Managerial Discretion and Earnings Informativeness: A Structural Approach

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Abstract

Earnings informativeness is a key issue in accounting policy and practice. We investigate a managerial choice subject to discretion, and important to earnings: depreciation policy. We build and estimate a structural model to understand the depreciation decision and its effect on earnings informativeness. In the first stage, we find that a firm-by-firm two parameter model fits well in explaining depreciation for the majority of our sample of publicly traded U.S. firms. In the second stage, the counterfactual depreciation policy yielding the best fit of earnings to stock returns—the value relevance preferred policy—shows how markets perceive firms’ financial reporting: conservative or aggressive. A clear majority of firms falls into the aggressive reporting category. These results have interesting implications for understanding firms’ accounting choices and are unexpected in light of the perceived conservatism of GAAP. Furthermore, the difference between the estimated and market-inferred policies is correlated with financial reporting quality, as proxied by financial restatements.

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1 Introduction

Value relevance is a perennial topic in accounting as well as asset pricing and finance in
general (Francis and Schipper [1999], Barth et al. [2001]). A clear issue in value relevance is
earnings informativeness (Dechow et al. [2010]), focal in financial reports and accounting pol-
icy. Tied to accounting policy is the practice and implementation of accounting conservatism
(Watts [2003a], Watts [2003b]). We focus on a managerial choice subject to discretion,¹ and
important to earnings: depreciation policy.

Firms use an accounting system to aggregate information inputs, such as transaction data
and asset values, to generate outputs like earnings. The market uses these reported earnings,
along with other information, such as cash flows, macroeconomic variables, and industry
factors, to price these firms. We adopt a conceptual framework that allows us to investigate
the process by which accounting systems and the market both aggregate information to
describe and value economic performance.²

We use a structural model to uncover the market’s inference about discretion over de-
preciation as being either conservative or aggressive, through the lens of earnings informa-
tiveness. The clear structure connecting depreciation and capital expenditures makes this
decision amenable to empirical modeling. By first modeling the depreciation decision us-
ing structural restrictions, we can describe the depreciation policies of individual firms from
their accounting numbers. By varying this depreciation choice, we calculate counterfactual
earnings and then consider their value relevance. We compare the value relevance preferred
policy to the policy which best fits the accounting data and we find the level of conservatism
or aggressiveness in accounting firm by firm. Certainly there are many roles for depreciation
in accounting policy. However, our methodology uncovers the extent to which depreciation
policy may serve as a channel for value relevance through earnings.

¹In fact, "depreciation expense is one of the larger accruals over which managers exercise discretion
(Keating and Zimmerman [1999])."
²For optimal incentive mechanisms in accounting and intertemporal agency, see Rogerson [1997], Reichel-
stein [1997], Dutta and Reichelstein [2002], and Rajan and Reichelstein [2009].
In the first stage of our estimation, we model a firm’s depreciation policy as a choice over two parameters: the effective useful life of capital investments, and the fraction of investment to be depreciated. We first conclude that a two parameter model explains the data better than a single parameter model—the intuition is straightforward: not all investment is depreciable, such as land, so observed depreciation will remain systematically lower than that implied by a single parameter model. It is standard to divide depreciation by total depreciable assets (Lindenberg and Ross [1981]), to find the depreciation rate, however this ignores much of the data available. We employ the wealth of data in yearly depreciation and capital expenditures to fit our two parameter model. We calculate depreciation schedules according to this structure and fit them to the data. This procedure allows us to model 559 out of 892 firms (63%), which is reasonable, given issues with accounting for disposals,\(^3\) amortization, and asset mix. Issues such as property, plant, and equipment purchases spread throughout the year, and early retirement or disposal of these assets will increase noise in our estimates, however we still explain significant variation in our sample. We find that the median effective useful life is seven years, and that most firms’ depreciable fractions (the fraction of investment to be depreciated) cluster near unity. When we summarize depreciation policy with a single variable, estimated useful life divided by the depreciable fraction, we find that manufacturing has the fastest depreciation and real estate companies use the slowest, as expected.

