Can past informality impede registered firms' access to credit?

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Abstract

Using a large firm-level dataset from the World Bank Enterprise Surveys, which covers 134 countries from 2006 to 2023 and includes over 134,000 observations, we examine whether past informality affects the credit constraints of registered firms. Estimations, based on the entropy balancing method, indicate that registered firms that began operations informally are more likely to be credit-constrained than those that started in the formal sector. This finding is extremely robust to a variety of robustness tests, including instrumental variables, propensity score matching, potential omitted variables, restricted samples, alternative measures of credit constraints, different specifications such as Linear Probability, Logit, and Probit models, and clustering standard errors at the country level. Heterogeneity analysis reveals that the detrimental impact of past informality lessens with firm size, firm age, and better structural factors like regulatory quality, trade openness, entrepreneurial dynamism, and public spending. Productivity, competition from the informal sector, and the quality of financial statements are key channels through which past informality increases credit constraints for registered firms.

Keywords: Past informality status; Credit constraints; Entropy balancing
JEL Codes: G20; O12; O16; O17

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1 Introduction

What drives the credit constraints of firms? A large body of literature in both development economics and finance has sought to answer this question by analyzing the determinants of credit constraints in firms worldwide (see Asiedu et al., 2013; Banerjee and Duflo, 2014; Briggeman et al., 2009; Brown et al., 2014; Cheng and Yang, 2022; Distinguin et al., 2016; Kim, 2006; Rand, 2007, among others).[1] Analyzing these determinants is crucial, as credit constraints directly hinder firm investment (García-Posada Gómez, 2019), which in turn limits innovation and overall performance. Indeed, when firms face credit constraints, they are less likely to invest in new technologies or processes (Hall, 2002; Hottenrott and Peters, 2012; Pellegrino and Savona, 2017), leading to decreased productivity and slower growth. This stagnation not only affects the firms themselves but also translates into fewer job opportunities, as firms are unable to expand or hire more staff. The reduction in innovation and firm performance can have widespread consequences, stalling economic progress and undermining social development within countries. By understanding the factors that contribute to these credit constraints, policymakers can devise targeted strategies to alleviate them. Effective policy interventions can, therefore, enhance firm investment and performance, spur innovation, and boost economic and social development. Consequently, tackling the roots of credit constraints is essential for fostering a dynamic and thriving economy.

A thorough review of the literature, however, reveals that the role of past informality status (i.e., the fact that a firm currently registered was not registered when it began operations) in explaining the credit constraints of registered firms has not been analyzed, despite the existence of informality in all countries worldwide[2], and the potential lasting effects of informal origins – including low productivity and weak innovation capacity (Fu et al., 2018; Kouakou, 2023b) – on registered firms' operations.[3][4] We believe that past informality can

[1]For some stylized results on the financing constraints of firms, see Carreira and Silva (2010). The literature has also extensively focused on measuring financing constraints. For seminal contributions on this topic, see Fazzari et al. (1988, 2000) and Kaplan and Zingales (1997, 2000), among others.

[2]Indeed, informality exists in all countries worldwide, but it is more prevalent in developing countries, particularly in Africa. For recent estimates of the size of the informal economy worldwide, see Elgin et al. (2022).

[3]Informality may also have some benefits (e.g., informal employment can serve as a safety net; see Loayza and Rigolini (2011)). See Kouakou (2023a) and Ulyssea (2018) for a discussion of some of these benefits. However, the literature generally finds that negative effects prevail. For instance, Meghir et al. (2015) propose an equilibrium wage-posting model involving heterogeneous firms that can choose to operate in either the formal or informal sector, and workers who search randomly both on and off the job. The study explores the potential costs and benefits of informality and demonstrates that the negative effects of informality outweigh the positives, concluding that enhanced enforcement to reduce informality improves overall welfare in the economy.

[4]At the macroeconomic level, informality also has adverse effects on the economy, particularly through tax evasion, which reduces the tax base and revenue mobilization, thereby weakening the government's ability

impact registered firms' probability of being credit-constrained for at least three reasons.

First, past informality status may increase registered firms' probability of being credit-constrained by reducing their productivity. Indeed, past informality reduces a firm's innovativeness, as demonstrated recently by Mendi and Mudida (2018). Firms with a history of informality often lack openness to international markets, which is detrimental to their innovativeness. Increased competition from such exposure typically encourages firms to innovate (Balsmeier, 2017). Additionally, these firms face severe informational disadvantages compared to their formal counterparts due to weaker professional networks. Moreover, firms that transition to the formal sector may develop a negative perception of the need to innovate (Mendi and Mudida, 2018). In fact, informal firms usually produce goods similar to those produced in the formal sector but of lower quality (Banerji and Jain, 2007), and such imitation behavior may persist even years after formalization. Furthermore, starting as an informal firm can foster a long-term culture of risk aversion and limited strategic planning, which may further diminish the likelihood of innovation.

The decrease in innovation reduces firms' productivity (Crespi and Zuniga, 2012; Fu et al., 2018; Goedhuys et al., 2013; Geroski, 1989). Indeed, a decline in innovation causes processes to stagnate and technologies to become outdated, leading to reduced efficiency and increased production costs. This stagnation hampers a firm's ability to optimize resource use and limits opportunities for new sales, resulting in decreased output per unit of input. The decline in productivity, in turn, increases firms' probability of being credit-constrained (Distinguin et al., 2016). In fact, a drop in productivity typically results in reduced profitability and cash flow, weakening a firm's financial position and making it more challenging to meet debt obligations. Consequently, lenders may perceive the firm as a higher risk, leading to stricter credit terms or even denial of credit. This restriction on credit further hinders the firm's capacity to invest in initiatives that could enhance productivity, creating a vicious cycle of declining performance and financial strain.

Second, past informality may increase a firm's probability of being credit-constrained by intensifying competition from the informal sector. Indeed, informal firms often compete with formal firms (Heredia Pérez et al., 2018; Kouakou, 2023a; Mendi and Mudida, 2018; Tokman, 1978), typically by producing goods similar to those of their formal counterparts but of lower quality (Banerji and Jain, 2007), as previously discussed. These goods often succeed because they are cheaper and better align with the financial capacities of consumers, particularly in developing countries (Kouakou, 2023a). Informal firms generally compete with registered firms of similar size and scale, using comparable production methods. Firms with a history of informality are more likely to fit this profile. As a result, these firms are expected to face

to support economic and social development.

greater competition from the informal sector.

Competition from the informal sector, in turn, increases the probability of registered firms to be credit-constrained, as highlighted by Distinguin et al. (2016).[5] This aligns with the entrepreneurial perspective and the "parasite" view of informality, which suggest that informal firms can compete with registered firms and diminish their profits (Farrell, 2004; Levy, 2008; Siqueira et al., 2016). Indeed, such competition can significantly reduce the profit margins of registered firms, primarily by eroding their market share (Kouakou, 2023a). This reduction in profits makes it more challenging for registered firms to present a strong financial position to lenders. Additionally, registered firms often face high operational costs due to the burden of regulations and taxes, which exacerbates the financial strain caused by competition from informal firms. Furthermore, the unregulated nature of informal firms contributes to market instability, increasing the risk for lenders and heightening the likelihood of credit constraints for registered firms.

Third, past informality can increase a firm's probability of being credit-constrained by reducing the quality of financial statements. Indeed, a firm's history of operating informally can impact its ability to produce high-quality financial statements once it becomes registered. Informal operations often lack the structured financial practices and rigorous bookkeeping necessary for transparent and accurate record-keeping (La Porta and Shleifer, 2014). This absence of formal financial controls can pose challenges when the firm transitions to a formal status and faces the stringent requirements of external audits. Additionally, firms with informal origins might have developed a culture of minimal compliance, in contrast to those

[5] It can be imagined that firms recently transitioning to the formal sector may suffer more from competition with informal firms, which could incentivize them to innovate more, improve their performance, and potentially enhance their access to credit. However, Kouakou (2023a) shows that severe competition from the informal sector leads firms to significantly reduce their commitment to key innovation activities, especially investment in research and development (R&D), thereby weakening their innovation capacity. This reduction is due to a diminished self-financing capacity following losses in market share and profits (Kouakou, 2023a). For further discussions on the detrimental effects of competition from the informal sector on market share and profits, see also Amin (2023), Mendi and Costamagna (2017), and Perry et al. (2007), among others. Lower innovativeness and capacity to innovate negatively impact firms' performance, especially productivity (Fu et al., 2018). The author uses a dataset of Ivorian firms, primarily small and medium-sized enterprises (SMEs), which often emerge from the informal sector and fit the profile of firms recently transitioning to the formal sector. Similarly, Mendi and Costamagna (2017), using firm-level data from African and Latin American countries, find an inverted U-shaped relationship between competition from the informal sector and a firm's probability to innovate. This indicates that severe competition from the informal sector significantly reduces firms' probability to innovate, consistent with the findings of Kouakou (2023a). Furthermore, Distinguin et al. (2016), using data from SMEs across 86 countries – which are more likely to have started informally, as previously explained –, show that competition from the informal sector significantly increases the probability of registered firms to be credit-constrained. Additionally, firms recently transitioning to the formal sector are typically small, and the literature extensively demonstrates that small firms are more likely to be credit-constrained than medium-sized and large firms (see Asiedu et al., 2013; Beck et al., 2005; Distinguin et al., 2016, among others). Based on this discussion, it seems unlikely that firms recently transitioning to the formal sector would be less credit-constrained.

that started in the formal sector. Consequently, these firms may be less inclined to prioritize or invest in the external certification of their financial statements. Thus, registered firms with a history of informal operations may be less likely to produce high-quality financial statements compared to those that began as formally registered entities.

A firm's likelihood of facing credit constraints can increase if its financial statements are of poor quality. Indeed, these statements significantly impact financing decisions (Beck et al., 2005). Firms with subpar financial reports often have difficulty supplying the detailed information that lenders need to evaluate their creditworthiness. This inadequacy can result in increased credit constraints as inaccurate or incomplete financial records may lead creditors to perceive these firms as high-risk investments. Without reliable financial statements, firms struggle to showcase their financial stability and ability to repay loans, which complicates efforts to obtain financing or favorable credit terms. Moreover, the lack of transparency and accountability in financial reporting can dissuade potential investors and creditors, further aggravating the firm's credit constraints.

In summary, past informality may reduce firm productivity and the quality of financial statements, increase competition from the informal sector, and these factors, in turn, should elevate the probability of registered firms to be credit-constrained. Given this possibility, it is essential to conduct an econometric analysis to formally explore the relationship between past informality and the credit constraints faced by registered firms. A significant and positive impact of past informality would underscore the need for public policies that provide strong incentives for firms to start operations in the formal sector. The rationale would be that once a firm begins informally, its informal origins can have a lasting effect on its ability to secure external financing, even after transitioning to the formal sector. This, in turn, can harm the firm's growth, profitability, and capacity to hire, potentially impeding the country's economic and social development.

This paper addresses the gap in the literature by analyzing the effect of past informality on registered firms' probability of being credit-constrained, using firm-level data from the World Bank Enterprise Surveys, which cover 134 countries from 2006 to 2023. The dataset comprises repeated cross-sections, includes only registered firms, and contains over 134,000 observations. By employing the entropy balancing method to correct for the endogeneity of past informality status, we find that registered firms that began operations informally are more likely to be credit-constrained compared to those that started in the formal sector. This finding is extremely robust across various robustness tests, including instrumental variables, propensity score matching, potential omitted variables, restricted samples, alternative measures of credit constraints, different model specifications such as Linear Probability, Logit, and Probit models, and clustering standard errors at the country level. Additionally, heterogeneity analysis reveals that the detrimental impact of past informality diminishes with firm size, firm age, and improved structural factors like regulatory quality, trade openness, entrepreneurial dynamism, and public spending. Finally, we analyze three transmission channels through which past informality may affect the likelihood of registered firms to be credit-constrained. We demonstrate that reductions in the quality of financial statements and firm productivity, along with increases in competition from the informal sector, are key channels through which past informality heightens credit constraints for registered firms.

This paper contributes to the literature on multiple levels. First, it is the first to demonstrate, to the best of our knowledge, that past informality significantly increases the probability of registered firms to be credit-constrained, using a large global sample. This finding is crucial as it reveals an unexamined link between a firm's historical informality and its current credit constraints, highlighting the lasting impact of informal origins on access to finance. The use of a large global sample enhances the applicability and relevance of this research, deepening our understanding of how past operational practices affect financial opportunities across various economic contexts. Second, we provide evidence that firm productivity, the quality of financial statements, and competition from the informal sector are key transmission channels through which past informality impacts credit constraints. Identifying these specific mechanisms is significant as it helps policymakers and financial institutions design more targeted interventions to address the root causes of credit constraints and improve access to finance for firms with informal origins. Third, we find that the adverse impact of past informality diminishes with certain firm characteristics such as size and age, as well as improvements in structural factors like regulatory quality, trade openness, entrepreneurial dynamism, and public spending. This insight is valuable for policymakers, as it highlights ways to mitigate the long-term disadvantages associated with informal origins. Focusing on enhancing structural conditions can help reduce these persistent challenges and support firm growth and stability.

The rest of the paper is organized as follows. Section 2 presents the econometric methodology. Section 3 describes the data, variables, and descriptive statistics. Section 4 presents and discusses the baseline results. Section 5 provides a series of analyses to test the robustness of our findings. Section 6 presents the heterogeneity analysis. Section 7 analyzes the transmission channels. Section 8 concludes the paper and discusses policy implications and potential extensions.

2 Methodology

This paper aims to analyze how past informality affects the credit constraints of registered firms, a notable challenge due to the non-random nature of past informality status. Indeed, the probability of having past informality status can be correlated with various factors, including firm size, firm age, sector of activity, economic development, economic conditions, and financial development. This correlation introduces a self-selection issue. Additionally, these factors can significantly influence credit constraints, leading to omitted variable bias and making past informality status endogenous.

To address these issues, we employ the entropy balancing impact evaluation method developed by Hainmueller (2012), which has gained considerable traction in the literature. For instance, Apeti (2023) and Apeti and Edoh (2023) investigate the effects of mobile money adoption on consumption volatility and tax revenue, respectively. Balima (2020) analyzes the effect of a coup d'état on debt. Gasmi et al. (2024) study the effect of the provision of basic goods on citizen political participation in the Middle East and North Africa region. Gasmi et al. (2024) analyze the effect of firm informality on the introduction of sustainable and responsible innovation in registered firms in Nigeria. Neuenkirch and Neumeier (2016) investigate the effect of U.S. sanctions on poverty.

