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High-quality financial statements, credit constraints, and labor productivity

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Abstract

Using a large firm-level dataset from the World Bank Enterprise Surveys covering the period 2006-2024, which includes 146 countries and over 158,900 observations, this paper employs an instrumental variable strategy to show that firms with high-quality financial statements (HQFS)—defined as financial statements checked and certified by an external auditor—exhibit significantly higher labor productivity, approximately 46% higher. This result is robust across various tests. A decline in credit constraints is highlighted as the key channel through which HQFS increases labor productivity. Heterogeneity analysis reveals that the effect of HQFS diminishes with increasing firm size and age, as well as with higher levels of structural factors, including real GDP per capita, domestic credit to the private sector, and control of corruption. This indicates that the effect of HQFS on labor productivity is primarily observed among small, young firms in developing countries.

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1 Introduction

The determinants of labor productivity in firms have been widely studied (e.g., Ballot et al., 2006; Bloom et al., 2010; Fu et al., 2018), as labor productivity is essential to a firm's overall performance, affecting costs, profitability, and competitiveness. Understanding it helps identify inefficiencies, improve workforce capabilities, and optimize task distribution, boosting output without expanding labor. Additionally, analyzing labor productivity helps balance cost control and fair wages, promoting sustainability and employee retention.

However, a thorough review of the literature indicates that high-quality financial statements (HQFS)—defined as financial statements checked and certified by an external auditor—has not been analyzed as a determinant of labor productivity, despite the possible effect of HQFS on firms' access to credit. This paper contributes to filling this gap in the literature by analyzing the effect of HQFS on the labor productivity of firms worldwide. We believe that HQFS can affect labor productivity through the channel of reduced credit constraints.

Indeed, the literature indicates that HQFS reduces the probability that firms face credit constraints (Briozzo & Albanese, 2020; Kampouris et al., 2022; Kouakou, 2025). Reliable financial statements are essential for demonstrating a firm's financial health and its capacity to repay debts. Without them, securing financing or favorable credit terms becomes more challenging (Minnis, 2011). HQFS signals reliable and transparent reporting, enhancing the firm's perceived creditworthiness and thereby reducing the risk of credit constraints. Specifically, HQFS lowers the cost for lenders to verify a firm's financial information and increases their trust in the firm's financial position, thereby improving the firm's ability to obtain financing, ceteris paribus.

The decline in credit constraints, in turn, boosts labor productivity. In fact, easing credit constraints facilitates investments that enhance labor productivity, such as worker training programs and research and development (R&D), significantly boosting firms' labor productivity (Ballot et al., 2006). Furthermore, reduced financial constraints help prevent the overuse of labor (Lee & Chambers, 1986), leading to an additional increase in labor productivity for firms.

In summary, HQFS should reduce credit constraints, which, in turn, should boost labor productivity. This suggests that HQFS likely increases labor productivity, with credit constraints as a potential transmission channel.

Using a large firm-level dataset from the World Bank Enterprise Surveys—covering 146 countries from 2006 to 2024 and including over 158,900 observations—and employing an instrumental variable strategy to address the endogeneity of HQFS, we find that HQFS significantly increases labor productivity. This result is robust to various tests. Furthermore, the results indicate that credit constraints are a key channel through which HQFS enhances labor productivity. The findings also reveal heterogeneity in the effects of HQFS across firm sizes, firm ages, and structural factors such as real GDP per capita, domestic credit to the private sector, and control of corruption. In particular, the results indicate that the effect of

HQFS on labor productivity is primarily observed among small, young firms in developing countries. This outcome is consistent with the idea that access to credit for small and young firms is closely related to the quality of information displayed in their financial statements (Chavis et al., 2011; Elemes & Filip, 2022; Palacín-Sánchez et al., 2022; World Bank, 2017).

