Measurement Matters: Financial Reporting and Productivity*

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Abstract

We examine the relation between financial measurement practices and firm-level productivity. Using two proprietary data sets, including a comprehensive panel of firm tax returns, we find that financial measurement quality explains 10-20% of the intra-industry dispersion of total factor productivity (TFP), a magnitude similar to that of other structured management practices identified in prior studies. We provide evidence of two mechanisms for this result. First, cross-sectional and panel analyses are consistent with high-quality measurement as a management practice causing higher productivity. Second, using plausibly exogenous differences in misreporting incentives, we show that external auditors attenuate reporting biases in administrative data. Thus we show that a portion of measured productivity heterogeneity is the direct result of reporting differences across firms. While short of identifying causal treatment effects, the economic magnitude of our results suggests that firms' accounting practices are an important area for explaining the vast heterogeneity in reported productivity.

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1 Introduction

Research finds substantial and persistent differences in productivity across firms, even within well-defined industries. For example, Syverson (2004a) finds that within four-digit SIC industries in the U.S. manufacturing sector, the average difference in logged total factor productivity (TFP) between an industry's 90th and 10th percentile plant is 0.651. This estimate implies that firms in the 90th percentile produce almost twice the amount of output with the same level of measured input as the 10th percentile plant. Other studies have found similar dispersion in productivity within industries (Dhrymes, 1991; Doms and Bartelsman, 2000; Syverson, 2004b; Hsieh and Klenow, 2009; Fox and Smeets, 2011).

Reasons for the wide dispersion in firm-level productivity is a topic of significant debate (Syverson, 2011; Bloom et al., 2013). One explanation for heterogeneity in firm-level productivity considers how researchers measure productivity. A rich literature shows how differing assumptions and measurements lead to differing estimates of firm-level productivity.[1] A second approach explains residual productivity by examining the link between managerial practices and productivity. For example, Bertrand and Schoar (2003) point to manager-specific effects relating to firms' policy decisions and outcomes. More recent studies document an association between specific management practices, such as hiring and firing policies, and firm-level productivity outcomes (Bloom and Reenen, 2007).

While both the management practices and measurement explanations have begun to "put faces on" the dispersion in intra-industry productivity, much-unexplained variation remains (Syverson (2011), pg. 330). However, one prominent source of variation across firms potentially affecting both the actual level of productivity and the reported level of productivity in administrative data sets which remains relatively unexplored is a firm's investment in its accounting and financial reporting system. Accounting is the functional mapping of economic transactions into financial reports. Information produced from this process both provides

[1] See for example, Olley and Pakes (1996); Levinsohn and Petrin (2003); Van Biesebroeck (2007); Foster et al. (2016); Kim et al. (2016); Haltiwanger et al. (2018); Collard-Wexler and Loecker (2016).

managers with useful information when making decisions (e.g., Bushman and Smith (2001); Kanodia and Sapra (2016))[2] and populates prominent data sets used by researchers to study productivity (e.g., Compustat, IRS, Economic Census).

In this paper, we examine the relation between firm-level financial measurement practices and productivity using data from two independently compiled data sets of private U.S. firms. The first source of data is the comprehensive panel of tax returns for all private U.S. firms with at least $10 million of assets provided by the Internal Revenue Service (IRS). The second is a panel of small-to-medium sized privately held U.S. firms sourced from accounting firms and compiled by Sageworks, a financial data analytics firm. The data sets cover different time periods and firm sizes and include different variables assuaging concerns about robustness and generalizability. Importantly, a key distinction of the private U.S. firm setting is that financial reporting is not mandated by a regulatory body, thus allowing for substantial variation, akin to other practices such as setting targets and providing incentives.

Using these data, we closely follow the econometric approaches of prior research to confirm vast productivity heterogeneity across firms within well-defined industries and provide plausible benchmarks of our economic magnitudes. We then measure financial reporting quality as the combination of high-quality standards and external verification of the financial report. We find that variation in financial reporting quality explains approximately 10% to 20% of the spread between the 10th and the 90th percentile of TFP, which is very similar in economic magnitude to other productivity drivers such as information technology, human capital, and management practices (Bloom et al., 2018). Moreover, these inferences are unaffected by a battery of robustness tests, including alternative measures of productivity and various specifications controlling for factors driving financial reporting differences across firms (e.g., firm size and capital structure)

One advantage of our data relative to the Census of Manufacturers is that our IRS data

[2]Examples of studies investigating the "real effects" of accounting include: McNichols and Stubben (2008), Cheng et al. (2013), Shroff (2017), and Harp and Barnes (2018). For discussions of the literature see Leuz and Wysocki (2016) and Roychowdhury et al. (2018).

set includes the comprehensive panel of all private firms across all industries. We exploit the cross-sectional breadth and panel dimensions to consider two possible mechanisms for the link between productivity and investment in financial measurement quality. First, we examine the explanation that high-quality financial measurement is a management practice leading to higher *actual* productivity. Cross-sectional analyses show that our results are stronger in settings in which information is more essential and where firm experience and sophistication is lower. Specifically, we find stronger results for firms in more competitive industries and younger firms, and our results are weaker for firms in high innovation industries.

We then exploit the time-series variation in two ways. First, prior literature finds that more productive firms are more likely to survive (e.g., Syverson (2011)). We find a 7 percent increase in the two-year survival likelihood for firms with more investment in financial measurement. Including both TFP and financial measurement quality in the same specification slightly attenuates both coefficients (consistent with a relation between the two), but both remain significant. We also compare changes in future productivity and growth (conditional on survival) and find that firms with better reporting measurement become more productive and grow faster, consistent with better managed and more productive firms attracting more resources.

Second, we exploit the panel structure of the data to examine the pattern of measured productivity following a *change* in reporting quality regime. Because auditors typically do most of their examination after a firm's year-end, there is little scope for improved information causing higher productivity in the first year. However, while an external audit identifies most discretion, errors, and bias in the first year of the audit engagement, there are considerably less reporting effects in subsequent audits. Thus, changes in reported productivity in years after the first audit would provide evidence consistent with a learning channel. We use a firm fixed effects design to 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 an insignificant change in reported TFP in the first year of an audit, but a significant increase in TFP in the second year. While this test is subject to several limitations, it is consistent with auditing improving actual productivity by helping managers learn over time from higher quality financial measurement.[3]

Finally, we provide evidence of a second mechanism: differences in *reported* productivity are manifestations of the reporting process, such as bias in reported production. To investigate this channel, we exploit heterogeneity in incentives to bias reports driven by differences in firm-level taxation. Firms face an incentive to misreport their level of production to minimize taxes (e.g., Beck et al. (2014); Balakrishnan et al. (2018)). External auditors, however, can reduce this misreporting bias (DeFond and Zhang, 2014). Therefore, differential financial measurement quality could lead to measured productivity dispersion because of differential firm-level reporting biases in administrative data sets. Exploiting cross-sectional heterogeneity in firms' incentive to bias reports based on state-level taxation differences, we find that the relation between reporting quality and productivity is almost half the magnitude in states with lower tax misreporting incentives (e.g., Texas) compared to states with higher misreporting incentives (e.g., California). This evidence suggests that one source of measured TFP dispersion using administrative data is differences in the amount of under-reported production which varies with the extent of external auditor engagement.[4]

Collectively, we show that firms' financial measurement practices are significantly related to reported firm-level productivity and highlight two potential mechanisms for this relation. In doing so, our paper contributes to both the economics and accounting literature. First, we contribute to the recent literature in economics which shows that management practices, such as hiring talent and providing incentives, can be viewed as a "technology" that enhances firm-level productivity (e.g., Bloom and Reenen (2007); Bloom et al. (2018)). We extend

[3]Because firms endogenously choose to engage an auditor, one threat to a learning channel inference is that firms engaging an auditor are doing so because they are experiencing significant growth which is associated with both engaging an auditor and higher levels of productivity. In the absence of random assignment, we cannot rule out this type of explanation which is why we suggest this evidence is consistent with a productivity enhancing learning channel.

[4]This is a complementary finding to the disciplining mechanism of tax audits on financial reporting (i.e., the reverse direction) as documented by Hoopes et al. (2012) and Hanlon et al. (2014).

this insight to an important and widespread management practice: the firm's decision to produce, and have verified, high-quality financial statements.