The entropy balancing method offers several benefits over conventional treatment effects techniques, such as propensity score matching and difference-in-differences. Among these benefits, first, entropy balancing ensures a higher degree of covariate balance. Second, since it does not rely on a treatment model, it mitigates model dependency, thereby reducing issues of multicollinearity and endogeneity. Third, entropy balancing uses a reweighting approach that minimizes information loss by maintaining weights close to their original values. Fourth, Hainmueller (2012) shows through Monte Carlo simulations and empirical analyses that entropy balancing surpasses many traditional methods, including propensity score matching, genetic matching, and Mahalanobis distance matching, in terms of bias and root mean squared error. Fifth, this method accommodates the panel structure of data by incorporating individual and year fixed effects in the estimation of treatment effects.

In this paper, past informality status is considered as a "treatment" and is represented by a binary variable that takes the value 1 if the firm began operations as an informal firm (i.e., it was not registered at the start), and 0 otherwise. The "treated group" includes observations with past informality status, while the "control group" includes observations without past informality status. The outcome variable is credit constraints, a binary variable that takes the value 1 if the firm is credit-constrained, and 0 otherwise. Our focus is on measuring the average treatment effect on the treated (ATT), which indicates the impact of past informality on a registered firm's probability of being credit-constrained and is calculated as follows:

$$\tau_{ATT} = E\left(constrained_{(1)} \middle| T = 1\right) - E\left(constrained_{(0)} \middle| T = 1\right) \quad (1)$$

where *constrained* and T represent the outcome and treatment variables, respectively. Here, $T = 1$ indicates that the firm has past informality status, while $T = 0$ indicates that it does not. The term $E\left(constrained_{(1)} \middle| T = 1\right)$ refers to the expected outcome given past informality status, and $E\left(constrained_{(0)} \middle| T = 1\right)$ represents the expected outcome if the firm had not experienced past informality status, also known as the counterfactual outcome of past informality status.

A significant challenge arises because $E\left(constrained_{(0)} \middle| T = 1\right)$ is unobservable. To address this, a common strategy is to match observations that have experienced the treatment with those that have not, ensuring that the matched non-treated observations are as similar as possible to the treated observations in terms of observable characteristics. These covariates are assumed to be related to both the outcome and the treatment variables. This matching process provides an appropriate proxy for $E\left(constrained_{(0)} \middle| T = 1\right)$. Within this framework, equation (1) is transformed as follows:

$$\tau_{ATT} = E\left(constrained_{(1)} \middle| T = 1, X = x\right) - E\left(constrained_{(0)} \middle| T = 0, X = x\right) \quad (2)$$

where $X = x$ represents a vector of observable characteristics that are correlated with both credits constraints and past informality status. The terms $E\left(constrained_{(1)} \middle| T = 1, X = x\right)$ and $E\left(constrained_{(0)} \middle| T = 0, X = x\right)$ denote the expected outcomes with and without past informality status, respectively, for observations with characteristics $X = x$.

The estimation of the ATT using the entropy balancing method involves two steps. First, weights are calculated for the control group. These weights are designed to satisfy balancing constraints related to the sample moments of the observable characteristics. In the literature, the focus is on balancing the first moment (see Apeti, 2023; Apeti and Edoh, 2023; Balima, 2020; Gasmi et al., 2024,0; Neuenkirch and Neumeier, 2016, among others), which involves ensuring that the means of the observable characteristics are equal between the treated and control groups. The goal is to make the observations without past informality status, on average, as similar as possible to those with past informality status.

In the second step, these weights are incorporated into a regression analysis where the dependent variable is credit constraints. The main explanatory variable is past informality, and the covariates used in the first step are included as controls. We also include year and country fixed effects in the second step of entropy balancing. This estimation allows us to obtain the ATT. More precisely, given the binary nature of the dependent variable, the second step involves estimating a Logit model that includes the entropy balancing weights.[6] We then compute the average marginal effect to obtain the ATT. Including the covariates in this second step enhances the efficiency of the estimation (Gasmi et al., 2024; Neuenkirch and Neumeier, 2016) and is analogous to including control variables in a randomized experiment (Neuenkirch and Neumeier, 2016). Country and year fixed effects allow us to control for country-specific factors (such as the population's financial culture) and macroeconomic shocks (such as global pandemics and financial crises) that may influence both the probabilities of being credit-constrained and having past informality status.

Besides, note that despite its previously discussed advantages, entropy balancing, like any impact evaluation method, may have some limitations. Indeed, it may fail to address endogeneity issues resulting from unobserved time-varying factors affecting both the probabilities of past informality status and credit constraints, as well as potential reverse causality. To test the robustness of our results, we complement the entropy balancing method with alternative estimation methods, including the Instrumental Variable method (IV), four variants of the Propensity Score Matching method (PSM) (namely Nearest Neighbor Matching, Radius Matching, Kernel Matching, and Local Linear Regression Matching), Logit, Probit, and Linear Probability regressions. To further address potential omitted variable issues, we incorporate a wide range of additional controls or potential omitted covariates in our entropy balancing specification (see Apeti and Edoh, 2023, for the same approach), in addition to including country and year fixed effects as previously explained. We also consider alternative specifications in the second step of the entropy balancing method. Additionally, we consider alternative measures of credit constraints to test the robustness of our findings to measurement errors. We also assess the sensitivity of our results to restricted samples. In the final robustness check, we cluster standard errors at the country level.

3 Data, variables, and descriptive statistics

3.1 Data sources

We utilize firm-level data from the World Bank Enterprise Surveys (WBES), covering 134 countries from 2006 to 2023.[7] The dataset comprises repeated cross-sections, includes only registered firms, and contains over 134,000 observations. The WBES are comprehensive, nationally representative surveys that gather data from top managers and business owners in over 150 countries. These surveys provide valuable insights into various aspects of firms'

[6]As will be seen in the robustness checks section, using either a Linear Probability model or a Probit model in the second step, instead of the Logit model, yields similar results.

[7]The list of countries is presented in Table A1 of Appendix A.

activities, including informality, access to finance, firm performance, ownership, exports, and other relevant areas. The extensive data collected facilitate comparisons across different economies and over time. The information and data from these surveys are publicly accessible at `https://www.enterprisesurveys.org/`.

The WBES are our primary data source, which we complement with macroeconomic variables to account for country-level factors that may be correlated with both the probabilities of credit constraints and having past informality status. Macroeconomic data on regulatory quality and corruption, publicly accessible at `https://www.govindicators.org/`, are sourced from the Worldwide Governance Indicators (WGI) database developed by Kaufmann et al. (2010). The remaining macroeconomic variables are obtained from the World Development Indicators (WDI) database of the World Bank, which is also publicly accessible at `https://datatopics.worldbank.org/world-development-indicators/`.

3.2 Variables

3.2.1 Credit constraints

Our dependent variable is "Credit constraints." This is a binary variable equal to 1 if the firm is credit-constrained, and 0 otherwise.[8] Based on the WBES and the literature (see, for instance, Distinguin et al., 2016), a firm is considered credit-constrained if it either applied for a loan and was denied, or if it needed a loan but chose not to apply due to various constraints such as complex application procedures, high interest rates, and substantial collateral requirements. A firm is not regarded as credit-constrained if it successfully obtained financing or possesses sufficient capital. Figure 1 gives more details on how the "Credit constraints" variable is constructed.

[Insert Figure 1 here]

3.2.2 Past informality

Our independent variable is "past informality." This is a binary variable that takes the value of 1 if the firm began operations informally (i.e., it was not registered at the start), and 0 otherwise. To construct this variable, we use the following question asked in the WBES: "*B.6a: Was this establishment formally registered when it began operations?*" A firm has past informality status if the answer to this question is "no." In contrast, the firm does not have past informality status if the answer is "yes."

[8]Distinguin et al. (2016) adopt the same approach to measuring credit constraints.

3.2.3 Matching covariates or control variables

The matching covariates or control variables are selected from variables that are correlated with both the probabilities of being credit-constrained and having past informality status. This approach helps mitigate issues related to potential omitted variable bias and enhances estimation efficiency. Based on the literature on the determinants of credit constraints, informality, and the transition to the formal sector, we select the following covariates: firm size, firm age, sector of activity, affiliation with a large firm, private foreign ownership, real GDP per capita (as a proxy for economic development), inflation (as a proxy for economic conditions), and domestic credit to the private sector (as a proxy for financial development). Macroeconomic variables are included to control for country-level factors that may be correlated with both the probabilities of being credit-constrained and having past informality status.

Financial constraints tend to diminish as firms become larger (Asiedu et al., 2013; Beck et al., 2005; Distinguin et al., 2016). Larger firms often enjoy better access to capital markets, allowing them to obtain funding more easily and at lower costs compared to smaller firms. Additionally, these larger entities benefit from more diversified income streams and assets, as well as a stronger capacity for self-financing. This combination reduces the perceived risk for lenders and investors, thereby further alleviating credit constraints. The literature also suggests that larger firms are less likely to have started operations in the informal sector because the advantages of formalization become more significant as a firm expands (Distinguin et al., 2016; Perry et al., 2007). Indeed, while entrepreneurs can often manage implicit contracts with a few clients in small-scale operations, the need for formal contracts and legal protections becomes more pronounced as the business grows, leading them to formalize their operations (Distinguin et al., 2016). Additionally, informal firms are typically small (La Porta and Shleifer, 2014), and they rarely become large firms after formalization. Therefore, a large firm is more likely to have started operations in the formal sector rather than in the informal sector. Firm size is measured by the natural logarithm of the total number of full-time employees, adjusted to account for temporary workers. We anticipate that firm size will be negatively associated with both the probabilities of being credit-constrained and having past informality status.

Older and more established firms usually have stronger ties with financial institutions, a solid credit history, and a better reputation, which often results in more favorable credit terms and conditions, thereby decreasing the likelihood of facing credit constraints (Carreira and Silva, 2010; Distinguin et al., 2016). These firms often started as small-scale, informal operations and transitioned to a formal status as they grew and sought legitimacy and access to additional resources. Firm age is measured as the natural logarithm of the number of years since the firm commenced operations. We expect firm age to be negatively correlated with credit constraints and positively correlated with the likelihood of having started operations informally.

Firms in the WBES are categorized into the manufacturing and services sectors, and the literature highlights notable differences between these sectors, particularly in terms of financial constraints (Beck et al., 2005; Carreira and Silva, 2010). Recent research by Distinguin et al. (2016) using WBES data indicates that SMEs in the manufacturing sector are more likely to experience credit constraints compared to those in the services sector. This disparity may arise because manufacturing firms often face higher financial vulnerability and rely more heavily on external credit due to significant capital investments in machinery and inventory. Conversely, service firms generally have lower startup and capital requirements. The substantial startup costs in manufacturing may also lead new firms to operate informally initially to overcome financial barriers before transitioning to a formal status. The sector of activity is represented by a binary variable: 1 for manufacturing and 0 for services. We anticipate that the sector of activity will be positively correlated with both the probabilities of being credit-constrained and having a history of informality.

Affiliation with a large firm or a group is likely to decrease the probability of facing credit constraints, as it provides access to broader capital resources (Mendi and Costamagna, 2017). Furthermore, firms associated with a large firm or a group often exhibit higher levels of professionalism and are more inclined to operate formally (Gasmi et al., 2024). We measure this affiliation using a binary variable, where 1 indicates that the firm is part of a large firm and 0 otherwise. We anticipate that such affiliation will be negatively correlated with both the likelihood of being credit-constrained and the probability of having a history of operating informally.

Furthermore, financial barriers are typically lower for foreign-owned firms compared to domestic ones (Asiedu et al., 2013; Aterido et al., 2013; Beck et al., 2006; Blalock et al., 2008; Carreira and Silva, 2010). Indeed, private foreign ownership is associated with reduced credit constraints due to the additional financial support provided by foreign investors (Un and Cuervo-Cazurra, 2008). Additionally, foreign investors generally prefer businesses that are already formalized to ensure legal protection and regulatory compliance. They are drawn to stable and transparent environments and often engage with or acquire established firms. The involvement of foreign ownership usually entails stringent due diligence and regulatory scrutiny, which further diminishes the likelihood of a history of informal operations. Private foreign ownership is measured as the natural logarithm of the percentage of the firm owned by private foreign individuals, companies, or organizations. We expect private foreign ownership to be negatively correlated with both the probabilities of experiencing credit constraints and having a background in informal operations.

Besides, the literature suggests that both economic and financial development help mitigate financial constraints, reducing the probability of firms to be credit-constrained (Beck et al., 2006). Indeed, higher economic and financial development improves market conditions and infrastructure, making it easier for firms to access financing. Specifically, advancements in financial systems and services increase the availability of credit, thereby lowering the probability of credit constraints (Asiedu et al., 2013). Additionally, it is well-established that the size of the informal sector tends to shrink as a country's level of development increases (La Porta and Shleifer, 2014), which in turn reduces the likelihood that registered firms began their operations informally. Similarly, greater financial development enhances the opportunities for financing formal businesses, thus decreasing the chances that firms start out informally. We use real GDP per capita (in natural logarithm) as a proxy for economic development, and domestic credit to the private sector (also in natural logarithm) as a proxy for financial development.[9] We anticipate that each variable will be negatively correlated with both the probabilities of being credit-constrained and having past informality status.

Inflation serves as an indicator of economic conditions, which can influence both the likelihood of credit constraints and the probability of having past informality status. Findings by Asiedu et al. (2013) and Distinguin et al. (2016) indicate that firms are more likely to experience credit constraints in countries with high inflation rates. This is because inflation reduces the real value of revenues and assets, increasing uncertainty and making it more difficult for firms to meet collateral requirements and secure financing. Additionally, rising prices and economic instability may drive firms to operate informally in an effort to avoid higher taxes and regulatory costs. Economic conditions are measured by the annual inflation rate. We anticipate that inflation will be positively correlated with both the probabilities of being credit-constrained and having past informality status.[10] A summary of the definitions of the variables can be found in Appendix B.

3.3 Descriptive statistics and covariate balance

We begin this subsection by evaluating the performance of the entropy balancing method. This is done by presenting descriptive statistics obtained before and after applying the en-

[9]For a similar approach to measuring financial development, see Asiedu et al. (2013) and Beck et al. (2005), among others.

[10]Note that economic development (proxied by real GDP per capita), financial development (proxied by domestic credit to the private sector), and economic conditions (proxied by inflation) are structural factors. These factors often exhibit hysteresis, meaning their current levels are correlated with their past levels. Therefore, including these variables also helps control, at least in part, for recent changes in economic development, economic conditions, and financial development across countries.

tropy balancing weighting used to estimate the treatment effect of past informality on registered firms' probability of being credit-constrained. Table 1 provides the sample mean of each covariate in the treated (observations with past informality status) and control (observations without past informality status) groups in columns (1) and (2), respectively, obtained before applying the balancing weighting. The difference between (2) and (1) is presented in column (3), along with the level of statistical significance.