Indeed, small and young firms often have weaker banking relationships, lower self-financing capacity, shorter credit histories, and less established reputations compared to their larger and older counterparts. These characteristics heighten their financial constraints (Beck et al., 2005; Carreira & Silva, 2010; Fohlin, 1998; Kouakou, 2025; Petersen & Rajan, 1994), making HQFS especially crucial for accessing credit. As a result, HQFS tends to reduce credit constraints more strongly for smaller and younger firms, which in turn amplifies its effect on labor productivity. Moreover, since credit constraints are typically higher in environments with weaker financial, economic, and institutional development (Beck et al., 2006, 2005, 2008; Distinguin et al., 2016), the importance of HQFS is even greater for small, young firms operating in developing countries. These countries often exhibit weaker corruption control and lower levels of financial development, further underscoring the role of HQFS in improving credit access and enhancing labor productivity. Additionally, many small and young registered firms in developing countries have informal origins—i.e., they initially operated in the informal sector before later registering. Such firms often produce lower-quality financial statements, as their informal beginnings may instill a culture of non-compliance (Kouakou, 2025). For these firms, HQFS becomes even more critical for gaining access to credit, thereby reinforcing its positive impact on labor productivity.

The rest of the paper is organized as follows. Section 2 presents the data, variables, and methodology. Section 3 discusses the main result and the transmission channel. Section 4 tests the robustness of our main result. Section 5 covers the heterogeneity analysis. Section 6 concludes.

2 Data, variables, and methodology

We use a large firm-level dataset from the World Bank Enterprise Surveys (WBES) for the 2006-2024 period. Accounting for missing data on certain variables, the final dataset covers 146 countries (including developed, emerging, and developing countries worldwide[1]) for the 2006-2024 period and includes over 158,900 firm observations. The dataset consists of repeated cross-sections, and all firms are registered. The WBES are global surveys conducted in over 150 countries, providing insights into various aspects of firm operations and the business environment. The dataset enables cross-country and time-based comparisons. We control for macroeconomic factors that may influence our results, using data from the World Development Indicators (WDI) and Worldwide Governance Indicators (WGI) databases.

The dependent variable is labor productivity (*labprod*), measured as the natural logarithm of the ratio of total annual sales to the total number of permanent, full-time employees, adjusted for temporary workers. The independent variable of interest is HQFS ($hqfs$), a

[1]The list of the countries is available upon request.

binary variable equal to 1 if the firm's annual financial statements are checked and certified by an external auditor, and 0 otherwise.

Control variables are chosen based on the literature. They include: firm size, firm age, affiliation with a large firm, foreign ownership, real GDP per capita (a proxy for economic development), domestic credit to the private sector (a proxy for financial development), inflation (a proxy for economic conditions and macroeconomic stability), and control of corruption (a proxy for institutional quality). Table 1 summarizes the definitions of the variables, and Table 2 provides descriptive statistics. Among these statistics, approximately 53% of the observations are subject to HQFS, indicating that financial statement checks and certification by an external auditor are not uncommon in our data.

Table 1. Definitions of the variables.

	Definition
Labor productivity	Ratio of total annual sales to the total number of permanent, full-time employees, adjusted for temporary workers (in log). Source: WBES.
HQFS	Dummy=1 if the firm has its annual financial statements checked and certified by an external auditor. Source: WBES.
Control variables	
Firm size	Total number of permanent, full-time employees, adjusted for temporary workers (in log). Source: WBES.
Firm age	Age of the firm (in log). Source: WBES.
Affiliation with a large firm	Dummy=1 if the firm is part of a large firm. Source: WBES.
Foreign ownership	Percentage of the firm owned by foreign entities (in log). Source: WBES.
Real GDP per capita	GDP per capita based on purchasing power parity (PPP) in constant 2021 international dollars (in log). Source: WDI.
Domestic credit to the private sector	Domestic credit to the private sector as a percentage of GDP (in log). Source: WDI.
Inflation	Annual growth rate of the GDP implicit deflator. Source: WDI.
Control of corruption	Control of corruption indicator. Source: WGI.
Transmission channel	
Credit constraints	Dummy=1 if the firm is credit-constrained. Source: Kouakou (2025).

Table 2. Descriptive statistics of the variables.

	Observation	Mean	Standard deviation	Minimum	Maximum
Labor productivity	158,983	13.467	2.706	0	28.142
HQFS	158,983	0.526		0	1
Firm size	158,983	3.435	1.322	0	14.330
Firm age	158,983	2.747	0.797	0	5.829
Affiliation with a large firm	158,983	0.167		0	1
Foreign ownership	158,983	0.415	1.263	0	4.615
Real GDP per capita	158,983	9.423	0.911	6.823	11.788
Domestic credit to the private sector	158,983	3.631	0.841	-5.644	5.578
Inflation	158,983	8.071	8.393	-27.632	84.683
Control of corruption	158,983	-0.259	0.755	-1.534	2.239
Credit constraints	155,790	0.327		0	1

Note: Standard deviations for binary variables are not reported, as they do not provide meaningful interpretations.

