

Measurement Matters: Financial Reporting and Productivity*

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December 1, 2025

Abstract

We examine how differences in financial reporting practices shape firm productivity. Leveraging new audit questions in the U.S. Census Bureau’s 2021 Management and Organizational Practices Survey (MOPS), and complementary tax return data from the Internal Revenue Service (IRS) and detailed financial records from Sageworks, we find that (i) variation in reporting quality explains 10–20 percent of intra-industry total factor productivity dispersion, and (ii) evidence of complementarity between the effects of financial audits and management practices driving firm productivity. We then examine the underlying mechanisms. First, audits function as a managerial technology, improving the precision of internal information and raising efficiency, with stronger effects in competitive, low-margin industries and among younger firms. Second, exploiting cross-state variation in tax incentives, we show that audits constrain underreporting and mitigate the downward bias in measured productivity. Together, these results highlight the underrated importance of financial reporting quality driving firm productivity.

Keywords: Management, productivity, accounting, auditing.

JEL Classification Numbers: D24, G3, L2, M2, M40, O33.

*We thank Philip Berger, Nicholas Bloom, Matthias Breuer, Steve Davis, Michelle Hanlon, Chang-Tai Hsieh, Pete Klenow, Christian Leuz, Valeri Nikolaev, Raffaella Sadun, Nemit Shroff, Andrew Sutherland, Chad Syverson, John Van Reenen, Thomas Wollmann, Luigi Zingales and workshop participants at Carnegie Mellon, MIT, Tilburg, UCLA and the Empirical Management Conference at Harvard for valuable comments. We thank June Huang and Blair Moore for excellent research assistance. This research was conducted using administrative tax data under formal agreements with the IRS. All statistics are presented in the aggregate according to IRS disclosure rules and have been authorized for release. Any opinions are those of the author and do not necessarily reflect the views of the Internal Revenue Service. Any opinions and conclusions expressed herein are those of the authors and do not represent the views of the U.S. Census Bureau. The Census Bureau has ensured appropriate access and use of confidential data and has reviewed these results for disclosure avoidance protection (Project 9040800: CBDRB-FY25-CES007-01).

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1 Introduction

A central fact in productivity research is the large and persistent dispersion in firm performance, even among firms producing similar goods with similar inputs. In U.S. manufacturing, for example, plants at the 90th percentile of total factor productivity (TFP) produce nearly twice as much output as those at the 10th percentile using comparable labor and capital (Syverson, 2004a). Similar dispersion appears across countries, industries, and datasets (Dhrymes, 1991; Doms and Bartelsman, 2000; Syverson, 2004b; Hsieh and Klenow, 2009; Fox and Smeets, 2011).¹ These patterns raise a fundamental question: *why do ostensibly similar firms produce such different outcomes?* (Syverson, 2011; Bloom et al., 2013).

Two broad explanations have dominated the literature. The first stresses measurement: different methodological assumptions and data sources produce different productivity estimates, so part of the cross-firm variation simply reflects differences in how output and inputs are recorded. The second emphasizes real heterogeneity, particularly variation in managerial capabilities. Managers differ in how they hire, monitor, incentivize, and organize workers, and these differences show up in measured productivity (Bertrand and Schoar, 2003; Bloom and Reenen, 2007; Bloom et al., 2019).

While both mechanisms matter in explaining intra-industry productivity dispersion, a significant portion of it remains unexplained (Syverson, 2011). We argue that a key and underexplored determinant of productivity is that of the quality of firms' financial reporting systems. Accounting is not simply a passive camera that records economic activity. It is an information-production technology. Firms choose reporting conventions, the precision of internal tracking systems, and the degree of external verification. These choices affect two things at once: (i) the information managers rely on to allocate resources, and (ii) the information researchers (and policymakers) observe when they compute productivity from financial statements. Better reporting reduces noise and bias in managers internal signals (Bushman and Smith, 2001; Kanodia and Sapra, 2016), while heterogeneity in reporting

¹For an overview of productivity dispersion and its drivers, see Syverson (2011).

systems translates directly into heterogeneity in measured output, costs, and productivity.

In this paper, we bring financial reporting quality into the productivity discussion. We combine three independent datasets on U.S. private firms, including new audit questions from the 2021 Management and Organizational Practices Survey, to study how variation in financial measurement practices correlate with productivity. Private firms, unlike public companies, do not face uniform disclosure mandates. As a result, the quality of financial reporting varies widely across firms (Allee and Yohn, 2009; Lisowsky and Minnis, 2020). We exploit this natural heterogeneity to study financial measurement as an endogenous managerial choice, analogous to goal-setting, monitoring, and incentive design. Using variation in external audits and adherence to higher-quality reporting regimes, we show how financial reporting choices shape both firms reported productivity and their interaction with structured management practices.

In partnership with the U.S. Census Bureau, we added new external-audit questions to the 2021 Management and Organizational Practices Survey (MOPS), which measures establishment-level management practices following Bloom et al. (2019). These new questions let us place financial reporting quality directly alongside structured management practices and examine whether audits operate as a complementary managerial technology. Because MOPS covers only manufacturing establishments, we supplement it with two additional datasets. The first dataset is a comprehensive panel of tax returns for all private U.S. firms with at least \$10 million in assets, obtained by the Internal Revenue Service (IRS), covering years 2008-2010. The second is the Sageworks dataset, which contains detailed financial information on small-to-medium-sized privately held U.S. firms, covering years 2002-2008. Together, these datasets span a broad range of firm sizes, industries, and years, allowing us to study financial measurement quality in a comprehensive and consistent way.

Our primary analysis yields two key findings. First, consistent with previous research, we document substantial heterogeneity in firm productivity within well-defined industries. Second, we show that financial measurement quality, the adherence to higher-quality re-

reporting standards and external verification through audits or reviews, explains a meaningful share of this dispersion. Across all three datasets, variation in reporting quality accounts for roughly 1020 percent of the 9010 TFP spread. The magnitude is comparable to other well-known drivers of productivity, including information technology, human capital, and structured management practices (Bloom et al., 2019). In addition, these estimates are robust across specifications including propensity-score matching, weighted regressions, and alternative productivity measures and remain stable after controlling for firm size, industry, and capital structure. The consistency of these results indicates that financial reporting quality is not merely a proxy for broader firm characteristics, but an independent and economically significant determinant of firm-level productivity.

A natural question raised by these results is whether financial reporting quality is simply capturing broader managerial sophistication. Firms with strong management systems may also be the ones that choose higher-quality reporting, making it difficult to disentangle whether audits themselves matter or whether they merely signal better-run firms. The 2021 MOPS data allows us to address this directly because it jointly measures structured management practices and our new audit indicator at the establishment level. We begin by documenting that the two are positively correlated: firms with stronger management practices are more likely to obtain higher-quality financial reporting. We then estimate regressions that include both measures as predictors of TFP. When entered together, the coefficients on both variables decline slightly relative to single-variable specifications but remain large, statistically significant, and economically meaningful. Moving from no external verification to a full audit is associated with an increase of 10% to 12% in TFP, similar in magnitude to the productivity gains associated with the adoption of structured management practices. These results show that audits are not simply redundant with management practices; financial reporting quality operates as a distinct managerial technology that contributes independently to productivity.

Having established that financial reporting quality is strongly associated with produc-

tivity, we explore the channels behind their relationship. Financial reporting can affect productivity through two conceptually distinct channels. First, accounting systems generate the information managers use to run the firm. More precise information can improve decisions and raise actual productivity. Second, reporting choices directly influence the data used to construct measured productivity. Higher-quality reporting may therefore reduce bias in reported output, independent of any real efficiency gains. We examine both channels.

First, accurate and timely financial information sharpens managers internal signals (David et al., 2016), allowing for more efficient allocation of resources and better responses to competitive conditions. Consistent with this view, cross-sectional analyzes reveal that the productivity benefits of high-quality financial measurement are particularly pronounced in settings where information precision is critical for operational efficiency, such as highly competitive industries where even marginal efficiency gains provide a competitive advantage. Similarly, younger firms, those still in the process of developing robust managerial systems, exhibit larger productivity gains, suggesting that financial measurement quality plays a critical role in firm learning and strategic decision-making. In contrast, in high-innovation industries, where long-term investments in R&D and intangible assets drive growth (as opposed to information quality, *per se*), the relationship between financial reporting quality and productivity is weaker. This suggests that the value of precise financial information depends on the nature of the firms production technology.

We further explore the relationship between financial measurement quality and firm performance by leveraging the panel structure of the IRS data. Prior literature suggests that more productive firms are more likely to survive over time (Syverson, 2011). Consistent with this, we find that firms with higher investment in financial measurement quality experience a significant increase in their likelihood of survival. Specifically, those who conduct audits are about 7% more likely to survive over a two-year horizon compared to firms with weaker financial reporting practices. This survival persists even when controlling for baseline productivity levels, indicating that financial reporting quality plays a meaningful role in firm

longevity.

Next, we examine how productivity changes when firms upgrade their reporting quality. Because auditors conduct most of their work after the fiscal year-end, improved internal information should have little effect on productivity in the first audit year. The first audit primarily corrects discretion, errors, and bias; subsequent audits involve far fewer adjustments. Thus, any increase in productivity after the initial audit year would be consistent with a learning channel in which better reporting improves managerial decisions over time. Using a firm fixed-effects design, we compare firms that increased their reporting quality in one year (i.e., engaged an external auditor) to firms which maintained a consistent reporting regime. We find no significant change in TFP in the first year of an audit, but a substantial increase in the second year, consistent with a learning effect. Although this test has limitations, the timing pattern suggests that higher-quality financial reporting contributes to real productivity gains by improving the information managers use to run the firm.

The second mechanism operates through measurement bias. Firms have incentives to understate production to reduce tax liabilities (Balakrishnan et al., 2018), and these incentives can distort measured productivity. External audits constrain this discretion and reduce misreporting (DeFond and Zhang, 2014). To test this channel, we exploit cross-state differences in tax regimes, which generate variation in firms incentives to bias reports. For example, in high-tax states such as California, where the incentives to under-report income is strongest (and, thus, the level of production for a given level of inputs), the association between reporting quality and measured productivity is nearly twice as large as in low-tax states such as Texas. This pattern indicates that external audits curb under-reporting and reduce spurious dispersion in measured productivity. Auditing therefore serves as an important mechanism for ensuring the reliability of financial data, particularly in environments where misreporting incentives are strongest.²

Our findings contribute to the economics of productivity and management by identifying

²See also Hoopes et al. (2012); Hanlon et al. (2014) on the disciplining effects of tax authority monitoring and enforcement.

financial measurement quality as a distinct and understudied source of productivity dispersion. A well-established body of research views structured management practices, such as goal-setting, employee monitoring, and performance incentives, as a “technology” that systematically improves efficiency (Bloom and Reenen, 2007; Bloom et al., 2019). We extend this perspective by showing that a firm’s investment in high-quality financial reporting is itself a managerial decision that influences productivity. Measurement is not merely a passive backdrop to managerial decision-making; it is part of the technology that managers use to run the firm.

This perspective departs from traditional frameworks that treat accounting as a standardized, mechanical mapping from economic activity to reported outcomes. In practice, firms adopt heterogeneous reporting conventions and invest differentially in verification and monitoring. We show that this heterogeneity generates systematic differences in both reported and actual productivity. Moreover, by directly comparing the quality of financial measurement to structured management practices, our findings reveal that high-quality financial reporting is comparable to management practices to explain productivity. Financial measurement quality is therefore not simply correlated with performance; it is a meaningful input into the production of information that managers use to make decisions.