[Insert Table 1 here]

From Table 1, we observe that observations with past informality status are characterized by significantly (at the 1% level) lower firm size, higher firm age, higher percentage of manufacturing firms, lower percentage of affiliation with a large firm, lower percentage of private foreign ownership, lower real GDP per capita (a proxy for economic development), higher inflation (a proxy for economic conditions), and lower domestic credit to the private sector (a proxy for financial development). These results confirm the expected relationships between the covariates and firms' probability of having past informality status. More importantly, they confirm that past informality status does not occur at random, indicating the necessity of constructing an appropriate synthetic control group to correctly estimate the treatment effect of past informality status on firms' probability of being credit-constrained.

In Table 2, we present the sample mean of each covariate in the treated and control groups in columns (1) and (2), respectively, obtained after applying the balancing weighting. Column (3) presents the difference between (2) and (1), along with the level of statistical significance. We see from Table 2 that the differences observed in the previous table have disappeared, indicating the effectiveness of the entropy balancing method. Thus, the entropy balancing method allows us to construct a perfect control group comprising observations that are closely similar to treated observations in terms of the means of the matching covariates. This enables a correct estimation of the treatment effect of past informality status on firms' probability of being credit-constrained.

[Insert Table 2 here]

To gain an initial insight into the relationship between past informality and credit constraints, we present in Table 3 statistics on credit constraints in the treated and control groups. Columns (1) and (2) report the percentage of observations subject to credit constraints in the treated and control groups, respectively. Column (3) reports the difference between (2) and (1), along with its statistical significance level. From Table 3, we observe that 46% of the observations with past informality status are subject to credit constraints, compared to 32% of those without past informality status, with a difference of -14% that is statistically significant at the 1% level. Although no causal relationship between past informality and credit constraints can be derived from these descriptive results, they provide an indication of both the nature (whether positive or negative) and the significance of the treatment effect of past informality.

[Insert Table 3 here]

Table A2 in Appendix A presents the correlation matrix of the baseline variables. There are two key insights from this table. First, we observe that past informality is highly significantly and positively correlated (at the 1% level) with credit constraints. This result aligns with those presented in Table 3, suggesting that past informality status is likely positively related to a firm's probability of being credit-constrained. Second, columns (1) and (2) of Table A2 show that our matching covariates are all highly significantly correlated (at the 1% level) with both past informality status and credit constraints. This supports the relevance of the matching covariates considered in our analysis. Additionally, the signs of all the covariates correspond to the expected relationships between them and both past informality and credit constraints, further reinforcing the relevance of our choice of matching covariates.

Furthermore, in Table A3 in Appendix A, we present descriptive statistics of the baseline variables, which provide an overview of the percentage of observations that are subject to credit constraints and past informality status. We observe that around 33% of observations are subject to credit constraints, which is relatively significant. Meanwhile, 10% of observations are subject to past informality status.

4 Baseline results

Using the synthetic controls in Table 2, we estimate the effect of past informality on registered firms' probability of being credit-constrained (ATT) using the weighted maximum likelihood method. Table 4 reports the results of the estimations.

[Insert Table 4 here]

Columns (1) to (4) present the results without including the matching covariates used in the first step of the entropy balancing methodology to compute the synthetic controls group. Column (1) excludes year and country fixed effects from the second step. Columns (2) and (3) include only year and country fixed effects, respectively, whereas column (4) includes both year and country fixed effects. Columns (5) to (8) repeat this exercise with the only difference being that the matching covariates, including firm size, firm age, sector of activity, affiliation with a large firm, private foreign ownership, real GDP per capita, inflation, and domestic credit to the private sector, are included in all four cases. Including year and country fixed effects in the second step of entropy balancing eliminates any year- or country-specific effects in the assessment of the effect of past informality on registered firms' probability of being credit-constrained, whereas including matching covariates improves estimation efficiency.

We see from Table 4 that, irrespective of the specification, past informality significantly increases (at the 1% level) registered firms' probability of being credit-constrained. The magnitude of the effects ranges between 0.050 (see column (4)) and 0.075 (see column (1)), with an average of 0.063. This means that the probability of being credit-constrained increases by around 6% in registered firms that began operations as informal compared to those firms that started as formal. The relative stability of the coefficients across all eight specifications is a first indication that this effect is robust. We further check the robustness of this finding in the next section.

5 Robustness checks

Our results show that past informality significantly increases registered firms' probability of being credit-constrained. This section aims to test the robustness of this finding.

5.1 Alternative specifications

This subsection tests the robustness of our results to alternative specifications in the second step of entropy balancing. Given the binary nature of the credit constraints dependent variable (see also Distinguin et al., 2016), the second step of the entropy balancing method involved estimating a Logit model using the weighted maximum likelihood method and computing marginal effects. One could also estimate either a Linear Probability model or a Probit model instead of a Logit model. We analyze the results obtained using these two alternative specifications. The results of the estimations are presented in Table 5. The upper part, labeled as "(A)," of the table reports results for the Linear Probability model, whereas the lower part, labeled as "(B)," is about the Probit model.

[Insert Table 5 here]

Irrespective of the specification, past informality significantly increases the probability of registered firms to be credit-constrained (at the 1% level) in all eight estimations. For the Linear Probability model, the magnitude of the effects ranges between 0.050 (see column (4); the same minimum value as with the Logit) and 0.076 (see column (1); against 0.075

for the Logit), with an average of 0.064 (against 0.063 for the Logit). Similarly, for the Probit model, the magnitude of the effects ranges between 0.050 (see columns (3)-(4)) and 0.075 (see column (1)), with an average of 0.063, the same results as with the Logit model. Overall, in each specification, the magnitudes of the effects are very similar to those obtained with the Logit model (see Table 4) across all eight estimations. Hence, using either a Linear Probability model or a Probit model in the second step instead of the Logit model does not alter the results. This demonstrates the robustness of our findings to the specification used in the second step of the entropy balancing method.[11]

5.2 Additional controls or potential omitted covariates

In this subsection, we test the robustness of our results to potential omitted covariates by introducing in the analysis a wide range of additional controls, including both firm and country characteristics, that may be correlated with both the probabilities of a firm being credit-constrained and having past informality status. This is achieved by incorporating these additional controls in the second step of our entropy balancing specification (see also Apeti and Edoh, 2023, for the same approach). These variables include: manager's experience, manager's gender, total sales, firm's export capacity, criminality in the business environment, taxation, real lending interest rate, interest rate spread, bank nonperforming loans, real GDP growth, unemployment, foreign direct investment (FDI), gross fixed capital formation, banking accessibility, new business density (a proxy for entrepreneurial dynamism), remittances, public spending, urbanization, debt, and corruption. Appendix B summarizes the definitions of the additional controls, while Table A4 in Appendix A presents the descriptive statistics.

The results of the estimations are reported in Table 6. We start by including additional controls one at a time in the second step of the entropy balancing method. This allows us to analyze the sensitivity of our findings to the inclusion of each control. These results are reported in columns (1)-(20). Then, in a final estimation presented in column (21), we include all the additional controls simultaneously. The results indicate that including additional controls yields similar results to the initial findings.

[Insert Table 6 here]

Moreover, as in theory any factors that can predict a firm's likelihood of experiencing past informality can be a source of endogeneity provided they impact credit constraints,

[11] More generally, all results presented in the paper have also been obtained using the Linear Probability and Probit models in the second step of the entropy balancing method. These results are available upon request.

we include the additional controls in the first step of entropy balancing to construct the synthetic control group. The results are presented in Table 7, from column (1) to column (21), and are similar to the initial findings. Since including in the second step of entropy balancing the matching covariates used in the first step improves estimation efficiency, in a final analysis, we include the additional controls in both the second and first steps of entropy balancing. Table 8 presents the results of the estimations, which are similar to the initial findings.[12]

[Insert Table 7 here]

[Insert Table 8 here]

In summary, including additional controls in our entropy balancing specification does not alter our initial findings. This indicates that these findings are not driven by omitted variable bias.

5.3 Alternative estimation methods

This subsection aims to analyze the robustness of our results to alternative estimation methods. To do so, we conduct three different analyses.

First, we estimate the effect of past informality on credit constraints using standard discrete choice models. More precisely, we estimate Linear Probability, Probit, and Logit models. We start with the model containing our baseline covariates and then add additional control variables one by one cumulatively. The results are presented in columns (1) to (21) of Tables 9, 10, and 11. From these tables, we observe that the results are similar to the initial results. Including additional controls cumulatively does not alter the significance of the effect of past informality.

[Insert Table 9 here]

[Insert Table 10 here]

[Insert Table 11 here]

Second, we use the Propensity Score Matching method (PSM) as an alternative matching method. PSM is an impact evaluation method introduced by Rosenbaum and Rubin (1983) that corrects for endogeneity issues, especially those stemming from selection bias. We

[12] In all the specifications considered, unreported results show that the balancing property is satisfied. These results are available upon request.

employ four variants of PSM[13], namely Nearest Neighbor Matching, Radius Matching, Kernel Matching, and Local Linear Regression Matching.[14] Tables 12 presents the results of the estimations of the effect of past informality (ATT). Irrespective of the matching method, the ATT is significant (at the 1% level) and positive, indicating that the effect of past informality is independent of the alternative matching method used. This demonstrates the consistency of our findings. Tables 12 reports Rubin's B and R statistics to assess the balancing property. For the covariates to be sufficiently balanced, the B statistic should be lower than 25%, and the R statistics should lie in the [0.5; 2] interval (Rubin, 2001). As can be seen, this is the case in all estimations, meaning that the covariates are balanced.

[Insert Table 12 here]

Third, we use the Instrumental Variable method (IV) to estimate the effect of past informality status on credit constraints. This method corrects for endogeneity issues, especially for possible reverse causality problems. We use two country-level variables to instrument past informality status: the percentage of firms inspected by tax officials over the 12 months preceding each survey and the average frequency of such inspections during the same period. These variables are likely related to a firm's probability of transitioning to the formal sector, as high and frequent inspection rates increase the chances of detecting firms operating informally, pressuring them to formalize. This potential influence on the probability of having past informality status underscores the relevance of these instruments. Additionally, it is assumed that these variables do not correlate with the error term in the credit constraints equation, meaning they influence a firm's current credit constraints only through their effect on the firm's probability of having past informality status. Typically, tax inspection policies are influenced by broader regulatory objectives rather than the specific creditworthiness of individual firms, making these instruments exogenous. Consequently, by fulfilling these criteria, the country-level tax inspection variables effectively isolate the causal effect of past informality status on registered firms' credit constraints.

Given the binary nature of both the past informality and credit constraints variables, the IV regression involves estimating a Recursive Bivariate Probit with IVs. In the first equation, the dependent variable is credit constraints, and the independent variables are past informality and the main controls. In the second equation, the dependent variable is past informality, and the independent variables are the IVs and the main controls. Year and country fixed effects are included in both equations. A z-test on the correlation coefficient

[13]These variants were also recently used by Apeti (2023) and Apeti and Edoh (2023) to test the robustness of the results obtained by entropy balancing.

[14]For theoretical details on PSM, see Abadie and Imbens (2016) and Dehejia and Wahba (2002). Caliendo and Kopeinig (2008) provide practical guidance on the implementation of PSM.

(ρ) of the two equations allows us to test for the exogeneity of past informality status. A significant correlation coefficient would confirm the endogeneity of past informality status, which, as will be seen later, is indeed confirmed. Note that testing the validity and strength of the IVs within the framework of Categorical and Limited Dependent Variable (CLDV) modeling, especially with binary endogenous variables, is challenging.[15] As is commonly done in the literature (see Gebreeyesus and Mohnen, 2013; Girma et al., 2008, among others, for similar approaches), we estimate the linear version of the model and perform tests of validity and weakness of the IVs, assuming that if the IVs are weak and not valid in the linear model, they will also be in the Recursive Bivariate Probit model.

The results of the estimations are presented in Table 13. They confirm the consistency of our initial findings, as the effect of past informality is significant (at the 1% level) and positive. The correlation coefficient (ρ) between the two equations is significant at the 1% level. Therefore, we reject the null hypothesis of exogeneity of past informality status, as expected. The p-value of Hansen's test of overidentifying restrictions is equal to 0.105, indicating that we fail to reject the null hypothesis of the validity of the IVs. As for the weak identification test, the Cragg-Donald statistic (Cragg and Donald, 1993) is equal to 187.086, which is higher than the Stock-Yogo maximum critical value of 19.93 (Stock and Yogo, 2005). This suggests that the null hypothesis that the IVs are weak is rejected.

[Insert Table 13 here]

5.4 Alternative measures of credit constraints

In this subsection, we employ alternative measures of credit constraints. This approach allows us to test the robustness of our results against endogeneity issues that may arise from possible measurement errors. Following Asiedu et al. (2013) and Beck et al. (2008), we measure credit constraints based on responses to the following question from the WBES: "*K.30: To what degree is access to finance an obstacle to the current operations of this establishment?*" The answers are: "no obstacle," "minor obstacle," "moderate obstacle," "major obstacle," or "very severe obstacle." We construct three measures of credit constraints based on the rationale that firms identifying access to finance as an obstacle are considered credit-constrained.

First, we create a binary variable, labeled as the "First alternative measure of credit constraints," which is equal to 1 if access to finance is reported as an obstacle (minor, moderate, major, or very severe), and 0 if it is not reported as an obstacle. Second, we develop another binary variable, called the "Second alternative measure of credit constraints," which

[15]For theoretical details on CLDV modeling, see Maddala (1983).

is equal to 1 if access to finance is reported as a moderate, major, or very severe obstacle, and 0 otherwise. Third, we construct a binary variable, referred to as the "Third alternative measure of credit constraints," which is equal to 1 if access to finance is reported as a major or very severe obstacle, and 0 otherwise.

Using these alternative measures of credit constraints, we estimate the effect of past informality on credit constraints (ATT) employing the entropy balancing method. The results are presented in Table 14. The upper part of the table, labeled as "(A)," displays the results for the first alternative measure of credit constraints. The middle part, labeled as "(B)," shows the results for the second alternative measure. The bottom part, labeled as "(C)," presents the results for the third alternative measure. From Table 14, we observe that the results of all these estimations confirm our initial findings, suggesting that they are not driven by measurement errors.

[Insert Table 14 here]

5.5 Additional robustness: Clustering standard errors at the country level

Since some of our control variables are macroeconomic, we cluster standard errors at the country level in our final robustness check. For brevity, the estimation results are presented in Table C1 of Appendix C, covering columns (1) to (8).

Across all specifications, the effect of past informality on credit constraints remains positive and significant at the 1% level, confirming our initial findings. Notably, clustering standard errors at the country level does not affect the significance level of the effect of past informality. This outcome was expected since our treatment variable is measured at the firm level, while the macroeconomic variables in question serve only as controls. These results demonstrate the robustness of our findings.

6 Heterogeneity

Our results indicate that past informality significantly increases credit constraints for registered firms. In this section, we analyze the sensitivity of this finding across different sectors of activity, categories of firm size, categories of firm age, sub-samples of countries, and varying levels of structural factors.

