EFD_j x $Fintech_{ct}$	0.005**	0.022***	0.445**	0.026**	0.005*	0.024***	0.416**	0.023*	0.005**	0.024***	0.383**	0.023*
	(1.984)	(2.952)	(2.279)	(2.145)	(1.935)	(2.745)	(2.099)	(1.820)	(2.182)	(3.297)	(2.027)	(1.912)
$Controls_{ijct}$												
Size	0.009***	0.018***	0.107***	0.038***	0.009***	0.016***	0.106***	0.041***	0.010***	0.019***	0.128***	0.039***
	(3.838)	(2.854)	(4.518)	(2.804)	(3.699)	(2.621)	(4.291)	(3.013)	(3.754)	(2.956)	(4.921)	(2.709)
Solv	0.236***	0.450***	0.142***	−0.006	0.238***	0.445***	0.149***	−0.013	0.238***	0.448***	0.177***	−0.011
	(31.064)	(16.392)	(2.869)	(−0.412)	(30.758)	(16.290)	(2.984)	(−0.811)	(29.825)	(15.744)	(3.326)	(−0.677)
Leve	0.198***	0.503***	0.120	0.124***	0.193***	0.489***	0.152	0.136***	0.199***	0.501***	0.058	0.124***
	(22.388)	(17.688)	(1.293)	(3.107)	(22.699)	(17.696)	(1.611)	(3.547)	(21.833)	(17.070)	(0.576)	(3.168)
Liqu	−0.004***	−0.012***	−0.026***	−0.006***	−0.004***	−0.012***	−0.025***	−0.006***	−0.004***	−0.012***	−0.028***	−0.006***
	(−14.427)	(−16.981)	(−7.922)	(−5.193)	(−13.040)	(−16.046)	(−7.696)	(−5.121)	(−14.209)	(−16.493)	(−8.609)	(−5.000)
FixA	−0.124***	−0.340***	−0.647***	−0.017	−0.121***	−0.333***	−0.619***	−0.027*	−0.124***	−0.340***	−0.681***	−0.017
	(−25.239)	(−24.194)	(−8.225)	(−1.000)	(−24.079)	(−23.437)	(−8.361)	(−1.715)	(−24.080)	(−23.297)	(−8.189)	(−1.022)
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
SIC × Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Country × Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
# Countries	20	20	20	20	20	20	20	20	17	17	17	17
# Industries	22	22	22	22	21	21	21	21	22	22	22	22
*N (Firm*Year)*	303,396	303,396	116,368	171,801	270,142	270,142	105,735	152,292	291,816	291,816	104,826	167,213
Adj. R^2	0.509	0.370	0.055	0.061	0.513	0.373	0.055	0.061	0.509	0.370	0.057	0.061

triggering a reverse causality. For example, increased internet access due to technical development might correlate with a rise in fintech transactions. Therefore, the most high-tech intensive industry (i.e., SIC36 Electronic & Other Electric Equipment in Panel B, Table 2) is dropped in columns 5–8. Thirdly, it is also plausible to expect a larger reverse causality bias in countries where the financially vulnerable industries represent a significant portion of GDP. Consequently, we exclude, in columns 9–12, the top 3 countries with a high share of external-finance dependence (EFD) relative to GDP. We quantify this proportion as the product of each industry's EFD and its value-added in a country divided by the country's GDP.

The results are broadly consistent with those in Table 5. Removing potentially influential firms, industries, and countries does not alter the original findings in terms of both the significance level and the magnitude of the coefficient $EFD \times Fintech$.

We also apply the instrumental variable (IV) approach using the total value of fintech in all other countries and the institutional investor funding in all other countries, each interacted with EFD, as two potential instruments.[13] We empirically verify that the instruments are statistically significantly correlated with the instrumented variable, indicating that the instruments are relevant and strong. Regarding the exclusion restrictions, it is reasonable to assume that the aggregate (global) fintech or institutional investor funding in other countries does not directly impact a firm's performance in a given country. We also add numerous control variables and control for a host of interactive fixed effects that might potentially correlate with the instrumental variables. The identifying assumption is that any remaining factors in the error term are not correlated with the instruments and that the instruments influence firm performance through the interaction term. The IV regression results support our main conclusion (available upon request).

Unfortunately, there is no empirical test for exclusion restriction. Despite our efforts to control for numerous potential confounders, we cannot rule out the possibility of some unobserved factors threatening the validity of our instruments. However, it is reassuring to see that the IV outcomes are consistent with our other regression results.

4.3. Other sensitivity tests

We test the robustness of the baseline results to alternative measures of our main variable of interest. The regression outputs are reported in Table 8. Firstly, we measure the variable EFD in two alternative ways: i) loan to assets (LTA) using data from Cetorelli and Strahan (2006) in columns 1–4, and ii) R&D intensity using data from Hsu et al. (2014) in columns 5–8. Secondly, we use the fintech credit to the business sector as a percentage of GDP for '$Fintech_{ct}$' in columns 9–12. Note that $Fintech_{ct}$ specified in other regressions implies fintech lending across all economic sectors.

Our main conclusion holds when we use LTA; the coefficients on the interaction term retain their sign and statistical significance in columns 1–4. The results in columns 5–8 reveal a relatively weak effect of fintech, as indicated by the size of the $EFD_j \times Fintech_{ct}$ coefficients. It is marginally significant at the 10 % level when the dependent variable is *ROA* and statistically insignificant when the dependent variable is *EmpG*. The original measure of EFD is capital expenditures minus cash flow divided by capital expenditures. We use R&D intensity as a proxy for EFD, assuming that R&D requires a high level of external finance. Although the effects are weak, they are not different from the baseline results and still manifest the robustness of our initial results. Regarding the results in columns 9–12, it is not surprising to find a relatively large size of coefficients, as firms are more sensitive to fintech credit to the business sector. The only exception is *ValG* (column 11), which is statistically insignificant. There is little doubt that the findings in columns 1–12 support the baseline results.[14]

We also use the ratio of a firm's sales to its assets as an alternative measure of firm performance, and the results hold (available upon request). Finally, a large proportion of firms in our sample are from China and South Korea. Excluding South Korea does not influence the results. However, removing China significantly reduces the number of observations, affecting the statistical significance of the results.[15]

4.4. Heterogeneity analysis

4.4.1. Decomposing fintech financing models

Fintech platforms vary in their lending criteria, risk structures, and operating methods (Philippon, 2016; Fuster et al., 2019). In terms of risk-bearing, fintech lending models function according to distinct frameworks. The P2P platform matches services between

[13] For country *c*, we calculate the aggregate fintech (institutional investor) funding in all countries, leaving out country *c*.

[14] Claessens et al. (2012) adapt the original Rajan and Zingales (1998) methodology to the firm level by computing the external finance dependence as the difference between capital expenditures and cash flow, scaled by capital expenditures. We follow their methodology and construct the firm-level measure of financial dependence. The interaction term continues to exhibit a positive and statistically significant effect on both measures of financial performance – *ROA* and *ROE*. However, the effect is statistically insignificant when the dependent variable is *ValG*, and even negative when the dependent variable is *EmpG*. These effects on real performance, may reflect a potential issue of reverse causality arising from a firm-level finance dependency measure. Full results are reported in Appendix 4, Table A3.