Our results also have implications for the economics of productivity measurement. Widely used datasets, including IRS returns, the Economic Census, and Compustat, rely on firm-reported financial and production data. If firms differ in how precisely they measure and report economic activity, these differences can bias productivity estimates and inflate measured dispersion. Our evidence suggests that heterogeneity in financial measurement quality is a first-order consideration when interpreting productivity statistics, with implications for empirical work in labor, IO, public finance, and macro-productivity.

Finally, we contribute to the accounting literature linking financial reporting quality to real firm-level outcomes. Prior research emphasizes effects on investment efficiency, tax strategies, and managerial decision-making (McNichols and Stubben, 2008; Cheng et al.,

2013; Feng et al., 2015; Shroff, 2017; Choi, 2021; Breuer, 2018). For example, Holzman et al. (2020) consider the attributes of the manager and find that entrepreneurs with accounting background start companies that are more likely to achieve profitability. We complement this literature by reframing financial reporting not merely as a compliance requirement but as a managerial input that directly shapes firm performance. In this sense, accounting quality belongs alongside management, capital, and technology as a key determinant of productivity.

2 Financial Reporting Measurement and Productivity

This section develops a simple framework that connects financial reporting decisions of firms with productivity dispersion. We first show how variation in accounting standards and attestation generates systematic differences in reported outputs and inputs. We then demonstrate how these reporting differences feed directly into standard productivity measures, potentially distorting comparisons across firms. We conclude by outlining how higher-quality financial reporting can raise actual productivity by improving the information managers use to allocate resources.

2.1 Financial Reporting Heterogeneity: Accounting Standards and Attestation

In evaluating firm performance, economists and policymakers often rely on reported financial statements to measure inputs, outputs, and profitability. However, the extent to which these reported metrics capture true economic activity remains an open question. Firms choose accounting standards that govern how they recognize revenues and expenses, and they may also face varying levels of attestation, such as independent audits, that constrain managerial discretion. These reporting decisions can produce substantial heterogeneity in measured performance, with real implications for understanding productivity, investment decisions, and economic growth.

2.1.1 Accounting Standards as Transformation Function

Financial reporting is not merely a mechanical documentation of economic events. Instead, it is the product of firms selecting and applying *accounting standards* that transform true economic activity into reported financial outcomes. Formally, let X_i be the underlying economic activity—e.g., real outputs or costs—of firm i . We denote its reported financial outcomes by:

$$R_i = g(X_i), \tag{1}$$

where $g(\cdot)$ represents a transformation function determined by the accounting framework chosen and the discretionary implementation of the firm.

GAAP and Accrual-Based Accounting. In the United States, publicly traded firms must generally adhere to *Generally Accepted Accounting Principles (GAAP)*, which is accrual-based: revenues and expenses are recognized when an economic event occurs, not when cash is exchanged. Formally, we write:

$$g_{\text{GAAP}}(X_i) \approx X_i. \tag{2}$$

This approach seeks to align reported performance with actual economic activity. While it reduces temporal mismatches, GAAP still allows managers some discretion—e.g. in estimating bad debt reserves or depreciation schedules.³

Tax-Based Accounting. Many private firms use tax-based accounting to minimize taxable income. This can be captured as:

$$g_{\text{Tax}}(X_i) = X_i - \delta_i, \tag{3}$$

³Outside the U.S., many firms adopt *International Financial Reporting Standards (IFRS)*, which share similarities with GAAP but differ in specific rules for revenue recognition and asset valuation. Cross-country studies often reveal further heterogeneity stemming from IFRS/GAAP divergences, cultural norms, and local enforcement environments. As with GAAP, IFRS is designed to approximate economic reality, but subtle differences may still produce variation in reported outcomes.

where δ_i includes strategic deductions, e.g., accelerated depreciation. Two firms with identical operational profiles may report different profits if one emphasizes tax minimization, while the other follows GAAP.

Cash Accounting. In contrast, cash-based accounting records transactions only upon actual cash exchange:

$$g_{\text{Cash}}(X_i) = X_i \mathbb{I}[\text{cash at time } t]. \quad (4)$$

Under cash accounting, uncollected receivables or unpaid bills remain off the books until actual payment occurs, creating a timing mismatch between real economic events and their reported outcomes. This simplicity can be advantageous for smaller firms, reducing administrative burdens and bookkeeping complexity. However, cash-based accounting introduces a sizable temporal distortion in reported revenues and expenses.

Such distortions are especially pronounced in periods when a firm experiences significant delays in collecting payments or large swings in accounts payable. Cash-based firms might therefore appear highly profitable in one period and minimally profitable (or even loss-making) in the next, despite consistent underlying economic performance. When constructing productivity measures, this volatility complicates efforts to estimate a firm’s actual output trends or cost structure. In addition, comparing a firm cash-based performance to that of a GAAP-based one can conflate timing-driven fluctuations with genuine efficiency differences.

2.1.2 Attestation and Auditing as Verification Mechanisms

Even within an accounting framework, managerial discretion while applying accounting rules can produce heterogeneous reports. We therefore introduce *attestation* as an additional layer of verification. An *audit* or *review* involves an external party validating the firm’s financial statements. Formally:

$$R_i^* = g_j(X_i) + \epsilon_i, \quad (5)$$

where R_i^* is the *verified* outcome, $g_j(\cdot)$ is the chosen accounting transformation, and ϵ_i represents either intentional misreporting or errors that an audit attempts to correct. By requiring evidence-based substantiation of reported items—e.g. confirming inventories, and cross-checking payables—auditing narrows the scope for manipulation.

Although publicly listed companies in the U.S. must file GAAP-compliant audited statements, private non-listed firms, comprising the majority of U.S. businesses, typically face no universal audit mandate (Allee and Yohn, 2009). As a result, private firms can choose whether to engage in an audit, where firms balance costs, such as audit fees or disclosure, against benefits, such as reduced financing frictions or better internal information.

Finally, attestation occurs to different degrees: *compilation* (minimal checks), *review* (analytical procedures and inquiries), and *full audit* (in-depth testing, verification, and opinion issuance). Each higher level of attestation reduces ϵ_i , improving the reliability of financial statements and potentially improving the precision of subsequent productivity analysis.

Financial Reporting as an Economic Choice Both accounting frameworks and attestation levels are strategically chosen by companies. The U.S. provides a natural setting for examining variation in reporting practices, as publicly traded firms are required to file GAAP-compliant audited financial statements under SEC regulations, whereas private firm-constituting 99 percent of all U.S. businesses and nearly half of non-government GDP face no such mandate. Instead, private firms select their accounting standards and attestation levels based on cost-benefit trade-offs (Allee and Yohn, 2009; Lisowsky and Minnis, 2020).

Figure 1 illustrates this variation, showing the proportion of firms that adhere to GAAP and obtain an audit across industries. The figure reveals substantial heterogeneity, with audit rates ranging from 20 to 60 percent, reflecting industry-specific demand for financial transparency. The literature often frames firms’ financial reporting choices within an *agency theory* perspective, positing that attestation mitigates asymmetric information between managers and external capital providers. However, even among firms with significant external

debt and dispersed ownership, many opt out of audits or GAAP compliance, as shown in Figure 2. This suggests that financial reporting serves functions beyond external financing, potentially affecting internal resource allocation and firm productivity.

2.2 Financial Reporting Bias and Measured Productivity

To illustrate how financial reporting practices affect measured productivity, consider a standard Cobb-Douglas production function:

$$Y_{it} = A_{it} K_{it}^{\alpha} L_{it}^{\beta}, \quad (6)$$

where Y_{it} denotes firm i 's true output in period t , K_{it} is the capital input, L_{it} is labor input, and A_{it} is the firm's total factor productivity (TFP). Empirically, TFP is often treated as the residual from a log-linearized version of (6):

$$\log \hat{A}_{it} = \log Y_{it} - \hat{\alpha} \log K_{it} - \hat{\beta} \log L_{it}. \quad (7)$$

In principle, \hat{A}_{it} captures all efficiency differences not explained by capital and labor. However, when researchers measure Y_{it} , K_{it} , or L_{it} using firms' financial statements, any systematic misreporting or noise induced by an accounting regime ends up in the TFP residual. Although errors in reporting labor or capital could also matter, we focus on the relation between the missing measurement and TFP.⁴

Since financial statements do not necessarily mirror real economic activity, the reported output R_{Y_i} can differ from the firm's true output Y_i via an accounting transformation function $g_Y(\cdot)$. For example, a cash-based regime may shift revenue recognition into later periods, while a GAAP-based regime records revenue when it is earned. Thus, even if two firms have

⁴For instance, a firm using tax-based accounting might under-report revenues to reduce taxable income, thereby inflating the TFP residual when capital and labor are reported more accurately or remain less manipulable.

the same underlying production technology and true output, they may show different values of R_{Y_i} for the same period.

As a result, when we substitute $\log R_{Y_i}$ for $\log Y_i$ in (7), the TFP residual, $\log \hat{A}_{it}$, potentially reflects both true productivity differences and discrepancies in how output is recorded. Firms adopting aggressive revenue-recognition methods or strategic cost shifting could appear more or less productive than peers whose accounting closely tracks economic reality. This conflation creates a fundamental identification challenge: is a high TFP residual indicative of genuine operational efficiency, or merely the outcome of favorable (or strictly compliant) financial reporting? Conversely, a low TFP estimate might reflect under-reporting of revenues by firms seeking to minimize tax liability, rather than actual operational inefficiency.

Similarly, cross-firm comparisons of \hat{A}_{it} may overstate the true productivity dispersion if some share of the variation reflects differences in accounting treatments rather than differences in production technology or managerial capabilities.

In sum, different financial reporting standards or attestation levels systematically shape R_{Y_i} . Since TFP is derived as a residual, these reporting-based distortions become embedded in \hat{A}_{it} , potentially masking or exaggerating underlying productivity differences.

2.3 Financial Measurement as a Managerial Technology

High-quality financial reporting can also serve as a *managerial technology* that raises a firm's *actual* productivity. In other words, financial reporting practices impact real operational efficiency by enhancing information precision and managerial decision-making.

Following David et al. (2016), let a firm's true productivity be A_i , which can be expressed in logs as $S_i = \log(A_i)$. Although managers aim to allocate resources (capital, labor, R&D, etc.) optimally based on their productivity level, they do not observe S_i directly. Instead, they receive a noisy internal signal:

$$S_i^* = S_i + \nu_i, \quad \nu_i \sim \mathcal{N}(0, \sigma_\nu^2), \quad (8)$$

where ν_i captures the imprecision in the firms accounting system, operational data, and managerial reports. A higher σ_ν^2 implies greater uncertainty about the underlying productivity of the firm, which can lead to suboptimal choices in capital expenditures, hiring, or inventory management.

To formalize how accounting oversight affects productivity, let $\gamma \geq 0$ represent the strength of the oversight regime, reflecting factors such as the rigor of external auditing or the robustness of internal controls. Higher oversight strength (γ) directly reduces the noise (σ_ν) in managers' internal signals about their firm's true productivity ($S_i = \log(A_i)$). Formally, this implies $\sigma_\nu = \sigma_\nu(\gamma)$ with $\partial\sigma_\nu/\partial\gamma < 0$: as the oversight improves, the internal productivity signal becomes more precise.