Instrumental variable strategy. HQFS is endogenous because more productive firms may have the financial means to afford financial statements checks and audits, leading to potential reverse causality. Additionally, HQFS is not a random event, as it may depend on unobserved firm characteristics, suggesting self-selection. These characteristics may also influence labor productivity, inducing endogeneity due to omitted variable bias. To address the endogeneity of HQFS, we use the instrumental variable (IV) method. Specifically, we apply the "cell-average method" to construct the IV (see Amin & Soh, 2021; Distinguin et al., 2016; Fisman & Svensson, 2007; Kouakou, 2025, among others). This method instruments the endogenous variable for firm i by averaging it across other firms in the same cell, excluding firm i. It is commonly applied at the industry or country level (see Amin & Soh, 2021; Distinguin et al., 2016; Fisman & Svensson, 2007; Kouakou, 2025, among others).

Auditing requirements vary considerably across countries and industries, primarily due to differences in legal frameworks, regulatory authorities, accounting standards, and industry-specific compliance and risk considerations. Furthermore, these requirements may change over time, as they are influenced by evolving legislation, updated regulations, revised standards, and shifting risk landscapes. Therefore, for a given year, the HQFS variable for firm i is instrumented with the proportion of firms with HQFS in its industry, within the country it is operating in, excluding firm i's data. This means that the cell is defined by industry-country-year. Excluding firm i's data ensures that the instrument is correlated with HQFS while being independent of firm i's specific HQFS (Kouakou, 2025).[2]

Our instrument reflects the idea that a firm's decision to have HQFS is influenced by industry-level and country-level norms and practices, the latter of which can change over time, as previously explained. Indeed, a firm's decision to adopt HQFS is shaped not only by internal characteristics but also by industry and country norms. Firms often follow peers, so widespread HQFS adoption in a firm's industry increases its likelihood of adoption to remain competitive. Country-specific regulations and auditing standards add further pressure. These norms and regulations evolve over time, influencing adoption rates annually. By considering industry-country-year patterns, the instrument captures external influences on HQFS adoption without directly correlating with firm productivity.

In a nutshell, the more auditing of financial statements is practiced in a firm's industry and in the country where it operates—reflecting the dynamics of auditing in the firm's economic and institutional environment—the more likely the firm is to adopt HQFS. This suggests that the instrument is likely not weak and should be positively and significantly correlated with HQFS. Additionally, our instrument can be considered exogenous, as it is influenced by broader regulatory, risk, legal, and legislative factors rather than the specific labor productivity of any single firm. The exclusion restriction is likely to hold, as the percentage of firms with HQFS in a firm's industry and country in a given year does not inherently impact the labor productivity of firms. Instead, it impacts labor productivity by increasing firms' likelihood of having HQFS. It reflects the overall level of auditing of financial

[2]Formally, let firm i operate in industry q, country c, and year t. Firm i's cell, denoted $h(i, q, c, t)$, is defined as the interaction of the industry, country, and year in which firm i operates. Now, consider a general firm k in this cell, $k = 1, 2, \ldots, N_{h(i,q,c,t)}$. Our IV for firm i is constructed as the proportion of firms in the same cell that have HQFS, excluding firm i itself:

$$Z_{iqct} = \frac{\sum_{k \neq i} hqfs_{kqct}}{N_{h(i,q,c,t)} - 1}$$

statements in the market without directly affecting any single firm's labor productivity. As a result, by meeting these criteria, our instrument successfully isolates the causal effect of HQFS on the labor productivity of firms.[3]