In the second stage of estimation, we model the effect of depreciation choices on earnings informativeness. This methodology depends on the ability of markets to internalize the mechanical effects of depreciation policy on book earnings. Indeed, Beaver and Dukes [1973] document this phenomenon, and show that the market recognizes managerial discretion in this dimension of earnings.\(^4\) As a benchmark, we start with the standard earnings informa-

\(^3\) A measure of net disposals is usually available from the cash flow statement, however there are several problems with incorporating it in our analysis. One issue is that we do not know gross disposals. A second issue is that we do not know which vintages of depreciable investments are being disposed.

\(^4\) In the context of revenue recognition, Srivastava [2014] finds that a rule that limited the scope of managerial discretion led to reduced earnings informativeness.
tiveness regression as in Lev and Zarowin [1999]—performed firm by firm—attempting to explain stock returns with the level and first difference of earnings. Earnings reflect many choices, including managerial discretion over depreciation policy. Using the structural model of depreciation, we recalculate the counterfactual time series of earnings for each feasible depreciation policy. We run returns regressions for each set of counterfactual earnings, finding the informativeness of earnings under each counterfactual regime. We next choose the policy which maximizes the explanatory power of earnings, revealing the depreciation policy inferred by the market. This reveals the market’s interpretation of a firm’s depreciation policy as aggressive (extending the effective useful life of its assets) or conservative (shortening the effective useful life of its assets). Givoly et al. [2007], while investigating the Basu [1997] measure of conservatism, emphasize the importance of developing alternative measures of conservatism. Our second stage follows this line of inquiry by broadening the perspective on measuring conservatism (for other recent approaches, see Khan and Watts [2009] and Callen et al. [2010]).

According to our measure, there is marked heterogeneity in levels of conservatism and aggressiveness. Strikingly, we find that a clear majority of firms falls into the aggressive reporting category across all samples, specifications, and robustness checks. Within this group, expensing investment would maximize earnings informativeness for a large minority of cases. Expensing is a policy which could feasibly be imposed by standard setters. As such, it would be interesting to know the consequences on earnings informativeness of such a reform. We employ our methodology to examine a move to the expensing regime. We find that value relevance is actually improved in 46% of cases in the full sample, and 60% of cases in a restricted sample in which our method best captures variation in depreciation. This prevalence of improvements is unexpected given the chasm between expensing and common depreciation policies.

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5This result comes from a focus on the income statement role of depreciation. It is possible that depreciation could be too fast to match economic depreciation while at the same time too slow to best explain stock returns.
That our results point to the pervasiveness of aggressive, rather than conservative, reporting may at first glance seem surprising given the perceived conservatism imposed by GAAP (Kothari et al. [2010]). However, depreciation policy is an area where auditor oversight may be of limited use because of a critical dependence on managerial estimates of what will happen to assets in the potentially far distant future. One possible explanation is that accounting standards are stricter in the sense of being conservative in areas where this is feasible, to counteract the aggressiveness borne of the discretion inherent in other areas.

While we form interesting estimates of accounting conservatism (here, aggressiveness) in depreciation policy, our measure has a magnitude component as well, which illustrates the amount the market must reinterpret earnings through depreciation. We are interested in showing the external validity of our measure in the context of financial reporting quality. To this end, we measure reporting quality as the implied truthfulness of reporting based on our firm-level measure. We compare our measure with a proxy for reporting quality, the issuance of financial restatements. This comparison yields the result that an increase in our measure of reporting quality is negatively correlated with the likelihood of a firm making a restatement.

Although there is a vast literature on the use of accruals to accomplish earnings management (Healy and Wahlen [1999]), with an attendant effect on earnings informativeness, there are relatively few papers which investigate depreciation policy specifically. Keating and Zimmerman [1999] find that managers change depreciation policies in predictable ways, which supports the importance of studying the effects of these policies on the quality of accounting earnings; in our paper, we use cross-sectional differences in policies to study this question. Jackson et al. [2009] investigate the determinants of these policy choices, starting with the methodology of Bowen et al. [1995]. They find that changing depreciation methods influences capital investment decisions, with less investment following a switch away from accelerated to straight line depreciation.