Reduction in the noise of the signal allows managers to make better informed decisions regarding resource allocation, capital investments, and operational efficiency. In practice, enhanced oversight, through rigorous accrual-based accounting, meticulous record keeping, and thorough auditing, enables managers to accurately identify high-return investment opportunities, eliminate inefficient cost centers, and channel resources more effectively to profitable business segments.⁵

Because $A_i = e^{S_i}$ is the firms true productivity, we obtain the following predictions:

$$\frac{\partial A_i}{\partial \sigma_\nu} < 0 \quad \text{and} \quad \frac{\partial A_i}{\partial \gamma} > 0. \quad (9)$$

Thus, increasing oversight (γ) reduces signal noise (σ_ν), clarifies managerial perceptions of true productivity (S_i), and ultimately improves the actual productivity of the firm (A_i).

To see why stronger oversight can raise productivity, consider a stylized setup in which a firm decides on an input level K (capital, R&D, etc.) based on its perceived productivity

⁵An alternative view of financial reporting quality is that audited financial reports serve primarily as a financial communication tool for external investors rather than as an internal decision-making aid. For example, the stated objective of GAAP is to provide investors with information about a firm's future cash flows. This orientation suggests that auditing and GAAP primarily improve the external information environment rather than directly improving internal resource allocation.

S_i^* . Specifically, let the firm's profit Π be given by:

$$\Pi = \exp(S_i) f(K) - rK,$$

where $f(K)$ is concave in K (capital, broadly conceived) and r is the cost of capital. In the absence of noise ($\sigma_\nu^2 = 0$), a manager observing S_i would choose the optimal K^* to maximize Π . However, with imperfect information $S_i^* = S_i + \nu_i$, the chosen capital level $K = \phi(S_i^*)$ can deviate from K^* if ν_i is large. This deviation reduces expected profits and productivity. Oversight (γ) that reduces σ_ν keeps the managers chosen K closer to K^* , increases Π and increases A_i .

External audits exemplify the practical role of oversight strength (γ). While the primary objective of auditing is to verify the accuracy and credibility of reported financial information, the audit process typically extends beyond accounting records to include an examination of internal operational practices, such as inventory management, payroll systems, and procurement processes. Through detailed testing of transactions and verification of supporting documentation, auditors frequently uncover operational inefficiencies or irregularities previously unnoticed by internal management, such as redundant labor practices or excessive inventory holdings.

Consequently, auditing functions as an *information-refining technology*, providing managers not only with more accurate financial figures (affecting measured TFP) but also with valuable insights to inform strategic decision-making and operational improvements. Thus, any observed correlation between stronger auditing oversight and higher measured productivity may reflect not only cleaner reporting, but genuine improvements in firm efficiency resulting from improved managerial resource allocation (see Feng et al., 2015).⁶

In sum, while variations in financial reporting regimes can create measurement biases

⁶Internal accounting systems and managerial controls similarly refine the firm's information environment. Practices such as regular variance analysis, frequent managerial reporting, and high-quality bookkeeping reduce information noise (σ_ν^2) independently of external audits. Investigating the direct productivity impacts of these internal practices constitutes a promising area for future research, although it falls outside the scope of the current study.

in the TFP residual, they can also shape actual TFP by influencing the quality of the firm’s internal information. Firms that systematically adopt more accurate reporting and stricter oversight are better positioned to identify unproductive activities, invest in profitable opportunities, and respond effectively to changing market conditions. The result is a potential *positive feedback loop*: better information promotes better decisions, which in turn can generate higher profitability and possibly more willingness to maintain (or strengthen) high-quality reporting structures.

3 Data

U.S. Census Data. Our main dataset is the Management and Organizational Practices Survey (MOPS) from 2021, which is a supplement to the 2021 Annual Survey of Manufactures (ASM). We partnered with the U.S. Census Bureau to include three new audit-related questions that we helped design specifically for this survey. The unique feature of this dataset is that we can now correlate variation on financial audits and productivity at the establishment or firm level.

From the 2021 MOPS, we construct two primary variables: a Management Score and an Audit Score. The Management Score is derived following the methodology of Bloom et al. (2019), summarizing responses to 16 management practice questions into a normalized value between 0 (worst) and 1 (best). The Audit Score is constructed from responses to the audit-related question, In 2021, did your company retain an external Certified Public Accountant to conduct an audit, review, or compilation of its financial statements? Responses are mapped to a scale: 1 for audits, $\frac{2}{3}$ for reviews, $\frac{1}{3}$ for compilations, and 0 for no engagement. Establishments responding Do not know are excluded.

The MOPS data is merged with the ASM, providing establishment-level measures of capital, labor, sales, profits, cost of goods sold, educational attainment of employees, and other production factors. Aggregation to the firm level is necessary for multi-unit firms,

using sales-weighted averages for management scores and modal responses for audit scores. The state and industry assignments are based on the establishment with the highest sales.

IRS Data. The IRS dataset provides comprehensive panel data covering medium-to-large private U.S. firms, capturing detailed information on their financial reporting practices, income statements, expenses, and balance sheet items. Firms included in the dataset span a wide range of industries, offering extensive cross-sectional coverage of the private-firm landscape. However, the representation of firm-years across NAICS sectors differs notably from that observed in publicly available datasets such as Compustat. Specifically, the IRS data exhibit a higher prevalence of firms in sectors such as Construction and Wholesale Trade, compared to Manufacturing and Technology sectors, which tend to dominate public-firm datasets. This difference in industry composition aligns closely with the known structure of the broader population of privately held U.S. firms, accurately reflecting the significant economic contribution of sectors typically underrepresented in public data (see Lisowsky and Minnis (2020)). For example, Construction and Wholesale Trade collectively constitute a substantial fraction of the dataset, consistent with their outsized role in employment, revenue generation, and economic activity among private enterprises. Table 1 further details the distribution of firm-years across NAICS sectors, highlighting these distinct patterns and underscoring the key contrasts between the IRS dataset and commonly used public-firm samples, particularly the notably lower representation of Manufacturing firms. Understanding these sectoral differences is crucial, as they inform the external validity of analyses conducted using the IRS dataset, particularly regarding the generalizability of findings to the broader private-firm population.

Sageworks Data. Finally, we use the Sageworks dataset to complement IRS data by focusing primarily on smaller firms, capturing detailed financial information such as income statements, balance sheets, and labor metrics. Similarly to the IRS dataset, the distribution of firm years across NAICS sectors in Sageworks highlights a stronger focus on industries

like Construction and Wholesale trade, which aligns with the characteristics of privately held firms in the U.S. economy. However, slight differences in representation are evident compared to the IRS dataset, particularly in the Retail trade sector.⁷ As shown in Table 1, the distributions in both datasets broadly reflect the economic realities of private firms while highlighting the unique characteristics of smaller versus larger businesses.

4 Results: Reporting Quality and Productivity

In this section, we examine the link between financial reporting quality and firm productivity. We begin with descriptive evidence on how productivity distributions shift across reporting regimes. We then probe the robustness of our results along the dimensions of size, capital access, and industry.

4.1 Baseline associations and dispersion shares across datasets

We begin with descriptive evidence on the link between reporting quality and productivity. Table 2 reports the descriptive statistics (mean, median, variance and interquartile ranges) for firm-level total factor productivity (TFP-VA) for firms grouped by reporting quality levels. Across the Census, IRS, and Sageworks datasets, we find that the mean and median TFP-VA increase monotonically with reporting quality, while dispersion remains stable. These patterns indicate that higher-quality financial measurement shift the distribution of productivity upward rather than compressing it.

We next examine the distribution of TFP-VA by reporting practice across industries using the IRS and Sageworks data in Figure 3. Figure 3 shows, consistent with our theoretical framework, that the entire distribution shifts rightward as reporting quality improves: firms using cash- or tax-based accounting without verification lie at the lower end, while

⁷Our measure of productivity, TFP, is estimated using a standard Cobb-Douglas production function, separately for the IRS and Sageworks datasets. Detailed descriptions of the estimation procedures, including the specification, fixed effects, and matching procedures used, are provided in Appendix A.

GAAP-compliant audited firms occupy the upper end. This shift is broad-based and is not concentrated around the mean, consistent with a variance-preserving shift, suggesting widespread improvements rather than gains restricted to a subset of firms.

These initial descriptive patterns suggest an economically significant role for financial reporting quality in shaping productivity outcomes. However, such cross-sectional comparisons may also capture size, financing, or industry composition, we next turn to a multivariable analysis to isolate the distinct contribution of reporting quality.

4.2 Regression Evidence on Reporting Quality and Productivity

We formally assess the relationship between the quality of financial reporting as measured by an audit and productivity through regression analyses. Table 3 reports estimates from regressions of firm-level TFP-VA (constructed as described in Appendix A) on indicators of reporting quality. Our specification takes the following form:

$$\widehat{TFP}_{ijt} = \beta_0 + \beta_1, ReportingQuality_{ijt} + \gamma_{jt} + \varepsilon_{ijt}, \quad (10)$$

where \widehat{TFP}_{ijt} is the estimated productivity residual for firm i in industry j at time t , $ReportingQuality_{ijt}$ is our measure of financial reporting quality (e.g. external audit indicator) and γ_{jt} represents fixed effects of industry year. Standard errors are clustered at the industry-year level to account for the possible correlation between groups in errors.

Columns 1 – 3 of Table 3, report the results for the Census sample. The baseline pooled specification (Column 1), yields a coefficient of 0.098, equal to 6.9% of the unconditional 9010 productivity spread. Propensity-score matching (Column 2) and weighted regressions (Column 3) produce larger estimates of 0.124 and 0.136, suggesting that the effect is not driven by differences in size or input use. Columns 4 – 6 report results from the IRS sample. The pooled estimate in Column 4 produces a highly significant coefficient of 0.108, or 8.4% of the 9010 spread, with similar magnitudes under matching (0.087) and weighted estimation

(0.100). Column 79 uses the Sagework sample, where the gradation between compilations, reviews, and audits allows for sharper contrasts. Moving from a compilation to an audit is associated with roughly 0.31 log points higher productivity, approximately 20% of the 9010 spread. Matching and weighted regressions (Columns 8 and 9) confirm large, stable effects (0.272 and 0.311).

Taken together, the evidence from Census, IRS and Sageworks underscore the robust association between improved financial reporting practices and firm productivity. The consistency and magnitude of these estimates across multiple datasets and specifications strongly suggest that better financial measurement systems are not merely a superficial aspect of firm management; rather, they likely play a critical role in facilitating efficient resource allocation and improving operational decision making.

4.3 Benchmarking Financial Reporting Audits Against Management Practice

We next benchmark reporting quality against structured management practices using the Census MOPS data. Table 4 reports the distribution of firms financial reporting choices—ranging from audited financial statements to no external verification—across quintiles of the Management Practice Scores. Table 4 documents a strong positive correlation: firms with higher management scores are more likely to employ external audits. In the lowest quintile of the management distribution, only 12% of firms report audited statements, while nearly a third have no external verification. At the top quintile, 62% of firms obtain audits and fewer than 6% forgo external verification. These patterns highlight a close alignment between high-quality management and rigorous financial reporting.

We then formally assess whether reporting quality contributes beyond management practices in explaining productivity and profitability. We perform a direct comparative analysis (horse race) in Table 5, where we regress firm productivity (value added per worker, $\log(VA/L)$) and profitability (profits over sales) on our standardized GAAP audit indica-

tors (CPA_i), standardized Management Practice Scores ($Manag_i$), and their interaction. We find that both dimensions matter independently. Firms with audits are about 2.5–3% more productive and 0.7–0.8% more profitable, while firms with stronger management practices show similar gains of 2.7–3.4% and 0.8–0.9%, respectively. Including both measures attenuates the coefficients slightly, but each remains statistically and economically significant. Overall, these results indicate that the quality of financial reporting is not simply a proxy for structured management. Instead, it stands alongside management practices as an independent determinant of firm performance.