We estimate the following model using the two-stage least squares (2SLS) method:

$$\begin{aligned} labprod_{iqct} &= \beta_0 + \beta hqfs_{iqct} + \mathbf{X}'_{1,iqct}\boldsymbol{\theta_1} + \mathbf{X}'_{2,ct}\boldsymbol{\theta_2} + \lambda_q + \delta_c + \gamma_t + \epsilon_{iqct} \\ hqfs_{iqct} &= \alpha_0 + \alpha Z_{iqct} + \mathbf{X}'_{1,iqct}\boldsymbol{\omega_1} + \mathbf{X}'_{2,ct}\boldsymbol{\omega_2} + \lambda_q + \delta_c + \gamma_t + \upsilon_{iqct} \end{aligned} \tag{1}$$

where $labprod_{iqct}$ and $hqfs_{iqct}$ denote the labor productivity and HQFS variables of firm i in industry q, country c, and year t, respectively. $\mathbf{X}_{1,iqct}$ and $\mathbf{X}_{2,ct}$ are sets of firm-level and country-level control variables, respectively (see Table 1). Z_{iqct} is the IV. β_0 and α_0 are constants, while β and α are parameters to be estimated. $\boldsymbol{\theta_1}$, $\boldsymbol{\theta_2}$, $\boldsymbol{\omega_1}$, and $\boldsymbol{\omega_2}$ are vectors of parameters to be estimated.

λ_q, δ_c, and γ_t represent industry, country, and year fixed effects, respectively, allowing us to control for unobserved heterogeneity. ϵ_{iqct} and υ_{iqct} are error terms. Standard errors are clustered at the industry, country, and year levels to account for correlations in the error terms within industries, countries, and years.

3 Main result and transmission channel

The 2SLS estimates are reported in Table 3.

We find that firms with HQFS exhibit significantly higher labor productivity—approximately 46%[4] higher—suggesting that having HQFS boosts firm labor productivity. The relevance of the instrument is tested using the Kleibergen-Paap underidentification test. To assess the strength of the instrument, we use the Kleibergen-Paap weak identification statistic and compare it to the Stock-Yogo critical values. Additionally, we examine the significance and sign of the coefficient of the instrument in the first-stage regression. As shown in Table 3, all these tests meet the required standards.

To analyze the transmission channel, credit constraints[5], we follow Apeti & Edoh (2023) and Kouakou (2025) and adopt a two-step approach. First, we assess the relevance of credit

[3]As discussed later in the robustness checks section, we tested three alternative instruments. The results from these estimations confirm the findings obtained with our main instrument.

[4] $= [\exp(0.377 - 0.5 \times 0.020^2) - 1] \times 100$. See Kennedy (1981). Halvorsen & Palmquist (1980) show that the parameter value used in this calculation, $\hat{\beta} = 0.377$, is an estimate of $\beta = \ln(1+g)$, where $100 \times g$ is the correct measure of the effect of HQFS on labor productivity. This suggests that g can be estimated by $\hat{g} = \exp(\hat{\beta}) - 1$. Kennedy (1981) shows that this is a biased estimator and demonstrates that a better estimator is $g^* = \exp(\hat{\beta} - 0.5 \times \hat{V}(\hat{\beta})) - 1$, where $\hat{V}(\hat{\beta})$ is an estimate of the variance of $\hat{\beta}$.

[5]Credit constraints are measured using a binary variable that equals 1 if a firm is credit-constrained and 0 otherwise. Figure 1 illustrates its construction. The measurement of credit constraints through a binary variable is standard in the literature. For recent references, see Distinguin et al. (2016) and Kouakou (2025), among others.

Table 3. Effect of HQFS on labor productivity.

HQFS	0.377***
	(0.020)
Firm size	0.091***
	(0.006)
Firm age	0.096***
	(0.007)
Affilation with a large firm	0.217***
	(0.015)
Foreign ownership	0.098***
	(0.004)
Real GDP per capita	2.231***
	(0.277)
Domestic credit to the private sector	0.152*
	(0.091)
Inflation	0.073***
	(0.006)
Control of corruption	0.173
	(0.149)
Constant	-6.490***
	(2.133)
Year fixed effects	Yes
Country fixed effects	Yes
Industry fixed effects	Yes
Clustering level of standard errors	Industry-Country-Year
Kleibergen-Paap underidentification test (p-value)	0.0000
Kleibergen-Paap weak identification statistic	3,910.267
Stock-Yogo highest critical value	16.38
	First-stage regression
Instrument	1.196***
	(0.019)
Adjusted R^2	0.737
Observations	158,983

Notes: 2SLS estimates reported. Standard errors are presented in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

constraints as a potential transmission channel by regressing labor productivity on credit constraints while including control variables, fixed effects, and clustering standard errors at the industry, country, and year levels, as previously done. This estimation, conducted using the ordinary least squares (OLS) method, provides the correlation between the two variables. The results, reported in Panel A of Table 4, indicate that credit constraints are significantly and negatively associated with labor productivity, suggesting that they are likely a relevant transmission channel.