Our paper is methodologically related to Lev and Sougiannis [1996], who estimate firm-
level R&D capital for a large sample of public companies and then investigate its value relevance. A substantive difference, and one of our primary contributions, is that our analysis uncovers the optimally fitted counterfactual depreciation policy for explaining returns. Our methodology not only considers market equilibrium, but depends on it for identification of perceived accounting conservatism (conversely, aggressiveness) in earnings.

The remainder of the paper proceeds as follows: Section 2 describes the data, Section 3 discusses the estimation of the model of depreciation, Section 4 uses the estimated depreciation parameters to investigate earnings informativeness, Section 5 investigates a noise benchmark, alternative specifications, and the relationship between our measure of reporting quality and financial restatements and Section 6 concludes.

2 Data

We collect accounting data on publicly traded U.S. firms from Compustat and get fiscal year total stock returns from CRSP. To be included in the main estimation sample, firms must have non-missing depreciation expense, capital expenditures and earnings before extraordinary items in each year from 1980 to 2007. In addition, firms must have non-missing total annual stock returns for each fiscal year in the 2003-2007 window for the returns regressions in the second stage of the estimation procedure. There are 892 firms satisfying these restrictions. We discuss survivorship and show that selection on firm tenure does not appear to bias our results in Section 5.1. Summary statistics for these firms are displayed in Table 1.

From the table, it is clear that requiring 28 years of data restricts our sample. By looking at publicly traded firms with relevant data from 1980 to 2007, we will necessarily be including larger firms, which are less risky, and have more consistent returns—due in no small part to survivorship bias. We would also expect that the quality of financial statements is higher—

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6The sample period for stock returns is post Sarbanes-Oxley, which means we avoid the issue identified by Cohen et al. [2008] that accrual based earnings management decreased significantly due to the reform.
Table 1: In this table we report medians for key variables for the 892 firms in our sample and the remaining 7,691 firms with relevant data from Compustat for 2005. Total assets and total sales are in millions of dollars. Return on assets, profit margin, capital expenditures, leverage, and the depreciation rate are all ratios. We see that our sample is biased towards larger firms with more sales, that make a higher return on average, a higher profit margin, invest more, have more leverage, and exhibit a lower depreciation rate.

<table>
<thead>
<tr>
<th>Sample Median</th>
<th>Compustat Median</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total Assets</td>
<td>1,613</td>
</tr>
<tr>
<td>Sales</td>
<td>1,601</td>
</tr>
<tr>
<td>Return on Assets</td>
<td>.052</td>
</tr>
<tr>
<td>Profit Margin</td>
<td>.058</td>
</tr>
<tr>
<td>Capital Expenditures</td>
<td>.043</td>
</tr>
<tr>
<td>Leverage</td>
<td>.159</td>
</tr>
<tr>
<td>Depreciation Rate</td>
<td>.143</td>
</tr>
</tbody>
</table>

something which is promising for our analysis—and this is related to several factors, including a track record of financial performance and producing financial statements, economies of scale in auditing, relative prevalence of financial analyst forecasts and reports, and institutional ownership. We also see that returns on assets and profit margins are higher within our sample, which are likewise indicative of more successful firms.

The data requirements mean that our sample also excludes some types of firms. In particular, firms which were acquired during the sample period as well as any firm which went public after 1980 cannot be included. These restrictions are especially pertinent to the high-tech sector, for which depreciation might be expected to be an important factor, given significant capital investment. In addition, earnings informativeness tends to be lower for high-tech firms (Lougee and Marquardt [2004]). The effective useful life of depreciable assets is likely very low in the high-tech industry, due to the short life of most relevant investments. This is borne out in the data, given the much larger depreciation rate for the Compustat firms outside of our sample.
3 An Empirical Model of Depreciation

Firms make disclosures about their depreciable assets and depreciation policy in the footnotes of their financial statements. Collecting and organizing the information contained in these footnotes would be difficult but perhaps feasible. However, there are two significant problems with using these data to find the effective useful lives assumed by firms. The first problem is that firms usually specify, for a coarse category of depreciable assets, only a range of years for the effective useful life, and this range is often too wide to be of much use. Secondarily, the proportion of depreciable assets which fall into each category is not typically disclosed, which renders a precise, or even approximate, calculation of the firm’s average assumed useful life impossible. We therefore need a technique for evaluating the depreciation expense and how it relates to the history of capital expenditures in order to uncover the depreciation policy of a firm.