4.4 Robustness Analysis

We conduct several robustness tests to further validate our main results. Specifically, we address three central concerns: (i) firm size, (ii) differential access to capital markets, and (iii) generalizability across industries. These analyses aim to ensure that our documented relationship between financial reporting quality and productivity is not spuriously driven by correlated firm characteristics.

Firm Size and Propensity Score Matching. As shown in Table 2, higher-quality financial reporting increases with firm size. Since larger firms may benefit from scale economies or face agency frictions that require better reporting, this correlation could confound our results.⁸

To address this, we match firms within industry-year cells on inputs (log labor and log capital), using a 0.03 caliper without replacement. Columns 2, 5, and 8 of Table 3 show that the audit premium remains large and significant after matching: 0.124 in Census (8.7% of the 9010 gap), 0.087 in IRS (6.7%), and 0.272 in Sageworks (18.3%). These results indicate that observable size and input differences do not drive our main findings.

⁸Note that standard productivity models predict that better-managed (and hence more productive) firms attract more resources and thus become larger over time (see, e.g., Syverson (2011); Bloom et al. (2017)). Therefore, firm size is commonly an outcome, rather than a control variable, and explicitly controlling for firm size may understate the true productivity differences stemming from improved reporting quality.

Capital Market Access and Capital Structure. Firms often adopt audited statements to ease financing, raising the concern that our results simply capture capital access effects (Hsieh and Klenow, 2009; Rajan and Zingales, 1998). However, Figure 2, Panel B shows substantial variation in reporting quality even among firms with minimal or no external debt, suggesting that capital market access alone is unlikely to explain the observed productivity differences entirely. To test this more directly, we leverage the detailed capital structure data available in the IRS sample. Specifically, Table 6 partitions IRS firms by leverage and ownership dispersion. The auditTFP association remains positive and significant in all groups, with the highest coefficients among highly leveraged firms with dispersed ownership, arguably a setting where agency conflicts are most severe. Although both capital structure and reporting are endogenous, these patterns suggest that financing access alone does not explain our results.

Generalizing results across Industries. Finally, we estimate industry-specific production functions (Table A1) and audit regressions (Table 3) for sectors with at least 500 observations. Figures 3a and 3b show that the positive auditTFP relationship holds across industries in IRS and Sageworks samples, while Figure 4 documents the sizable contribution of reporting quality in explaining the proportion of within-industry 90-10 productivity dispersion. Additionally, results from the Census sample which also focus on manufacturing (Table 3, Columns 13), further bolster the generalization and credibility of our findings.

Across all three robustness dimensions, the evidence points to a consistent conclusion: the productivity premium associated with financial reporting quality is not an artifact of size, financing, or industry composition, but a pervasive and economically meaningful feature of firm performance.

5 Mechanisms: Management Technology and Measurement Bias

Thus far, we have demonstrated that financial reporting quality is robust and economically meaningful in its association with higher firm-level productivity. In addition, these associations persist even after controlling for firm size, capital market access, and industry composition. However, as highlighted in our conceptual framework, productivity measured via financial statements (the TFP residual) reflects two distinct but potentially complementary channels: (i) *improvements in managerial decision-making* stemming from higher-quality internal information, and (ii) *measurement biases* arising from differing financial reporting incentives, such as tax minimization.

5.1 Financial Reporting Quality as a Management Technology

If higher-quality reporting improves the information environment available to managers, it should operate as a managerial technology: increasing productivity directly, interacting with other practices, and producing persistent performance gains. We present three sets of evidence: (i) complementarity with structured management practices, (ii) heterogeneity across settings where managerial information is more or less valuable, and (iii) panel dynamics in firm survival and growth.

5.1.1 Complementarity with Management Practices

Table 5 shows that audits and structured management practices each predict higher productivity and profitability, with magnitudes on the order of 2.5–3.5% in productivity and 0.7–0.9% in profitability. When both measures are entered together, each remains statistically and economically significant. This confirms that reporting quality is not just a proxy for managerial ability already captured by the MOPS index, but an independent driver of performance

Importantly, the interaction between audits and management practices is positive and significant (Columns 4 and 8), suggesting that combining strong management with rigorous audits outperforms what would be expected from either practice alone. Productivity is roughly 2.2% higher and profitability 0.3% higher in firms adopting both. Within our conceptual framework, this pattern highlights the complementarity between these two distinct managerial technologies. Structured management systems discipline the use of labor and capital, while audits sharpen the underlying information on which those systems rely. When presented together, the two reinforce each other, better management increases the payoff from accurate measurement, and higher-quality measurement amplifies the effectiveness of structured management.

5.1.2 Cross-Sectional Evidence on Managerial Information Value

In our framework, audits improve decision-making by reducing noise in the firms internal signals, so their benefits should be largest where precise information has the highest marginal value. Three settings stand out. First, in industries with thin profit margins, small efficiency gains are critical, implying stronger returns to precise measurement. Second, in innovation-intensive industries, where productivity depends more on forward-looking R&D activity than on current operating efficiency, the value of improved financial measurement should be weaker. Third, younger firms, which lack established systems, should especially benefit from auditors guidance in shaping internal processes.

Table 7 tests these predictions. Columns 1 and 2 construct industry-level measures of competition (profit margins) and innovation intensity (R&D-to-sales) using Compustat data at the 3-digit NAICS level. Consistent with our framework, the audit premium is larger in low-margin industries, although not statistically significant. In contrast, the interaction between reporting quality and R&D intensity is negative and significant: audits are less valuable in innovation-driven contexts, where immediate operating efficiency is not the binding constraint. Column 3 uses IRS data to examine firm age. The positive and significant in-

teraction between audits and the Young Firm indicator confirms that younger firms benefit disproportionately from high-quality reporting. This pattern fits the mechanism: when internal processes are less developed, auditors involvement provides sharper information and discipline, translating into larger productivity gains.

5.1.3 Time-Series Evidence on Survival and Growth

We next exploit the panel structure of the IRS data to assess the dynamic consequences of audits. Survival provides a sharp test of whether firms can sustain operations beyond short-term reporting gains. Table 9 summarizes these results. Column 1 shows that estimated TFP strongly predicts survival between 2008 and 2010. Column 2 demonstrates that high-quality reporting also predicts survival on its own. When both are included (Column 3), each remains significant, though attenuated, indicating that reporting quality affects survival above and beyond baseline productivity. Firms with audited statements are 6.3% more likely to survive, equivalent to about one-quarter of the unconditional exit rate. This magnitude is nearly identical to the survival premium associated with structured management practices documented by Bloom et al. (2019), reinforcing the view that financial reporting quality functions as a managerial technology.

Columns 4 and 5 partition firms by size. The survival premium is larger among smaller firms, consistent with the idea that they depend more on external discipline given their thinner internal systems and limited resources. Columns 6 and 7 examine outcomes conditional on survival, showing that firms with higher reporting quality subsequently realize faster growth in productivity and sales. These findings suggest that audits not only help firms remain in operation, but also facilitate continued improvements in performance once they survive.

5.2 Financial Reporting Quality and Measurement Bias

The second channel in our framework emphasizes the disciplining role of audits. In the absence of external verification, managers retain substantial discretion to understate revenues or production, often to reduce tax liabilities. Such practices lead to systematically biased productivity measures. Rigorous audits constrain this discretion, forcing firms to report outcomes that more closely reflect their true economic activity. As a result, we would expect the impact of audits on measured productivity to be strongest in environments where incentives to misreport are particularly pronounced.⁹

5.2.1 Cross-Sectional Evidence from Tax Incentives

To examine this mechanism empirically, we exploit the cross-sectional variation in state-level tax incentives to misreport production. U.S. states vary substantially in their tax structures: Some tax corporate net income, others tax gross production directly, and many apply differing tax regimes for corporate entities (C-corporations) versus pass-through entities (such as partnerships). This variation creates differential incentives for firms to understate production. We capture this variation using two distinct measures of state-level tax incentives to under-report. First, we use the state corporate income tax rate, which exhibits significant cross-state variation; for example, the top corporate rates ranged from 0% to 12% in 2008 (see Figure 5). Second, we construct a broader measure using the per capita collection of corporate income, personal income, and sales taxes, capturing incentives relevant for both corporate and pass-through entities, albeit at the cost of additional measurement noise.

In Table 8, we revisit our main productivity regression (originally presented in Table 3, Column 4 using Sageworks data) by including interaction terms between our financial reporting quality variable and the two state-level tax incentive measures.¹⁰ All regressions

⁹Unlike temporary timing differences, such as shifting sales recognition across periods, our analysis focuses on permanent misreporting (i.e., Coppens and Peek (2005); Burgstahler et al. (2006); Beck et al. (2014); Hanlon et al. (2014)).

¹⁰Both tax incentive variables are rank transformed and categorized into three groups: states in the top quintile (high tax incentives, coded 1), the bottom quintile (low tax incentives, coded 0), and intermediate

include state-fixed effects (absorbing main effects of tax incentives) and industry-by-year fixed effects, with standard errors clustered at the state level due to state-specific variation in tax incentives.

Consistent with our framework, the interaction between audit quality and tax incentives is positive and statistically significant. In high-tax states, the productivity gap between audited and unaudited firms is substantially larger, indicating that audits curb tax-motivated underreporting.¹¹ This evidence supports the bias-reduction mechanism: by constraining underreporting, audits raise measured productivity in tax-intensive environments and reduce spurious dispersion in productivity statistics. We note that this channel complements the managerial technology mechanism, reinforcing the conclusion that reporting quality is a first-order determinant of productivity.

5.3 Disentangling Management Technology from Reporting Biases

Finally, we exploit the timing of productivity gains around the initiation of an audit, as a natural test of the two mechanisms in our framework. If the primary channel were bias correction, we would expect an immediate increase in measured productivity in the first audit year, when auditors constrain discretion and force firms to report more accurately. By contrast, if audits also operate as a managerial technology, their effects should appear with a lag, as managers internalize audit discipline and adapt their decision-making processes.

Column 8 of Table 9 implements this test using firms that adopted audits in 2009 and retained them in 2010. We find no significant change in productivity in the first audit year, suggesting limited immediate effects from bias correction once fixed effects are accounted for. In the second year, however, productivity rises significantly, consistent with managerial learning and genuine improvements in efficiency. This sequencing is important: it implies

states (coded as 0.5).

¹¹Unreported analyses show stronger effects among C-corporations, directly subject to corporate tax rates, and weaker effects for larger firms, consistent with evidence that smaller firms have greater scope to conceal production and that auditing is particularly effective in limiting such practices.

that audits initially clean the books by constraining misreporting, but their larger and more persistent contribution arises as firms integrate audit discipline into their operations.

Taken together, this dynamic evidence shows that both channels matter. Audits reduce misreporting in the short run, but the enduring productivity gains come through the managerial technology channel. This dual role reinforces our central argument: financial reporting quality not only affects how productivity is measured but also how it is created.

6 Conclusion

Large and persistent differences in productivity across seemingly similar firms have long puzzled economists. This paper shows that variation in the quality of financial reporting explains a meaningful share of this dispersion. Firms that engage independent accountants to verify their statements exhibit higher productivity, survival, and growth, with magnitudes comparable to those associated with well-established managerial practices.