Second, we analyze the effect of HQFS on credit constraints using the 2SLS method. The results, presented in Panel B of Table 4, indicate that HQFS significantly reduces credit constraints.

In summary, HQFS significantly reduces credit constraints, and this reduction, in turn, boosts labor productivity. Hence, a decline in credit constraints is a key channel through which HQFS increases labor productivity.

Furthermore, to reinforce the mechanism analysis, we include the credit constraints variable and its interaction with the HQFS variable in our baseline 2SLS specification. For brevity,

Table 4. Transmission channel.

Panel A: Correlation of credit constraints with labor productivity	OLS estimates
	Dependent variable: Labor productivity
Credit constraints	-0.200***
	(0.012)
Control variables	Yes
Year fixed effects	Yes
Country fixed effects	Yes
Industry fixed effects	Yes
Clustering level of standard errors	Industry-Country-Year
Adjusted R^2	0.735
Observations	159,499
Panel B: Effect of HQFS on credit constraints	**2SLS estimates**
	Dependent variable: Credit constraints
HQFS	-0.021***
	(0.006)
Control variables	Yes
Year fixed effects	Yes
Country fixed effects	Yes
Industry fixed effects	Yes
Clustering level of standard errors	Industry-Country-Year
Kleibergen-Paap underidentification test (p-value)	0.0000
Kleibergen-Paap weak identification statistic	4,130.375
Stock-Yogo highest critical value	16.38
	First-stage regression
Instrument	1.210***
	(0.019)
Adjusted R^2	0.122
Observations	170,538
Panel C: Interaction between HQFS and credit constraints (2SLS estimates)	
HQFS	0.361***
	(0.018)
Credit constraints	-0.196***
	(0.014)
HQFS×Credit constraints	0.035*
	(0.021)

Notes: In Panel B, we perform a 2SLS estimation instead of a maximum likelihood estimation of a recursive Bivariate Probit model with IV, as the latter does not accommodate specifications with a large set of fixed effects—in our case, country, year, and industry fixed effects—well. We do not report the constant terms of the regressions to maintain brevity, but they are included in the estimations. Standard errors are presented in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

we report only the coefficients of the HQFS, credit constraints, and interaction variables in the lower panel (Panel C) of Table 4. The coefficient of the interaction variable is positive and significant, indicating that for credit-constrained firms, the effect of HQFS on labor productivity is stronger than for unconstrained firms. When the interaction term is introduced into the model, the coefficient of HQFS becomes smaller, suggesting that its marginal effect (Kennedy, 1981) is weaker for unconstrained firms, as expected. Moreover, the coefficient of the credit constraints variable is negative and significant, indicating that limited access to credit hampers labor productivity, also as expected. Taken together, the results show that HQFS exerts a stronger positive effect on labor productivity for credit-constrained firms, supporting the view that easing credit constraints is a key mechanism driving this effect.