While these footnote disclosures are not sufficient for understanding the specifics of a firm’s depreciation policy, they can be used to investigate particular aspects of this policy. Depreciation policy for financial reporting purposes generally falls into two categories: straight line and accelerated. Jackson et al. [2009] find, looking from 1988 to 2006, that 80% of firms use straight line depreciation exclusively. This figure is likely an underestimate for firms in our sample for two reasons. The first is that the authors show that this number has increased monotonically over time, to 86% by 2006. Additionally, their categorization excludes from the straight line category all firms which use accelerated depreciation for any of their assets. The authors also find that straight line depreciation is the predominant method in most industries. Hence, we feel confident in studying straight line depreciation for the firms in our sample.

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7 Of the 20% in the accelerated category, 84% use a combination of straight line and accelerated.
8 Excluding these three industries (metal mining, oil and gas extraction, and petroleum refining), which make up only 9% of our sample, has no substantive effect on our results.
3.1 Methodology

In this section, we describe our procedure for producing structural estimates of firms’ depreciation policies. The parametric assumption is that depreciation choice is restricted to a straight line method with two vintages—one which is depreciated, and one which has an indefinite useful life, and so is not depreciated at all. In Section 3.2, we compare this parametrization with a single parameter model which only takes into account estimated useful life, and show that the two parameter model with vintages better describes the data. We also extend the model by including accelerated depreciation in B, and find that it does not affect our results.

Standard calculations for estimating useful life involve dividing reported depreciation expense by the book value of equity (Lindenberg and Ross [1981], Feltham and Ohlson [1996], and for issues with this method, Lewellen and Badrinath [1997]). While this is a useful metric, we are interested in employing the wealth of variation available in the full time series of annual depreciation and capital expenditure data. Identification using simple division only allows a single parameter to be estimated. However in our baseline case, we estimate a two parameter model, because the restrictions we impose allow yearly variation to identify up to as many parameters as there are degrees of freedom in the sample. This essentially involves varying the weighting of more recent versus older capital expenditures to estimate the effective useful life. The identifying variation we use comes from changing investment levels from year to year, as without such changes, these policies would involve only a rescaling of depreciation expense.

For each firm, we estimate the depreciation schedule using capital expenditures and reported depreciation expense. The two parameters we estimate are the effective useful life of the firm’s assets and the depreciable fraction, or the fraction of the book value of equity that the firm depreciates—some assets may have very long useful lives, such as real estate. We calculate a range of possible paths for depreciation expense using the time series of capital expenditures and varying the hypothetical effective useful life from one year through 19 years.
Then we regress the actual, reported depreciation on these counterfactual depreciation time series. Simultaneously varying the portion of assets to be depreciated, we pick the best fitting depreciation policy according to the $R^2$ fit in the regressions. This particular policy pair, a useful life and a depreciable fraction, is the estimated policy used for that firm in the rest of the paper. A more detailed explanation of our methodology is contained in A.1.

### 3.2 Model Selection

In this section, we consider the fit of alternative models of depreciation policy. In particular, we argue that representing a firm’s depreciation policy using an effective useful life and a depreciable fraction allows us to perform nuanced analysis without over-fitting—a common issue in asset pricing, for example. We first describe the use of a single parameter model, and how this restricts our ability to model depreciation policy without adding flexibility. We then discuss the use of accelerated depreciation.

The one parameter model can explain some variation (has a positive $R^2$) in depreciation for 357 out of a total 892 firms, whereas the two parameter model can explain some variation in depreciation for 559 out of the 892 firms—a 57% sample increase. In Figure 1 we show a histogram of $R^2$ fits for firms in our sample. The figure shows in blue the two parameter model and in black outline the one parameter model. The bars represent the number of firms binned by the amount of variation which can be explained by the respective models. It is clear from the figure that not only are more firms’ depreciation policies explained by the two parameter model, but they are explained better. The intuition is straightforward—if we ignore the fact that not all investment is depreciable, then the observed depreciation expense will be systematically under the level implied by the model. The level by which the blue bars extend beyond the black outlined bars indicates the additional explanatory power.