[15] We also restricted the sample to firms based in China, and our result for *EmpG* remains robust. However, the effect of the interaction variable becomes less precise and statistically insignificant when using the other dependent variables (available upon request). Further, we split the sample based on different percentiles of $EFD_j \times Fintech_{ct}$: below the 5th percentile, between the 5th and 60th percentiles, between the 60th and 95th percentiles, and above the 95th percentiles. For the lower percentiles, the interaction effect is statistically insignificant, whereas for the higher percentiles, it becomes statistically significant and positive. This pattern is consistent with our findings. The only exception is the effect on *EmpG*, which is unexpectedly negative in the subsample above the 95th percentile of $EFD_j \times Fintech_{ct}$. The results are presented in Appendix 5, Table A4.

Table 8
Other sensitivity tests.

	Using LTA instead of EFD, data from Ceterolli and Strahan (2006)				Using R&D-intensity instead of EFD, data from Hsu et al. (2014)				Using fintech credit to business sector (as % of GDP)			
	Financial perf.		Real performance		Financial perf.		Real performance		Financial perf.		Real performance	
	ROA	ROE	ValG	EmpG	ROA	ROE	ValG	EmpG	ROA	ROE	ValG	EmpG
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]
EFD_j x $Fintech_{ct}$	0.005**	0.021***	0.375**	0.025**	0.001*	0.003**	0.074***	0.003	0.012**	0.047**	0.560	0.064**
	(2.061)	(2.896)	(2.005)	(2.085)	(1.871)	(2.356)	(2.761)	(1.597)	(2.077)	(2.304)	(1.433)	(2.179)
$Controls_{ijct}$												
Size	0.009***	0.017***	0.106***	0.040***	0.009***	0.017***	0.106***	0.040***	0.009***	0.017***	0.106***	0.040***
	(3.800)	(2.854)	(4.501)	(2.809)	(3.798)	(2.851)	(4.505)	(2.807)	(3.801)	(2.855)	(4.504)	(2.809)
Solv	0.236***	0.449***	0.142***	−0.010	0.236***	0.449***	0.142***	−0.010	0.236***	0.449***	0.141***	−0.010
	(31.012)	(16.404)	(2.865)	(−0.631)	(31.008)	(16.400)	(2.867)	(−0.627)	(31.013)	(16.404)	(2.861)	(−0.628)
Leve	0.198***	0.503***	0.117	0.125***	0.198***	0.503***	0.117	0.125***	0.198***	0.503***	0.117	0.125***
	(22.393)	(17.680)	(1.271)	(3.236)	(22.389)	(17.671)	(1.268)	(3.232)	(22.395)	(17.682)	(1.268)	(3.236)
Liqu	−0.004***	−0.012***	−0.026***	−0.006***	−0.004***	−0.012***	−0.026***	−0.006***	−0.004***	−0.012***	−0.026***	−0.006***
	(−14.466)	(−17.049)	(−7.983)	(−5.182)	(−14.465)	(−17.042)	(−7.984)	(−5.187)	(−14.466)	(−17.046)	(−7.975)	(−5.184)
FixA	−0.124***	−0.339***	−0.645***	−0.018	−0.124***	−0.339***	−0.645***	−0.018	−0.124***	−0.339***	−0.645***	−0.018
	(−24.955)	(−24.180)	(−8.194)	(−1.106)	(−24.944)	(−24.171)	(−8.195)	(−1.111)	(−24.943)	(−24.171)	(−8.197)	(−1.101)
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
SIC × Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Country × Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
# Countries	20	20	20	20	20	20	20	20	20	20	20	20
# Industries	22	22	22	22	22	22	22	22	22	22	22	22
*N (Firm*Year)*	304,917	304,917	116,856	173,079	304,917	304,917	116,856	173,079	304,917	304,917	116,856	173,079
Adj. R^2	0.509	0.370	0.055	0.059	0.509	0.370	0.055	0.059	0.509	0.370	0.055	0.059

borrowers and investors, and the risk of default lies in the investors rather than the platform. As a consequence of this, P2P networks usually concentrate on small and medium-sized businesses with decent creditworthiness but not necessarily with official collateral. In contrast, balance sheet lending facilitates the entire loan transaction process, so the platform operator bears the risk of financial loss with the borrowers' default (Naceur et al., 2023). Balance sheet lenders are forced to be increasingly selective due to this risk exposure and have an incentive to lend to firms with stable revenue rather than high-risk borrowers. Crowdfunding, on the other hand, is the practice of funding investment projects by raising capital from a large number of investors who assume high risk since they may incur significant losses if the project or venture fails. Although the loan amounts tend to be small, as crowdfunding investors are private individuals rather than organizations, they are more available to high-risk or early-stage businesses. Crowdfunding is a popular financing source for startups and innovation-driven businesses, especially those seeking expansion (Belleflamme et al., 2015). Therefore, we decompose fintech financing into '*BSheet*, '*P2P*, '*CrowdF*, and '*Others*' to investigate whether the impact of $EFD_j \times Fintech_{ct}$ on firms' financial and real performance varies across these components.[16]

Table 9 reveals that all types of fintech financing except '*Others*' in column 12 have a positive effect on firm performance, with varying degrees of statistical significance and magnitude of the *EFD* × *Fintech* coefficient. Firms are most responsive to crowdfunding, in particular, in column 11 for *ValG* at 5.143, implying that a 1 % increase in crowdfunding results in a 5.1 % increase in the value-added, *ceteris paribus.* It is, however, hard to conclude that crowdfunding is the main driver of firm performance. As reported in Table 1, *P2P* is the largest component of fintech lending among others. Table 9 shows that the interaction terms are all statistically significant, at least at the 10 % level, indicating that external-finance dependent firms perform relatively better in a country with a high P2P lending activity. For *BSheet*, the coefficient of *EFD* × *Fintech* is positive and significant at the 5 % level, except in the specification where the dependent variable is *ValG*. Therefore, while the balance sheet fintech enhances firm performance, it appears to especially support financial performance rather than firm expansion, based on the lack of association with value-added growth (*ValG*). This aligns with its more conservative lending policies, which favor creditworthy firms over riskier firms with significant growth potential. Overall, due to different operations, procedures, and risks, each fintech model has merit in contributing to the performance of financially constrained firms in emerging economies, however, each model varies in its impact. P2P lending has a significant effect on real and financial performance. Although it has a lower impact on real performance, balance sheet lending enhances the firm's financial results. The biggest influence on value-added growth is shown in crowdfunding, underscoring its importance for real performance. Section 5 examines the mechanisms associated with each fintech model.

4.4.2. Firm age and financial sector characteristics

Previous studies document that young businesses have low access to funding (Beaumont et al., 2022) and are frequently unable to obtain bank loans (Lopez-de-Silanes et al., 2018). Given their fewer years in operation, younger firms suffer higher information asymmetry and thus stand to benefit significantly from the advancement of fintech. Additionally, the inherent variation in the characteristics of the financial markets across emerging markets is another source of heterogeneity. In this section, we estimate the regression models by separating the sample based on firm age and characteristics of the financial sector, namely, financial development and depth of credit information.