Our findings also build on the recent accounting research linking reporting attributes to firm-level outcomes. For example, various papers link financial reporting quality to managerial decision-making and investment efficiency (e.g., McNichols and Stubben (2008); Cheng et al. (2013); Feng et al. (2015); Shroff (2017); Choi (2018); Breuer (2018)). Miller et al. (2018) consider the attributes of the manager and find that entrepreneurs with accounting backgrounds start firms that are more likely to achieve profitability.[5] Our paper complements this literature by viewing accounting as a management practice which alters reported firm-level productivity. Moreover, our empirical approach also allows us to directly benchmark the economic magnitude of our results to that of the "management as a practice" literature. Perhaps more importantly, our paper re-frames the view of accounting — i.e., the measurement of inputs and outputs — in the economics literature from simply being homogeneous. Instead, firms use heterogeneous reporting conventions and invest deferentially in reporting quality, which we find is closely linked to econometricians' measurement of productivity.

Finally, it is important to note what inferences cannot be made from our findings. Consistent with the recent literature associating management practices with productivity, we do not measuring a treatment effect. Perhaps the most significant threat to causal inference is that firms with high-quality measurement practices are also those with high-quality management practices along other dimensions, such as those identified by Bloom et al. (2018) — i.e., firms "bundle" the management practices. This possibility is intriguing because it reflects that high-productivity managers choose to expend resources on financial reporting practices, which may be otherwise simply viewed as an external communication mechanism. A related caveat — and consistent with the initial literature investigating other structured management practices — is that we do not investigate the question of why firms choose not

[5] Another example of linking financial reporting information quality to decision-making is Gallemore and Labro (2015) who find that firms with higher internal information quality have higher tax efficiency (i.e., pay lower taxes).

to invest in improved financial measurement if it leads to enhanced productivity. Possibilities range from heterogeneous costs (and benefits — noting that we are only measuring potential reporting benefits for those firms choosing to invest in accounting practices) to competitive and behavioral explanations. Nevertheless, the magnitude of our associations (even using relatively coarse measures of accounting quality) demonstrate that accounting heterogeneity likely plays a first-order role in understanding firm-level economic phenomena.

2 Financial reporting measurement and productivity

2.1 Financial reporting heterogeneity: Accounting standards and attestation

The fundamental premise of the paper is that heterogeneity in financial measurement across firms is responsible for a portion of the variation in reported firm-level productivity. In this section, we first describe what we mean by financial reporting variation (and why it exists) and then describe why this variation can explain a portion of the reported productivity dispersion puzzle.

Financial reporting has two broad dimensions along which measurement practices can differ (see Figure 1A in the appendix). The first dimension is the set of accounting rules (i.e., accounting standards) followed by the firm. Accounting standards are the functional mapping of economic transactions to reported results. They dictate when, how much, and where economic activity gets reported in financial statements, and different standards recognize and measure economic transactions differently. For example, "cash basis" accounting recognizes economic activity as cash is paid and received by the firm. By contrast, "accrual basis" accounting recognizes transactions in conjunction with the economic activity, which is often distinct from when cash is paid or received.[6]

[6]Heterogeneity remains even within a given set of standards because managers have some discretion and frequently estimation plays an important role.

The second dimension of financial reporting is the extent to which an independent accountant examines and attests to the financial report.There is a continuum of attestation, but an audit is the most rigorous. During a financial statement audit, the independent accountant must collect evidence directly supporting the numbers reported by management in the financial statements. For example, auditors count inventory, observe property and equipment, and examine bank records for cash receipts from customers. Moreover, the independent accountant examines and tests the control systems firms use to record transactions and prepare the financial reports. Auditors typically examine how materials flow through the production process (i.e., are ordered, received, paid for, placed into production, and ultimately sold and delivered). Collectively, 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 according to the set of accounting standards followed by the firm. Appendix A provides additional description of the accounting process. Auditing exists because there is scope for both managerial discretion and errors in the accounting process(DeFond and Zhang, 2014). Managers decide how to implement the accounting rules, make estimates about future economic transactions, which introduces noise and can intentionally misstate economic activity, which biases the report. The role of the auditor is to examine the report to investigate the discretion, noise, and bias and mitigate the effects of these factors.

Collectively, a firm's financial report is a function of the accounting standards it follows and how rigorously the financial report has been examined. In the U.S. there is substantial variation in financial reporting because, while publicly traded firms are required by the Securities Exchange Commission (SEC) to file audited financial statements in accordance with Generally Accepted Accounting Principles (GAAP), privately held firms (which represent 99 percent of firms and approximately half of non-governmental GDP) face no such requirements. They are neither required to follow a particular set of rules nor engage an independent accountant. Instead, financial reporting is an economic good wherein private firms choose their set of accounting standards and attestation level based on costs and benefits (e.g., Allee and Yohn (2009); Lisowsky and Minnis (2018)). To highlight the extent of variation across firms in the economy, Figure 1 shows the percentage of firms that follow GAAP and receive an audit. The figure reveals heterogeneity both within as well as between industries, with attestation rates across sectors ranging between 20 to 60 percent of firms. Moreover, while prior literature motivates firms' reporting choices from the perspective of agency problems between the firm and capital providers, Figure 2 shows that significant variation in firms' attestation remains after conditioning on firm size, ownership, and debt. Thus, while ownership dispersion and debt are positively related to higher quality measurement practices, many firms with millions of dollars in external debt and large ownership dispersion still do not produce audited GAAP statements.

2.2 Linking financial measurement to productivity

In this section, we show how heterogeneity in financial reporting measurement can be responsible for variation in reported productivity. As standard in the literature, we assume firm-level production follows a Cobb-Douglas production function:

$$Y_{it} = A_{it} K_{it}^{\alpha} L_{it}^{\beta} \tag{1}$$

where Y is output measured as annual value added (sales less material inputs), K is the firm's capital stock, L is the annual labor inputs, and A is the (latent) total factor productivity (TFP) term. TFP is then estimated as the residual after regressing the log of value added on the log of the input factors:

$$log\hat{A}_{it} = logY_{it} - \hat{\alpha} logK_{it} - \hat{\beta} logL_{it} \tag{2}$$

Estimated TFP measures Hicksian-factor neutral productivity differences, which would include, for example, differences in management practices (Bloom and Reenen, 2007) or frictions in the capital markets (Hsieh and Klenow, 2009).[7]

We posit that variation in financial reporting practices creates differences in reported TFP for at least two reasons. The first is a relatively straight-forward measurement explanation: high-quality financial measurement can attenuate reporting errors and biases in administrative data sets. By some estimates, potentially half of the measured intra-industry TFP dispersion is the result of problems measuring inputs and outputs (Bloom and Reenen, 2007). Given that the level of financial report attestation varies significantly across firms — even within well-defined industries — and research shows that financial misreporting decreases with the level of attestation, then a portion of TFP measured using administrative data sets could be the result of different levels of bias and noise mitigated by auditors.[8] As just one example in the context of the production model above, firms which under-report production (say, to avoid taxation) will appear in the analyses as having low productivity. If some firms have auditors which force them to fully report their production while others do not, then this reporting difference generates heterogeneity in measured within-industry TFP.

The second explanation for a link between independent accountant attestation and firm-level productivity is that more rigorous financial measurement improves the *actual*, not just *reported*, level of productivity. Specifically, using a set of accounting standards which better reflects economic activity and engaging an independent auditor to ensure the accuracy of the report is a management practice technology akin to human resource policies, goal setting, or inventory management. Higher quality financial measurement and processes lead to better managerial information, which in turn lead to better decisions.

Under an information perspective, David et al. (2016) link imperfect information to resource misallocation and differentials in productivity. In a frictionless market, the opti-

[7]However, as has been discussed in the literature (e.g., Syverson (2011); Haltiwanger et al. (2018)), because TFP is estimated as the residual of the production function, it literally captures anything not accounted for by the explicit inputs measured.