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9This would be the same as maximizing a likelihood function, without imposing structure on the error term.
Figure 1: This figure shows the $R^2$ fit of the one parameter and two parameter straight line depreciation schedule models for the firms in our sample. Depicted on the horizontal axis is the level of $R^2$, and on the vertical axis is the number of firms which fit into the (0–0.2), (0.2–0.4), (0.4–0.6), (0.6–0.8), and (0.8–1.0) levels of explanatory power. There are a total of 357 firms depicted for the one parameter model, and 559 firms depicted for the two parameter model. The sample uses depreciation and capital expenditure data from 1980-2007 from Compustat. The $R^2$ has mean 0.60 for the one parameter model, restricting $R^2$ above 0, and mean 0.65 for the two parameter model, so the two parameter model explains the depreciation of more firms, and does it better.

The most important diagnostic to assess the success of the first stage estimation is the goodness of fit: how well can we explain a firm’s stream of depreciation expenses using its stream of capital expenditures? Figure 2 shows the goodness of fit. As can be seen, the distribution trends toward unity, with the mean at 0.65. Moving into Stage 2, it is these firms which make up the baseline sample. A restricted sample is also used which imposes a minimum $R^2$ of one half, producing a mean of 0.79.
Figure 2: This figure shows the $R^2$ fit for our model of depreciation. On the horizontal axis is the level of $R^2$ and on the vertical axis is the number of firms which fit into each $R^2$ bin. There are 559 out of 892 firms with $R^2$ greater than 0, depicted here. The mean $R^2$ for our model for these 559 firms has a mean of 0.65.

While most firms use exclusively straight line depreciation, and those that use any accelerated depreciation typically combine it with straight line, one may want to incorporate parameters which measure a proportion of assets being depreciated using accelerated methods. If firms are indeed using some accelerated depreciation, we may be concerned that not estimating this explicitly could bias our results in favor of finding faster or slower depreciation, which would be concerning given the importance of this metric to the analysis in the following section. B outlines a simple approach for allowing a mix of straight line and accelerated methods. We show that this extension does not alter the distribution of estimated effective useful lives and so conclude that alternative depreciation methods would not have a significant effect on the results in this paper.

There are a number of reasons why this modelling approach cannot perfectly fit the
depreciation policy of every firm in our sample. For example, a firm may dispose of assets before they are fully depreciated, which would cause a one time change to the depreciation expense and then lower than expected future expenses. Ideally, amortization expense would be subtracted from depreciation, given the way the latter is measured in Compustat—in Section 5.3, we show that this does not matter for our results. A further issue involves unobserved changes in accounting policy for existing assets or a change in the mix of assets in investment over time, which could bias our model in either direction and is somewhat unavoidable given the long time series necessary to identify the policy parameters. Extensions to deal with some of these issues are possible, and future research could add parameters to the depreciation model, though the fit of the two parameter model appears more than adequate.

3.3 Stage 1 Results

In this section we illustrate the depreciation policies estimated for the firms in our sample. The two parameters we estimate are the effective useful life and fraction of assets to be depreciated—we present results for each of these parameters, and then break down depreciation by industry to give an intuitive single dimensional summary of depreciation policies.

The distribution of effective useful life estimates is displayed in Figure 3 and appears to be reasonable in light of what is known about firms’ depreciation choices. While effective useful lives vary from one year, corresponding to expensing, to 19 years, the median effective useful life in the sample is seven years. The mean effective useful life is 8.3 years, meaning that the average firm depreciates 12% of its depreciable capital per year.
**Figure 3:** This figure shows the estimated effective useful lives of the 559 firms we modeled using a straight line depreciation schedule. On the horizontal axis is effective useful life in years. A level of 5 years is essentially depreciation of an asset over the course of five years using a straight line method. On the vertical axis is the number of firms that follow a particular effective useful life depreciation schedule, by year. For these firms, the effective useful life has a median of 7 years, an average of 8.3 years, and a mode of 5 years.