Firm age (young vs. mature)

Access to finance is crucial for business growth, particularly for startups and small and medium-sized enterprises (Beaumont et al., 2022), in particular, seed funding is scarce, causing large funding gaps for startups and ventures (Wilson et al., 2018). In addition, traditional equity and debt funding channels have proven to be substantially challenging, leaving young small firms with insufficient finance (Lopez-de-Silanes et al., 2018). Bollaert et al. (2021) point out that fintech lending has mainly been concentrated on financing start-ups and small firms. This subsection examines the fintech lending role for young firms' access to financing.

In Panel A of Table 10, firms are classified as young (<Mdn) or mature (>Mdn) based on their median age (Mdn). Based on the size and statistical significance of the coefficients for the interaction term, firm performance is generally more responsive to fintech finance for younger firms. Additionally, the magnitude of the estimated parameters for *EFD* × *Fintech* exceeds that of the baseline results (Table 5) when the dependent variable is *ROA*, *ROE*, or *ValG*. The results suggest that financially constrained startups are the primary beneficiaries of fintech lending. Beaumont et al. (2022) show that firms served by fintech platforms have fewer tangible assets than bank borrowers. An increase in bank credit only occurs when fintech borrowers invest in new assets and, subsequently become more likely to pledge collateral to banks. Fintech lenders are likely to improve young firms' credit access by providing unsecured loans and alleviating collateral constraints. This is contrasted with mature firms with the weak effect of fintech lending, where the benefit of fintech is likely to be limited. This is not unexpected, as access to bank credit or equity and bond markets is less challenging for large, established firms.

Financial sector characteristics

In Panels B and C in Table 10, we examine whether the impact of the interaction between fintech and EFD differs between an emerging country with a less financially developed system and one with a more financially developed sector. Firstly, the median of the degree of financial development is used in Panel B to split the sample into firms in less developed and more developed financial sectors. Secondly, the depth of credit information, which is also indicative of a degree of financial development, is considered by dividing the sample into low and high based on the median levels of depth in Panel C.

Positive and statistically significant estimates for *EFD* × *Fintech* are observed for firms in a developed financial sector (Panel B) or

[16] Future research may explore other types of heterogeneity, such as sectoral, geographical, and temporal, among others.

Table 9
Components of fintech credit.

	Financial performance								Real performance							
	ROA				ROE				ValG				EmpG			
	BSheet	P2P	CrowF	Others	BSheet	P2P	CrowF	Others	BSheet	P2P	CrowF	Others	BSheet	P2P	CrowF	Others
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[11]	[12]	[13]	[14]	[15]	[16]
EFD_j x $Fintech_{ct}$	0.048**	0.006*	0.403***	0.045	0.180**	0.025***	0.971*	0.287	0.970	0.502**	5.143*	−3.450**	0.272**	0.029**	1.614***	0.336
	(2.109)	(1.919)	(2.712)	(0.468)	(2.229)	(2.900)	(1.833)	(0.997)	(0.926)	(2.272)	(1.685)	(−2.518)	(2.331)	(1.982)	(2.816)	(0.941)
$Controls_{ijct}$	√	√	√	√	√	√	√	√	√	√	√	√	√	√	√	√
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
SIC × Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Country × Year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
# Countries	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20	20
# Industries	22	22	22	22	22	22	22	22	22	22	22	22	22	22	22	22
*N (Firm*Year)*	304,917	304,917	304,917	304,917	304,917	304,917	304,917	304,917	116,856	116,856	116,856	116,856	173,079	173,079	173,079	173,079
Adj. R^2	0.509	0.509	0.509	0.509	0.370	0.370	0.370	0.370	0.055	0.055	0.055	0.055	0.059	0.059	0.059	0.059

Table 10
Role of firm age and the financial sector characteristics.

	< Mdn.				> Mdn.			
	Financial performance		Real performance		Financial performance		Real performance	
	ROA	ROE	ValG	EmpG	ROA	ROE	ValG	EmpG
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
Panel A: Age (young vs. mature)								
EFD_j x $Fintech_{ct}$	0.008*	0.040***	0.817***	0.033	0.006*	0.015*	−0.049	0.021**
	(1.875)	(2.685)	(2.887)	(1.227)	(1.758)	(1.912)	(−0.224)	(2.202)
*N (Firm*Year)*	136,761	136,761	41,788	66,806	164,450	164,450	73,253	102,728
Adj. R^2	0.527	0.368	0.054	0.070	0.518	0.388	0.040	0.009
Panel B: Financial development (low vs. high)								
EFD_j x $Fintech_{ct}$	0.071*	0.161	−0.436	0.164	0.011***	0.029***	0.429**	0.037***
	(1.772)	(0.983)	(−0.433)	(0.673)	(3.716)	(3.140)	(2.100)	(3.476)
*N (Firm*Year)*	112,087	112,087	47,793	46,224	189,256	189,256	68,622	124,787
Adj. R^2	0.597	0.412	0.033	0.067	0.490	0.369	0.053	0.066
Panel C: Depth of credit information (low vs. high)								
EFD_j x $Fintech_{ct}$	−0.005	0.041	0.133	0.027	0.007***	0.020***	0.508**	0.025**
	(−0.293)	(0.689)	(0.484)	(0.294)	(2.979)	(2.705)	(2.286)	(2.101)
*N (Firm*Year)*	67,572	67,572	27,716	30,384	228,790	228,790	85,926	133,537
Adj. R^2	0.420	0.359	0.045	0.117	0.551	0.375	0.066	0.071
All panels								
$Controls_{ijct}$ (Size, Solv, Leve, Liqu, FixA)	√	√	√	√	√	√	√	√
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y
SIC × Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Country × Year FE	Y	Y	Y	Y	Y	Y	Y	Y
# Countries	20	20	20	20	20	20	20	20
# Industries	22	22	22	22	22	22	22	22

with a high depth of credit information (Panel C). It is intuitively plausible that firms with external finance dependence disproportionately perform well if they are in a developed financial sector with a high level of fintech lending due to a more efficient allocation of resources.

Finally, we further explore how firm-specific financial characteristics influence the impact of fintech financing. We conduct a split

Table 11
Bank penetration vs. fintech financing (supplementary or complementary). This table reports the results estimating $Performance_{ijct} = \Delta^f.EFD_j \times Fintech_{ct} + \Delta^b.EFD_j \times Branch_{ct} + \Delta^{fb}.EFD_j \times Fintech_{ct} \times Branch_{ct} + \gamma.Controls_{ijct} + \delta_i + \delta_{jt} + \delta_{ct} + \varepsilon_{ijct}$ where $Performance_{ijct}$ refers to the performance of firm *i* belonging to industry *j* for country *c* in year *t*, EFD_j measures the degree to which industry *j* depends on external sources of financing, $Fintech_{ct}$ denotes fintech lending as a percentage of GDP for country *c* in year *t*, $Branch_{ct}$ is number of bank branches in an economy, and $Controls_{ijct}$ is a vector of firm-level control variables. For detailed definition of variables, see Appendix, Table A1. All specifications contain a full set of firm (δ_i), industry-year (δ_{jt}) and country-year (δ_{ct}) fixed effects. The statistical inferences are based on robust standard errors (associated t-values reported in parentheses) clustered at the country-year level. ***, **, and * denote statistical significance at the 1 %, 5 %, and 10 % levels, respectively. Our sample includes 22 industries with two-digit SIC for 20 emerging economies over the period 2012–2020. Sample size varies across regression specifications because not all variables are available for all firms or years.