6.1 Different sectors of activity, categories of firm size, and categories of firm age

In this subsection, we assess the sensitivity of our baseline results to different sectors of activity, categories of firm size, and categories of firm age. Indeed, to fully grasp the relationship between past informality and credit constraints, it is essential to evaluate how our baseline findings vary across several factors, including sector, firm size, and firm age. For instance, different industries may experience varying levels of credit constraints due to sector-specific elements, such as capital requirements or market demand, which can affect the influence of past informality status. Firm size is another critical factor, with smaller firms usually facing more severe credit constraints compared to their larger counterparts (Asiedu et al., 2013; Beck et al., 2005; Distinguin et al., 2016) due to disparities in self-financing capacity and market influence, among others. Additionally, smaller firms are more likely to have begun operations in the informal sector than larger firms, as informal firms are typically small (La Porta and Shleifer, 2014) and rarely become large firms after their transition to the formal sector, which could influence the effect of past informality. Furthermore, a firm's age can impact its creditworthiness (and thereby affect access to credit) as well as its interactions with formal financial institutions, potentially influencing how past informality affects current credit constraints. Our analysis is organized into three parts.

First, we estimate the effect of past informality for the different sectors of activity, including the manufacturing and services sectors, and the results are reported in Table 15. Columns (1) and (2) present the results for the manufacturing and services sectors, respectively. Irrespective of the sector, the effect of past informality is significant (at the 1% level) and positive. The effect is slightly higher in the services sector. This may be due to newly formalized service firms' ongoing reliance on informal networks and personal relationships, complicating the shift to the formal credit system.

[Insert Table 15 here]

Second, we estimate the effect of past informality for the following three categories of firm size: small (<20 employees), medium (20-99 employees), and large (≥100 employees). The results are presented in Table 16 in columns (1) to (3), respectively. From Table 16, we observe that the larger the firm size, the lower the effect of past informality. This confirms our previous intuition. Indeed, larger firms usually face weaker credit constraints and are less likely to have started operations informally compared to their smaller counterparts, resulting in a lower magnitude of the effect of past informality.

[Insert Table 16 here]

Third, we estimate the effect of past informality for the following categories of firm age: <5 years, 5-9 years, 10-19 years, 20-39 years, and ≥ 40 years. The results are reported in Table 17 from column (1) to column (5). From Table 17, we observe that the older the firm, the lower the effect of past informality on credit constraints. This also confirms our intuition. Indeed, older firms have been found in the literature to face lower financial obstacles (see Beck et al., 2006; Carreira and Silva, 2010, among others). As firms become older, they amass financial records, build credit histories, and establish strong relationships with financial institutions. This mitigates the detrimental influence of their informal origins on access to credit.

[Insert Table 17 here]

6.2 Sub-samples of countries

This subsection aims to test the sensitivity of our findings to sub-samples of countries. Conducting this investigation is worthwhile because countries or groups of countries possess diverse institutional frameworks, varying levels of financial market development, and different regulatory environments, all of which can affect the relationship between past informality and credit constraints. Analyzing sub-samples can reveal whether the observed effects are consistent across different economic contexts or if they are influenced by specific regional characteristics. We consider six different sub-samples of countries, with the results of the estimations presented in Table 18.

[Insert Table 18 here]

We start by restricting the sample to G20 countries, which include the most developed economies in the world. Firms in these countries face lower financial constraints due to higher financial development compared to firms in the rest of the world. Additionally, the level of informality is generally lower in these countries, as the scope of the informal economy decreases with higher development (La Porta and Shleifer, 2014). In this context, it is worthwhile to examine how past informality influences credit constraints for registered firms in these countries. The results of the estimations are reported in column (1).

Next, we restrict the sample by removing G20 countries to assess whether the effect of past informality is stronger or weaker in the rest of the world compared to the most developed economies represented by the G20 countries. The results are presented in column (2).

Furthermore, we focus on two regions where informality is most pervasive: sub-Saharan Africa (SSA) and Latin America and the Caribbean (LAC). Firms from these regions also face significant credit constraints. Given the importance of informality in these regions, it is valuable to investigate whether the influence of past informality persists when focusing on firms from each region individually or when excluding them. To explore these issues, we consider SSA countries only in column (3) and exclude SSA in column (4). We repeat this exercise for LAC in columns (5) and (6), respectively.

From Table 18, we observe that, irrespective of the sub-sample considered, past informality has a significant (at the 1% level) and positive effect on credit constraints. The magnitude of the effect is larger for G20 countries, being almost double that of the rest of the world. This greater impact in G20 countries suggests that past informality is more detrimental in developed economies, potentially due to their more advanced financial systems and stringent regulatory frameworks. Indeed, the high standards for transparency and creditworthiness in most G20 countries make past informality a more significant problem.

The magnitudes of the effect of past informality in SSA and when excluding SSA are similar. There are also similar to the one obtained with the full sample. However, for LAC, there is a notable difference: the magnitude of the effect of past informality when restricting the sample to the LAC region is half that observed in the full sample and less than half that of the rest of the world. Financial institutions in LAC may have developed a deeper understanding of the challenges associated with informal firms and adjusted their lending practices accordingly. More precisely, the region's long-standing experience with high levels of informality might have led to more flexible and inclusive financial practices, which help mitigate the detrimental effects of past informality on access to credit.

6.3 The role of structural factors

In this subsection, we analyze whether the effect of past informality depends on the level of certain structural factors. We focus on four different structural factors.

First, we analyze the effect of past informality on registered firms' credit constraints at varying levels of regulatory quality. Indeed, regulatory environments are pivotal in shaping how easily firms can obtain credit (Carreira and Silva, 2010). In countries with high-quality regulation, financial systems tend to be more transparent and efficient, which can lessen the negative effects of past informality by providing clearer and fairer pathways for integrating informal firms into the formal economy. Conversely, in countries with weaker regulatory quality, financial systems may lack transparency and efficiency, potentially intensifying the challenges that firms with informal histories face when seeking credit. Examining the role of regulatory quality helps determine whether robust regulatory frameworks mitigate or exacerbate the impact of past informality on access to credit. To test this, we include both regulatory quality and its interaction with the past informality variable in the second step of entropy balancing. The results are presented in the first graph of Figure 2, which shows the effect of past informality on registered firms' probability of being credit-constrained at varying levels of regulatory quality. We observe that the higher the regulatory quality, the lower the detrimental effect of past informality on credit constraints. This finding highlights that improving regulatory quality could boost financial inclusion and lower barriers for firms moving from the informal to the formal sector.

Second, we explore the effect of past informality at varying levels of trade openness. The degree of a country's openness to international trade can significantly influence its financial environment and development (Baltagi et al., 2009; Kim et al., 2010). Indeed, in countries with high trade openness, firms encounter greater global competition and are often compelled to adhere to stricter financial practices. This pressure can help firms address issues related to their informal past, as increased competition encourages greater transparency and formality, thereby easing credit constraints. In contrast, in countries with low trade openness, firms may not face the same international pressures, which might result in less emphasis on overcoming past informality. By examining the role of trade openness, we can determine whether participation in the global market facilitates better access to credit for firms with informal histories. To analyze this, we include both trade openness and its interaction with the past informality variable in the second step of entropy balancing. The results are presented in the second graph of Figure 2, which shows the effect of past informality on registered firms' probability of being credit-constrained at varying levels of trade openness. It emerges that the higher the level of trade openness, the lower the effect of past informality. This confirms our intuition and indicates that fostering openness to international trade could help countries improve financial inclusion and mitigate the detrimental effects of informal origins.

Third, we analyze the effect of past informality on registered firms' credit constraints at varying levels of entrepreneurial dynamism, as proxied by new business density. A dynamic entrepreneurial environment can indeed influence access to credit. High new business density signals a vibrant entrepreneurial ecosystem where competition and innovation flourish, potentially leading to more robust financial systems and improved access to credit. In such environments, firms with an informal past may find it easier to transition into the formal financial sector and overcome financial constraints due to the supportive infrastructure and resources available for new and growing businesses. Conversely, in countries with low new business density, the entrepreneurial ecosystem might be less developed, offering fewer resources and support systems for firms moving from informality, thereby exacerbating credit constraints. This analysis helps determine whether a thriving entrepreneurial environment can mitigate the harmful effects of past informality on access to credit. To explore this role, we include both new business density and its interaction with the past informality variable in the second step of entropy balancing. The results are presented in the third graph of Figure 2, which shows the effect of past informality on registered firms' probability of being credit-constrained at varying levels of new business density. We see from this graph that the higher the level of new business density, the lower the effect of past informality on registered firms' probability of being credit-constrained, confirming our intuition. This indicates that a thriving entrepreneurial environment can improve access to credit and mitigate the lasting effects of starting operations informally.

Last but not least, we examine the effect of past informality on registered firms' credit constraints at varying levels of public spending. Indeed, public spending significantly shapes the economic environment and the support available for businesses. High public spending often results in better financial infrastructure, business support programs, and regulatory enforcement, which can facilitate easier access to credit for firms with a history of informality. Investments in education, infrastructure, and technology also contribute to a favorable business climate, mitigating the detrimental impacts of past informality. In contrast, low public spending can lead to weaker financial systems and reduced support for businesses, making it more challenging for firms with informal backgrounds to secure credit. By examining the role of public spending, we can determine whether increased public spending aids firms in overcoming credit constraints related to their informal past. To study this role, we include both public spending and its interaction with the past informality variable in the second step of entropy balancing. The results are presented in the fourth graph of Figure 2, which shows the effect of past informality on the probability of being credit-constrained at varying levels of public spending. We observe that the higher the level of public spending, the lower the detrimental effects of past informality, which confirms our intuition. Hence, public spending could help mitigate financial constraints for firms with an informal history.

[Insert Figure 2 here]

7 Channels

Our results indicate that past informality significantly increases the probability of registered firms to be credit-constrained. In this section, we investigate the transmission channels of this effect. As discussed in the introduction, we test three potential channels: firm productivity, competition from the informal sector, and the quality of financial statements. Productivity is measured as the natural logarithm of the ratio of turnover to the total number of full-time employees, adjusted for temporary workers. Competition from the informal sector is measured by a binary variable equal to 1 if the firm faces competitors from the informal sector, and 0 otherwise. The quality of financial statements is captured by a binary variable equal to 1 if the firm's annual financial statements are audited and certified by an external auditor, and 0 otherwise. We define high-quality financial statements as those that are audited and certified by an external auditor.

We start by analyzing the relevance of our potential channels to credit constraints by estimating a Logit model. Year and country fixed effects are included to control for both time-varying and country-specific factors that can affect both credit constraints and the channels. This approach aims to determine if the three potential channels identified are correlated with credit constraints (see Apeti and Edoh, 2023, for a similar approach). The results of the estimations are presented in Table 19. We observe that firm productivity, competition from the informal sector, and the quality of financial statements are highly correlated (at the 1% level) with a firm's probability of being credit-constrained. More precisely, productivity and the quality of financial statements are negatively correlated with credit constraints, whereas competition from the informal sector is positively correlated with credit constraints, as expected. This suggests that these factors represent potentially relevant channels through which past informality heightens registered firms' probability of being credit-constrained.

[Insert Table 19 here]

Now that we have assessed the relevance of our three potential transmission channels, we use the entropy balancing method to analyze whether past informality is related to each channel, employing the same matching covariates as our baseline specification and including year and country fixed effects (see Apeti and Edoh, 2023, for a similar approach). The results of the estimations are presented in Table 20. We observe that past informality is significantly associated (at the 1% level) with lower productivity, a lower probability of high-quality financial statements, and a higher probability of competition from the informal sector.[16] In summary, taking into account the results presented in both Table 19 and Table 20, past informality significantly heightens credit constraints for registered firms by reducing productivity and the quality of financial statements, and increasing competition from the informal sector.

[Insert Table 20 here]

[16]As an alternative specification, we have estimated the effect of past informality on each channel using the IV method, employing the same IVs used previously in subsection 5.3. The results confirm those obtained by entropy balancing. To maintain brevity, these results are not reported in this paper. They are available upon request.

8 Concluding remarks, policy implications, and extensions

This paper analyzes the effect of past informality on the credit constraints of registered firms using firm-level data from the World Bank Enterprise Surveys, which cover 134 countries from 2006 to 2023. The dataset comprises repeated cross-sections, includes only registered firms, and contains over 134,000 observations. By employing the entropy balancing method to address the endogeneity of past informality status, we find that past informality significantly increases a firm's probability of being credit-constrained. This finding is extremely robust across various tests and analyses, with the magnitude of the effect of past informality varying by sector, firm size, firm age, country sub-sample, and structural factors. Specifically, the detrimental impact of past informality diminishes with firm size, firm age, and improved structural factors such as regulatory quality, trade openness, entrepreneurial dynamism, and public spending. We show that firm productivity, competition from the informal sector, and the quality of financial statements are the primary transmission channels through which past informality heightens the credit constraints faced by registered firms. Our results provide empirical support for the idea that past informal operations can have lasting harmful effects on firms' activities. This insight is particularly relevant for policymakers and financial institutions working to improve access to credit for firms, especially SMEs, which often emerge from the informal sector.

Our findings suggest several key policy implications. First, our results suggest that public policies should prioritize providing firms with sufficient incentives to start operations in the formal sector to avoid the lasting detrimental effects of informality. By increasing the number of firms that begin operations formally, such policies could help reduce the credit constraints faced by registered firms. In practice, public authorities might consider offering exemptions from minimum wage requirements and corporate taxes for a certain period to firms that start in the formal sector. As noted by Kouakou (2023a), such measures should be provisional and limited to ensure they do not hinder progress toward fairer competition.

Second, as a complement to the previously discussed policy, public authorities should implement measures to provide sufficient incentives for informal firms to transition to the formal sector, even though newly formalized firms may still face some constraints compared to those that started as formal, especially regarding credit constraints. Indeed, newly formalized firms generally face lower credit constraints compared to their informal counterparts. This reflects the traditional development policy approach to formalization.[17] A recent

[17] For recent studies suggesting this policy, see Amin (2023), Distinguin et al. (2016), Gasmi et al. (2024), Heredia Pérez et al. (2018), Jessen and Kluve (2021), and Kouakou (2023a), among others.

meta-analysis by Jessen and Kluve (2021) demonstrated that tax incentives combined with information campaigns are an effective policy approach to increasing the rate of formalization of informal firms. Such a policy approach should be adopted by countries to boost the rate of formalization.

Third, our findings indicate that the detrimental effects of past informality diminish with improvements in regulatory quality, trade openness, entrepreneurial dynamism, and public spending. Hence, it is crucial to implement regulatory reforms that enhance transparency, efficiency, and fairness within the financial system. These reforms should also simplify the process for informal firms to transition to formal status, making the benefits of formalization clear and accessible. Governments should explore trade agreements and incentives designed to integrate newly formalized firms into the global market, thereby improving their access to credit. Building a supportive entrepreneurial ecosystem is essential; investments in infrastructure, education, and technology can stimulate business creation and growth. Support programs for startups and SMEs are particularly important, as they provide the resources and networks needed for informal firms to formalize. Similarly, increased public spending on initiatives that promote firm formalization and growth can alleviate credit constraints. Resources should be directed toward programs offering financial assistance, mentorship, and access to market for firms with a history of informality. This may include grants, subsidized loans, and tax incentives for newly formalized firms as previously discussed.