The second parameter is the fraction of investment that is depreciated, which is restricted to lie in the unit interval. The distribution of this parameter is shown in Figure 4, and, as expected, is clustered close to unity, which means that for most firms close to all investment is depreciated. While this parameter is not significantly smaller than one for most firms, it does allow us to better model firms with a vintage of depreciable assets with an indefinite or extended useful life.
Figure 4: This figure shows the estimated depreciable fraction for the 559 firms we modeled using a straight line depreciation schedule. On the horizontal axis is the depreciable fraction, or the fraction of book value of equity that the firm depreciates—some assets may not be depreciated, such as land. On the vertical axis is the number of firms which fit into each bin of depreciable fractions. The mean depreciable fraction is 0.81.

A useful way to investigate whether the estimated depreciation policies are valid is to make a break down by industry. This is done in Figure 5 using the average, by industry, of the estimated useful life divided by the depreciable fraction, as a way of summarizing each firm’s policy with a single parameter. This variable will be largest for firms with long useful lives, and investment in extended useful life assets, land, or assets with high residual values. The values we obtain are consistent with what one might expect by industry, with manufacturing using the fastest depreciation and real estate companies using the slowest.
Figure 5: This figure shows the estimated effective depreciation length for the 559 firms we modeled using a straight line depreciation schedule. On the horizontal axis is the effective depreciation length, or the estimated effective useful life divided by the depreciable fraction. This illustrates the effective depreciation which a firm is using in one summarizing factor. A larger effective depreciation length corresponds to more assets which have indefinite useful lives. On the vertical axis are industries for which we have more than 10 firm observations. Manufacturing has the lowest effective depreciation length at 10.3 years, and real estate has the highest at 21.9 years. Similar low numbers are depicted for information, mining and wholesale, and high numbers for utilities and accommodation and food services, as one might expect.

4 Counterfactual Depreciation Policy and Earnings Informativeness

We calculate a set of counterfactual earnings time series by varying firms’ depreciation choice and then assess the informativeness of these earnings using a regression of stock returns on measures of these earnings. Comparing the most likely policy as perceived by the market—the value relevance preferred policy—to the policy which best fits observed depreciation
expense, we find the level of conservatism or aggressiveness in reporting for each firm.

Our method uses the market’s pricing of firms to uncover the process by which the market may allocate capital expenditures over time to value performance. While asset pricing remains a proverbial ”black box,” pulling together earnings, book value, cash flows and external variables such as macroeconomic conditions to form valuations of firms, we use this mechanism to uncover the value relevance of depreciation policy. We are agnostic about precisely how the market turns information inputs into pricing outputs—why we use a regression earnings informativeness approach—but we do wish to positively describe how accounting policy may differ from that which is most reflective of the market’s view. Our work is related to the development of a cost allocating estimation theory in Brief and Owen [1970]. In estimation theory, the authors attempt to codify measures of performance across periods to evaluate rate of return on a single asset, extending this analysis to a multiple asset framework (as in a firm) in Brief and Owen [1973]. These methods are extended more generally by Ohlson and Zhang [1998], though most importantly, the authors make clear the choices necessarily made by accounting systems and how they influence the measure of economic performance. Beyond accounting systems, our goal is to rely on the market to determine the optimal allocation of costs. Using earnings informativeness, we infer the value relevance preferred policy.

4.1 Methodology

We are interested in measuring the value relevance of earnings, or essentially the effect of earnings on stock returns. The regression of returns on earnings can tell us about the value of the firm as reflected in earnings. We first describe the specifics of our methodology for measuring earnings informativeness. Then we generate counterfactual earnings numbers

\footnote{Ohlson and Zhang [1998] delineate the inputs to financial statements, the potential outputs, and the class of functional mappings from these transactions to outputs. The authors stress the restrictions noninvertibility (aggregation) in accounting naturally entails, but attempt to formulate the properties accrual rules satisfy. While their analysis depends on so-called soft as well as hard information being included in equity, they are able to meet some desirable conceptual criteria through an efficient accounting mechanism. For further discussion, see Liang [2001] and Arya et al. [2002].}
using different structural depreciation schedules. Estimating the returns regressions with these counterfactual earnings gives us earnings informativeness under a variety of effective useful life assumptions. We can then choose the effective useful life, and consequently the structural depreciation schedule, which yields the most informative earnings.