	Financial performance		Real performance	
	ROA	ROE	ValG	EmpG
	[1]	[2]	[3]	[4]
EFD_j x $Fintech_{ct}$	0.058***	0.173***	0.676*	0.180**
	(3.186)	(2.869)	(1.877)	(2.109)
EFD_j x $Branch_{ct}$	−0.000	0.004	−0.004	0.001
	(−0.264)	(1.168)	(−0.269)	(0.203)
EFD_j x $Fintech_{ct}$ x Branchct	−0.006***	−0.017**	−0.035	−0.017*
	(−2.974)	(−2.568)	(−1.011)	(−1.879)
$Controls_{ijct}$	√	√	√	√
Firm FE	Y	Y	Y	Y
SIC × Year FE	Y	Y	Y	Y
Country × Year FE	Y	Y	Y	Y
# Countries	20	20	20	20
# Industries	22	22	22	22
*N (Firm*Year)*	304,806	304,806	116,745	173,012
Adj. R^2	0.509	0.370	0.055	0.059

analysis based on firms' leverage (measured by debt to assets ratio). Panel A of Table A5 in the Appendix examines firms with high and low leverage. The results indicate that fintech financing has a significantly stronger impact on firms with higher leverage, reinforcing the idea that fintech serves as an important source of external financing for firms that rely more heavily on debt. This finding is consistent across multiple firm performance measures, highlighting the role of fintech in easing financing constraints for leveraged firms. In contrast, the lack of significance for low-leverage firms aligns with expectations, as these firms are typically less financially constrained and rely more on internal financing rather than external debt. Panel B reports the results for the subsample analysis based on financial stability (Z-score). While we observe some evidence that firms with higher Z-scores experience performance improvements with fintech financing, the effect is less pronounced than in the leverage-based split. The observed improvements for higher-Z-score firms suggest that fintech lending may be more accessible to firms that maintain financial stability.

4.5. Substitution or complementary effects

We explicitly examine whether fintech lending substitutes for or complements banks by interacting fintech and EFD with the number of branches (Branch) as an indicator of bank penetration. The results, which are found in Table 11, confirm the baseline findings with the statistically significant coefficient of *EFD* × *Fintech*. However, the statistically insignificant effects of *EFD* × *Branch* suggest that an increased penetration through the increased bank branches is unlikely to contribute to firm performance.

A crucial observation is the negative and statistically significant coefficients for the triple interaction term, *EFD* × *Fintech* × *Branch*, in all regressions except for *ValG* regression (column 3). This implies that fintech finance promotes firm performance, but when interacted with bank branches, an adverse impact emerges. The potential interpretation is that the performance of firms with an external-finance dependence improves with fintech lending but this effect diminishes with increased bank penetration. It may be a sign that fintech lending is a substitute for bank penetration.[17]

With respect to the substitution hypothesis, fintech lending is said to have a competitive advantage over banks (Naceur et al., 2023). Due to strict Basel regulations after the subprime crisis in 2008, banks faced higher capital requirements and liquidity ratios. Thus, in the post-crisis period, banks might have reduced their lending activities. When it comes to offering innovative financial products to a wider range of customers, fintech firms that are not as closely regulated are more flexible. Furthermore, compared to traditional banks, fintech firms are more efficient in processing loan applications and screening borrowers (Fuster et al., 2019; Berg et al., 2020; Hau et al., 2021). Consequently, financial institutions are said to be experiencing a detrimental effect on their performance. In the study by Naceur et al. (2023), where the fintech transactions are directly regressed on bank profitability, a negative impact on bank profitability is found due to a reduction in interest income and an increase in operational costs. This may be reflected in our findings that when firms with a high external-finance dependence operate in a less developed country, their overall performance contracts. This is because, in these countries, bank loans are the main source of finance, yet the supply of bank loans is limited or the loan rates are raised to compensate for the reduced interest income due to the emergence of fintech lending. Our empirical finding is complementary to that of Naceur et al. (2023).

5. Tests of potential mechanisms

The fundamental mechanisms underlying the influence of external finance availability on firm performance in financially dependent industries are further examined in this section. In particular, we evaluate whether the documented gains in firm performance can be explained by improvements in capital investments, borrowing costs, or total factor productivity.

One potential channel through which fintech credit influences firm performance is by facilitating capital investments. Firms that face financial constraints often forgo profitable investment opportunities due to limited access to external financing (Fazzari et al., 1998; Hubbard, 1998). By improving credit availability, fintech lenders enable firms to undertake capital expenditures that would otherwise be infeasible. These investments may include the acquisition of new machinery, expansion of production capacity, or upgrading technology, all of which contribute to firm growth (Ayyagari et al., 2011). The gap is bridged effectively by fintech financing, which makes it possible for businesses to invest in profitable assets that might not have been available. For instance, it has been proven that increased access to new sources of funding in emerging economies improves capital goods investments (Bekaert et al., 2005; Fidrmuc et al., 2024; Gupta & Yuan, 2009). The ability to finance capital investments is particularly important for firms in industries that rely heavily on external finance, as these firms typically require continuous funding to sustain their operations and expand their productive capabilities (Rajan & Zingales, 1998).

We utilize the growth rate of machinery and plant assets to measure capital investments, which capture the amount firms invest in long-term productive assets. To test this mechanism, we update the baseline regression by substituting our capital investment measure for the dependent variable, while maintaining the same controls for firm characteristics and fixed effects. Similar to Table 9, fintech is decomposed into *BSheet*, *P2P*, and *CrowdF*. The findings, which are shown in Table 12 (Panel A, Columns 1–4), indicate that the interaction term *EFD* × *Fintech* loads a significant positive coefficient, indicating that fintech financing increases the growth rate of machinery and plant assets, especially for firms that are financially constrained. Additionally, when we break down the results by the individual fintech model, we observe that *CrowdF* is not related to increased capital investment growth, but *BSheet* and *P2P* are.

[17] The negative sign on the triple interaction term may be partially explained by the law of diminishing returns to scale. For example, in an economy with high bank penetration, the financial capital is relatively abundant. Diminishing returns to scale would suggest that an additional increase in financial resources by the emergence of fintech will increase performance by *a lesser degree*.

Table 12
Channels This table reports the results estimating $X_{ijct} = \Delta.EFD_j \times Fintech_{ct} + \gamma.Controls_{ijct} + \delta_i + \delta_{jt} + \delta_{ct} + \varepsilon_{ijct}$ where X_{ijct} refers to either capital investment growth, cost of debt or TFP of firm *i* belonging to industry *j* for country *c* in year *t*, EFD_j measures the degree to which industry *j* depends on external sources of financing, $Fintech_{ct}$ denotes fintech lending as a percentage of GDP for country *c* in year *t*, and $Controls_{ijct}$ is a vector of firm-level control variables. For detailed definition of variables, see Appendix, Table A1. All specifications contain a full set of firm (δ_i), industry-year (δ_{jt}) and country-year (δ_{ct}) fixed effects. The statistical inferences are based on robust standard errors (associated t-values reported in parentheses) clustered at the country-year level. ***, **, and * denote statistical significance at the 1 %, 5 %, and 10 % levels, respectively. Our sample includes 22 industries with two-digit SIC for 20 emerging economies over the period 2012–2020. Sample size varies across regression specifications because not all variables are available for all firms or years.