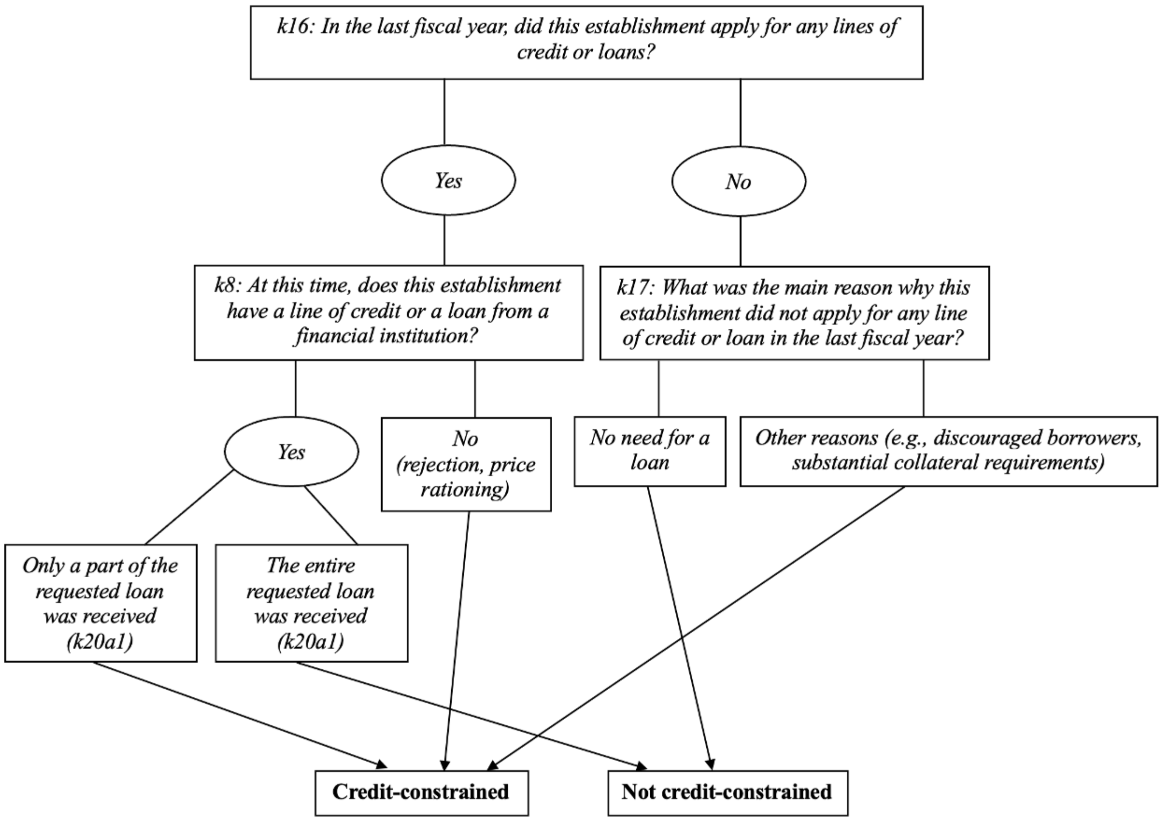

Figure 1. Construction of the credit constraints variable based on the WBES.
Source: Kouakou (2025).

4 Robustness checks

Our results indicate that HQFS significantly increases the labor productivity of firms. This section aims to test the robustness of this finding.

4.1 Propensity score matching

We test the robustness of our main result using four variants of the Propensity Score Matching (PSM) method (Rosenbaum & Rubin, 1983), namely Nearest Neighbor Matching, Radius Matching, Kernel Matching, and Local Linear Regression Matching. PSM is widely recognized for addressing endogeneity issues arising from selection bias. The results of the estimations are reported in Table 5, where the average treatment effect on the treated (ATT) reflects the effect of HQFS on labor productivity.

As shown in Table 5, irrespective of the PSM variant, HQFS significantly (at the 1% level) increases labor productivity. This demonstrates the robustness of our main finding. The

Table 5. 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		
ATT	0.377***	0.382***	0.380***	0.373***	0.374***	0.370***	0.370***	0.373***
	(0.028)	(0.025)	(0.024)	(0.023)	(0.022)	(0.021)	(0.021)	(0.028)
Rubin's B statistic (%)	6.8	7.6	7.5	7.4	7.7	9	8.9	6.8
Rubin's R statistic	0.95	0.93	0.92	0.93	0.93	1.10	1.08	0.95
Observations	160,387	160,387	160,387	160,387	160,387	160,387	160,387	160,387

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

ATTs are close to the 2SLS estimates, further reinforcing the robustness of our results. Rubin's B and R statistics, reported in Table 5, assess the balancing quality. In all variants of PSM, the B statistic is below 25%, while the R statistic falls within the interval $[0.5, 2]$, indicating that the balancing property is achieved.

4.2 Additional robustness checks

We conducted a variety of additional robustness checks.

First, we estimated the effect of HQFS using the Entropy Balancing method (Hainmueller, 2012), an alternative approach to correcting for potential endogeneity arising from selection bias. *Second,* we included a wide range of additional control variables. *Third,* we employed heteroscedasticity-robust standard errors without clustering. *Fourth,* we tested three alternative instruments. On the one hand, we applied the "cell-average method" at the industry-year and country-year levels separately, instead of the industry-country-year level, to construct two alternative instruments. On the other hand, we used an indicator for whether the firm was inspected by tax officials in the past 12 months as an instrument.[6]

Results from all these estimations show that HQFS significantly increases labor productivity, confirming our main finding. These results are not reported in the paper for brevity but are available upon request.