[8]For example, using variation in the level of attestation, Minnis (2011) finds that accruals are more predictive of future cash flows for firms with audits compared to firms with reviews or compilations.

mal allocation of input factors across productive units requires the equalization of marginal products. Deviations from this outcome represent a misallocation of resources and translate into sub-optimal aggregate outcomes and lower productivity. At a micro level, when a firm chooses inputs under limited information about their idiosyncratic fundamentals, the information frictions in the firm lead to a misallocation of factors.[9] Under this framework, we can think of the firm facing a learning problem. While the firm and managers can learn from a variety of sources, the measured internal information is a prominent source of information for managers.[10]

Auditing also does more than assure the quality of the financial report. Auditors examine firms controls and procedures. For example, they test for the existence and operational integrity of physical capital. They examine human resources and payroll policies to mitigate fraudulent (i.e., nonexistent) employees. Moreover, they provide advice about weaknesses in production processes such as inventory controls. Thus, the financial reporting system can be considered an integral and essential component of the economic environment that determines how firms and managers allocate resources.[11]

A causal link between high-quality reporting and productivity is not a certainty, however.

[9] At a macro level, misallocation across firms in an ex-post sense reduces aggregate productivity and output. The size of this misallocation is a function of the residual uncertainty at the time of the input choice, which is a function of the volatility of the fundamental shocks and the quality of information at the firm level (David et al., 2016). Empirically, Sadka (2004) shows that countries with more transparent reporting regimes have higher levels of productivity. Hann et al. (2018) show that productivity dispersion is smaller in industries with better transparency. Both papers infer that financial reporting plays a role in capital allocation *across* firms.

[10] This decision-theoretic analysis of information has a long history in economics and accounting (see Pratt et al. (1965); Feltham (1968); Feltham and Demski (1970); Demski (1972)). Moreover, research in accounting has shown that changes in accounting standards shape changes in firms behavior. For example, Amir and Benartzi (1999) suggest that firms avoid the recognition of an additional pension liability under SFAS 87 by reducing the volatility of pension assets. Amir et al. (2010) provide evidence consistent with firms changing their pension asset allocations to mitigate expected equity volatility from pension accounting changes in the U.K. and U.S. Shroff (2017) shows that changes in accounting standards may cause firms to learn new information from their internal systems, which in turn leads to higher investment efficiency.

[11] Prior research finds that the management accounting systems that are used for internal decision making are closely linked to the financial accounting systems that are used for external reporting (Kaplan (1984); Dichev et al. (2013)). Recent studies have begun to examine the extent to which managers act on faulty information as a result of their own earnings management decisions or ineffective internal controls over the financial reporting. These studies find that misreporting and deficiencies in the internal controls lead to inefficient investment (e.g., McNichols and Stubben (2008); Cheng et al. (2013)) and performance (Feng et al., 2015).

A plausible alternative view is that the primary purpose of audited financial reports is to serve merely as a financial communication designed for external users and not to facilitate internal decision-making. For example, a primary stated objective of GAAP is to provide investors with information about a firm's future cash flows to facilitate external investment decisions. The orientation of auditing and GAAP, therefore, is about improving the external information environment.

3 Data

We use two independently collected, proprietary data sets of private U.S. firms, each with their relative advantages. Our first data set is a comprehensive panel data set of all business tax returns for the years 2008 to 2010 for firms with at least $10 million in assets. The data set is provided confidentially by the IRS and includes all filings for C-corporations, S-corporations, partnerships, and limited liability companies, encompassing not only manufacturing but all industries. The fields in this data set include income and expense line items (i.e., "page 1" items from the tax form used to calculate operating income) as well as balance sheet line items from Schedule L and firms' NAICS industry codes. Importantly for our study, the IRS forms also require firms to reveal two characteristics of their financial reporting system: the set of accounting standards the firm uses and whether the firm had its financial statements audited by an independent accountant.

The second data set we use is provided by Sageworks, Inc., a financial data analytics firm. Accounting firms enter their clients' data into Sageworks' cloud-based interface, and Sageworks provided us with the underlying anonymized panel data set for the years 2002 to 2008. For each firm-year, the data set includes fields for income statement and balance sheet line items, the number of employees, NAICS industry code, U.S. state of location, and, importantly for this study, the extent of financial statement verification provided by the accounting firm. The data set also provides a broad categorization of accounting standards but does not provide the specific set of standards followed. Therefore, we follow Minnis (2011) and only use firms which follow an "accrual" basis of accounting.

We conduct analyses using both data sets because they offer relative advantages and complementarities, ensuring the robustness and generalizability of our results. The IRS data set is focused on medium-to-larger firms (those with at least \$10 million in assets), while the Sageworks data set contains mostly smaller firms (the vast majority have less than \$10 million in assets). While the Sageworks data set reports the number of employees, the IRS data set does not, so we measure labor inputs using the wage bill for the IRS analyses and the labor headcount for the Sageworks analyses. Moreover, Sageworks provides the state of location for each firm, whereas the IRS did not provide us with firms' location data. The data sets also cover different time periods: our Sageworks panel covers 2002 to 2008; while the IRS data set covers 2008 to 2010. In addition, while the Sageworks data set is sourced from accounting firms which have opted to be customers of Sageworks (and therefore one may be concerned about participation bias), the IRS data set is a comprehensive set of filings, minimizing participation bias and allowing us to track the survival of firms from one year to the next with minimal error. A final difference between the two data sets is the financial measurement quality specification we use. The IRS only asks firms if an independent accountant audits their financial statements; whereas the Sageworks data set records whether firms' financial statements are audited, reviewed, or compiled. Therefore, report quality is a binary variable for the IRS analyses (an indicator equal to 1 if the firm prepares and has audited a GAAP financial statement; and 0 otherwise) and a count variable for Sageworks analyses (equal to 1 for an audit; 0.5 for a review; and 0 for a compilation).

Table 1 presents the distribution of firms years across NAICS sectors for both data sets. The distributions are relatively similar across industries with slight differences in Construction and Retail trade. Compared to public firms in data sets such as Compustat, private firms in both data sets are less focused in Manufacturing industries and more focused in Construction and Wholesale trade, which is more reflective of the distribution of the population of U.S. firms (see Lisowsky and Minnis (2018)).

We measure output, in both data sets, as the log value added (*ln(va)*) calculated as the log of sales minus the cost of goods sold; capital as the log of total property, plant, and equipment (*ln(ppent)*); and materials as the log of cost of goods sold (*ln(cogs)*).[12] In the analyses using the IRS data, we measure labor (*ln(labor)*) as the log of the wage bill; whereas with Sageworks, we use the log of the number of employees. Table 2 presents the descriptive statistics for these variables and reveals several aspects of the data. First, because of the minimum size threshold, firms in the IRS data set are larger, on average, compared to the Sageworks firms. Second, firms with better reporting and financial measurement practices are larger, on average, than firms with lower quality measurement practices. However, while there are differences in size conditional on report type, there is also significant common support across the distributions — i.e., there are many large and small firms choosing each of the quality levels of financial measurement as graphed in Figure 2.[13] Nevertheless, we further consider these size differences in robustness analyses below. We also note from Table 2 that the majority of firms choose lower quality financial measurement practices, consistent with the accounting literature investigating these choices (e.g., Lisowsky and Minnis (2018)). However, as Figure 1 shows, there is still substantial variation in financial reporting quality across sectors.

[12]Because cost of goods sold includes more than just the materials bill, such as labor and capital stock charges, this line item technically double counts certain costs of production with labor and capital stock. As such, in additional analyses, we replicate our results using gross revenue based productivity (i.e., TFP-R) and our inferences are identical with larger economic magnitudes than what we report using TFP-VA. We use TFP-VA to facilitate comparability to Bloom et al. (2018).

[13]To further ensure common support, we have truncated the distributions of both data sets based on size. In the IRS (Sageworks) data set, we require a minimum of $10 million ($500k) and a maximum of $1 billion ($250 million) in assets.