Panel A: Capital investment growth and cost of debt								
	Capital investment growth				Cost of debt			
	Total	BSheet	P2P	CrowF	Total	BSheet	P2P	CrowF
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
EFD_j x $Fintech_{ct}$	0.077***	0.717***	0.092***	2.747	−1.178***	−7.313*	−1.478***	−46.080
	(3.875)	(3.103)	(3.948)	(1.211)	(−3.190)	(−1.821)	(−3.428)	(−1.215)
$Controls_{ijct}$	√	√	√	√	√	√	√	√
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y
SIC × Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Country × Year FE	Y	Y	Y	Y	Y	Y	Y	Y
# Countries	20	20	20	20	20	20	20	20
# Industries	22	22	22	22	22	22	22	22
*N (Firm*Year)*	53,396	53,396	53,396	53,396	22,623	22,623	22,623	22,623
Adj. R^2	0.087	0.087	0.087	0.087	0.302	0.302	0.302	0.302

Panel B: TFP								
	TFP (Wooldridge)				TFP (Levinsohn and Petrin)			
	Fintech financing				Fintech financing			
	Total	BSheet	P2P	CrowF	Total	BSheet	P2P	CrowF
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
EFD_j x $Fintech_{ct}$	0.089**	0.033	0.122**	2.818***	0.140***	0.105	0.178***	3.276***
	(2.053)	(0.070)	(2.273)	(3.048)	(3.319)	(0.232)	(3.349)	(3.682)
$Controls_{ijct}$	√	√	√	√	√	√	√	√
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y
SIC × Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Country × Year FE	Y	Y	Y	Y	Y	Y	Y	Y
# Countries	17	17	17	17	17	17	17	17
# Industries	22	22	22	22	22	22	22	22
*N (Firm*Year)*	192,193	192,193	192,193	192,193	191,731	191,731	191,731	191,731
Adj. R^2	0.948	0.948	0.948	0.948	0.956	0.956	0.956	0.956

We investigate the decrease in the cost of borrowing as a second mechanism affecting firm performance. To mitigate the risk of lending to small and medium-sized businesses, traditional lenders frequently charge high interest rates or demand collateral. In contrast, fintech platforms provide more accurate risk assessments and lower transaction costs by utilizing big data, machine learning, and alternative credit evaluation techniques (Fuster et al., 2019; Thakor, 2020; De Roure et al., 2022). We utilize the ratio of financial charges to total bank loans to calculate the cost of debt, which accounts for the effective borrowing costs that firms must pay on borrowed capital. The results show that borrowing costs are considerably decreased by fintech financing. Reducing the financial burden releases funds for viable projects. Note, similar to our findings on capital investment growth, we find that the cost of debt is most affected by *BSheet* lending but is unaffected by *CrowdF* (Panel A, Columns 5–8).

Total factor productivity is an additional mechanism through which fintech could improve firm performance. TFP measures how efficiently firms use their inputs to generate output and, as such, is considered a crucial factor in determining a firm's competitiveness and long-term growth. An emerging body of research documents how credit constraints in developing countries diminish firms' ability to invest in capital goods and limit productivity growth (Tybout, 2000). Improvements in TFP are potentially attributable to fintech financing, thus helping firms augment the productivity of invested capital.

We use firm-level data on output, labor, capital, and intermediate inputs to estimate the residuals from a Cobb-Douglas production function to calculate TFP.[18] We utilize the two estimates of TFP as the dependent variable (Rovigatti & Mollisi, 2018): one estimate is based on Wooldridge's (2009) method in columns 1–5 of Table 12, and the other is based on Levinsohn and Petrin's (2003) approach in columns 6–10. Both methods are widely used in literature (e.g., Chemmanur et al., 2014; Ding et al., 2018; Fiorini et al., 2021). We can observe that the coefficients of *EFD* × *Fintech* in total fintech (columns 1 and 6) are positive and statistically significant, supporting that fintech positively contributes to the TFP of financially constrained firms. Another finding is that, whereas *BSheet* is not linked with TFP,

[18] The estimation details are shown in Appendix 7.

P2P and *CrowdF* exhibit significant association (columns 3, 4, 8, and 9). These results align with the economic foundations of these lending models: balance sheet lenders, which typically assume credit risk, prefer financially safer firms that use borrowing to expand capital and boost financial profitability. Crowdfunding, on the other hand, attracts riskier firms that invest in intangible assets, which contribute to productivity more than to tangible capital accumulation.

Although potential reverse causality and endogeneity issues do not allow us to make a causal claim, our analysis of capital investment, cost of debt, and the TFP mechanisms as channels to firm performance provides a preliminary insight into understanding the economic consequences of the growth of fintech financing. Our results support the notion that various fintech models improve firm performance using unique economic channels. Fintech financing offers solutions to specific firm needs, such as limited capital, high cost of debt, and productivity issues, that improve both financial and real performance. This is especially true for financially dependent firms in emerging nations.

6. Conclusion

The exponential growth in digital financing has led to emerging academic research on the impact of financial technology on access to capital and business performance. We extend the existing literature by providing firm-level evidence from emerging economies that fintech financing has a more significant positive effect on the real and financial performance of firms with external-finance dependence.

We demonstrate the robustness of our results by using alternative measures for the treatment variable and conducting additional tests to account for omitted variables and potential reverse causality. We further support the causal relationship by applying the instrumental variables method to address the potential endogeneity of our main variable of interest: the interaction between fintech and external-finance dependence. In addition, we show that fintech financing affects firm performance through increased capital investments, lower cost of borrowing, and augmented TFP of firms with external-finance dependence. These findings are novel and point to potential mechanisms that link digital financing to firm performance. The reported evidence implies a significant potential contribution of fintech financing to the economies of developing countries, where financial constraints are a major barrier to business activities.

Our auxiliary analysis provides several insights into the nature of the relationship between fintech financing and firm performance. First, our main results are driven by balance sheet lending, P2P, and crowdfunding, highlighting the heterogeneous effect of fintech models. Second, young firms with external finance dependence disproportionately benefit from digital financing. Fintech platforms' ability to offer credit solutions to firms without a long financial history helps capital reach productive young firms that might otherwise be excluded from the conventional banking system. This is indicative of the important role of innovative digital financial technologies in expanding economic activities. Third, fintech financing has a greater influence on the firm performance of finance-dependent industries in emerging countries with more developed financial sectors. Fourth, there is evidence of a substitution relationship between conventional bank lending and digital finance, which warrants further research scrutiny.

Our empirical evidence reveals that promoting fintech in emerging countries benefits financially constrained young firms in financially developed emerging countries. The policy implications drawn from our empirical findings include the regulatory support by the governments. For instance, entry restrictions can be eased by simplifying licensing processes for fintech start-ups, or financial incentives can be provided, such as grants, subsidies, or tax concessions. To improve broadband infrastructure, investment in infrastructure development is mandatory. Note also that policies aimed at developing a nation's financial and banking systems in emerging economies are important in reaping the full benefit of fintech.