Our conceptual framework highlights two channels through which financial reporting shapes productivity. First, as a managerial technology, audits enhance the precision of internal information and improve decision-making. Their effects are strongest in settings where accurate operating data is most valuable such as competitive, low-margin industries and younger firms and weaker in innovation-driven sectors where near-term measurement is less central. Dynamic evidence further shows that productivity gains emerge with a lag after audit adoption, consistent with learning rather than immediate reporting corrections. Moreover, financial reporting quality complements structured management practices: both independently predict productivity and profitability, and their interaction is positive and significant. Firms that combine strong management with rigorous audits achieve gains greater than the sum of each alone, placing financial reporting squarely alongside other core management practices.

Second, audits mitigate measurement bias by limiting managers' discretion to understate

production for tax purposes. Using variation in state-level tax regimes, we show that the productivity premium from audits is significantly higher in high-tax states, especially for smaller firms with greater scope for concealment. This finding underscores the disciplining role of audits in ensuring that reported figures reflect true economic activity more closely.

These findings should be interpreted with appropriate scope. Consistent with the broader literature on management practices, we do not estimate causal treatment effects. Firms that choose high-quality reporting may also excel along other organizational dimensions, raising the possibility that high-productivity firms bundle complementary practices. Rather than viewing this as a limitation, it highlights an important insight: sophisticated managers appear to treat financial reporting as part of their broader management system, not merely as a compliance requirement. A second open question concerns why some firms do not invest in better reporting despite its apparent benefits. Costs, organizational frictions, strategic opacity, or managerial myopia may all play a role. Understanding these choices is a promising direction for future work, especially in settings where policy changes alter firms reporting incentives.

Despite these caveats, our evidence points to a simple conclusion: financial reporting quality is a first-order determinant of both actual and measured firm productivity. Auditing, often viewed as a regulatory formality, also functions as an economically significant managerial tool. By reframing financial measurement as an active input into firm performance, our study connects insights from economics and accounting and opens new avenues for research on the origins of productivity heterogeneity.

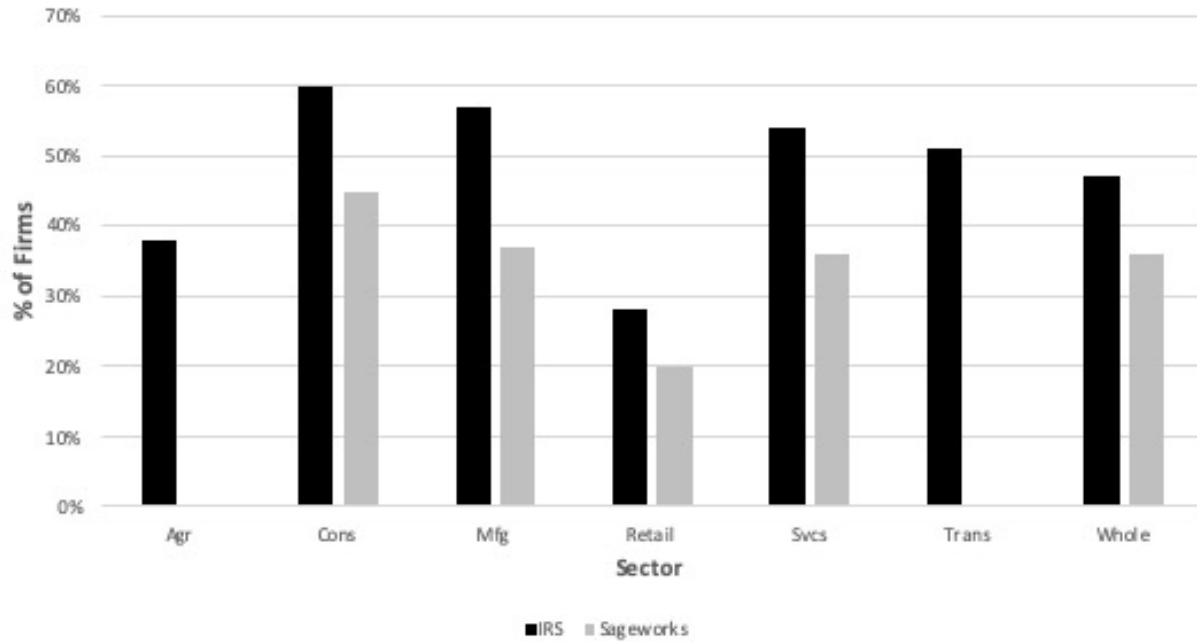
References

- Allee, K. and T. L. Yohn, “The Demand for Financial Statements in an Unregulated Environment: An Examination of the Production and Use of Financial Statements by Privately Held Small Businesses,” *The Accounting Review*, 2009, 84 (1), 1–25.
- Balakrishnan, K., J. Blouin, and W. Guay, “Tax Aggressiveness and Corporate Transparency,” *The Accounting Review*, 2018. forthcoming.
- Beck, T., C. Lin, and Y. Ma, “Why Do Firms Evade Taxes? The Role of Information Sharing and Financial Sector Outreach,” *Journal of Finance*, 2014, 69, 763–817.
- Bertrand, M. and A. Schoar, “Managing with Style: The Effect of Managers on Firm Policies,” *The Quarterly Journal of Economics*, 2003, 118 (4), 1169–1208.
- Bloom, N. and J. Van Reenen, “Measuring and Explaining Management Practices Across Firms and Countries,” *The Quarterly Journal of Economics*, 2007, 122 (4), 1351–1408.
- , B. Eifert, A. Mahajan, D. McKenzie, and J. Roberts, “Does management matter? Evidence from India,” *The Quarterly Journal of Economics*, 2013, 128 (1), 1–51.
- , R. Sadun, and J. Van Reenen, “Management as a Technology?,” Working Paper Series, National Bureau of Economic Research 2017.
- Bloom, Nicholas, Erik Brynjolfsson, Lucia Foster, Ron Jarmin, Megha Patnaik, Itay Saporta-Eksten, and John Van Reenen, “What drives differences in management practices?,” *American Economic Review*, 2019, 109 (5), 1648–1683.
- Breuer, M., “How Does Financial-Reporting Regulation Affect Market-Wide Resource Allocation?,” 2018. Working Paper.
- Burgstahler, D., L. Hail, and C. Leuz, “The importance of reporting incentives: Earnings management in European private and public firms,” *The Accounting Review*, 2006, 81 (5), 983–1016.
- Bushman, Robert M. and A. Smith, “Financial accounting information and corporate governance,” *Journal of Accounting and Economics*, 2001, 32 (1-3), 237–333.
- Cheng, M., D. Dhaliwal, and Y. Zhang, “Does Investment Efficiency Improve after the Disclosure of Material Weaknesses in Internal Control over Financial Reporting?,” *Journal of Accounting and Economics*, 2013, 56 (1), 1–18.
- Choi, Jung Ho, “Accrual accounting and resource allocation: A general equilibrium analysis,” *Journal of Accounting Research*, 2021, 59 (4), 1179–1219.
- Coppens, L. and E. Peek, “An Analysis of Earnings Management by European Private Firms,” *Journal of International Accounting, Auditing, and Taxation*, 2005, 14 (1), 1–17.
- David, J., H. Hopenhayn, and V. Venkateswaran, “Information, Misallocation, and Aggregate Productivity,” *The Quarterly Journal of Economics*, 2016, 131 (2), 943–1005.

- DeFond, M. and J. Zhang**, “A review of archival auditing research,” *Journal of Accounting and Economics*, 2014, 58, 275–326.
- Dhrymes, P.**, “The Structure Of Production Technology Productivity And Aggregation Effects,” Working Paper 91-5, Center for Economic Studies, U.S. Census Bureau 1991.
- Doms, M. and E. Bartelsman**, “Understanding Productivity: Lessons from Longitudinal Microdata,” *Journal of Economic Literature*, 2000, 38 (3), 569–594.
- Feng, M., C. Li, S. McVay, and H. Skaife**, “Does Ineffective Internal Control over Financial Reporting Affect a Firm’s Operations? Evidence from Firms’ Inventory Management,” *The Accounting Review*, 2015, 90 (2), 529–57.
- Fox, Jeremy T and Valérie Smeets**, “Does input quality drive measured differences in firm productivity?,” *International Economic Review*, 2011, 52 (4), 961–989.
- Hanlon, M., J. Hoopes, and N. Shroff**, “The effect of tax authority monitoring and enforcement on financial reporting quality,” *The Journal of the American Taxation Association*, 2014, 36 (2), 137–170.
- Holzman, Eric, Brian P Miller, Brian Williams, and Teri Lombardi Yohn**, “Accounting and Small Business Profitability,” *Kelley School of Business Research Paper*, 2020, (18-7).
- Hoopes, J., D. Mescall, and J. Pittman**, “Do IRS Audits Deter Corporate Tax Avoidance?,” *The Accounting Review*, 2012, 87 (5), 1603–1639.
- Hsieh, C. and P. Klenow**, “Misallocation and Manufacturing TFP in China and India,” *The Quarterly Journal of Economics*, 2009, 124 (4), 1403–48.
- Kanodia, C. and H. Sapra**, “A real effects perspective to accounting measurement and disclosure: Implications and insights for future research,” *Journal of Accounting Research*, 2016, 54 (2), 623–676.
- Lisowsky, Petro and Michael Minnis**, “The silent majority: Private US firms and financial reporting choices,” *Journal of Accounting Research*, 2020, 58 (3), 547–588.
- McNichols, M. and S. Stubben**, “Does Earnings Management Affect Firms’ Investment Decisions?,” *The Accounting Review*, 2008, 83 (6), 1571–1603.
- Rajan, R. G. and L. Zingales**, “Financial Dependence and Growth,” *The American Economic Review*, 1998, 88 (3), 559–586.
- Shroff, N.**, “Corporate Investment and Changes in GAAP,” *Review of Accounting Studies*, 2017, 22 (1), 1–63.
- Syverson, C.**, “Market Structure and Productivity: A Concrete Example,” *Journal of Political Economy*, 2004, 112 (6), 1181–1222.

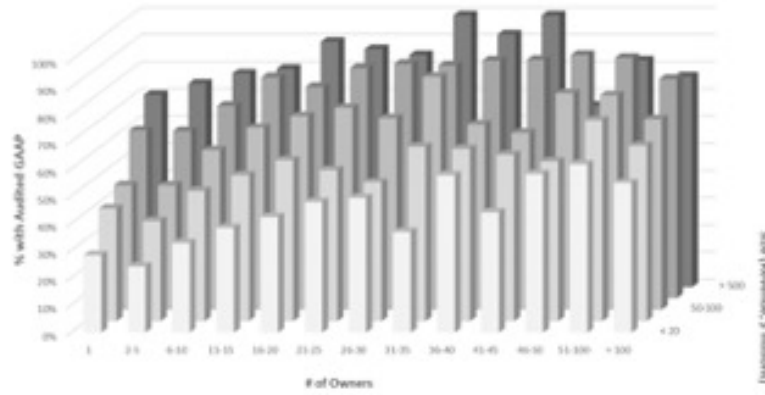
- , “Product Substitutability and Productivity Dispersion,” *The Review of Economics and Statistics*, 2004, *86* (2), 534–50.
- , “What Determines Productivity?,” *Journal of Economic Literature*, 2011, *49* (2), 326–65.