4 Results

4.1 Relation between reporting quality and productivity

We begin by estimating TFP-VA in Table 3. Columns 1, 2, & 3 (4, 5 & 6) report the results for the IRS (Sageworks) sample. Both sets of analyses include 4-digit NAICS industry by year fixed effects, while the Sageworks regressions also include state fixed effects for firms' location. Columns 1 & 4 include the full sample; whereas Columns 2 & 5 are estimated on propensity-matched samples, where matching is based on the level of inputs (i.e., *ln(labor)* and *ln(ppe)*) within industry-years. Finally, columns 3 & 6 are weighted OLS, where the weights are the firms' output, to ensure that smaller firms (which are more numerous) are not exclusively driving the results. The reported coefficients represent the elasticities of production for labor and capital.[14] The residuals from these regressions are the estimated firm-level logged TFP-VA.[15]

We begin with an initial assessment of the relation between TFP and financial measurement quality in Figure 3. Figure 3 plots the TFP distribution conditional on report type and sector using the Sageworks and IRS data. Consistent with the hypothesis that higher quality measurement is associated with higher productivity, we find that TFP increases as financial measurement quality increases across sectors for both datasets. This result holds not only at the mean but across the distribution of TFP. Additionally, we note that the variance of TFP-VA is not lower for higher reporting practices. Instead, there is a variance preserving rightward shift in the distribution.

We formally test the relation between better measurement systems and productivity in Table 4. We regress estimated TFP-VA on our measure of financial report quality. Standard

[14] These elasticities are of similar magnitude to those estimated in Bloom and Reenen (2007) and Hsieh and Klenow (2009).

[15] We also conduct our analyses in "one-stage" wherein we include the report variable directly in the production function estimation in Table 3. Not surprisingly, this leads to nearly identical inferences. Moreover, in additional supplementary analyses, we then fully interact the report variable with labor and capital to assess whether the elasticities of production differ conditional on the report type. We find that the estimated coefficients on labor and capital do not differ across report types. We tentatively infer that this suggests that financial measurement is a Hicks-neutral outward shift in productivity.

errors are clustered at the industry by year level. Column 1 reports a significant coefficient of 0.108 on our report measure, which explains approximately 8.4% of the 10/90 unconditional TFP-VA spread in the IRS data set. For the Sageworks sample, Column 3 reports a significant coefficient of 0.310, which indicates that going from a compilation to an audit is associated with a 20% increase in TFP-VA relative to the unconditional spread between the 10th and 90th percentile of TFP. The explanatory power of our financial measurement quality variable is comparable to those estimated in the management practice literature (Bloom et al., 2018). For example, the 16-dimensional management score used in Bloom et al. (2018) explains approximately 18% of the 10/90 TFP spread in U.S. firms, while Bloom and Reenen (2007) finds that management practices explain approximately 12% of the interquartile spread in TFP across four countries.[16]

We conduct several robustness analyses. First, we consider two important observable differences across firms: size and access to capital markets. Concerning size, we note from Table 2 and Figure 2 that while there is common support in the distribution of firm size (i.e., there are both very large and very small firms in each of the high and low-quality reporting buckets), higher financial measurement quality is also associated with larger firm size, on average. Thus, a concern is that firm size may be spuriously driving our results (i.e., larger firms are both more productive and have higher agency problems). If independent financial report verification is more likely to be used in the presence of agency problems, then the relation between measurement quality and productivity is not the result of financial measurement quality, but rather spuriously driven through firm size.[17]

Regarding capital market access, differential access to capital markets is a standard fric-

[16]Because of differences in data availability and measurement, the comparisons across papers are not perfect. The closest comparison of economic magnitudes between management practices and financial reporting is our IRS analysis (Table 4, column 1) with Bloom and Reenen (2007) Table 1, column 2. Both use sales as the measure of production and include labor, capital, and materials as factors, along with time and 6-digit industry fixed effects.

[17]We note that a prediction from models of productivity is that better-managed firms attract more resources, grow more quickly, and therefore, are predicted to be larger than poorly managed firms (e.g., Syverson (2011); Bloom et al. (2017)). Therefore, the amount of resources controlled (i.e., firm size) has been used as an outcome variable rather than a control variable, thus "controlling" for firm size is potentially working against our results.

tion in productivity models predicting heterogeneity in productivity (e.g.,Hsieh and Klenow (2009); Rajan and Zingales (1998)). Firms with better access to capital markets can purchase more productive capital leading to observed heterogeneity across firms. This could be problematic for inferences, as a standard reason for improving financial measurement (e.g., engage an auditor) is to access external capital. However, this concern seems muted as Figure 2 panel B shows a substantial percentage of firms engaging in high financial measurement even in the absence of debt. Nevertheless, our financial measurement variable could simply be identifying differential capital market access.

We examine the robustness of our reporting quality estimates with respect to firm size and capital market access in two ways. First, we propensity score match firms based on the level of inputs.[18] We force a match within 2-digit industry by year and require a caliper of 0.03 without replacement. Table 4, columns 2 and 5 report the results after including only those propensity-matched observations. The results are only slightly attenuated from those in columns 1 and 4. Second, we consider differences in capital structure across firms. In Table 5 we two-way sort firms in the IRS sample based on leverage and ownership dispersion.[19] In each cell, we report the sample size and the proportion of firms in the cell receiving a GAAP audit. We also re-estimate the specification in column 1 of Table 4 within the partition and report the coefficient on report. In doing so, we attempt to mitigate the concern that the productivity benefits of higher quality financial measurement are derived only from a capital market channel (i.e., those with better reporting have better access to capital markets, and thus, more access to productive inputs). Table 5 shows that the relation between financial measurement quality and productivity is positive across all cells

[18]Specifically, in the Sageworks data we create a variable comp which equals 1 if the firm receives a compilation (the lowest report quality level) and 0 otherwise (effectively grouping observations receiving reviews and audits). Using comp as the dependent variable essentially results in mostly a comparison between compilations and reviews given the smaller number of audit observations. This also results in matches of the smaller firms in the sample. If we alternatively use an indicator for the firm receiving an audit as the dependent variable (which groups compilations and reviews) we have a much smaller sample (because of the smaller number of audit observations) but the results — both economically and statistically — remain very similar.

[19]We cannot do this in the Sageworks data because we do not have ownership data.

(marginally insignificant in the upper left cell) and becomes somewhat more positive when controlling for capital market access (e.g., the largest magnitude is the cell with the most leverage and ownership dispersion). While Table 5 is subject to the caveat that both capital structure and reporting quality are both equilibrium outcomes, these results suggest that differences in capital structure do not explain our results.

Finally, we consider the generalizability of our results across industries. The analyses thus far include 4-digit industry by year fixed effects, but we do not allow either the factor elasticities or the relation between reporting and productivity to differ across industries. Therefore, we re-estimate Table 3 and Table 4 regressions for each sector reported in Table 1 with at least 500 observations (still including 4-digit industry by year fixed effects). Figures 3a and 3b plot the results. The figures show a persistent positive relation between TFP-VA and reporting measurement quality in each of the sectors in both data sets. Figure 4 reports the fraction of intra-industry 10/90 TFP dispersion explained by reporting measurement quality. Consistent with our prior results, we find statistically and economically significant results across all industries; thus, our results are not specific to a particular industry despite the heterogeneity. Nevertheless, the results in Figure 4 suggest potentially interesting variation across industries, which we will exploit in the next section.

To this point, we have shown that financial measurement reporting quality is strongly associated with firm-level productivity, of similar magnitude to other structured management practices; that differences in size or access to capital do not appear to explain the results; and that the association is persistent across industries. However, there is still economically important heterogeneity across industries, which leads us to explore two plausible mechanisms for these results.

4.2 Mechanisms: Management practice and measurement bias

In this section we examine the evidence for two possible explanations for a relation between financial reporting quality and productivity: (i) *actual* improvement in the level of productivity and (ii) differences in *reported* production caused by biased reporting on the part of firms.

4.2.1 Actual productivity differences: Financial measurement quality as a management practice

A positive relation between financial measurement quality and firm-level productivity could arise as a result of external verification improving the productivity of the firm — i.e., the processes and information inside the firm are better because of the auditor's involvement. Ideally, to test this hypothesis, we would randomly assign treatment to firms; unfortunately, similar to much of the literature studying management practices (with the notable exception of Bloom et al. (2013)) we are unable to do so. As a result, we examine this issue exploiting both cross-sectional and time-series variation. Of course, these results remain suggestive and not causal.