Our paper should contribute to understanding the link between fintech development in emerging countries and firm performance. However, the research is not without limitations. Generally, much of the data in fintech is subject to data privacy due to regulatory constraints, limiting the data availability. Hence, available data may be biased or limited to specific platforms, making it difficult to conduct complete insights. Also, due to the rapid evolution of fintech technologies and related financial regulations, the findings in our research and existing literature may become outdated over time. The academic research on fintech is relatively infant, yet by incorporating the effect of global fintech regulations with the improved data availability, forward-looking research will keep pace with this dynamic research field and enhance the impact of fintech finance.

CRediT authorship contribution statement

Khusrav Gaibulloev: Writing – original draft, Data curation, Writing – review & editing, Methodology. **Ali Mirzaei:** Investigation, Data curation, Writing – original draft, Methodology, Formal analysis, Conceptualization. **Tomoe Moore:** Conceptualization, Writing – original draft, Writing – review & editing, Investigation. **Mohsen Saad:** Visualization, Writing – review & editing, Writing – original draft, Investigation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix

A. Overview of fintech development in emerging countries

On the supply side, opportunities for fintech firms have expanded due to improved infrastructure. For example, the value of fintech financing reached almost USD 361 billion in 2017 in 20 emerging economies, far exceeding the volume in 22 advanced economies at about USD 56 billion. Similarly, the total fintech volume over the entire study period is around USD 1,055 billion in emerging economies, as opposed to USD 423 billion in advanced economies. This pattern is expected to continue, with the Asia-Pacific region poised to overtake the U.S. by 2030 as the world's top fintech region in terms of market value (BCG, 2023). The annual growth rate is predicted to reach 27 %, driven mostly by countries such as China, India, and Indonesia, which are characterized by a high penetration of fintech firms, yet businesses are still in need of external sources of financing (https://www.bcg.com/press/3may2023-fintech-1–5-trillion-industry-by-2030). See Fig. A1 below.

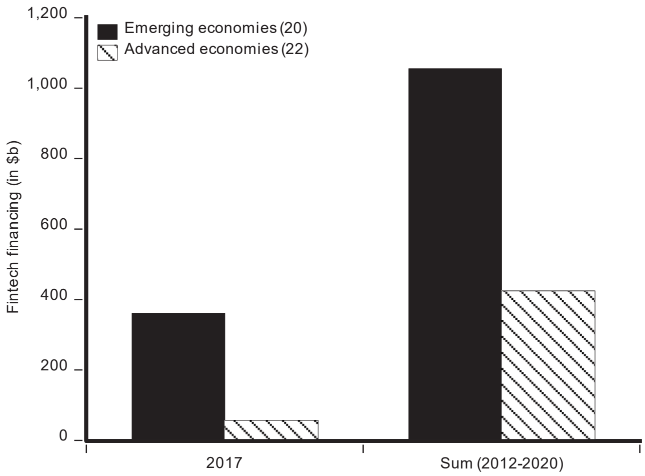

Fig. A1. Total fintech financing ($ billion) in 20 emerging economies versus 22 advanced economies for year 2017 and sum over the period 2012–2020.

Appendix 1

A. Comparative analyses of fintech impacts for emerging and developed countries

It is pointed out that countries with high levels of financial exclusion significantly benefit from the development of fintech, which fosters financial inclusion and deepening (Sahay et al. 2020). See also Demir et al. (2022) and Kanga et al. (2021).

In the study by Cevik (2024), the relationship between fintech development and financial inclusion is examined in a panel of 84 countries over the period 2012–2020. Financial inclusion is measured by the percentage of adults with an account at financial institutions.[19] The findings reveal a distinctive effect of fintech between advanced and developing countries: Fintech is found to exert a negative effect, though insignificant, on financial inclusion for the developed countries, whereas it has a positive and statistically significant effect for the developing countries. The empirical result implies that fintech helps expand financial inclusion in emerging economies, which is consistent with the findings of Basten and Ongena (2020) and Hau et al. (2021), who document that fintech expands services to underserved rural areas in China. Fintech is seen as transformational, addressing fundamental financial gaps where traditional banks are absent or inefficient, leading to increased financial inclusion in emerging economies.

However, for advanced economies, it appears that fintech fails to promote financial inclusion. It is argued that fintech platforms may exacerbate financial exclusion, particularly for vulnerable groups (Cevik 2024). In developed economies, bank branches have been considerably reduced in favor of digital service delivery in response to fintech competition. This has a detrimental effect on accessibility, in particular, for customers in rural or underserved regions, as they may face reduced access to bank services (Makortoff, 2025). There is also the issue of algorithmic bias. To decide on credit, fintech firms utilize data-driven algorithms, which can amplify bias. Hence, the credit scoring can inadvertently introduce biases. Algorithms can propagate discrimination if the data are trained to reflect historical inequalities, for instance, lower credit history within marginalised groups (Vidal & Menajovsky, 2019). If this effect is strong, then fintech is unlikely to cause financial inclusion. This may be reflected in the insignificant effect of fintech on financial inclusion in developed countries.

The study conducted by Qi et al. (2024) further supports the view that fintech improves financial inclusion in emerging countries.

[19] Other studies such as Kanga et al. (2022) and Yang and Zhang (2022) rely on indirect measures of fintech, for example, mobile phone penetration, broadband access or digital payments.

Qi et al. (2024) verify that the enhancement of fintech has a more positive effect on firms' access to capital in regions with low levels of industrialization amongst Chinese listed companies. The area variable, representing the differences in regional economies, is employed as a moderator variable. Qi et al. (2024) show that based on the interaction term between area and fintech, when the regional business economy is underdeveloped, fintech has a strong positive impact on corporate investment, whereas when it is developed, a weak impact is observed. The positive effect is more pronounced in areas where traditional financial services are less developed, with lower levels of growth. Their finding highlights fintech's role in improving firm performance more in emerging than in developed economies.

Emerging countries appear to benefit more from fintech in terms of financial inclusion. However, this is not the case when it comes to credit risk. It is possible that in some emerging economies, the lack of an established credit analysis process and the related regulation may result in an inaccurate evaluation of risk, raising the default rate. In such an environment, the adoption of rapid digital lending entails a transition toward financial practices where the risk assessment of borrowers is inadequate. Moreover, Murinde et al. (2022) argue that the lack of regulations is likely to contribute to technology failures, data breaches and fraudulent activities. Therefore, it is likely that loans could be extended to less creditworthy borrowers (Anestiawati et al., 2025). On the other hand, the credit risk can be minimized due to the established regulatory structure and credit evaluation in many developed countries. Digital financial transactions are closely monitored in highly regulated environments, mitigating the occurrence of non-performing loans.

Anestiawati et al. (2025) explore fintech's global impact on credit risk in the top 20 emerging and 20 mature economies, separately. Note that data for fintech used in their study is for bank fintech. They find that digital lending has a significant positive influence on the rise of the default of loans in emerging countries, whereas the relationship is found to be significantly negative in developed countries, supporting the above argument. The finding manifests the fact that a rapidly adopted fintech has often outpaced the establishment of regulatory frameworks and risk management, with the consequence of increased non-performing loans in emerging countries.