[6]While we acknowledge that the alternative instrument based on tax inspections appears particularly strong and might merit consideration as the primary identification strategy, we elected to relegate it to a robustness check, as from a conceptual and theoretical perspective, some arguments suggest that it may fail to fully satisfy the exclusion restriction and exogeneity conditions. For instance, by discouraging informal labor, tax inspections may incentivize the hiring of formally contracted, often more qualified workers, thereby improving labor productivity. Additionally, tax inspections are not random events: firms that are more productive are more visible to tax authorities and, ceteris paribus, more likely to undergo inspections. Nevertheless, with our data, empirical tests provide no evidence against the relevance of this alternative instrument, which motivates its use as a robustness check.

5 Heterogeneity

We analyze how the effect of HQFS on labor productivity varies across different firm sizes, firm ages, and structural factors, including real GDP per capita, domestic credit to the private sector, and control of corruption. The results are presented in Figure 2, along with the 95% confidence intervals.

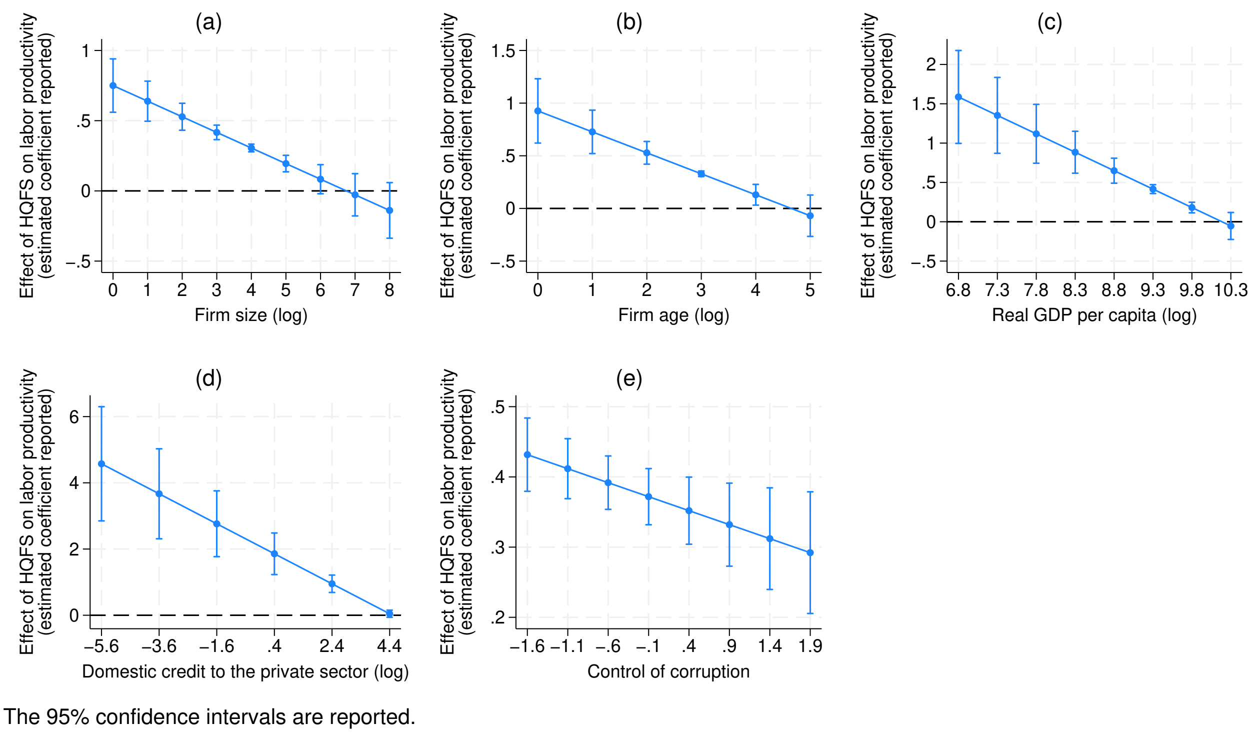

Figure 2. Heterogeneity analysis.