Our cross-sectional tests stem from one of two basic logical paths. First, if better financial measurement improves managers' information set to make better productivity-related decisions, then our results should be stronger in cases were better measurement is more critical. Two settings in which the relative value of financial measurement might differ are (i) firms competing in industries with low margins and (ii) firms in industries reliant on innovation (i.e., developing new products through creativity and research). While firms in low margin industries — typically characterized by high competition — have little room for error regarding production decisions, and thus make high-quality financial information particularly relevant, firms in high RD industries, in contrast, may not benefit from high-quality financial measurement for productivity purposes given the forward-looking nature of innovation.

The second motivating hypothesis for our cross-sectional tests is if firms have opportunities to gather information from their own experiences over time (i.e., learn) then this learning attenuates the relative importance of financial measurement quality for productivity. We proxy for a firms "learning from itself" by its age. Older firms likely have more established processes; whereas newly established firms have the most to benefit from the insights of auditors reviewing their still developing processes.

We examine these cross-sectional predictions in Table 6. Columns 1 and 2 use data from Compustat to construct the industry-based cross-sectional variables.[20] We measure these two cross-sectional variables in deciles scaled to the interval [0,1] to facilitate interpretation of the coefficient as a comparison between the top and bottom decile. The use of industry by year fixed effects absorb the main effects of the cross-sectional variables. Column 1 measures margins at the industry median and are measured to be consistent with the Lerner index approach. We find that the relation between financial measurement and productivity is economically higher in low-margin industries, but not statistically significant at the 10% level. In column 2, we measure the R&D intensity as the industry median level of R&D scaled by sales. We find that the ability for financial measurement quality to explain productivity dispersion is lower in high innovation industries. Finally, in column 3, we exploit firms' founding year on the corporate tax forms to measure firm age. We create an indicator *Young Firm* which equals 1 for firms less than 4 years old.[21] We find that the interaction between *Young Firm* and *report* is significantly positive, supporting the idea that firms processes become more efficient as they learn, muting the need for outside counsel. Overall, the cross-sectional tests of Table 6 reveal that financial measurement quality behaves consistently with a management practice technology.

To further explore financial measurement as a productivity-enhancing management technology, we exploit the panel structure of the IRS data set and examine several time-series

[20]We use Compustat data to construct the industry based cross-sectional variables in Table 6 for two reasons. First, it allows us to use data "outside the system" to mitigate any mechanical or endogenous link between financial measurement and profitability levels. Second, R&D is not reported in either the IRS or Sageworks data sets. We define industry at the 3-digit level to consider the trade-off between a sufficient number of observations within each industry, while at the same time recognizing that industries can be very different at high levels of aggregation. We cluster standard errors at the 3-digit level to address the fact that variation in the cross-sectional variables occurs at this level.

[21]The sample size is smaller in column 3 of Table 6 because we are only able to use data from corporations filing form 1120 (or 1120S). The year founded was not provided to us for other entity types. We use "less than 4 years old" as the indicator for a young firm because Lisowsky and Minnis (2018)) find that the relation between age and propensity to have audited GAAP financial statements begins to flatten significantly around four years.

tests. We begin by considering firm survival. A consistent finding in the economics literature is that productivity is strongly associated with firm survival. We revisit these results and examine whether financial measurement is associated with survival. Using the complete set of IRS tax returns, we define survive as 1 if the firm continues to file tax returns in the year and 0 if not. In the primary analysis, we use the year 2008 as the base year, and measure survive in 2010, but the results are virtually identical if we restrict to one year ahead.

Table 7 replicates the result that TFP predicts survival. Column 1 reveals that our firm-level estimates of TFP-VA are strongly associated with firm survival. In column 2, we show that financial measurement quality is also associated with firm survival. This positive association holds even when both TFP-VA and financial measurement are included in column 3. The coefficients on both remain significant, though both are slightly attenuated. For example, we observe a 6.3% higher likelihood of survival for firms with high report quality compared to those with low report quality. We benchmark this estimate in two ways. First, we note that this magnitude is slightly smaller than going from the 10th percentile to the 90th in TFP, which results in a 9% increase in the probability of surviving from 2008 to 2010 (0.070 x 1.284 = 0.09). Second, we also compare the magnitude to that found in Bloom et al. (2018) using their management practice survey. They find that a one standard deviation increase in their management score explains approximately 22% of the unconditional exit rate of their sample (their estimate of 0.153 times a one standard deviation in the management score of 0.172 divided by an unconditional exit rate of 11.8%, see Table 3). The IRS data has an unconditional exit rate from 2008 to 2010 of 24%, indicating that high financial measurement quality explains approximately 26% of this rate, similar to Bloom et al. (2018).

Columns 4 - 5 examine the relation between reporting quality and survival after conditioning on firm size. Specifically, we split the sample based on median sales size and continue to find positive survival effects from reporting quality, with the effect being larger for smaller firms. In columns 6 - 7, we look at changes in firm-level performance, conditional on survival until 2010 and the financial measurement quality and level of performance in 2008. We find that firms with high-quality financial measurement increase their productivity and sales. However, similar to the previous cross-sectional tests, these tests still do not establish causation. For example, one could be concerned that firms anticipating future growth are those that engage an independent accountant ex-ante (e.g., to attract external capital to facilitate the growth), resulting in an endogenous positive association between financial measurement quality and growth. At this point, we can only say that our results are consistent with prior literature investigating management practices and are consistent with financial measurement quality facilitating higher firm performance.

Our final analysis relies on changes to assess financial measurement quality as a management practice. Recall the two possible channels through which we suggest independent accountants can affect measured TFP: they can reduce bias in the financial report (i.e., improve reported productivity) and they make the financial system more informative (i.e., improve actual productivity). These two channels are not mutually exclusive. However, one way to potentially disentangle these explanations is to observe what happens when firms first engage an independent accountant. If the primary channel for the effects is through a reduction in bias (or other changes in the reported numbers), then these effects should arise in the first year. If there are effects related to improving actual productivity, then these effects likely take time.[22]

Column 8 of Table 7 reports our changes analysis. We restrict the sample to firms that exist in all three years of the panel and either (i) receive audited GAAP statements all three years; (ii) do not receive audited GAAP statements in any of the three years; or (iii) change from not receiving audited GAAP statements in 2008 to doing so in 2009 and continuing to do so in 2010. We then regress TFP-VA on firm fixed effects plus indicators for whether the firm initiated a GAAP audit. The coefficient on *Start GAAP Audit x 2009* measures the change in TFP in the first year of the audit and the coefficient on *Start GAAP Audit x 2010* measures

[22]An auditor does much of the audit-related work after a firms fiscal year has already ended. Therefore, they can affect the numbers as they are reported in the first year, but likely do not have an opportunity to affect actual productivity.

the incremental change in TFP-VA in 2010. The coefficient on *Start GAAP Audit x 2009* is positive but small and insignificant, suggesting little evidence of auditors substantially adjusting the reports for under-reporting bias in these firms. However, the coefficient on *Start GAAP Audit x 2010* is more substantial and significant. Therefore, compared to firms that did not change their financial measurement quality, those that improved their financial measurement quality had an increase in TFP in the second year of the engagement, but not the first, supporting a learning channel. This test remains subject to several limitations (e.g., if in the first year of an audit, auditors are just as likely to be reducing upward bias in financial reports as downward bias, then this test does not rule out the reported productivity channel), but the time series evidence is consistent with a learning channel.

4.2.2 Reported productivity differences: Tax incentives to misreport

A second mechanism for the finding that higher reporting quality is associated with higher productivity is that firms with lower quality reporting bias their reported level of production.[23] For example, firms have incentives to under-report production to reduce tax liabilities and one role of external verification by independent auditors is to ensure managers do not bias the reported financial results (e.g., Coppens and Peek (2005); Burgstahler et al. (2006); Beck et al. (2014); Hanlon et al. (2014)). If financial statement verification reduces managements' under-reporting bias, then this could generate a positive relation between financial measurement quality and productivity.[24] Specifically, we expect that in situations in which incentives to misreport are high, there is a larger difference in the reported productivity of audited and unaudited firms.