Overall, the impacts of fintech vary depending on the level of income and growth across countries. Although positive impacts of fintech are empirically found among emerging economies, there is a possibility of a higher risk of default as compared with developed economies. Given that fintech can be potentially one of the driving forces for growth in less developed economies, it warrants exclusive focus in emerging countries.

Appendix 2

Table A1
Variables definition and sources.

Variable	Definition	Source
Firm performance$_{ijct}$		
ROA	Return on assets, which is defined as profit before tax as a percentage of average assets of a firm. It determines whether a company uses its assets efficiently to generate a profit.	Bureau van Dijk, ORBIS, and own calculation.
ROE	Return on equity, which is defined as profit before tax as a percentage of average equity of a firm. It shows how well a company is managing the capital that shareholders have invested in it.	"
ValG	Year-over-year growth in a firm's value added. Value added is computed as the sum of earnings before taxes, depreciation and labor expense. It measures the contribution of a firm to an economy through its production process..	"
EmpG	Year-over-year growth in a firm's number of employees. A higher growth rate indicates that the company is growing.	"
Fintech financing$_{ct}$		
Total	Total volume of digital lending and capital raising activities (BSheet, P2P, CrowF and Other) in a country as percentage of its GDP.	Cambridge Center for Alternative Finance. Ziegler et al. (2021).
BSheet	Total volume of Balance Sheet lending activities in a country as percentage of its GDP. The platform entity provides a loan directly to the consumer borrower, business borrower, or secured against a property, ascribed to on-balance sheet nonbank lending.	"
P2P	Total volume of P2P lending activities in a country as percentage of its GDP. Individuals or institutional funders provide a loan to a consumer borrower, business borrower, or secured against a property, commonly ascribed to off-balance sheet lending.	"
CrowF	Total volume of raising funds through crowdfunding in a country as percentage of its GDP. It includes several ways, including: (i) equity-based crowdfunding: Individuals or institutional funders purchase equity issued by a company, (ii) real estate crowdfunding: Individuals or institutional funders provide equity or subordinated debt financing for real estate, (iii) revenue/profit sharing: Individuals or institutions purchase securities from a company, such as shares or bonds, and share in the profits or royalties of the business, (iv) reward-based crowdfunding: Backers provide funding to individuals, projects or companies in exchange for non-monetary rewards or products, and (v) donation-based crowdfunding: Donors provide funding to individuals, projects or companies based on philanthropic or civic motivations with no expectation of monetary or material.	"
Other	Total volumes of funds raised through other alternative finance models, including community shares, pension-led funding, and other models that fall outside the above taxonomy in a country as percentage of its GDP.	"

(*continued on next page*)

Table A1 (*continued*)

Variable	Definition	Source
External financial dep.$_j$		
EFD	External financial dependence of U.S. firms by 2-digit SIC codes. This is an industry-level median of the ratio of capital expenditures minus cash flow over capital expenditures. Cash flow is defined as the sum of funds from operations, decreases in inventories, decreases in receivables, and increases in payables. Capital expenditures include net acquisitions of fixed assets.	Duygan-Bump et al (2015).
Controls$_{ijct}$		
Size	Natural logarithm of a firm's total assets.	Bureau van Dijk, ORBIS, and own calculation.
Solv	Firm shareholder's capital to total assets ratio. It indicates the amount of the assets on which shareholders have a residual claim.	"
Leve	Firm total debt to total assets ratio. It shows the degree to which a company has used debt to finance its assets.	"
Liqu	Liquidity ratio, which is calculated by taking current assets less inventories, divided by current liabilities. A higher ratio indicates the firm can better pay its obligations.	"
FixA	Firm fixed assets to total assets ratio. It indicates the extent to which a firm's operations rely on its fixed assets to generate revenue.	"
Other variables		
Bank Credit	Domestic credit to private sector by banks, which refers to financial resources provided to the private sector by deposit taking corporations except central banks, such as through loans.	World Bank – WDI.
Branch	Commercial bank branches (per 100,000 adults). Commercial bank branches are retail locations of resident banks that provide financial services to customers. It represents financial inclusion and access to finance in an economy.	"
Internet	Secure Internet servers (per 1 million people), which is the number of distinct, publicly trusted TLS/SSL certificates found in the Netcraft Secure Server Survey. It indicates the quality of an economy's infrastructure.	"
GDP Growth	GDP growth (YOY) of a country.	"
Inflation	GDP price deflator.	"
KKZ index	KKZ institution index is an aggregate indicator of the quality of institutional development in the country. The index is calculated using the average indicators of information on six issues: voice accountability, political stability, government's effectiveness, regulatory quality, rule of law, and control of corruption. Higher value indicates higher institutional quality.	Worldwide Governance Indicator. Kaufman et al. (2010).

Appendix 3

Table A2
Controlling for institutional quality.

	Financial performance		Real performance	
	ROA	ROE	ValG	EmpG
	[1]	[2]	[3]	[4]
EFD$_j$ x Fintech$_{ct}$	0.006**	0.022**	0.355*	0.018
	(2.002)	(2.330)	(1.917)	(1.165)
Controls$_{ijct}$				
Size	0.009***	0.017***	0.106***	0.040***
	(3.800)	(2.865)	(4.509)	(2.820)
Solv	0.236***	0.449***	0.140***	−0.009
	(30.963)	(16.379)	(2.820)	(−0.607)
Leve	0.198***	0.502***	0.114	0.125***
	(22.355)	(17.608)	(1.230)	(3.231)
Liqu	−0.004***	−0.012***	−0.026***	−0.006***
	(−14.499)	(−17.005)	(−7.950)	(−5.179)
FixA	−0.124***	−0.339***	−0.645***	−0.018
	(−24.939)	(−24.196)	(−8.189)	(−1.104)
Controls2$_{j*ct}$				
EFD$_j$ x Bank Credit$_{ct}$	−0.000	−0.000	0.003	−0.001
	(−1.208)	(−0.558)	(0.690)	(−0.515)
EFD$_j$ x Branch$_{ct}$	−0.001	0.004	−0.019	−0.001
	(−0.587)	(0.780)	(−1.172)	(−0.123)
EFD$_j$ x Internet$_{ct}$	−0.000	0.000	−0.000	0.000
	(−0.715)	(0.232)	(−1.592)	(1.130)
EFD$_j$ x GDP Growth$_{ct}$	−0.000	0.003	0.001	−0.002
	(−0.119)	(1.152)	(0.162)	(−0.543)
EFD$_j$ x Inflation$_{ct}$	−0.001	−0.002	0.017*	−0.003
	(−1.331)	(−0.638)	(1.725)	(−0.702)

(*continued on next page*)

Table A2 (*continued*)

	Financial performance		Real performance	
	ROA	ROE	ValG	EmpG
	[1]	[2]	[3]	[4]
EFD_j x KKZ_{ct}	0.025*	0.077	0.243	0.212*
	(1.668)	(1.566)	(1.600)	(1.898)
Firm FE	Y	Y	Y	Y
SIC × Year FE	Y	Y	Y	Y
Country × Year FE	Y	Y	Y	Y
# Countries	20	20	20	20
# Industries	22	22	22	22
*N (Firm*Year)*	304,806	304,806	116,745	173,012
Adj. R^2	0.509	0.370	0.055	0.059

Appendix 4

Table A3
Constructing external financial dependence at the firm level.