We see from Figure 2 that the effect of HQFS on labor productivity decreases with higher firm size and firm age, indicating that HQFS is more relevant for labor productivity in smaller and younger firms. Indeed, both larger and older firms usually face lower credit constraints (Asiedu et al., 2013; Distinguin et al., 2016), typically due to stronger financial positions, better access to capital markets, a solid credit history, stronger ties with financial institutions, and a better reputation. These factors reduce the importance of HQFS as a stimulus for labor productivity through the channel of easing credit constraints.

Figure 2 also shows that the effect of HQFS on labor productivity decreases with greater structural factors, including higher real GDP per capita, greater domestic credit to the private sector, and better control of corruption. This suggests that HQFS is likely more relevant to labor productivity in less economically developed countries, countries with lower domestic credit mobilization, and countries with weaker control of corruption. Indeed, firms operating in countries with greater domestic credit to the private sector have more access to credit (Asiedu et al., 2013), mitigating the importance of HQFS. Similarly, developed countries possess strong financial institutions, higher levels of investor trust, increased access to collateral, and more advanced capital markets, all of which contribute to a more efficient lending environment, limiting the importance of HQFS. Finally, in environments with lower control of corruption, having HQFS is likely more crucial for access to credit, reinforcing its effect on labor productivity.

Furthermore, we complement Figure 2c,d,e with estimations of the effect of HQFS on labor productivity in subsamples of countries. We consider the IMF country classification, which categorizes countries in the world into three groups: 41 advanced economies (AEs), 96 emerging market and middle-income economies (EMMIEs), and 58 low-income developing countries (LIDCs).[7] This allows us to further specify the nature of the relationship between HQFS and labor productivity in various institutional contexts. The results are reported in Table 6, with columns (1), (2), and (3) reporting estimated coefficients for LIDCs, EMMIEs, and AEs, respectively. We see that HQFS significantly increases labor productivity by approximately 70%,[8] 45%,[9] and 25%[10] in LIDCs, EMMIEs, and AEs, respectively. This indicates that the effect of HQFS decreases with higher levels of development and better institutional settings, and supports the results presented in Figure 2c,d,e. All diagnostic tests are reported in the bottom part of Table 6 and are satisfactory.

Table 6. Subsamples of countries.

	(1) Low-income developing countries	(2) Emerging market and middle-income economies	(3) Advanced economies
HQFS	0.533***	0.371***	0.225***
	(0.048)	(0.022)	(0.032)
Control variables	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes
Clustering level of standard errors	Industry-Country-Year	Industry-Country-Year	Industry-Country-Year
Kleibergen-Paap underidentification test (p-value)	0.0000	0.0000	0.0000
Kleibergen-Paap weak identification statistic	2,101.157	2,185.874	637.417
Stock-Yogo highest critical value	16.38	16.38	16.38
		First-stage regression	
Instrument	1.289***	1.243***	0.885***
	(0.028)	(0.027)	(0.035)
Adjusted R^2	0.622	0.787	0.636
Observations	33,658	103,801	21,524

Notes: 2SLS estimates reported. We do not report the constant terms of the regressions to maintain brevity, but they are included in the estimations. Standard errors are presented in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

6 Conclusions

The main conclusions of the present research are threefold. *First,* HQFS significantly increases labor productivity, by approximately 46%. This finding advances our understanding of the drivers of labor productivity, underscoring the central role of firms' financial transparency. The implication is that firms should invest in verifying and certifying their annual financial statements through external auditors to strengthen performance. Firm strategy may incorporate this by allocating a dedicated budget for such audits and ensuring their systematic implementation. *Second,* access to external finance is a key mechanism underlying

[7] See `https://www.imf.org/external/datamapper/datasets/FM`.

[8] $= [\exp(0.533 - 0.5 \times 0.048^2) - 1] \times 100$. See Kennedy (1981).

[9] $= [\exp(0.371 - 0.5 \times 0.022^2) - 1] \times 100$. See Kennedy (1981).

[10] $= [\exp(0.225 - 0.5 \times 0.032^2) - 1] \times 100$. See Kennedy (1981).

the HQFS-labor productivity relationship. *Third,* the effect of HQFS on labor productivity is heterogeneous across firm sizes, firm ages, and key economic, financial, and institutional factors. Notably, this effect is primarily observed among small, young firms in developing countries.

Data availability statement

The data and code used in this research are available from the author upon request.

Conflict of interest

None.

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