Fourth, based on the identified pathways through which past informality influences credit constraints, policymakers should focus on two main areas: managing competition from the informal sector and enhancing financial literacy and reporting standards. This can involve implementing stricter enforcement of business regulations and reducing the costs associated with formalization. Additionally, initiatives aimed at improving financial literacy among business owners and managers are essential. Providing training programs and support services to help firms adopt more rigorous accounting practices can enhance the quality of their financial statements. This, in turn, will improve their creditworthiness and facilitate better access to credit.

Fifth, by highlighting the lasting detrimental effects of operating informally on credit constraints, this research underscores the need to address informality to promote financial inclusion. Greater financial inclusion would help reduce disparities among firms and foster equitable economic growth.

This paper can be extended in various ways. First, while we believe that the three transmission channels we identified are the main pathways through which past informality heightens credit constraints for registered firms, there may be additional channels. Future studies should investigate more transmission channels. Similarly, future research could explore additional structural factors in the heterogeneity analysis. Second, since credit constraints can adversely affect firm performance, future research might analyze how past informality impacts firms' performance, including growth and profitability. Third, to the best of our knowledge, the question of when the detrimental effects of past informality disappear after formalization (if they do at all) remains unexplored. Investigating this could be a fruitful avenue for future research. Fourth, in this paper, we used a binary measure of past informality to indicate whether a registered firm began operations in the informal sector. If available, data on the duration of time spent in the informal sector before transitioning to the formal sector could provide additional insights into our research.

Fifth, since our main finding indicates that registered firms starting operations in the formal sector are less credit-constrained than those that began in the informal sector, it is crucial to investigate the factors that might increase a firm's likelihood of starting operations in the formal sector. A comparative analysis of potential firm-specific, sector-specific, and country-specific determinants could help in better understanding what drives a firm's decision to begin operations in the formal sector.

Data availability statement

The data are available upon request.

Declaration of interest

None.

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Table 1. Descriptive statistics before weighting

	(1) Past informality	(2) No past informality	(3)=(2)-(1) Difference
Firm size	2.973	3.472	0.499***
Firm age	2.849	2.74	-0.109***
Sector of activity	0.624	0.557	-0.067***
Affiliation with a large firm	0.119	0.171	0.052***
Private foreign ownership	0.237	0.451	0.214***
Real GDP per capita	8.99	9.391	0.401***
Inflation	6.427	6.001	-0.426***
Domestic credit to the private sector	3.292	3.578	0.286***
Observations	13,920	124,369	

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 2. Descriptive statistics after weighting

	(1) Past informality	(2) No past informality	(3)=(2)-(1) Difference
Firm size	2.973	2.973	0
Firm age	2.849	2.849	0
Sector of activity	0.624	0.624	0
Affiliation with a large firm	0.119	0.119	0
Private foreign ownership	0.237	0.237	0
Real GDP per capita	8.99	8.99	0
Inflation	6.427	6.427	0
Domestic credit to the private sector	3.292	3.292	0
Observations	13,920	124,369	
Total of weights	13,920	13,920	

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3. Credit constraints among firms with and without past informality status

	(1) Past informality	(2) No past informality	(3)=(2)-(1) Difference
Percentage of observations that are subject to credit constraints	46%	32%	-14%***

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4. The effect of past informality on the credit constraints of registered firms in 134 countries worldwide, using data from the 2006 to 2023 World Bank Enterprise Surveys

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Past informality	0.075***	0.073***	0.051***	0.050***	0.073***	0.070***	0.055***	0.054***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)	(0.005)	(0.005)
Covariates in the second step	No	No	No	No	Yes	Yes	Yes	Yes
Year fixed effects in the second step	No	Yes	No	Yes	No	Yes	No	Yes
Country fixed effects in the second step	No	No	Yes	Yes	No	No	Yes	Yes
Observations	134,050	134,050	134,050	134,050	134,050	134,050	134,050	134,050

Robust standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 5. Robustness checks: Alternative specifications in the second step of entropy balancing

	(A) Linear Probability model in the second step of entropy balancing							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Past informality	0.076***	0.073***	0.051***	0.050***	0.075***	0.072***	0.056***	0.055***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)	(0.005)	(0.005)
Covariates in the second step	No	No	No	No	Yes	Yes	Yes	Yes
Year fixed effects in the second step	No	Yes	No	Yes	No	Yes	No	Yes
Country fixed effects in the second step	No	No	Yes	Yes	No	No	Yes	Yes
Observations	134,050	134,050	134,050	134,050	134,050	134,050	134,050	134,050
	(B) Probit model in the second step of entropy balancing							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Past informality	0.075***	0.073***	0.050***	0.050***	0.074***	0.070***	0.055***	0.054***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)	(0.005)	(0.005)
Covariates in the second step	No	No	No	No	Yes	Yes	Yes	Yes
Year fixed effects in the second step	No	Yes	No	Yes	No	Yes	No	Yes
Country fixed effects in the second step	No	No	Yes	Yes	No	No	Yes	Yes
Observations	134,050	134,050	134,050	134,050	134,050	134,050	134,050	134,050

Robust standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 6. Robustness checks: Additional controls in the second step only

	(1) Manager's experience	(2) Manager's gender	(3) Total sales	(4) Firm's export capacity	(5) Criminality	(6) Taxation	(7) Real lending interest rate	(8) Interest rate spread	(9) Bank NPLs	(10) Real GDP growth
Past informality	0.053***	0.052***	0.050***	0.054***	0.053***	0.047***	0.062***	0.058***	0.047***	0.054***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.0 05)	(0.006)	(0.005)
Covariates in the second step	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects in the second step	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country fixed effects in the second step	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	131,533	117,631	119,346	133,111	133,218	116,661	106,806	95,849	100,308	134,050

	(11) Unemployment	(12) FDI	(13) Gross fixed capital formation	(14) Banking accessibility	(15) New business density	(16) Remittances	(17) Public spending	(18) Urbanization	(19) Debt	(20) Corruption
Past informality	0.053***	0.054***	0.052***	0.054***	0.059***	0.054***	0.043***	0.053***	0.053***	0.054***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.0 05)	(0.005)	(0.005)
Covariates in the second step	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects in the second step	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country fixed effects in the second step	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	132,750	133,988	126,658	131,638	109,396	134,050	103,197	133,386	113,237	134,050

	(21) All covariates
Past informality	0.033***
	(0.012)
Covariates in the second step	Yes
Year fixed effects in the second step	Yes
Country fixed effects in the second step	Yes
Observations	22,563

NPLs: nonperforming loans. Robust standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 7. Robustness checks: Additional controls in the first step only

	(1) Manager's experience	(2) Manager's gender	(3) Total sales	(4) Firm's export capacity	(5) Criminality	(6) Taxation	(7) Real lending interest rate	(8) Interest rate spread	(9) Bank NPLs	(10) Real GDP growth
Past informality	0.053***	0.052***	0.056***	0.054***	0.052***	0.048***	0.062***	0.059***	0.048***	0.054***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.005)
Covariates in the second step	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects in the second step	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country fixed effects in the second step	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	131,533	117,631	119,346	133,111	133,218	116,661	106,806	95,849	100,308	134,050
	(11) Unemployment	(12) FDI	(13) Gross fixed capital formation	(14) Banking accessibility	(15) New business density	(16) Remittances	(17) Public spending	(18) Urbanization	(19) Debt	(20) Corruption
Past informality	0.053***	0.054***	0.052***	0.055***	0.059***	0.054***	0.044***	0.052***	0.054***	0.055***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.005)	(0.005)	(0.005)
Covariates in the second step	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects in the second step	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country fixed effects in the second step	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	132,750	133,988	126,658	131,638	109,396	134,050	103,197	133,386	113,237	134,050
	(21) All covariates									
Past informality	0.047***									
	(0.012)									
Covariates in the second step	Yes									
Year fixed effects in the second step	Yes									
Country fixed effects in the second step	Yes									
Observations	22,563									

NPLs: nonperforming loans. Robust standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 8. Robustness checks: Additional controls in both the second and first steps

	(1) Manager's experience	(2) Manager's gender	(3) Total sales	(4) Firm's export capacity	(5) Criminality	(6) Taxation	(7) Real lending interest rate	(8) Interest rate spread	(9) Bank NPLs	(10) Real GDP growth
Past informality	0.053***	0.052***	0.050***	0.054***	0.053***	0.047***	0.062***	0.059***	0.048***	0.054***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.005)
Covariates in the second step	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects in the second step	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country fixed effects in the second step	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	131,533	117,631	119,346	133,111	133,218	116,661	106,806	95,849	100,308	134,050

	(11) Unemployment	(12) FDI	(13) Gross fixed capital formation	(14) Banking accessibility	(15) New business density	(16) Remittances	(17) Public spending	(18) Urbanization	(19) Debt	(20) Corruption
Past informality	0.053***	0.054***	0.052***	0.055***	0.059***	0.054***	0.044***	0.052***	0.054***	0.055***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.005)	(0.005)	(0.005)
Covariates in the second step	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects in the second step	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country fixed effects in the second step	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	132,750	133,988	126,658	131,638	109,396	134,050	103,197	133,386	113,237	134,050

	(21) All covariates
Past informality	0.046***
	(0.012)
Covariates in the second step	Yes
Year fixed effects in the second step	Yes
Country fixed effects in the second step	Yes
Observations	22,563

NPLs: nonperforming loans. Robust standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 9. Robustness checks: Linear Probability regression

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)
Past informality	0.062***	0.061***	0.060***	0.055***	0.054***	0.053***	0.046***	0.053***	0.050***	0.044***	0.044***	0.044***	0.044***	0.038***	0.038***	0.050***	0.050***	0.048***	0.048***	0.045***	0.034***
	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)	(0.007)	(0.007)	(0.008)	(0.008)	(0.010)	(0.010)	(0.011)	(0.011)	(0.012)	(0.012)
Firm size	-0.045***	-0.045***	-0.043***	-0.024***	-0.022***	-0.022***	-0.021***	-0.022***	-0.027***	-0.027***	-0.027***	-0.027***	-0.028***	-0.025***	-0.021***	-0.018***	-0.018***	-0.017***	-0.017***	-0.017***	-0.029***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.007)
Firm age	-0.013***	-0.014***	-0.015***	-0.014***	-0.014***	-0.014***	-0.013***	-0.015***	-0.012***	-0.015***	-0.015***	-0.015***	-0.015***	-0.014***	-0.014***	-0.016***	-0.016***	-0.013***	-0.013***	-0.012**	-0.018*
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)	(0.010)
Sector of activity	0.043***	0.043***	0.041***	0.034***	0.038***	0.039***	0.038***	0.040***	0.041***	0.040***	0.040***	0.040***	0.040***	0.038***	0.036***	0.036***	0.036***	0.037***	0.037***	0.039***	0.030**
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)	(0.012)
Affiliation with a large firm	-0.030***	-0.029***	-0.028***	-0.023***	-0.023***	-0.024***	-0.023***	-0.012**	-0.027***	-0.024***	-0.024***	-0.023***	-0.023***	-0.021***	-0.025***	-0.024***	-0.023***	-0.015**	-0.015*	-0.017*	-0.040**
	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)	(0.008)	(0.008)	(0.009)	(0.018)
Private foreign ownership	-0.007***	-0.006***	-0.007***	-0.004***	-0.003***	-0.003***	-0.003***	-0.004***	-0.003*	-0.001	-0.001	-0.001	-0.001	-0.001	-0.001	0.000	0.000	0.001	0.001	0.001	-0.006
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.005)
Real GDP per capita	-0.109***	-0.130***	-0.094***	-0.059	-0.057	-0.058	-0.030	0.077	0.113**	0.159**	0.159**	0.168**	0.144*	0.159**	-0.001	0.286	0.985***	1.100***	0.843	1.461**	2.605***
	(0.029)	(0.030)	(0.034)	(0.037)	(0.037)	(0.037)	(0.038)	(0.048)	(0.051)	(0.075)	(0.075)	(0.074)	(0.076)	(0.076)	(0.093)	(0.203)	(0.228)	(0.245)	(0.608)	(0.660)	(0.897)
Inflation	0.001***	0.001***	0.001	0.001*	0.001*	0.001*	0.002*	0.004***	0.006***	-0.003	-0.003	-0.004	-0.004*	-0.004	-0.014***	-0.003	0.015**	-0.003	-0.003	-0.011	-0.047**
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.005)	(0.006)	(0.009)	(0.009)	(0.032)	(0.023)
Domestic credit to private sector	0.004	0.003	0.018*	0.020*	0.019*	0.021**	0.001	-0.026*	-0.033**	-0.040***	-0.041***	-0.043***	-0.052***	-0.056***	0.040**	-0.001	-0.135***	-0.063	-0.073	0.567*	0.516**
	(0.008)	(0.008)	(0.009)	(0.010)	(0.010)	(0.010)	(0.011)	(0.013)	(0.014)	(0.015)	(0.015)	(0.015)	(0.016)	(0.017)	(0.020)	(0.042)	(0.046)	(0.056)	(0.061)	(0.292)	(0.222)
Manager's experience		0.004**	0.005**	0.006**	0.006**	0.006**	0.002	0.003	0.003	0.008**	0.008**	0.008**	0.008**	0.008**	0.009**	0.011***	0.011***	0.009**	0.009**	0.016***	0.004
		(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.009)
Manager's gender			-0.000	-0.003	-0.002	-0.002	-0.001	-0.003	-0.005	-0.003	-0.003	-0.004	-0.004	-0.005	-0.004	-0.006	-0.007	-0.008	-0.008	-0.009	-0.031**
			(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)	(0.007)	(0.007)	(0.008)	(0.014)
Total sales				-0.018***	-0.018***	-0.018***	-0.018***	-0.018***	-0.018***	-0.017***	-0.017***	-0.017***	-0.017***	-0.018***	-0.021***	-0.023***	-0.022***	-0.023***	-0.023***	-0.024***	-0.015***
				(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.004)
Firm's export capacity					-0.007***	-0.007***	-0.007***	-0.009***	-0.007***	-0.008***	-0.008***	-0.008***	-0.008***	-0.007***	-0.006***	-0.005***	-0.005***	-0.005**	-0.005**	-0.005**	-0.005
					(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.005)
Criminality						0.015***	0.014***	0.014***	0.017***	0.016***	0.016***	0.015***	0.015***	0.019***	0.018***	0.014**	0.014**	0.016**	0.016**	0.013	0.001
						(0.004)	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)	(0.007)	(0.007)	(0.007)	(0.007)	(0.008)	(0.015)
Taxation							-0.003	-0.026*	-0.029**	-0.190***	-0.191***	-0.180***	-0.191***	-0.187***	-0.162***	-0.182***	-0.033	0.144	0.136	-0.242***	-0.162
							(0.011)	(0.014)	(0.014)	(0.024)	(0.024)	(0.025)	(0.026)	(0.028)	(0.029)	(0.062)	(0.067)	(0.096)	(0.097)	(0.087)	(0.102)
Real lending interest rate								0.005***	0.008***	0.011***	0.011***	0.010***	0.010***	0.010***	-0.006*	0.001	0.027***	-0.000	-0.002	-0.057**	-0.099***
								(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.005)	(0.006)	(0.010)	(0.010)	(0.024)	(0.031)
Interest rate spread									-0.004*	-0.008***	-0.008***	-0.007***	-0.007***	-0.007***	0.008**	0.006	-0.015**	-0.007	-0.008	0.135***	0.205***
									(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.006)	(0.007)	(0.008)	(0.009)	(0.038)	(0.056)
Bank NPLs										0.024***	0.023**	0.013	0.005	0.005	-0.013	0.029	0.066**	-0.012	-0.009	-0.042	0.068
										(0.008)	(0.009)	(0.010)	(0.012)	(0.012)	(0.012)	(0.030)	(0.030)	(0.044)	(0.044)	(0.078)	(0.060)
Real GDP growth											-0.001	0.000	0.000	0.000	0.000	-0.002	0.002	0.019**	0.021**	-0.095	-0.061**
											(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.006)	(0.006)	(0.009)	(0.010)	(0.059)	(0.029)
Unemployment												0.036*	0.034*	0.037**	0.025	0.038	0.114**	0.122*	0.171	-0.278	-0.157
												(0.018)	(0.018)	(0.018)	(0.018)	(0.046)	(0.049)	(0.065)	(0.123)	(0.251)	(0.141)
FDI													-0.001**	-0.001*	-0.000	0.001	0.002***	0.000	0.000	-0.168**	-0.246***
													(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.081)	(0.085)
Gross fixed capital formation														0.010	-0.024	-0.131	-0.129	0.400*	0.416*	-0.329	0.529*
														(0.037)	(0.038)	(0.115)	(0.115)	(0.231)	(0.232)	(0.322)	(0.302)
Banking accessibility															-0.130***	-0.159***	-0.116*	-0.255***	-0.243***	-0.877**	-1.186***
															(0.024)	(0.060)	(0.060)	(0.083)	(0.088)	(0.436)	(0.444)
New business density																-0.031	0.032	0.059**	0.052	-0.803**	-1.048***
																(0.024)	(0.026)	(0.030)	(0.033)	(0.372)	(0.366)
Remittances																	0.326***	0.160**	0.138*	-0.675**	-1.237***
																	(0.054)	(0.072)	(0.082)	(0.277)	(0.410)