	Financial performance		Real performance	
	ROA	ROE	ValG	EmpG
	[1]	[2]	[3]	[4]
EFD_j x $Fintech_{ct}$	0.000**	0.001***	0.000	−0.001***
	(2.549)	(3.333)	(0.368)	(−3.653)
$Controls_{ijct}$				
Size	0.014***	0.037***	0.115***	0.046**
	(4.097)	(3.703)	(4.370)	(2.547)
Solv	0.237***	0.519***	0.143**	−0.038*
	(24.232)	(13.521)	(2.598)	(−1.880)
Leve	0.157***	0.403***	0.199**	0.134***
	(12.952)	(11.983)	(2.235)	(3.528)
Liqu	−0.004***	−0.013***	−0.026***	−0.005***
	(−13.277)	(−15.025)	(−8.090)	(−3.247)
FixA	−0.133***	−0.341***	−0.654***	−0.044**
	(−27.971)	(−23.101)	(−8.937)	(−2.354)
Firm FE	Y	Y	Y	Y
SIC × Country FE	Y	Y	Y	Y
SIC × Year FE	Y	Y	Y	Y
Country × Year FE	Y	Y	Y	Y
# Countries	20	20	20	20
# Industries	22	22	22	22
*N (Firm*Year)*	199,905	199,905	115,197	123,890
Adj. R^2	0.513	0.374	0.057	0.051

Appendix 5

Table A4
Splitting the sample based on different percentiles of $EFD_j \times Fintech_{ct}$.

Table A4: Percentile regressions

	Financial performance		Real performance		Financial performance		Real performance	
	ROA	ROE	ValG	EmpG	ROA	ROE	ValG	EmpG
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
	Panel A: < 5 percentile				**Panel B:** >= 5 percentile and < 60 percentile			
EFD_j x $Fintech_{ct}$	−0.065	−0.052	49.109***	−0.021	0.103	0.162	−0.152	0.723***
	(−0.457)	(−0.139)	(16.652)	(−0.070)	(1.518)	(0.655)	(−0.116)	(2.628)
*N (Firm*Year)*	15,272	15,272	908	11,874	149,070	149,070	60,044	67,655
Adj. R^2	0.580	0.444	0.092	0.035	0.549	0.403	0.060	0.075

(*continued on next page*)

Table A4 (*continued*)

Table A4: Percentile regressions	Financial performance		Real performance		Financial performance		Real performance	
	ROA	ROE	ValG	EmpG	ROA	ROE	ValG	EmpG
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
	Panel C: >= 60 percentile and < 95 percentile				**Panel D:** >= 95 percentile			
EFD_j x $Fintech_{ct}$	0.150***	0.454***	−0.510	−0.068	0.267***	0.227***	8.667**	−0.232***
	(2.817)	(2.983)	(−0.337)	(−0.333)	(20.929)	(4.265)	(2.644)	(−4.994)
*N (Firm*Year)*	114,421	114,421	50,882	70,670	17,959	17,959	213	13,935
Adj. R^2	0.519	0.374	0.063	0.073	0.591	0.439	−0.073	0.007
All panels								
$Controls_{ijct}$ (Size, Solv, Leve, Liqu, FixA)	√	√	√	√	√	√	√	√
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y
SIC × Country FE	Y	Y	Y	Y	Y	Y	Y	Y
SIC × Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Country × Year FE	Y	Y	Y	Y	Y	Y	Y	Y
# Countries	20	20	20	20	20	20	20	20
# Industries	22	22	22	22	22	22	22	22

Appendix 6

Table A5
Controlling for firm's financial characteristics.

	< Mdn.				> Mdn.			
	Financial performance		Real performance		Financial performance		Real performance	
	ROA	ROE	ValG	EmpG	ROA	ROE	ValG	EmpG
	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
Panel A: leverage (less vs. more)								
EFD_j x $Fintech_{ct}$	0.000	−0.004	0.073	−0.019*	0.008***	0.044***	0.773*	0.078***
	(0.089)	(−0.677)	(0.418)	(−1.671)	(2.667)	(3.888)	(1.703)	(2.703)
*N (Firm*Year)*	115,851	115,851	45,410	68,391	181,833	181,833	68,260	98,054
Adj. R^2	0.573	0.518	0.058	0.050	0.488	0.360	0.066	0.073
Panel B: Zscore (low vs. high)								
EFD_j x $Fintech_{ct}$	0.003	0.016*	0.320	0.005	0.004	0.022**	0.561**	0.059**
	(0.926)	(1.688)	(1.141)	(0.314)	(1.326)	(2.187)	(2.182)	(2.526)
*N (Firm*Year)*	122,102	122,102	51,063	74,855	176,251	176,251	61,297	91,785
Adj. R^2	0.496	0.368	0.022	0.049	0.569	0.418	0.132	0.053
All panels								
$Controls_{ijct}$ (Size, Solv, Leve, Liqu, FixA)	√	√	√	√	√	√	√	√
Firm FE	Y	Y	Y	Y	Y	Y	Y	Y
SIC × Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Country × Year FE	Y	Y	Y	Y	Y	Y	Y	Y
# Countries	20	20	20	20	20	20	20	20
# Industries	22	22	22	22	22	22	22	22

Appendix 7. Derivation of TFP

We use the Cobb-Douglas production technology that translates the inputs used in the production process into the output for firm *i* in year *t* as follows:

$$Log(Y_{it}) = \alpha_0 + \alpha_1.Log(L_{it}) + \alpha_2.Log(K_{it}) + \alpha_3.Log(M_{it}) + w_{it} + \varepsilon_{it} \tag{2}$$

where Y_{it}, L_{it}, K_{it} and M_{it} denote output, labor, capital, and intermediate inputs, respectively. The random component w_{it} is the firm-specific and time-varying unobservable productivity term (TFP) that we aim to estimate, and ε_{it} is an idiosyncratic output shock.

The OLS estimates of equation (2) are inconsistent due to a correlation between unobservable firm-level productivity and observable firm input decisions, leading to biased estimates of TFP. To address this endogeneity issue, we estimate TFP (in natural logarithms) by using two recently developed methods (Rovigatti & Mollisi, 2018). Levinsohn and Petrin (2003) propose a two-step estimation procedure where intermediate inputs are used as a proxy variable for unobserved productivity (w_{it}). Wooldridge (2009) shows that the two-step approach can be implemented in a single step within a system GMM framework. A key advantage of

Wooldridge's technique is that it resolves a potential parameter identification issue that may arise in Levinsohn and Petrin's first stage if the free variables are correlated with the proxy variable for productivity (Rovigatti & Mollisi, 2018; Wooldridge, 2009).

Following Tian and Twite (2011), we use firm turnover as the output variable, the cost of materials as a proxy for intermediate input, the book value of fixed assets as a measure of capital, and the cost of employees as the labor input variable. All these variables are in logarithms and real terms. Since we estimate production functions at the country level, three countries are excluded from the sample due to the insufficient number of observations.[20]

Data availability

Data will be made available on request.

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[20] To account for different factor intensities across industrial sectors, we also tried to estimate the production function at the country-industry (SIC 2 digit) level. However, because we do not have enough firms per industry, we conduct our estimates at the country level.

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