While there are many ways to study earnings informativeness, we choose to regress returns on earnings and change in earnings, as in Lev and Zarowin [1999]. Most studies of earnings informativeness pool regressions across firms, cross-sectionally; however, we perform regressions firm by firm because both actual and counterfactual accounting policies vary at the firm level. For firm $i$ in year $t$, $Return_{i,t}$ is the total stock return, while $E_{i,t}^0$ and $\Delta E_{i,t,t-1}^0 (= E_{i,t}^0 - E_{i,t-1}^0)$ denote earnings and change in earnings relative to the prior period, as actually reported by the firm. The regression form is\(^{11}\)

$$Return_{i,t} = \alpha_i + \beta_{1i} E_{i,t} + \beta_{2i} \Delta E_{i,t,t-1} + \epsilon_{i,t} \quad (1)$$

Where $E_{i,t}$ (and $\Delta E_{i,t,t-1}$) represent either actual or counterfactual earnings (and the respective change therein), depending on the specification. We use the $R^2$ in the above regression as our measure of firm-level earnings informativeness,\(^{12}\) and are interested in the explanatory power of counterfactual earnings created by varying the depreciation policy. For each particular depreciation policy, varying by effective useful life, we recalculate depreciation expenses and use these to generate the counterfactual earnings for each depreciation policy. Then estimating equation 1 for each of these time series’ of earnings, we pick the one which best fits stock returns. The corresponding depreciation policy becomes our estimate of the market-inferred depreciation policy. Details of the estimation procedure can be found in A.2.

We use the years 2003-07 in each of the returns regressions. One limitation with using

\(^{11}\)More recent research on earnings informativeness recognizes that one aspect of information provided by earnings is its effect on expectations over future earnings. For simplicity and data constraints, we focus on this parsimonious model. Alternative specifications could involve other control variables such as book value. We investigate this in Section 5.3 and find similar results.

\(^{12}\)The sum of $\beta_{1i}$ and $\beta_{2i}$ is another possible measure of earnings informativeness at the firm level, though we employ $R^2$ as the simplest and most intuitive criterion.
five years of returns data is that the feasibility of including other covariates in the regressions is limited. In the baseline, we include earnings, change in earnings, and a constant term. If we were to pool together the data, as is standard in many earnings relevance papers, this would not be an issue; however, we model earnings relevance firm by firm, because we want to study policy at the individual firm level, rather than the aggregate, or average, policy. Of course, the time horizon for our study could be extended, though this would reduce the validity and precision of our results, because we would then be averaging over too many years to create a meaningful benchmark for the market’s interpretation of depreciation policy. In addition, we would have to include data prior to the Sarbanes-Oxley reform, or after the start of the financial crisis. Our chosen sample period is designed to strike a balance between these competing concerns.

4.2 Stage 2 Results

Our method attempts to illuminate part of the process by which the market prices firms by comparing the market-inferred, or value relevance preferred, policy to the true depreciation policy of the firm. If a firm were to depreciate their assets faster than the value relevance preferred policy, then we would interpret this as conservative accounting—the firm treats assets as having shorter effective useful lives than the market perceives, and so accelerates recognition of expenses. However, if a firm were to depreciate their assets slower than the value relevance preferred policy, then we would interpret this as aggressive accounting—the firm treats assets as having longer effective useful lives than the market perceives. Our results show that firms predominantly exhibit aggressive depreciation policies, which is striking given the perceived conservatism of GAAP. While there is significant heterogeneity in the way firm policies differ from market-inferred policies, nearly two thirds of our sample fall into the aggressive reporting category.