Figure 1: Variation in Financial Reporting Quality across Sectors

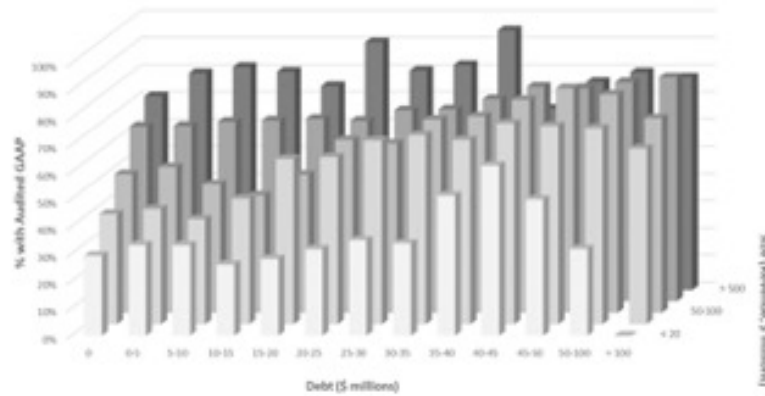


Notes: This figure reports the financial reporting quality variation within sector for those sectors with at least 500 observations. The data for the black bars is from the IRS data and reports the percentage of firms producing audited GAAP financial statements. The data for the gray bars is from the Sageworks data and reports the sector mean of the report variable, which equals 1 for audited, 0.5 for reviewed, and 0 for compiled financial statements. See Appendix A for definitions of these report types.

Figure 2: Variation in Financial Reporting Quality Conditional on Ownership and Debt



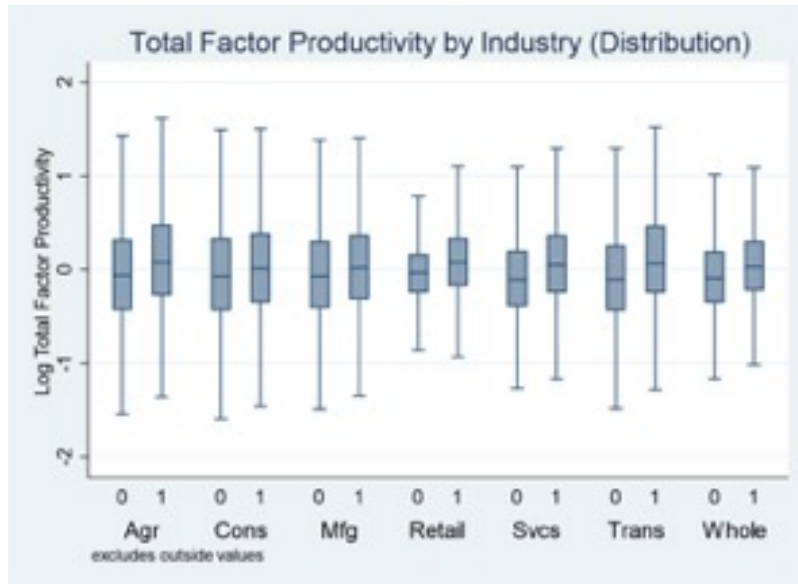
(a) Conditioning on Size and Ownership dispersion



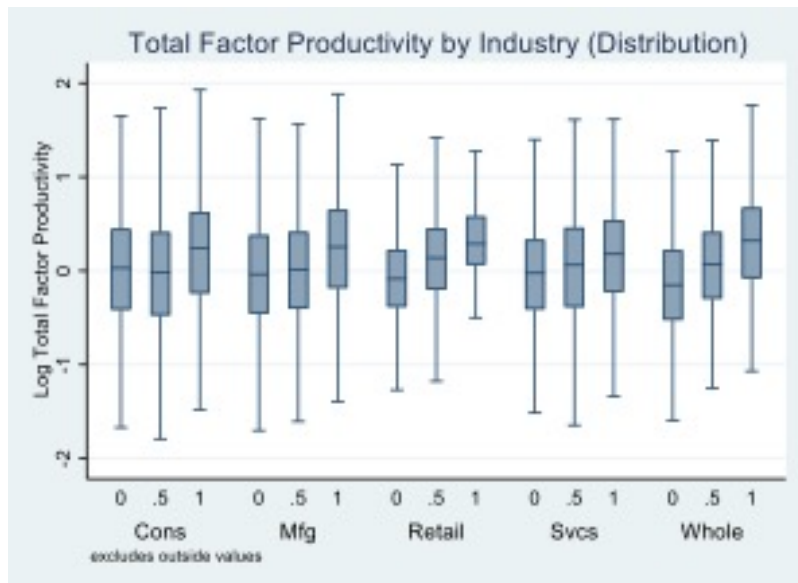
(b) Conditioning on Size and Debt

Notes: Figure 2a reports the financial report quality variation conditional on firm size (z-axis based on sales) and ownership dispersion (x-axis). The y-axis reports the percentage of firms producing audited GAAP financial statements. Figure 2b is identical but conditions on level of debt rather than ownership dispersion. The data for these plots is from the IRS data set.

Figure 3: Distribution of TFP-VA by Industry Conditional on Financial Reporting Quality



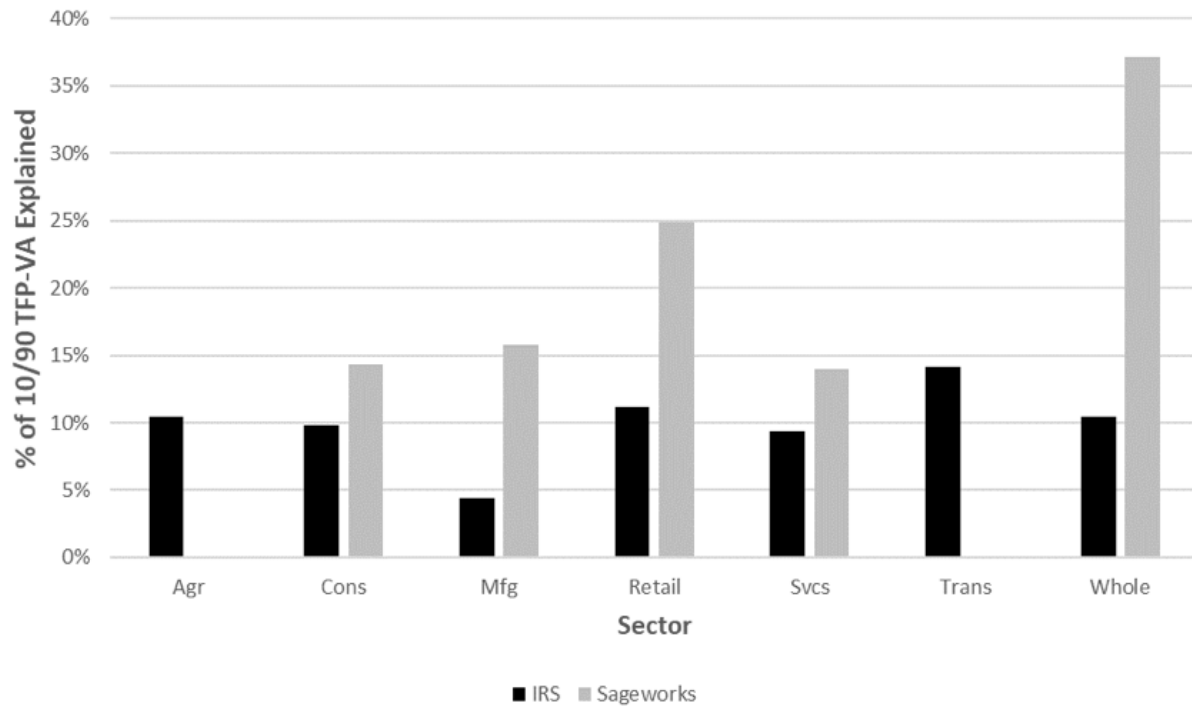
(a) IRS data



(b) Sageworks data

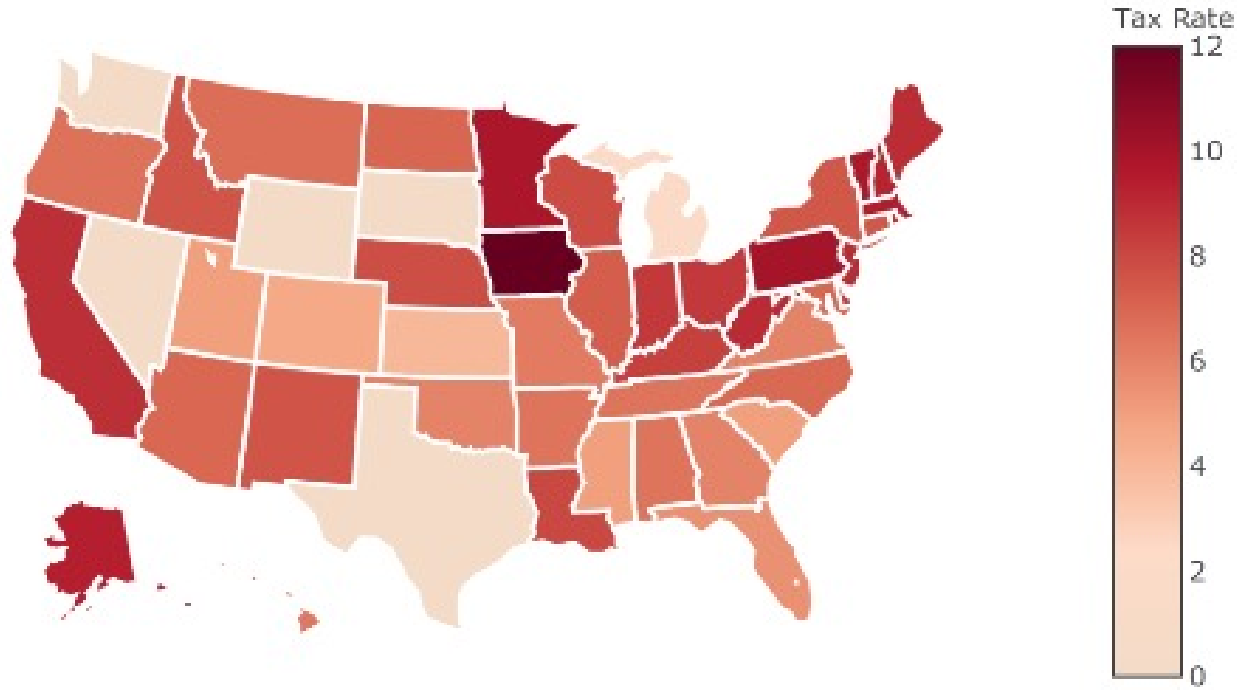
Notes: These figures plot the distribution of TFP-VA by sector (for those with at least 500 observations), conditional on financial report quality. Figure 3a plots the results from the IRS data, while Figure 3b plots the results from the Sageworks data.

Figure 4: Portion of 10/90 TFP-VA Spread Explained by Industry



Notes: This figure plots the portion of the 10/90 TFP-VA spread explained by financial reporting quality for both the IRS (black) and Sageworks (gray) data sets.

Figure 5: Corporate Taxation Rates across States



Notes: This map is shaded based on the corporate income tax rates for each state in the year 2008. Darker shades indicate higher corporate income taxes.

Table 1: Distribution of firm-years across industry

Industry	IRS		Sageworks	
	No.	%	No.	%
Agriculture	1,011	1.7	210	1.4
Construction	7,919	13.3	3,729	24.8
Manufacturing	16,469	27.8	3,731	24.8
Mining	940	1.6	70	0.5
Retail trade	10,860	18.3	2,194	14.6
Services	10,438	17.6	2,233	14.9
Transportation	1,312	2.2	276	1.8
Utilities	244	0.4	104	0.7
Wholesale trade	10,117	17.1	2,490	16.6
Total	59,310	100	15,037	100

Notes: This table reports the distribution of firm-year observations across NAICS sectors for the IRS (columns 1 and 2) and Sageworks (columns 3 and 4).