[23]While reduced measurement noise for inputs and outputs can reduce the dispersion in reported productivity, it would not generate a significantly positive relation between reporting quality and productivity. Also, note that we are investigating the link between financial report auditing and tax misreporting. By contrast, several papers in the accounting literature have investigated how tax-related auditing (i.e., audits by the tax authorities) might potentially mitigate financial misreporting (e.g., Hoopes et al. (2012); Hanlon et al. (2014)).

[24]It is important to note that these tests are not intended to identify temporary differences in the reported production such as recognizing sales in future periods, but rather permanent differences. An example of a permanent difference is when a firm does not report a cash sale in its output (e.g., the owner simply puts cash in her pocket and never reports it).

To examine this likelihood, we exploit differences in incentives for under-reporting production across states as driven by different tax regimes. States tax firm production under a variety of mechanisms. For example, many states tax corporations similar to the federal corporate regime in which net income is taxed. Other states tax the gross production directly. Moreover, tax regimes affect firms in different ways because firms may have different taxable entities (e.g., C-corporations versus pass-through entities such as partnerships). Because of this complexity, we measure tax incentives to under-report production in two ways. First, we use the states' corporate income tax rate. This rate varies significantly across states. For example, in , the top state corporate tax rate was 12%, while at the same time, four states had a 0% tax rate. Figure 5 demonstrates the extent of variation in corporate income tax rates across states in 2008. Second, we derive a more comprehensive measure of tax incentives by collecting the per capita dollar value of taxes collected for corporate income taxes, personal income taxes, and revenue (i.e., sales) taxes. This measure should be related to the incentives of both C-corporations and pass-throughs, though it likely has substantial noise given the breadth of the measure.

Table 8 re-estimates the results from Table 4, column 4 after adding an interaction term crossing the financial report quality variable with a variable measuring the state-level tax incentives to misreport production.[25] In column 1, the cross-sectional variable is based on the corporate tax rate; whereas column 2 uses the variable based on per capita collection of income and revenue tax collections. For consistency, we transform both variables into ranks. We classify the state as a "high tax state" if it is in the top quintile (equal to 1) and a "low tax state" if it is in the bottom quintile (equal to 0). The remaining states are classified as medium (equal to 0.5).[26] The coefficient on the two-way interaction is significantly positive. If the state and industry by year fixed effects identify all other differences across states, then this result implies that financial report quality (specifically, external verification) is

[25]We only use the Sageworks data for this analysis as the IRS data does not have the state of the firm's location.

[26]Note that the main effect of the cross-sectional tax variables is absorbed into the state fixed effect. We also cluster the standard errors at the state level because the cross-sectional variables vary by state.

particularly important in states with high incentives for firms to under-report production.[27]

5 Discussion and conclusion

The substantial heterogeneity in reported firm-level productivity across and within industries has been a topic of great interest. In this paper, we show that differential financial reporting measurement explains an economically large portion of this heterogeneity. Specifically, we find that firms engaging independent accountants, whose role is to examine firms' internal controls and provide assurance that the reported numbers materially represent the underlying economics of the firm, have significantly higher levels of reported productivity, survival, and growth and the magnitudes of these findings are consistent with research investigating a wide array of management practices.

We present evidence of two mechanisms for this relation. First, we find results consistent with enhanced financial measurement improving actual firm-level productivity. That is, engaging an outside auditor is akin to a management practice or a "technology" which creates a Hicksian-neutral outward shift in the level of productivity. Using cross-sectional tests, we show that the relation between auditing and productivity is stronger (weaker) where information precision is stronger (weaker): firms competing in low margin (high innovation) industries. Moreover, we find that learning by the firm moderates the auditing-productivity relation, further suggesting that the relation manifests through an information channel.

Second, we show that auditors reduce bias in financial reports. In particular, firms have incentives to report downward biased production figures to reduce tax burdens. Using plausibly exogenous cross-sectional variation in tax-based incentives across U.S. states, we show that outside auditors attenuate the downward bias of their audit clients, generating reported intra-industry productivity heterogeneity in those administrative data sets. This

[27]In untabulated results, we find that the coefficient on the interaction term increases if we restrict the sample to C-corporations, which are the firms affected by corporate tax rates. We also find that the results in column 1 attenuate with firm size, consistent with the finding that smaller firms have higher tax avoidance on a percentage basis and that auditing is particularly effective for these firms.

result is particularly acute in smaller firms consistent with findings in the tax literature that the majority of the "tax gap" is caused by small firms.

While our straightforward characterization of a firm's reporting system explains nearly as much variation in intra-industry productivity as more detailed management practices (Bloom and Reenen (2007) and Bloom et al. (2018)), we are cautious that, much like their findings, we have not directly measured a causal mechanism linking higher financial measurement quality to higher productivity. Moreover, a quite relevant threat to our inferences is that we are merely identifying those firms with "good" management practices along the very same dimensions as those studies. Nevertheless, our results are intriguing for at least two reasons. First, auditing is often viewed as a practice required of firms with agency problems. However, should our results simply be explained away by "good" management practices, this suggests that high-quality firms are more likely to engage auditors. Second, our approach to measuring reporting is parsimonious and inexpensive to assimilate in administrative data sets. Merging this variable into other confidential governmental data sets such as the Census would allow for historical panel-level analyses and would not require teams of surveys.

Finally, our characterization of financial measurement is but one aspect of a firm's reporting system, which may have systematic effects on measured productivity. Firms can account for the same economic transaction in a variety of ways which, in turn, would result in cross-sectional differences in productivity. At a minimum, our results suggest a more thorough accounting of firms' accounting would bear fruit in understanding productivity and its dispersion.

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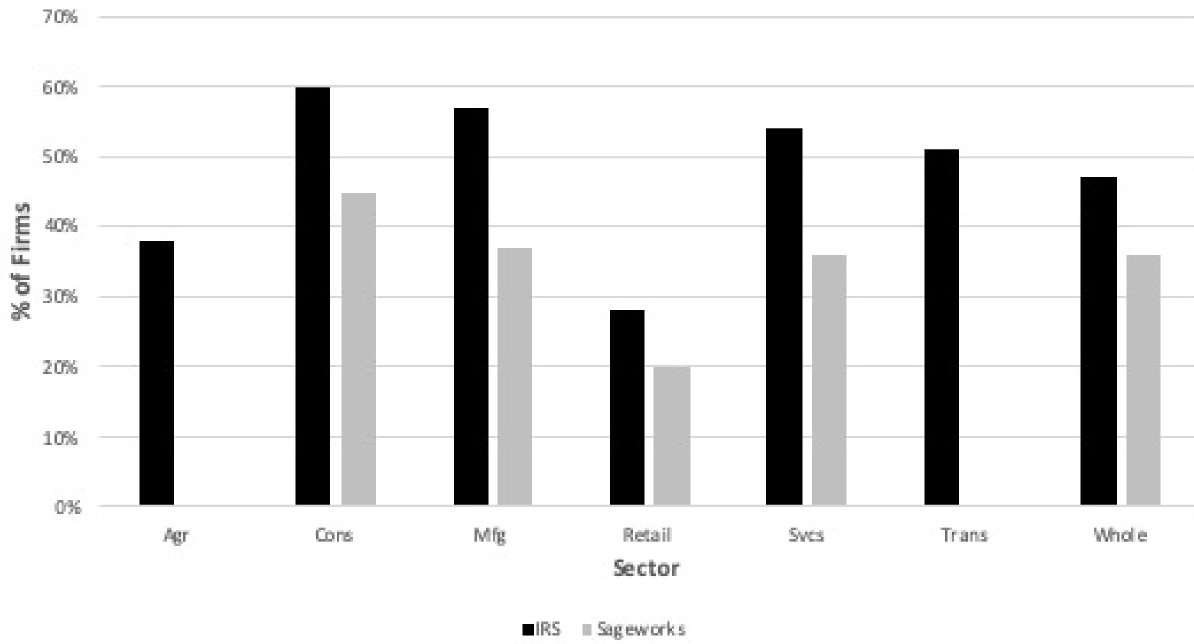
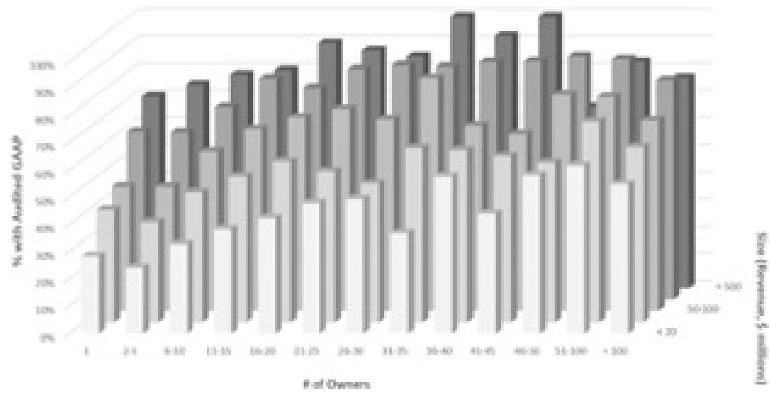
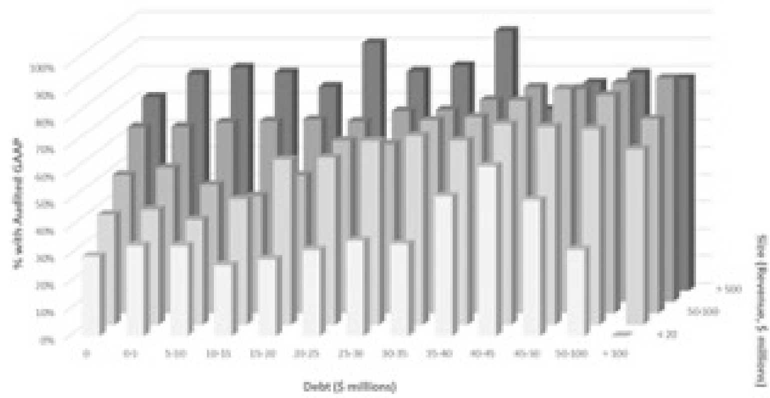