(continued on next page)

Table 9. (*continued*)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)
Public spending																		0.631***	0.498	-2.694	-3.080**
																		(0.198)	(0.360)	(1.793)	(1.503)
Urbanization																			-0.504	-9.509**	-13.734***
																			(1.098)	(4.611)	(4.634)
Debt																				-0.038	-0.092
																				(0.092)	(0.081)
Corruption																					0.067
																					(0.110)
Main controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects in the second step	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country fixed effects in the second step	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	134,050	131,533	115,775	102,662	102,198	101,893	87,818	68,870	58,856	44,835	44,835	44,660	44,660	41,859	41,308	31,162	31,162	27,229	27,229	22,563	22,563
R^2	0.122	0.123	0.116	0.124	0.125	0.125	0.129	0.122	0.126	0.120	0.120	0.120	0.120	0.116	0.119	0.122	0.123	0.126	0.126	0.119	0.145

NPLs: nonperforming loans. Robust standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 10. Robustness checks: Logit regression, average marginal effects reported

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)
Past informality	0.054***	0.053***	0.052***	0.047***	0.046***	0.046***	0.039***	0.047***	0.043***	0.036***	0.036***	0.036***	0.036***	0.032***	0.032***	0.042***	0.042***	0.041***	0.041***	0.039***	0.033***
	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.009)	(0.009)	(0.010)	(0.010)	(0.011)	(0.012)
Firm size	-0.048***	-0.048***	-0.046***	-0.027***	-0.025***	-0.025***	-0.024***	-0.025***	-0.031***	-0.031***	-0.031***	-0.030***	-0.031***	-0.028***	-0.024***	-0.021***	-0.021***	-0.020***	-0.020***	-0.020***	-0.031***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.007)
Firm age	-0.012***	-0.015***	-0.015***	-0.015***	-0.015***	-0.015***	-0.014***	-0.015***	-0.012***	-0.015***	-0.015***	-0.015***	-0.015***	-0.015***	-0.015***	-0.016***	-0.017***	-0.013***	-0.013***	-0.013**	-0.017*
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)	(0.010)
Sector of activity	0.044***	0.044***	0.042***	0.036***	0.038***	0.039***	0.038***	0.040***	0.042***	0.041***	0.041***	0.041***	0.041***	0.039***	0.037***	0.037***	0.037***	0.038***	0.038***	0.040***	0.031***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)	(0.007)	(0.012)
Affiliation with a large firm	-0.031***	-0.030***	-0.029***	-0.024***	-0.024***	-0.025***	-0.023***	-0.011**	-0.030***	-0.026***	-0.026***	-0.025***	-0.025***	-0.025***	-0.028***	-0.027***	-0.026***	-0.018**	-0.018**	-0.021**	-0.044**
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.006)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.008)	(0.008)	(0.009)	(0.009)	(0.010)	(0.021)
Private foreign ownership	-0.008***	-0.008***	-0.008***	-0.006***	-0.005***	-0.005***	-0.005***	-0.005***	-0.004**	-0.002	-0.002	-0.002	-0.002	-0.002	-0.002	-0.001	-0.001	0.000	0.000	0.000	-0.006
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.006)
Real GDP per capita	-0.097***	-0.117***	-0.081**	-0.041	-0.041	-0.042	-0.016	0.082*	0.111**	0.192**	0.191**	0.211***	0.190**	0.204***	0.028	0.338	1.251***	1.304***	0.802	1.396**	2.821***
	(0.028)	(0.029)	(0.032)	(0.034)	(0.035)	(0.035)	(0.036)	(0.047)	(0.048)	(0.079)	(0.079)	(0.079)	(0.080)	(0.079)	(0.094)	(0.231)	(0.285)	(0.295)	(0.813)	(0.656)	(0.903)
Inflation	0.001***	0.001***	0.001	0.002**	0.002**	0.002**	0.002**	0.005***	0.006***	-0.002	-0.002	-0.003	-0.004*	-0.003	-0.013***	-0.001	0.021***	-0.004	-0.004	-0.015	-0.052**
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.006)	(0.007)	(0.011)	(0.011)	(0.035)	(0.027)
Domestic credit to private sector	0.005	0.003	0.018*	0.017*	0.017*	0.018*	-0.001	-0.028**	-0.034***	-0.042***	-0.045***	-0.048***	-0.056***	-0.055***	0.037*	-0.037	-0.213***	-0.107	-0.122	0.481	0.551**
	(0.008)	(0.008)	(0.010)	(0.010)	(0.010)	(0.010)	(0.011)	(0.013)	(0.013)	(0.015)	(0.016)	(0.016)	(0.017)	(0.017)	(0.020)	(0.051)	(0.060)	(0.073)	(0.076)	(0.297)	(0.230)
Manager's experience		0.006***	0.006***	0.008***	0.008***	0.007***	0.004	0.005	0.005	0.010***	0.010***	0.010***	0.009***	0.010***	0.011***	0.013***	0.013***	0.011**	0.011**	0.018***	0.004
		(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)	(0.009)
Manager's gender			0.001	-0.002	-0.001	-0.001	0.001	-0.001	-0.004	-0.002	-0.002	-0.003	-0.003	-0.004	-0.003	-0.005	-0.005	-0.007	-0.007	-0.009	-0.029**
			(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)	(0.008)	(0.014)
Total sales				-0.017***	-0.017***	-0.017***	-0.017***	-0.017***	-0.017***	-0.016***	-0.016***	-0.016***	-0.016***	-0.017***	-0.020***	-0.021***	-0.021***	-0.021***	-0.021***	-0.023***	-0.013***
				(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.004)
Firm's export capacity					-0.008***	-0.008***	-0.008***	-0.010***	-0.008***	-0.008***	-0.008***	-0.008***	-0.008***	-0.007***	-0.007***	-0.006***	-0.006***	-0.005**	-0.005**	-0.004*	-0.005
					(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.005)
Criminality						0.014***	0.013***	0.013***	0.016***	0.015***	0.015***	0.014**	0.014**	0.018***	0.017***	0.013*	0.013*	0.015**	0.015**	0.012	0.000
						(0.004)	(0.004)	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)	(0.007)	(0.007)	(0.008)	(0.015)
Taxation							-0.002	-0.029**	-0.029**	-0.192***	-0.195***	-0.181***	-0.189***	-0.188***	-0.155***	-0.160***	0.013	0.183*	0.168	-0.212**	-0.188*
							(0.011)	(0.014)	(0.014)	(0.025)	(0.025)	(0.026)	(0.026)	(0.029)	(0.030)	(0.062)	(0.071)	(0.106)	(0.108)	(0.093)	(0.111)
Real lending interest rate								0.006***	0.008***	0.010***	0.010***	0.009***	0.009***	0.010***	-0.006*	0.000	0.033***	-0.003	-0.007	-0.058**	-0.108***
								(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.006)	(0.009)	(0.013)	(0.014)	(0.026)	(0.034)
Interest rate spread									-0.003	-0.007***	-0.008***	-0.006**	-0.006**	-0.006**	0.010**	0.010	-0.015*	-0.001	-0.002	0.132***	0.228***
									(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.006)	(0.008)	(0.009)	(0.010)	(0.038)	(0.057)
Bank NPLs										0.030***	0.029***	0.017	0.009	0.010	-0.005	0.071**	0.123***	0.039	0.042	-0.003	0.096
										(0.009)	(0.010)	(0.011)	(0.012)	(0.011)	(0.011)	(0.036)	(0.036)	(0.052)	(0.051)	(0.089)	(0.067)
Real GDP growth											-0.001	-0.000	-0.000	-0.000	0.001	0.005	0.012	0.028***	0.032**	-0.081	-0.065**
											(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.007)	(0.007)	(0.011)	(0.013)	(0.061)	(0.030)
Unemployment												0.045**	0.044**	0.046**	0.035*	0.087	0.142**	0.136*	0.230	-0.243	-0.224
												(0.019)	(0.019)	(0.019)	(0.019)	(0.056)	(0.056)	(0.077)	(0.162)	(0.255)	(0.148)
FDI													-0.001*	-0.001	-0.000	0.001	0.003***	0.001	0.000	-0.152*	-0.272***
													(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.082)	(0.087)
Gross fixed capital formation														-0.013	-0.034	-0.111	-0.076	0.470*	0.512*	-0.300	0.620*
														(0.037)	(0.039)	(0.123)	(0.125)	(0.262)	(0.269)	(0.352)	(0.325)
Banking accessibility															-0.123***	-0.140**	-0.091	-0.217**	-0.196**	-0.747*	-1.248***
															(0.025)	(0.063)	(0.063)	(0.092)	(0.097)	(0.439)	(0.448)
New business density																-0.029	0.057*	0.077**	0.061	-0.712*	-1.138***
																(0.026)	(0.030)	(0.034)	(0.041)	(0.374)	(0.370)
Remittances																	0.376***	0.152*	0.100	-0.617**	-1.373***
																	(0.068)	(0.091)	(0.120)	(0.283)	(0.429)

(continued on next page)

Table 10. (*continued*)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)
Public																		0.834***	0.596	-2.259	-3.365**
spending																		(0.229)	(0.423)	(1.819)	(1.539)
Urbanization																			-0.963	-8.777*	-15.522***
																			(1.454)	(4.642)	(4.805)
Debt																				-0.012	-0.106
																				(0.097)	(0.082)
Corruption																					0.053
																					(0.116)
Main controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects in the second step	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country fixed effects in the second step	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	134,050	131,533	115,775	102,662	102,198	101,893	87,818	68,870	58,856	44,835	44,835	44,660	44,660	41,859	41,308	31,162	31,162	27,229	27,229	22,563	22,563

NPLs: nonperforming loans. Robust standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 11. Robustness checks: Probit regression, average marginal effects reported