Table 2: Descriptive statistics**Panel A: Census**

		Mean	SD
Audit	Sales	398700	1912000
	Cost of Goods Sold	222400	1336000
	Value Added	176500	736100
	Labor	1558	6214
	Capital	101700	541000
	Management	0.64	0.143
Review	Sales	38000	120900
	Cost of Goods Sold	19040	73100
	Value Added	18990	53140
	Labor	273.8	500.9
	Capital	9123	28780
	Management	0.557	0.17
Compilation	Sales	17880	44030
	Cost of Goods Sold	8724	32060
	Value Added	9175	15880
	Labor	146.4	214.8
	Capital	3953	9750
	Management	0.503	0.186
No	Sales	69110	770800
	Cost of Goods Sold	39010	522700
	Value Added	30110	269700
	Labor	292	1406
	Capital	14470	125500
	Management	0.479	0.203
Observations	~ 14,500		

Table 2: Descriptive statistics (continued)**Panel B: IRS**

		Mean	SD	P10	P25	P50	P75	P99
Audit	ln(sales)	17.94	1.03	15.40	17.25	17.89	18.60	20.40
	ln(cogs)	17.42	1.40	12.92	16.74	17.52	18.27	20.20
	ln(va)	16.50	1.10	13.95	15.78	16.45	17.18	19.22
	ln(labor)	15.14	1.32	11.89	14.30	15.17	16.01	18.15
	ln(ppe)	15.18	1.67	10.69	14.15	15.30	16.30	18.77
Review	ln(sales)	17.39	1.00	14.69	16.85	17.43	17.99	19.88
	ln(cogs)	16.90	1.43	11.88	16.36	17.11	17.75	19.64
	ln(va)	15.89	0.97	13.40	15.33	15.88	16.44	18.51
	ln(labor)	14.56	1.24	11.14	13.85	14.66	15.34	17.45
	ln(ppe)	14.44	1.69	9.49	13.45	14.60	15.60	17.91
Observations	59,310							

Panel C: Sageworks

		Mean	SD	P10	P25	P50	P75	P99
Audit	ln(sales)	16.52	1.14	13.54	15.79	16.51	17.30	19.07
	ln(cogs)	16.10	1.33	12.55	15.31	16.16	17.04	18.92
	ln(va)	15.06	1.14	12.18	14.36	15.12	15.75	17.69
	ln(labor)	4.02	1.19	1.39	3.30	4.01	4.75	6.93
	ln(ppe)	14.23	1.71	10.01	13.22	14.26	15.41	17.88
Review	ln(sales)	15.82	0.95	13.83	15.16	15.78	16.42	18.32
	ln(cogs)	15.44	1.08	12.85	14.73	15.42	16.12	18.08
	ln(va)	14.39	1.00	12.06	13.74	14.36	15.03	16.76
	ln(labor)	3.47	0.98	1.10	2.83	3.47	4.08	5.87
	ln(ppe)	13.31	1.54	9.09	12.37	13.38	14.34	16.58
Comp	ln(sales)	15.35	0.92	13.46	14.69	15.27	15.92	17.89
	ln(cogs)	14.85	1.15	11.97	14.13	14.85	15.59	17.62
	ln(va)	14.12	0.91	11.96	13.53	14.09	14.70	16.56
	ln(labor)	3.12	0.98	0.69	2.48	3.09	3.71	5.65
	ln(ppe)	13.18	1.44	9.07	12.39	13.28	14.07	16.33
Observations	15,037							

Notes: This table presents summary statistics for the variables used in this paper partitioned by data set and conditional on financial reporting quality. Panel A reports the statistics from the Census data. Sales is total value of shipments. Cost of goods sold is calculated as sales minus value added. Labor is imputed and constructed as $PH * SW / WW$, where PH is total production hours, SW is the wage bill, and WW is the production wage bill. Capital is constructed by adding up the real capital stock in equipment and structures. Management is the management score from Bloom et al. (2019). Panel B reports the statistics from the IRS data set. ln(sales) is log gross sales; ln(cogs) is log cost of goods sold; ln(va) is log value added calculated as the difference between sales and cost of goods sold; ln(labor) is log of salaries and wages, all from page 1 of the tax return. ln(ppe) is lagged log property, plant, and equipment from Schedule L. Panel C reports the statistics from the Sageworks data set. ln(sales) is log of sales revenue; ln(cogs) is log of cost of goods sold; ln(va) is log value added calculated as the difference between sales and cost of goods sold; ln(labor) is lagged log of number of employees; ln(ppe) is lagged log property, plant, and equipment.

Table 3: Productivity and reporting quality

	Census			IRS			Sageworks		
	Pool TFP-VA (1)	Propensity TFP-VA (2)	Weighted TFP-VA (3)	Pool TFP-VA (4)	Propensity TFP-VA (5)	Weighted TFP-VA (6)	Pool TFP-VA (7)	Propensity TFP-VA (8)	Weighted TFP-VA (9)
Report	0.098*** (0.018)	0.124*** (0.023)	0.136** (0.058)	0.108*** (0.007)	0.087*** (0.008)	0.100*** (0.006)	0.310*** (0.022)	0.272*** (0.028)	0.311*** (0.051)
State fixed effects	Yes	Yes	Yes	No	No	No	Yes	Yes	Yes
Industry fixed effects	Yes	Yes	Yes	No	No	No	No	No	No
Industry x year fixed effects	No	No	No	Yes	Yes	Yes	Yes	Yes	Yes
Observations	~ 14500	~ 14500	~ 14500	59,310	38,636	59,310	15,037	8,423	15,037
Share of 90-10 explained	6.89%	8.73%	9.60%	8.4%	6.7%	8.4%	20.2%	18.3%	20.0%
R2	0.002	0.032	0.506	0.007	0.005	0.007	0.022	0.017	0.027

Notes: This table reports the results of regressing value added total factor productivity (TFP-VA) on financial measurement quality. Columns 1-3 present the results from the Census sample and defines report as a variable equals to 0, 1/3, 2/3, and 1 if the firm did not have any type of audit, compilation, review, and audit, respectively. Columns 4-6 present the results using the IRS sample and defines GAAP Audit as an indicator variable equal to 1 if the firm prepares financial statements according to GAAP and has them audited by an independent accountant, and 0 otherwise. Columns 7-9 present the results from the Sageworks sample and defines report as a variable equal to 0 (0.5, 1) if the firm has a compilation (review, audit). The sample used in Columns 2, 5, and 8 is restricted to the propensity matched samples as described in the text. The share of 90-10 explained is the estimated coefficient on report divided by the spread in productivity between the 10th and 90th percentiles. Presented below the coefficients are robust standard errors clustered at the industry x year level. *, **, *** indicate significance at 10%, 5%, and 1%, respectively.

Table 4: Deciles of Management Scores VS Auditing

	Count	Audit	Review	Compilation	No	DK
$0 \leq \text{Management} < 0.2$	~700	0.12	0.16	0.26	0.31	0.15
$0.2 \leq \text{Management} < 0.4$	~1900	0.192	0.241	0.247	0.226	0.094
$0.4 \leq \text{Management} < 0.6$	~4900	0.341	0.239	0.19	0.145	0.085
$0.6 \leq \text{Management} < 0.8$	~7300	0.538	0.185	0.0991	0.0781	0.0998
$0.8 \leq \text{Management} \leq 1$	~1000	0.62	0.15	0.077	0.057	0.096

Notes: The rows define 5 equally sized bins based on the management score. The bins are of size 0.2 from 0 to 1. For each bin, the table reports the share of firms that received an audit, a review, a compilation, no audits, or do not know if the firm received an audit.

Table 5: Benchmarking Financial Reporting Audit and Management Practices

	log (VA/L)				Profit/sales			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
GAAP Audit	0.028*** -0.006		0.024*** -0.006	0.027*** -0.007	0.008*** -0.002		0.007*** -0.002	0.008*** -0.002
Management		0.030*** -0.006	0.027*** -0.006	0.034*** -0.007		0.009*** -0.001	0.008*** -0.001	0.009*** -0.002
CPA \times Management				0.022*** -0.005				0.003** -0.001
N	~14500	~14500	~14500	~14500	~14500	~14500	~14500	~14500
R2	0.365	0.365	0.366	0.367	0.214	0.214	0.215	0.215
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table reports regression results evaluating the relationship between financial reporting quality (GAAP audits), management practice scores, and their interaction on firm productivity (log of value added per worker, $\log(VA/L)$) and profitability (profits scaled by sales). Columns (1)–(4) present results for productivity, while columns (5)–(8) report results for profitability. The variables “GAAP Audit” and “Management” represent standardized measures of audit status and management practice scores, respectively, derived from the Census Management and Organizational Practices Survey (MOPS). All specifications include standard firm-level controls: capital-to-labor ratio, materials-to-labor ratio, energy-to-labor ratio, labor input, and the share of employees holding bachelor’s degrees. Industry fixed effects are included in all specifications. Robust standard errors, clustered by industry, are reported in parentheses. Statistical significance is indicated by *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 6: Productivity and reporting quality conditional on capital structure

		<i>Leverage</i>		
		<i>None</i>	<i>>0 to 20%</i>	<i>>20%</i>
	<i>Owners</i>			
	<i>1</i>	0.053 (0.035) $R^2 = 0.166$ $n = 2,035$ %Aud = 38.5%	0.083*** (0.025) $R^2 = 0.130$ $n = 3,091$ %Aud = 50.0%	0.089*** (0.015) $R^2 = 0.122$ $n = 5,969$ %Aud = 42.6%
	<i>2 to 5</i>	0.091*** (0.022) $R^2 = 0.096$ $n = 5,456$ %Aud = 39.7%	0.076*** (0.017) $R^2 = 0.072$ $n = 7,488$ %Aud = 46.9%	0.142*** (0.013) $R^2 = 0.077$ $n = 14,199$ %Aud = 39.7%
	<i>>5</i>	0.095*** (0.024) $R^2 = 0.121$ $n = 4,082$ %Aud = 57.1%	0.155*** (0.018) $R^2 = 0.117$ $n = 6,456$ %Aud = 63.2%	0.203*** (0.016) $R^2 = 0.094$ $n = 9,271$ %Aud = 64.1%

Notes: This table presents estimates from the model in Table 3, Column 4 after conditioning the sample based on the number of owners and amount of leverage. Leverage is defined as total outside (i.e., nonowner) debt divided by total assets from Schedule L of the tax return. Each cell of the table reports the estimated coefficient on the report variable, the robust standard error clustered at the industry x year level, the R^2 , the sample size, and the portion of the sample in which report=1. *, **, *** indicate significance at 10%, 5%, and 1%, respectively.

Table 7: Cross-sectional variation

Dep variable	TFP-VA	TFP-VA	TFP-VA
Construct	Competition	Innovation	Sophistication
CS variable	Profit Margin	R&D	Young Firm
	(1)	(2)	(3)
Report	0.085** (0.01)	0.114*** (0.01)	0.098*** (0.01)
Report x CS var	0.032 (0.02)	-0.054*** (0.02)	0.072*** (0.02)
Young Firm			0.00340 (0.02)
Industry x Year FE	Yes	Yes	Yes
Observations	54,547	54,547	51,240

Notes: This table presents OLS regressions of value-added total factor productivity regressed on financial report measurement quality and various cross-sectional variables or time indicators. The dependent variable is firm-year-level TFP-VA estimated from industry level regressions. The cross-sectional variables in Columns 1-2 are sourced from Compustat data using 3-digit NAICS industries annually. Profit margin is calculated as 1 minus the profit margin of the median firm in each industry-year. R&D is R&D scaled by sales for the median firm in each industry-year. Each of the cross-sectional variables in Columns 1-2 are deciled each year and scaled between 0 and 1 such that the magnitude of the coefficient can be interpreted as going from the first to the tenth decile of the cross-sectional variable. The main effects of the cross-sectional variable are absorbed in the industry x year fixed effects. The cross-sectional variable in Column 3 is an indicator variable equal to 1 if the firm is less than 4 years old as reported on the corporate (Form 1120 or 1120S) tax return (i.e., firms filing Form 1065 are omitted from this test). All regressions include industry x year fixed effects. Presented below the coefficients are robust standard errors clustered at the industry x year level. *, **, *** indicate significance at 10%, 5%, and 1%, respectively.