Figure 1: Variation in Financial Reporting Quality across Sectors

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.



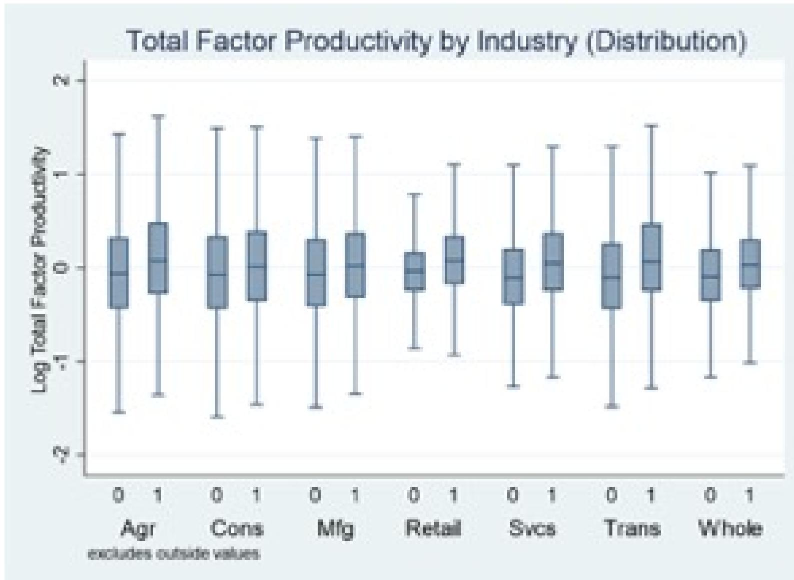
(a) Conditioning on Size and Ownership dispersion



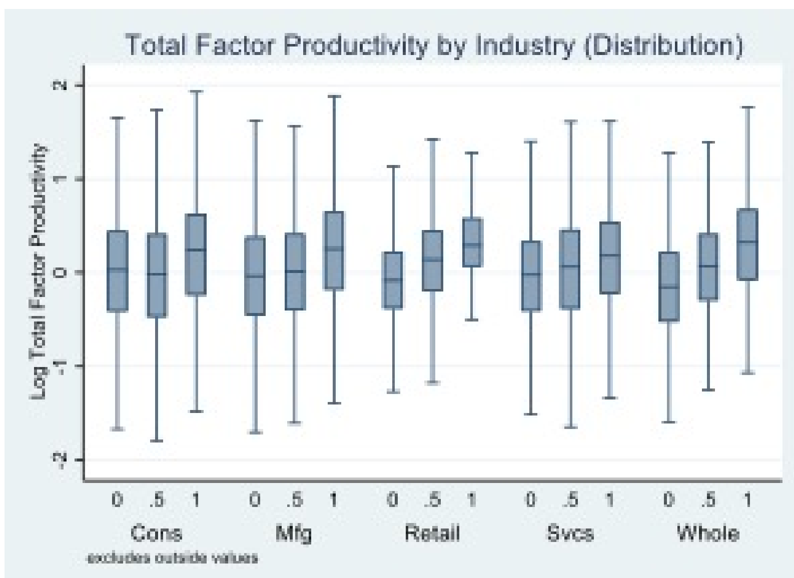
(b) Conditioning on Size and Debt

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

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.



(a) IRS data



(b) Sageworks data

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

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.

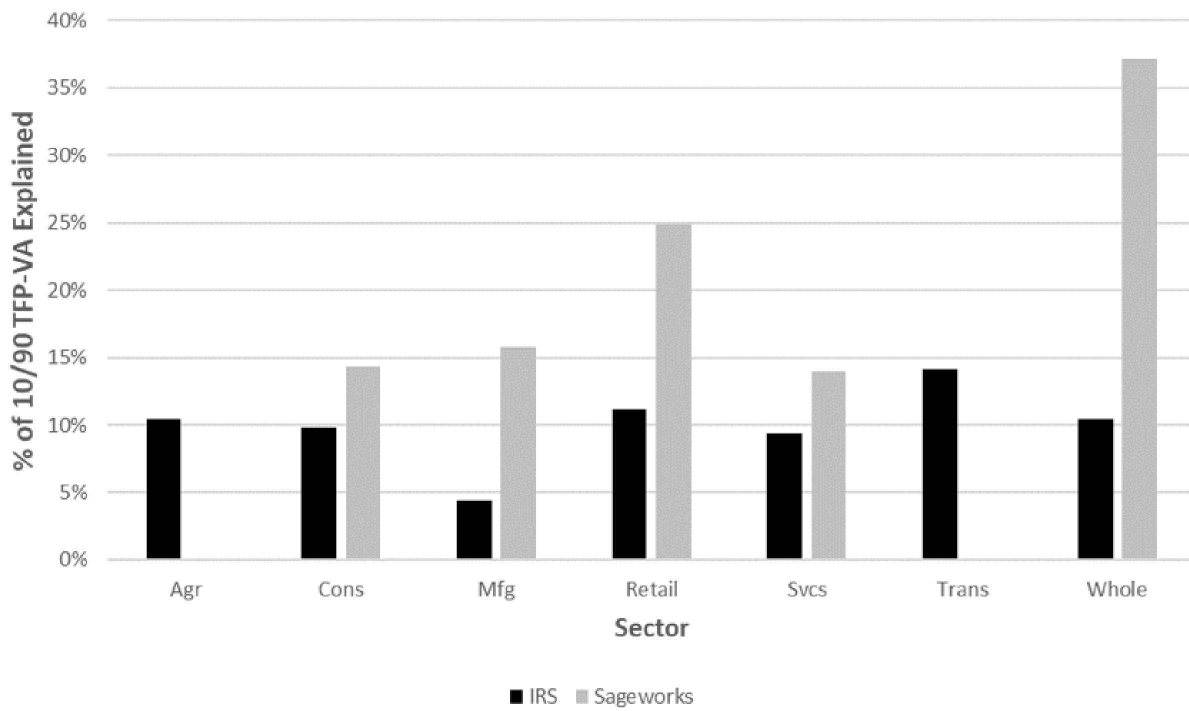


Figure 4: Portion of 10/90 TFP-VA Spread Explained by Industry

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.