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)
Past informality	0.055***	0.055***	0.054***	0.048***	0.048***	0.047***	0.041***	0.048***	0.044***	0.037***	0.037***	0.037***	0.037***	0.033***	0.032***	0.043***	0.043***	0.042***	0.042***	0.039***	0.032***
	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.009)	(0.009)	(0.010)	(0.010)	(0.011)	(0.012)
Firm size	-0.047***	-0.047***	-0.045***	-0.026***	-0.024***	-0.024***	-0.024***	-0.025***	-0.031***	-0.030***	-0.030***	-0.030***	-0.030***	-0.027***	-0.024***	-0.021***	-0.021***	-0.019***	-0.019***	-0.020***	-0.031***
	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.007)
Firm age	-0.013***	-0.015***	-0.015***	-0.015***	-0.015***	-0.015***	-0.014***	-0.015***	-0.012***	-0.015***	-0.015***	-0.015***	-0.015***	-0.015***	-0.015***	-0.017***	-0.017***	-0.014***	-0.014***	-0.013**	-0.017*
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)	(0.010)
Sector of	0.043***	0.044***	0.042***	0.035***	0.038***	0.039***	0.038***	0.040***	0.042***	0.041***	0.041***	0.041***	0.041***	0.039***	0.037***	0.037***	0.037***	0.038***	0.038***	0.040***	0.032***
activity	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)	(0.007)	(0.012)
Affiliation with	-0.030***	-0.030***	-0.029***	-0.024***	-0.024***	-0.025***	-0.023***	-0.011**	-0.028***	-0.024***	-0.024***	-0.023***	-0.023***	-0.022***	-0.025***	-0.025***	-0.024***	-0.016*	-0.016*	-0.019*	-0.043**
a large firm	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)	(0.008)	(0.008)	(0.009)	(0.009)	(0.010)	(0.020)
Private foreign	-0.007***	-0.007***	-0.008***	-0.005***	-0.004***	-0.004***	-0.004***	-0.005***	-0.003**	-0.002	-0.002	-0.002	-0.002	-0.002	-0.001	-0.000	-0.000	0.001	0.001	0.001	-0.006
ownership	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.006)
Real GDP	-0.108***	-0.128***	-0.091***	-0.055	-0.053	-0.054	-0.028	0.082*	0.113**	0.186**	0.185**	0.202***	0.182**	0.194**	0.018	0.318	1.150***	1.244***	0.773	1.351**	2.749***
per capita	(0.028)	(0.028)	(0.032)	(0.035)	(0.035)	(0.035)	(0.036)	(0.047)	(0.048)	(0.077)	(0.077)	(0.077)	(0.078)	(0.077)	(0.093)	(0.220)	(0.268)	(0.278)	(0.750)	(0.652)	(0.893)
Inflation	0.002***	0.001***	0.001	0.002**	0.002**	0.002**	0.002***	0.005***	0.006***	-0.003	-0.002	-0.004	-0.004*	-0.003	-0.014***	-0.002	0.019***	-0.003	-0.004	-0.015	-0.050**
	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.006)	(0.007)	(0.010)	(0.010)	(0.034)	(0.025)
Domestic credit	0.006	0.005	0.020**	0.019*	0.019*	0.020**	0.001	-0.029**	-0.035***	-0.042***	-0.044***	-0.047***	-0.055***	-0.054***	0.037*	-0.027	-0.188***	-0.095	-0.111	0.464	0.535**
to private sector	(0.008)	(0.008)	(0.009)	(0.010)	(0.010)	(0.010)	(0.011)	(0.013)	(0.013)	(0.015)	(0.016)	(0.016)	(0.016)	(0.017)	(0.020)	(0.048)	(0.056)	(0.068)	(0.071)	(0.293)	(0.226)
Manager's		0.006***	0.006***	0.007***	0.007***	0.007***	0.003	0.005	0.004	0.010***	0.010***	0.009**	0.009**	0.010***	0.010***	0.013***	0.013***	0.011**	0.011**	0.019***	0.004
experience		(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.005)	(0.009)
Manager's			0.001	-0.002	-0.001	-0.001	0.001	-0.002	-0.004	-0.003	-0.003	-0.003	-0.003	-0.004	-0.003	-0.005	-0.006	-0.007	-0.007	-0.009	-0.030**
gender			(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)	(0.008)	(0.014)
Total sales				-0.017***	-0.017***	-0.017***	-0.017***	-0.018***	-0.017***	-0.016***	-0.016***	-0.016***	-0.016***	-0.018***	-0.021***	-0.021***	-0.021***	-0.022***	-0.022***	-0.024***	-0.014***
				(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.004)
Firm's export					-0.008***	-0.008***	-0.008***	-0.010***	-0.007***	-0.008***	-0.008***	-0.008***	-0.008***	-0.007***	-0.007***	-0.006***	-0.006***	-0.005**	-0.005**	-0.004*	-0.005
capacity					(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.005)
Criminality						0.014***	0.014***	0.014***	0.016***	0.015***	0.015***	0.014**	0.014**	0.018***	0.017***	0.013*	0.013**	0.015**	0.015**	0.012	0.001
						(0.004)	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)	(0.007)	(0.007)	(0.008)	(0.015)
Taxation							-0.004	-0.031**	-0.032**	-0.191***	-0.193***	-0.180***	-0.188***	-0.187***	-0.158***	-0.168***	-0.003	0.175*	0.161	-0.206**	-0.180*
							(0.011)	(0.014)	(0.014)	(0.025)	(0.025)	(0.025)	(0.026)	(0.028)	(0.029)	(0.062)	(0.069)	(0.102)	(0.104)	(0.090)	(0.107)
Real lending								0.006***	0.008***	0.010***	0.010***	0.009***	0.009***	0.010***	-0.007**	0.000	0.030***	-0.002	-0.006	-0.056**	- 0.104***
interest rate								(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.006)	(0.008)	(0.012)	(0.013)	(0.025)	(0.033)
Interest rate									-0.003	-0.007***	-0.007***	-0.005*	-0.006**	-0.006**	0.010***	0.009	-0.014*	-0.002	-0.004	0.128***	0.220***
spread									(0.002)	(0.002)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.006)	(0.007)	(0.009)	(0.009)	(0.038)	(0.056)
Bank NPLs										0.031***	0.029***	0.017	0.010	0.011	-0.005	0.060*	0.107***	0.025	0.028	-0.006	0.088
										(0.009)	(0.009)	(0.011)	(0.011)	(0.011)	(0.011)	(0.034)	(0.034)	(0.049)	(0.049)	(0.085)	(0.064)
Real GDP											-0.001	0.000	0.000	0.000	0.001	0.003	0.009	0.025**	0.029**	-0.079	-0.064**
growth											(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.007)	(0.007)	(0.010)	(0.012)	(0.060)	(0.030)
Unemployment												0.045**	0.044**	0.046**	0.035*	0.073	0.138**	0.134*	0.222	-0.228	-0.207
												(0.019)	(0.019)	(0.019)	(0.019)	(0.053)	(0.054)	(0.074)	(0.151)	(0.251)	(0.145)
FDI													-0.001*	-0.001	-0.000	0.001	0.003***	0.001	0.000	-0.146*	-0.263***
													(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.081)	(0.085)
Gross fixed														-0.011	-0.037	-0.121	-0.101	0.450*	0.485*	-0.308	0.582*
capital formation														(0.037)	(0.038)	(0.121)	(0.122)	(0.252)	(0.258)	(0.341)	(0.315)
Banking															-0.119***	-0.140**	-0.093	-0.223**	-0.203**	-0.723*	-1.217***
accessibility															(0.025)	(0.062)	(0.062)	(0.089)	(0.093)	(0.435)	(0.444)
New business																-0.028	0.049*	0.073**	0.059	-0.687*	-1.104***
density																(0.025)	(0.029)	(0.032)	(0.038)	(0.370)	(0.366)
Remittances																	0.358***	0.154*	0.108	-0.588**	-1.321***
																	(0.064)	(0.085)	(0.109)	(0.279)	(0.419)

(*continued on next page*)

Table 11. (*continued*)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)	(21)
Public																		0.782***	0.550	-2.168	-3.273**
spending																		(0.219)	(0.404)	(1.796)	(1.520)
Urbanization																			-0.912	-8.390*	-14.964***
																			(1.346)	(4.594)	(4.711)
Debt																				-0.007	-0.101
																				(0.095)	(0.081)
Corruption																					0.050
																					(0.113)
Main controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects in the second step	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country fixed effects in the second step	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	134,050	131,533	115,775	102,662	102,198	101,893	87,818	68,870	58,856	44,835	44,835	44,660	44,660	41,859	41,308	31,162	31,162	27,229	27,229	22,563	22,563

NPLs: nonperforming loans. Robust standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 12. Robustness checks: Propensity Score Matching

	(1) Nearest Neighbor Matching			(2) Radius Matching			(3) Kernel Matching	(4) Local Linear Regression Matching
	N = 1	N = 2	N = 3	r = 0.005	r = 0.01	r = 0.05		
Past informality	0.065***	0.067***	0.072***	0.078***	0.078***	0.089***	0.087***	0.078***
	(0.007)	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.007)
Rubin's B statistic (%)	4.4	4.5	4.3	6.5	6.4	11.6	10.5	4.4
Rubin's R statistic	0.91	0.85	0.82	0.88	0.89	1.09	1.10	0.91
Observations	134,050	134,050	134,050	134,050	134,050	134,050	134,050	134,050

N and r denote the number of nearest neighbors and the radius, respectively. Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 13. Robustness checks: Recursive Bivariate Probit with Instrumental Variables, average marginal effects reported

Past informality	0.155***
	(0.026)
Firm size	-0.044***
	(0.001)
Firm age	-0.016***
	(0.002)
Sector of activity	0.040***
	(0.003)
Affiliation with a large firm	-0.028***
	(0.004)
Private foreign ownership	-0.006***
	(0.001)
Real GDP per capita	-0.099***
	(0.028)
Inflation	0.002***
	(0.000)
Domestic credit to the private sector	0.006
	(0.008)
Test of exogeneity (ρ)	-0.166***
	(0.044)
Hansen test of overidentifying restrictions (p-value)	0.105
Weak identification test (Cragg-Donald statistic)	187.086
Stock-Yogo weak identification maximum critical value	19.93
Year fixed effects	Yes
Country fixed effects	Yes
Observations	138,277

Robust standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 14. Robustness checks: Alternative measures of credit constraints

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	(A) First alternative measure of credit constraints							
Past informality	0.067***	0.065***	0.041***	0.040***	0.066***	0.064***	0.044***	0.043***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Covariates in the second step	No	No	No	No	Yes	Yes	Yes	Yes
Year fixed effects in the second step	No	Yes	No	Yes	No	Yes	No	Yes
Country fixed effects in the second step	No	No	Yes	Yes	No	No	Yes	Yes
Observations	135,675	135,675	135,675	135,675	135,675	135,675	135,675	135,675
	(B) Second alternative measure of credit constraints							
Past informality	0.056***	0.054***	0.032***	0.032***	0.055***	0.053***	0.036***	0.035***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Covariates in the second step	No	No	No	No	Yes	Yes	Yes	Yes
Year fixed effects in the second step	No	Yes	No	Yes	No	Yes	No	Yes
Country fixed effects in the second step	No	No	Yes	Yes	No	No	Yes	Yes
Observations	135,675	135,675	135,675	135,675	135,675	135,675	135,675	135,675
	(C) Third alternative measure of credit constraints							
Past informality	0.040***	0.040***	0.024***	0.026***	0.040***	0.038***	0.027***	0.027***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Covariates in the second step	No	No	No	No	Yes	Yes	Yes	Yes
Year fixed effects in the second step	No	Yes	No	Yes	No	Yes	No	Yes
Country fixed effects in the second step	No	No	Yes	Yes	No	No	Yes	Yes
Observations	135,675	135,675	135,675	135,675	135,675	135,675	135,675	135,675

Robust standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 15. Heterogegeity: Different sectors of activity

	(1) Manufacturing	(2) Services
Past informality	0.049***	0.058***
	(0.006)	(0.007)
Covariates in the second step	Yes	Yes
Year fixed effects in the second step	Yes	Yes
Country fixed effects in the second step	Yes	Yes
Observations	75,642	58,408

Robust standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 16. Heretogeneity: Different categories of firm size

	(1) Small (<20 employees)	(2) Medium (20-99 employees)	(3) Large (≥100 employees)
Past informality	0.054***	0.051***	0.040***
	(0.006)	(0.008)	(0.012)
Covariates in the second step	Yes	Yes	Yes
Year fixed effects in the second step	Yes	Yes	Yes
Country fixed effects in the second step	Yes	Yes	Yes
Observations	61,293	46,239	26,495

Robust standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 17. Heretogeneity: Different categories of firm age

	(1) <5 years	(2) 5-9 years	(3) 10-19 years	(4) 20-39 years	(5) ≥40 years
Past informality	0.065***	0.064***	0.061***	0.049***	0.033**
	(0.017)	(0.012)	(0.008)	(0.009)	(0.013)
Covariates in the second step	Yes	Yes	Yes	Yes	Yes
Year fixed effects in the second step	Yes	Yes	Yes	Yes	Yes
Country fixed effects in the second step	Yes	Yes	Yes	Yes	Yes
Observations	11,036	25,604	49,098	35,917	11,959

Robust standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 18. Heterogegeity: Sub-samples of countries

	(1) G20	(2) Removing G20	(3) SSA	(4) Removing SSA	(5) LAC	(6) Removing LAC
Past informality	0.081***	0.047***	0.058***	0.051***	0.025***	0.062***
	(0.011)	(0.005)	(0.009)	(0.005)	(0.009)	(0.005)
Covariates in the second step	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects in the second step	Yes	Yes	Yes	Yes	Yes	Yes
Country fixed effects in the second step	Yes	Yes	Yes	Yes	Yes	Yes
Observations	32,573	101,477	21,590	112,460	28,771	105,279

Robust standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 19. Correlation between the transmission channels and credit constraints

	(1) Credit constraints	(2) Credit constraints	(3) Credit constraints
Productivity	-0.015***		
	(0.001)		
Competition from the informal sector		0.036***	
		(0.002)	
Quality of financial statements			-0.045***
			(0.002)
Main controls	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes
Observations	156,950	155,058	170,617

Robust standard errors are in parentheses. Estimations are based on a Logit regression. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 20. Transmission channels

	(1) Productivity	(2) Competition from the informal sector	(3) Quality of financial statements
Past informality	-0.350***	0.061***	-0.099***
	(0.017)	(0.005)	(0.004)
Covariates in the second step	Yes	Yes	Yes
Year fixed effects in the second step	Yes	Yes	Yes
Country fixed effects in the second step	Yes	Yes	Yes
Observations	122,393	124,240	136,005

Robust standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

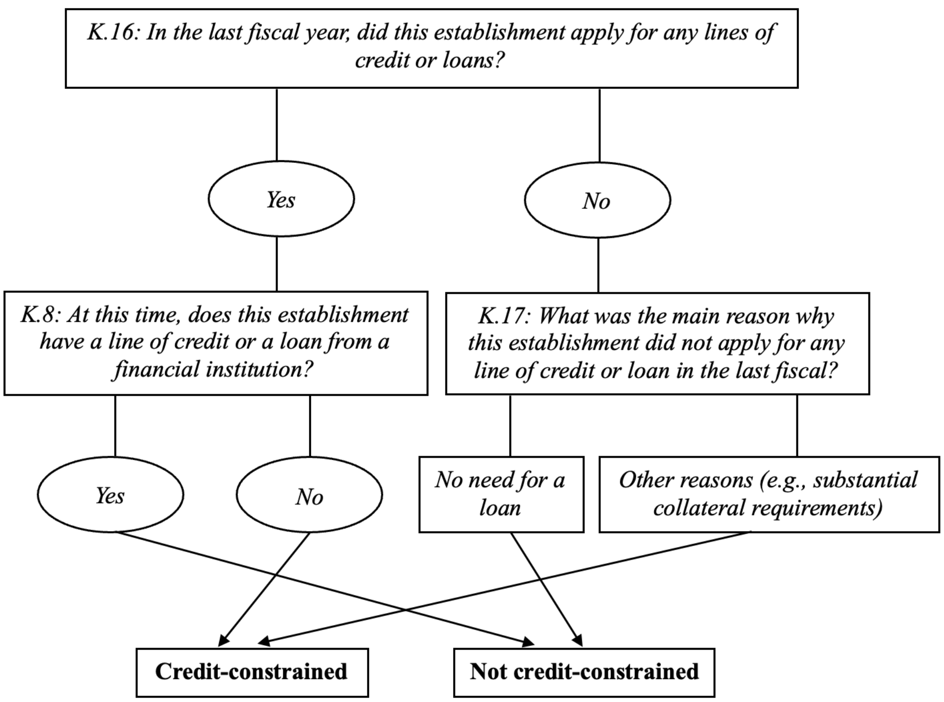

Figure 1. Method for constructing the credit constraints variable, based on the World Bank Enterprise Surveys
Source: Distinguin et al. (2016)