Table 8: Under-reporting bias and state taxation

	TFP-VA 1	TFP-VA 2
Report	0.221*** (0.04)	0.224*** (0.05)
Report X Corp Tax	0.179** (0.08)	
Report X Tax		0.161* (0.09)
State FE	Yes	Yes
Industry x Year FE	Yes	Yes
Observations	15,037	15,018

Notes: This table presents OLS regressions of TFP-VA regressed on financial report measurement quality and a variable measuring state level taxation intensity. The dependent variable is firm-year-level TFP-VA estimated from the regressions reported in Table 3, Column 4. The variable Corp Tax categorizes U.S. states into high (=1 for top 10 states), medium (=0.5 for states ranked 11 through 40), and low (=0 for states ranked in the bottom 10) based on corporate tax rates. The variable Tax categorizes U.S. states into high (=1 for states in the top 10), medium (=0.5 for states ranked 11 through 40), and low (=0 for states ranked in the bottom 10) based on the amount of sales, gross receipts, and income-based taxes collected per capita and excludes the District of Columbia. The main effects of state taxation are absorbed in the state fixed effects. Presented below the coefficients are robust standard errors clustered at the state level. *, **, *** indicate significance at 10%, 5%, and 1%, respectively.

Table 9: Survival and changes in performance

Analysis	Survival Analysis					Performance Analysis			
	Firm exists in 2008					Firm exists 2008 - 2010			
Sample	None	None	None	>Median	<=Median	None	None	None	None
Size restriction	Survive	Survive	Survive	Survive	Survive	TFP 2010	Sales 2010	TFP	TFP
Dep. variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(8)
TFP-VA	0.074*** (0.01)		0.070*** (0.01)	0.021 (0.01)	0.066*** (0.01)	0.741*** (0.02)			
GAAP Audit		0.071*** (0.01)	0.063*** (0.01)	0.029** (0.01)	0.051*** (0.01)	0.032*** (0.01)	0.017** (0.01)		
Sales in 2008							0.941*** (0.01)		
Start GAAP Audit X 2009								0.010 (0.01)	
Start GAAP Audit X 2010								0.022*** (0.01)	
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No
Firm FE	No	No	No	No	No	No	No	Yes	Yes
Year FE	No	No	No	No	No	No	No	No	Yes
Observations	14,793	14,793	14,793	7,382	7,384	10,484	10,484	28,701	
R2	0.053	0.049	0.058	0.049	0.079	0.554	0.899	0.859	

Notes: This table presents the results of the survival and performance analysis conditioning on current performance and financial reporting quality. All specifications are restricted to the IRS sample. Columns 1-5 examine firm survival where survive is an indicator equal to 1 if the firm exists in 2010 and equal to 0 if the firm is not in the IRS data set in 2010 and TFP-VA and GAAP Audit are measured in 2008. Column 4 limits the sample to firms above the median size by log sales and Column 5 limits the sample to firms below or equal to median size. The sample for the analyses in Columns 6 and 7 condition on the firm existing in all three years 2008 to 2010 in the IRS data set. Column 8 conditions the sample on firms which either have GAAP Audit = 1 each year, GAAP Audit = 0 each year, or change to GAAP Audit = 1 in 2009 and continue to have report = 1 in 2010 (i.e., eliminates firms which do not exist in all three years or reduce their report quality in any year or change their report quality more than once). The column reports a firm fixed effects regression of TFP-VA on indicators for firms beginning a GAAP audit in 2009. Columns 1-7 include industry fixed effects; Column 8 includes firm and year fixed effects. Presented below the coefficients are robust standard errors clustered at the industry x year level. *, **, *** indicate significance at 10%, 5%, and 1%, respectively.

A Estimating TFP-VA

We report the results of the estimation of a Cobb-Douglas production function in Table A1, where the dependent variable is the logarithmic value added (sales minus cost of goods sold). Columns 1 through 3 show results using the IRS sample, while Columns 4 through 6 present results using the Sageworks sample. All specifications include 4-digit NAICS industry-by-year fixed effects, with the Sageworks analyses additionally incorporating state fixed effects based on firms locations. Columns 1 and 4 use the full sample, while columns 2 and 5 employ propensity-matched samples, matched on input levels (log labor and log property, plant, and equipment) within industry-years. Columns 3 and 6 report weighted OLS regressions, where observations are weighted by firm output to prevent smaller, more numerous firms from disproportionately influencing the results.

The reported coefficients represent the estimated elasticities of the output with respect to labor and capital.¹² The residuals of these regressions of the production function constitute our firm-level estimates of logged TFP-VA.¹³

Due to disclosure constraints, detailed estimates using restricted access Census microdata, although consistent with the IRS and Sageworks analyzes, cannot be reported.

¹²These estimated elasticities are consistent in magnitude with prior literature, e.g., Bloom and Reenen (2007) and Hsieh and Klenow (2009).

¹³We also conducted a robustness check using a one-stage approach, directly incorporating the financial reporting quality measure into the production function estimation. As expected, this approach yielded nearly identical inferences. Furthermore, supplementary analyzes fully interacting with reporting quality with labor and capital inputs indicated that there were no significant differences in input elasticities between reporting regimes, suggesting that financial measurement quality corresponds to a Hicks-neutral shift in productivity.

Table A1: Estimating Cobb-Douglas Production Functions

	IRS			Sageworks		
	Pool TFP-VA (1)	Propensity TFP-VA (2)	Weighted TFP-VA (3)	Pool TFP-VA (4)	Propensity TFP-VA (5)	Weighted TFP-VA (6)
ln(labor)	0.598*** (0.008)	0.577*** (0.009)	0.625*** (0.007)	0.587*** (0.013)	0.593*** (0.017)	0.455*** (0.049)
ln(ppe)	0.110*** (0.005)	0.100*** (0.005)	0.108*** (0.004)	0.118*** (0.007)	0.0944*** (0.009)	0.258*** (0.027)
State fixed effects	No	No	No	Yes	Yes	Yes
Industry x year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	59,310	38,636	59,310	15,037	8,423	15,037
R^2	0.697	0.625	0.718	0.593	0.548	0.745

Notes: This table presents the results from estimating the Cobb-Douglas production function with value added (log of sales less cost of goods sold) as the dependent variable. Columns 1-3 present the results from the IRS sample. Columns 4-6 present the results from the Sageworks sample. In the IRS analyses, ln(labor) is measured as the log of salaries and wages; in the Sageworks analyses, ln(labor) is measured as the log of total employees. All regressions include fixed effects for industry (4-digit NAICS) by year. The Sageworks analyses further include fixed effects for the state of location. The samples used in Columns 2 and 5 are restricted to the propensity matched samples as described in the text. Presented below the coefficients are robust standard errors clustered at the industry x year level. *, **, *** indicate significance at 10%, 5%, and 1%, respectively.

B Financial Reporting Overview

Firm-level financial reporting has two broad dimensions: the set of accounting rules (or standards) followed by the firm and the extent of independent accountant attestation (if any). Figure A1 below illustrates the two dimensions as well as the set of choices (non-listed) U.S. firms have. Accounting is the set of rules mapping economic events into financial reports. Firms not publicly listed can choose from different sets of accounting rules (e.g., Allee and Yohn 2009; Lisowsky and Minnis 2018). The most straightforward set of accounting rules is known as “cash basis” accounting in which economic transactions are simply recorded when cash is paid or collected by the firm. An alternative basis of accounting is “tax basis” in which the firm follows rules set by the Internal Revenue Service. All firms are required to file their annual tax form according to the tax basis of accounting. However, tax accounting standards are established by politicians and the main objective of tax rules is to collect tax revenues, not necessarily to portray the economic reality of the firm (Desai 2003; Hanlon and Shevlin 2005; Slemrod 2016). So while all firms are required to follow tax rules for filing annual forms with the IRS, many also follow more sophisticated practices to enhance the informativeness and contractability of the financial reports.

The most commonly understood and studied set of rules — and those required of publicly traded companies by the SEC — are referred to as Generally Accepted Accounting Principles (GAAP). GAAP is established by the Financial Accounting Standards Board (FASB) and is an “accrual basis” of accounting wherein economic transactions can be realized and recorded prior to the receipt or payment of cash. By necessity, the recording of accruals requires

estimation on the part of managers because often one part of the economic transaction has not completed. For example, the firm has sold goods to a customer, but the customer has not yet paid. This transaction results in sales revenue and an accounts receivable accrual. The accounts receivable is essentially an estimate of how much cash will subsequently be collected from the customer. Financial statements contain significant accruals (and, thus, estimation) which are subject to both estimation error and biased misreporting (e.g., Dechow and Dichev 2002; Dechow et. al. 2010; Nikolaev 2017). Estimation error occurs when managers do not properly judge how future transactions will play out, but do so with noise (i.e., lack a direction to the future correction). Bias in the reports is an intentional — and directional — mischaracterization of the estimates often caused by various incentives. For example, managers compensated by annual bonuses could inflate the current years reported production to the detriment of future years performance (Healy 1985); while managers concerned with minimizing tax payments could under-report production levels by simply not recording sales (e.g., Slemrod 2016; Balakrishnan et. al. 2018).

To mitigate errors and bias in financial reports, managers (or owners and boards of directors) can choose to engage an independent accountant to verify the financial report prepared by managers, referred to as “attestation” (e.g., DeFond and Zhang 2014; Dedman et. al. 2014). The extent of work and testing independent accountants undertake when attesting to the financial report depends on the type of attestation engagement. The most rigorous — and the type of attestation required of public firms by the SEC — is an audit. During a financial statement audit, the independent accountant must collect evidence directly supporting the numbers reported by management in the financial statements. For example, accountants count inventory, observe property and equipment, and examine bank records for cash receipts from customers. Moreover, the independent accountant typically examines and tests the control systems firms use to record transactions and prepare the financial reports. For example, the accountants will examine how materials flow through the production process (i.e., are ordered, received, paid for, placed into production, and ultimately sold and delivered). Ultimately, the auditor assures that the financial statements present fairly, in all material respects, the financial position of the company and the results of the operations.

The second and third type of attestation engagements are significantly less rigorous than an audit (Minnis 2011). During a review engagement the accountant does not collect direct evidence supporting the reported balances in the financial statements, but instead conducts an inquiry of management about their financial reporting and management policies and performs high-level analyses of the financial reports (e.g., examines changes in balances over time and relationships between balances, looking for anything unusual). For a compilation engagement the independent accountant conducts no testing and provides no assurance about the balances in the reports at all. The purpose of the engagement is essentially “to assist management in presenting financial information in the form of financial statements” (AICPA 2016). Therefore, the independent accountant does little, if anything, to facilitate better reporting with a compilation engagement.

Figure A1: Two dimensions of financial reporting for non-listed U.S. firms

		Audit		No Audit		
GAAP		Qualified opinion	Review	Comp	Nothing	
No GAAP	Tax					
	Cash					
	IFRS/Statutory/other					