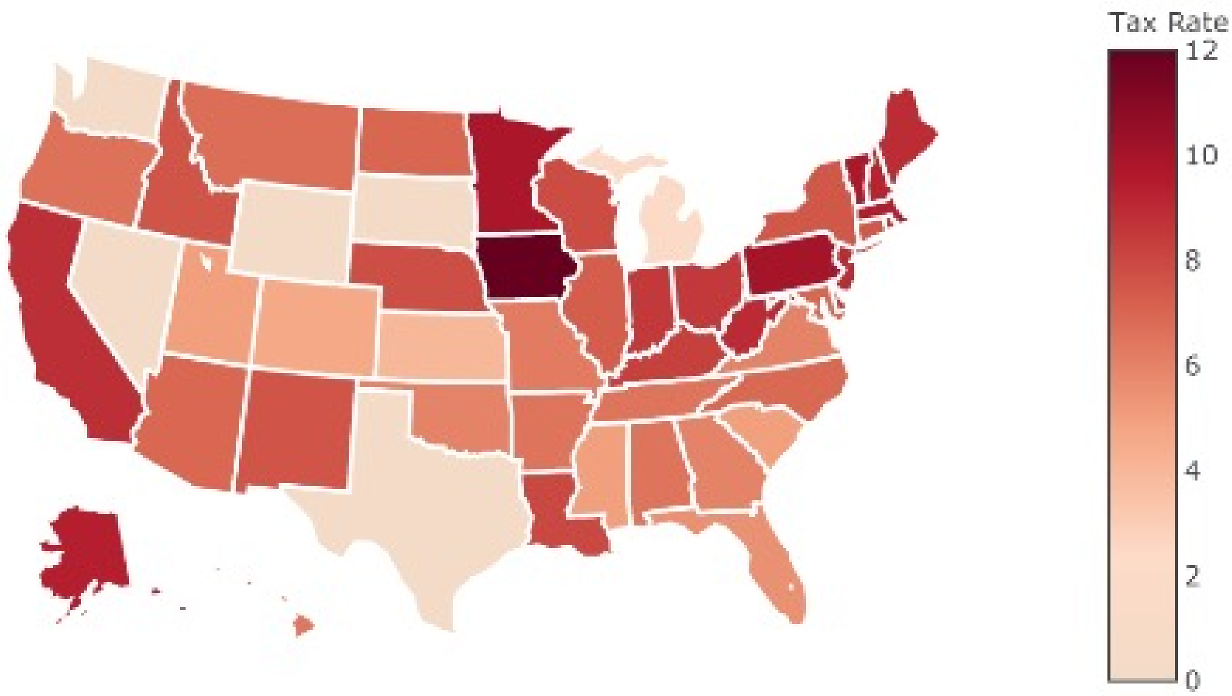


Figure 5: Corporate Taxation Rates across States

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

	IRS		Sageworks	
Industry	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

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) data sets.

Table 2: Descriptive statistics

Panel A: IRS

		Mean	SD	P10	P25	P50	P75	P99
	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
Audit	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
	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
Review	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 B: Sageworks

		Mean	SD	P10	P25	P50	P75	P99
	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
Audit	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
	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
Review	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
	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
Comp	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							

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 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 B 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: Estimating 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***	0.577***	0.625***	0.587***	0.593***	0.455***
	(0.008)	(0.009)	(0.007)	(0.013)	(0.017)	(0.049)
ln(ppe)	0.110***	0.100***	0.108***	0.118***	0.0944***	0.258***
	(0.005)	(0.005)	(0.004)	(0.007)	(0.009)	(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

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.

Table 4: Productivity and reporting quality

	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)
report	0.108***	0.087***	0.100***	0.310***	0.272***	0.311***
	(0.007)	(0.008)	(0.006)	(0.022)	(0.028)	(0.051)
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
Share of 90-10 explained	8.4%	6.7%	8.4%	20.2%	18.3%	20.0%
R2	0.007	0.005	0.007	0.022	0.017	0.027

This table reports the results of regressing value added total factor productivity (estimated as the residuals from the regressions in Table 3) on financial measurement quality. Columns 1-3 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 4-6 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 and 5 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 5: Productivity and reporting quality conditional on capital structure

Owners	Leverage: *None*	Leverage: *>0 to 20%*	Leverage: *>20%*
1	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%
2 to 5	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%
>5	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%

This table presents estimates from the model in Table 4, Column 1 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 R2 , the sample size, and the portion of the sample in which report=1. *, **, *** indicate significance at 10%, 5%, and 1%, respectively.

Table 6: 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)
GAAP Audit	0.085**	0.114***	0.098***
	(0.01)	(0.01)	(0.01)
GAAP Audit x CS var	0.032	-0.054***	0.072***
	(0.02)	(0.02)	(0.02)
Young Firm			0.00340
			(0.02)
Industry x Year FE	Yes	Yes	Yes
Observations	54,547	54,547	51,240

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 0,1 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 7: Survival and changes in performance

Analysis			**Survival Analysis**				**Performance Analysis**	
Sample			**Firm exists in 2008**				**Firm exists 2008 - 2010**	
Size restriction	None	None	None	>Median	<=Median	None	None	None
Dep. variable	Survive	Survive	Survive	Survive	Survive	TFP 2010	Sales 2010	TFP
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
TFP-VA	0.074***		0.070***	0.021	0.066***	0.741***		
	(0.01)		(0.01)	(0.01)	(0.01)	(0.02)		
GAAP Audit		0.071***	0.063***	0.029**	0.051***	0.032***	0.017**	
		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(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
Firm FE	No	No	No	No	No	No	No	Yes
Year FE	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

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.

Table 8: Under-reporting bias and state taxation

	TFP-VA	TFP-VA
	1	2
Report	0.221***	0.224***
	(0.04)	(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

This table presents OLS regressions of value added total factor productivity 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 column 1 of Table 3. 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.

A Financial Reporting

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.

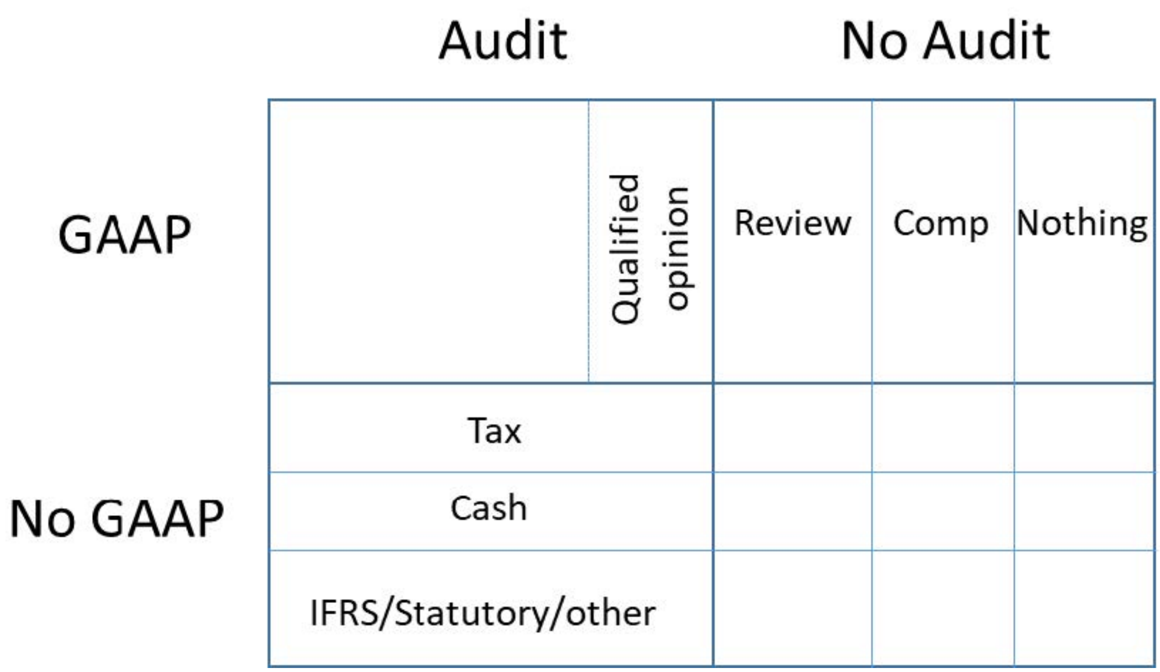


Figure A1: Two dimensions of financial reporting for non-listed U.S. firms