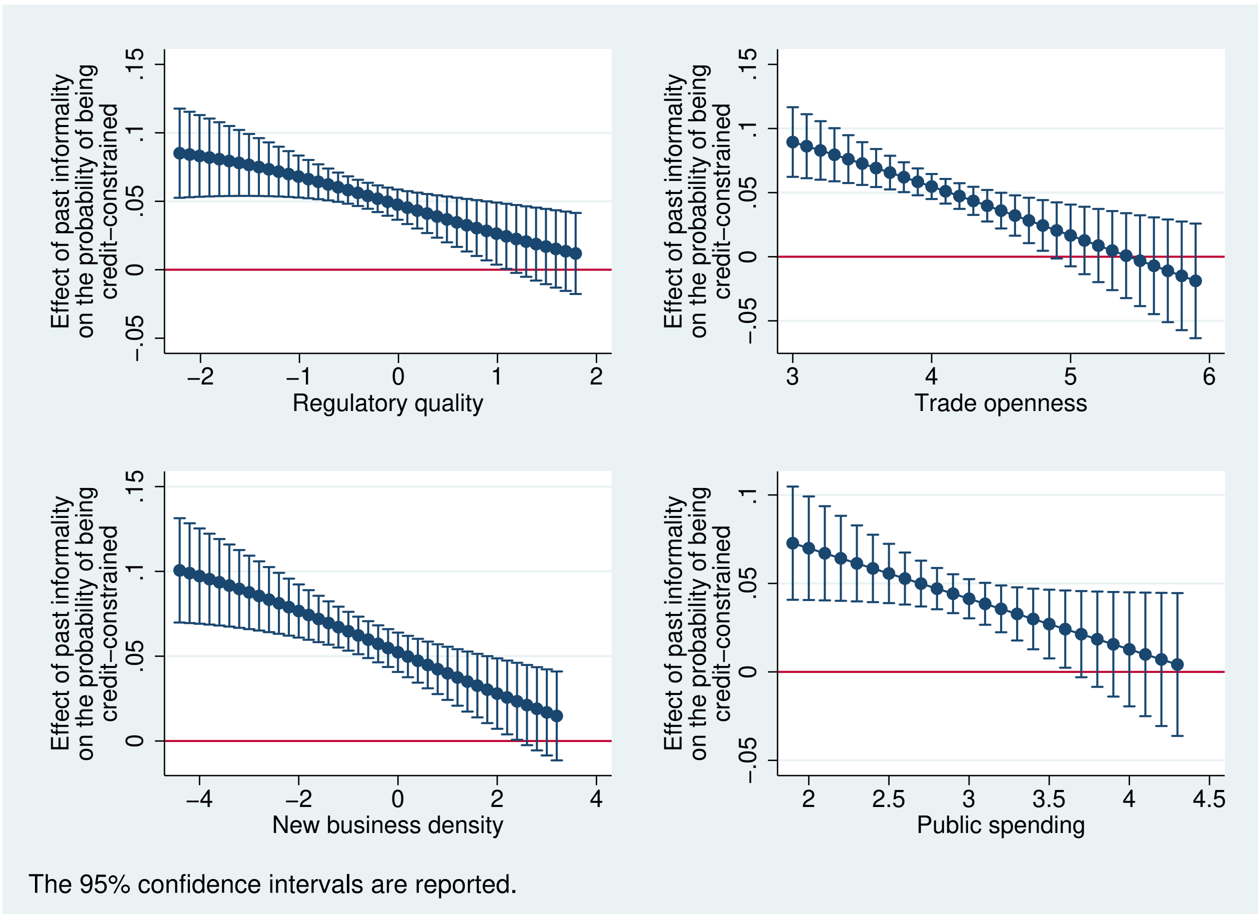

Figure 2. Heterogeneity: Effects of past informality on registered firms' probability of being credit-constrained at varying levels of structural factors

Appendix A

Table A1. List of countries

Afghanistan	Chad	Greece	Lithuania	Papua New Guinea	Suriname
Albania	Chile	Grenada	Madagascar	Paraguay	Tajikistan
Antigua and Barbuda	China	Guatemala	Malawi	Peru	Tanzania
Argentina	Colombia	Guinea	Malaysia	Philippines	Thailand
Armenia	Congo	Guyana	Mali	Poland	Timor-Leste
Azerbaijan	Costa Rica	Honduras	Malta	Portugal	Togo
Bahamas	Croatia	Hungary	Mauritania	Romania	Tonga
Bangladesh	Cyprus	India	Mauritius	Russia	Trinidad and Tobago
Belarus	Czechia	Indonesia	Mexico	Rwanda	Tunisia
Belize	Côte d'Ivoire	Iraq	Micronesia	Samoa	Türkiye
Benin	DRC	Israel	Moldova	Senegal	Uganda
Bhutan	Dominica	Italy	Mongolia	Serbia	Ukraine
Bolivia	Dominican Republic	Jamaica	Montenegro	Sierra Leone	Uruguay
Bosnia and Herzegovina	Ecuador	Jordan	Morocco	Slovak Republic	Uzbekistan
Botswana	Egypt	Kazakhstan	Mozambique	Slovenia	Vanuatu
Brazil	El Salvador	Kenya	Myanmar	Solomon Islands	Viet Nam
Bulgaria	Estonia	Kosovo	Nepal	South Africa	West Bank and Gaza
Burkina Faso	Eswatini	Kyrgyz Republic	Nicaragua	Spain	Zambia
Burundi	Fiji	Lao PDR	Niger	Sri Lanka	Zimbabwe
Cambodia	Gabon	Latvia	Nigeria	St. Kitts and Nevis	
Cameroon	Gambia	Lebanon	North Macedonia	St. Lucia	
Cape Verde	Georgia	Lesotho	Pakistan	St. Vin. and the Gren.	
Central African Republic	Ghana	Liberia	Panama	Sudan	

Table A2. Correlation matrix of the baseline variables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
(1) Credit constraints	1									
(2) Past informality	0.092***	1								
(3) Firm size	-0.143***	-0.110***	1							
(4) Firm age	-0.103***	0.043***	0.266***	1						
(5) Sector of activity	0.025***	0.037***	0.208***	0.131***	1					
(6) Affiliation with a large firm	-0.052***	-0.041***	0.206***	0.074***	-0.037***	1				
(7) Private foreign ownership	-0.050***	-0.047***	0.212***	-0.004**	0.017***	0.143***	1			
(8) Real GDP per capita	-0.226***	-0.129***	0.059***	0.168***	-0.010***	-0.006***	-0.027***	1		
(9) Inflation	0.066***	0.010***	-0.022***	-0.036***	0.028***	-0.023***	-0.048***	-0.105***	1	
(10) Domestic credit to the private sector	-0.185***	-0.113***	0.118***	0.150***	0.036***	0.031***	-0.038***	0.551***	-0.266***	1

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A3. Descriptive statistics of the baseline variables

	Observations	Mean	Standard deviation	Minimum	Maximum
Credit constraints	210,061	0.327		0	1
Past informality	157,252	0.100		0	1
Firm size	218,557	3.388	1.322	0	14.330
Firm age	216,609	2.766	0.746	0	5.832
Sector of activity	219,865	0.531		0	1
Affiliation with a large firm	216,311	0.168		0	1
Private foreign ownership	216,042	0.426	1.279	0	4.615
Real GDP per capita	217,298	9.397	0.938	6.881	11.781
Inflation	219,599	6.278	7.403	-26.700	59.027
Domestic credit to the private sector	191,773	3.553	0.887	-5.270	5.513

We do not report the standard errors of binary variables as they do not have a practical interpretation.

Table A4. Descriptive statistics of the additional controls

	Observations	Mean	Standard deviation	Minimum	Maximum
Manager's experience	213,600	2.764	0.687	0	4.331
Manager's gender	190,803	0.157		0	1
Total sales	196,974	16.811	3.135	0	35.532
Firm's export capacity	216,499	0.620	1.380	0	4.615
Criminality	193,243	0.167		0	1
Taxation	146,432	3.693	0.444	2.001	5.826
Real lending interest rate	160,282	6.712	8.732	-30.100	61.883
Interest rate spread	138,115	6.647	6.723	-8.516	48.834
Bank NPLs	129,445	1.415	0.783	-0.667	3.922
Real GDP growth	219,599	4.167	3.712	-14.839	18.333
Unemployment	217,987	1.740	0.708	-1.431	3.477
FDI	194,667	3.616	8.915	-22.289	203.625
Gross fixed capital formation	204,161	3.119	0.296	2.079	4.044
Banking accessibility	174,060	2.315	1.002	-3.219	4.525
New business density	159,498	-0.202	1.533	-4.399	3.208
Remittances	219,865	1.284	0.882	0	3.809
Public spending	136,895	3.132	0.444	1.943	4.291
Urbanization	219,122	3.936	0.419	2.264	4.605
Debt	157,373	2.737	0.874	0	5.095
Corruption	194,735	-0.337	0.748	-1.672	2.236

NPLs: nonperforming loans. We do not report the standard errors of binary variables as they do not have a practical interpretation.

Appendix B – Definition of the variables and data sources

Credit constraints: Binary variable equal to 1 if the firm is credit-constrained, and 0 otherwise. Source: World Bank Enterprise Surveys (WBES). Internet link to access the WBES: `https://www.enterprisesurveys.org/`

Past informality: Binary variable that takes the value of 1 if the firm began operations as an informal firm (i.e., it was not registered at the start), and 0 otherwise. Source: WBES.

Firm size: Natural logarithm of the total number of full-time employees, adjusted to account for temporary workers. Source: WBES.

Firm age: Natural logarithm of the number of years since the firm commenced operations. Source: WBES.

Sector of activity: Binary variable equal to 1 for manufacturing and 0 for services. Source: WBES.

Affiliation with a large firm: Binary variable equal to 1 if the firm is part of a large firm, and 0 otherwise. Source: WBES.

Private foreign ownership: Natural logarithm of the percentage of the firm owned by private foreign individuals, companies, or organizations. Source: WBES.

Real GDP per capita: Natural logarithm of GDP per capita based on purchasing power parity (PPP) in constant 2021 international U.S. dollars. Source: World Development Indicators (WDI) database of the World Bank. Internet link to access the WDI: `https://datatopics.worldbank.org/world-development-indicators/`

Inflation: Annual growth rate of the GDP implicit deflator. Source: WDI.

Domestic credit to the private sector: Domestic credit to the private sector as a percentage of GDP (in natural logarithm). Source: WDI.

Manager's experience: Natural logarithm of the number of years the top manager has worked in the firm's sector. Source: WBES.

Manager's gender: Binary variable equal to 1 if the manager is a woman and 0 if he is a man. Source: WBES.

Total sales: Natural logarithm of the firm's total annual sales. Source: WBES.

Firm's export capacity: Direct exports as a percentage of sales (in natural logarithm). Source: WBES.

Criminality: Binary variable equal to 1 if the firm experienced losses in the last fiscal year due to theft, robbery, vandalism, arson on its premises or from internet hacking or fraudulent internet transactions, and 0 otherwise. Source: WBES.

Taxation: Total tax and contribution rate as a percentage of profit (in natural logarithm). Source: WDI.

Real lending interest rate: Lending interest rate adjusted for inflation (in percentage). Source: WDI.

Interest rate spread: Interest rate charged by banks on loans to private sector customers minus the interest rate paid by commercial or similar banks for demand, time, or savings deposits (in percentage). Source: WDI.

Bank NPLs: Bank nonperforming loans (NPLs) as a percentage of total gross loans (in natural logarithm). Source: WDI.

Real GDP growth: Annual percentage growth rate of GDP based on constant 2015 U.S. dollars. Source: WDI.

Unemployment: Share of the total labor force that is unemployed but available for and seeking employment (in natural logarithm). Source: WDI.

FDI: Foreign direct investment net inflows as a percentage of GDP. Source: WDI.

Gross fixed capital formation: Gross fixed capital formation as a percentage of GDP (in natural logarithm). Source: WDI.

Banking accessibility: Natural logarithm of the number of commercial bank branches per

100,000 adults. Source: WDI.

New business density: Natural logarithm of new business density, measured as new business registrations per 1,000 people aged 15-64. Source: WDI.

Remittances: Personal remittances received as a percentage of GDP (in natural logarithm). Source: WDI.

Public spending: Measured by government expenditure as a percentage of GDP (in natural logarithm). Source: WDI.

Urbanization: Urban population as a percentage of the total population (in natural logarithm). Source: WDI.

Debt: Short-term debt as a percentage of exports of goods, services, and primary income (in natural logarithm). Source: WDI.

Corruption: Control of corruption indicator. Source: Worldwide Governance Indicators (WGI) database developed by Kaufmann et al. (2010). Internet link to access the WGI: `https://www.govindicators.org/`

Regulatory quality: Regulatory quality indicator. Source: WGI.

Trade openness: Sum of exports and imports of goods and services as a percentage of GDP (in natural logarithm). Source: WDI.

Productivity: Natural logarithm of the ratio of turnover to the total number of full-time employees, adjusted for temporary workers. Source: WBES.

Competition from the informal sector: Binary variable equal to 1 if the firm faces competitors from the informal sector, and 0 otherwise. Source: WBES.

Quality of financial statements: Binary variable equal to 1 if the firm has its annual financial statements audited and certified by an external auditor, and 0 otherwise. Source: WBES.

First alternative measure of credit constraints: Binary variable equal to 1 if the firm reports access to finance as an obstacle (minor, moderate, major, or very severe), and 0 if it does not consider it an obstacle. Source: WBES.

Second alternative measure of credit constraints: Binary variable equal to 1 if access to finance is reported as a moderate, major, or very severe obstacle, and 0 otherwise. Source: WBES.

Third alternative measure of credit constraints: Binary variable equal to 1 if access to finance is reported as a major or very severe obstacle, and 0 otherwise. Source: WBES.

First instrumental variable: Country-level variable representing the percentage of firms inspected by tax officials over the 12 months preceding each survey. Source: WBES.

Second instrumental variable: Country-level variable representing the average frequency of inspections by tax officials over the 12 months preceding each survey. Source: WBES.

Appendix C

Table C1. Robustness checks: Clustering standard errors at the country level

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Past informality	0.075***	0.073***	0.051***	0.050***	0.073***	0.070***	0.055***	0.054***
	(0.020)	(0.013)	(0.008)	(0.008)	(0.015)	(0.011)	(0.007)	(0.007)
Covariates in the second step	No	No	No	No	Yes	Yes	Yes	Yes
Year fixed effects in the second step	No	Yes	No	Yes	No	Yes	No	Yes
Country fixed effects in the second step	No	No	Yes	Yes	No	No	Yes	Yes
Clustering level of standard errors	Country	Country	Country	Country	Country	Country	Country	Country
Observations	134,050	134,050	134,050	134,050	134,050	134,050	134,050	134,050

Standard errors, shown in parentheses, are clustered at the country level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.