Figure 6 shows the difference between the optimal useful life estimated in Stage 2 and the estimated useful life from Stage 1. The top panel uses the main sample and shows significant
Figure 6: This figure shows the estimated effective useful life subtracted from the optimally fitted effective useful life for the 559 firms in our sample in the top panel, and for the 220 firms in the restricted sample in the bottom panel. Optimally fitted effective useful life is the effective useful life which produces earnings numbers which best describe returns in a simple earnings informativeness regression. The estimated useful life is the number of years as fitted using a straight line depreciation schedule. The restricted sample requires that $R^2 > 0.5$ in the first stage of estimation, that $R^2 > 0.05$ in the second stage, and that the improvement in explanatory power of the optimally fitted earnings of firms over the counterfactual estimated earnings increase by 10%. On the horizontal axis is the difference in years. On the vertical axis is the number of firms binned into each year differential. A negative number denotes aggressiveness in accounting, and a positive number denotes conservatism. For the main sample, the median and modal difference are both -3 years and the mean is -2.7 years. For the restricted sample, the median difference is -4, the modal difference is -3 years, and the mean is -4.5 years.
heterogeneity across firms, though there is a noticeable bias to the left—this means that the majority of firms are perceived by the market to be reporting aggressively, in the sense of using actual depreciation schedules which reduce the present value of expenses. Then in the process of backing out the true earnings of the firm, the market accelerates these expenses, yielding an inferred useful life which is shorter than that reported by the firm. The median difference in useful life in this figure is negative three.

The bottom panel of Figure 6 presents the same information, but for the restricted sample, where we require a good fit in the first stage and second stage, along with a minimum of 10% improvement in the $R^2$ the second stage. This distribution is in fact more skewed towards aggressive reporting, with a median difference in useful life from estimated to optimal of negative four—a deviation even larger than that observed for the main sample. This is reassuring, given that the restrictions imposed to arrive at this sample pick out the firms for which our procedure is best able to estimate the actual depreciation policy.

An important additional check on these results is to verify whether they reflect a meaningful change in informativeness. The concern would be that earnings are not very informative for some firms and so perhaps changes in depreciation policy do not have much effect. In such a case, a small amount of noise might be enough to generate large differences between the optimal and estimated depreciation policies. In other words, these two policies may not actually differ very much in their informativeness. The requirements of the restricted sample address this concern to some extent though it is useful to look directly at the $R^2$ improvement in this stage. Figure 7 shows this improvement for the restricted sample. The nature of the algorithm employed means that this improvement must be non-negative, and is only zero if the most informative policy exactly matches the expected policy. Fortunately, there appears to be significant improvement generated by the optimal policy.

\footnote{The minimum $R^2$ in the first stage is 0.5; in the second stage it is .05. Changing these cutoffs does not meaningfully impact the results.}
Figure 7: This figure shows the $R^2$ improvement of optimally fitted earnings over counterfactual estimated earnings in the standard earnings informativeness regression for the 220 firms in the restricted sample. The restricted sample requires that $R^2 > 0.5$ in the first stage of estimation, that $R^2 > 0.05$ in the second stage, and that the improvement in explanatory power of the optimally fitted earnings of firms over the counterfactual estimated earnings increase by 10%. On the horizontal axis is $R^2$ improvement and on the vertical axis is the number of firms which fit into each $R^2$ bin. The median improvement is 0.16, and the average improvement is 0.21.

A remaining concern is that the benchmark in these results is earnings calculated under the estimated depreciation policy, rather than actual reported earnings (i.e. with the actual depreciation policy). To investigate this issue, Figure 8 uses this alternative benchmark. Strikingly, earnings informativeness is improved under the optimal policy for 84% of firms, even though our procedure considerably restricts the depreciation policy relative to an actual, unobserved, policy which may in fact require a large or even infinite number of parameters to describe.
Figure 8: This figure shows the $R^2$ improvement of optimally fitted earnings over actual earnings in the standard earnings informativeness regression for the 220 firms in the restricted sample. The restricted sample requires that $R^2 > 0.5$ in the first stage of estimation, that $R^2 > 0.05$ in the second stage, and that the improvement in explanatory power of the optimally fitted earnings of firms over the counterfactual estimated earnings increase by 10%. On the horizontal axis is $R^2$ improvement and on the vertical axis is the number of firms which fit into each $R^2$ bin. The median improvement is 0.15, and the average improvement is 0.20.

Having considered the improvements in earnings informativeness our algorithm produces, we return to the binary conservative/aggressive reporting distinction. Specifically, summarizing these categories discretely helps to clarify the difference in reporting and permit further investigation. Table 2 shows the data by firm according to whether the market perceives a useful life that is higher (conservative) or lower (aggressive) than that estimated from the firm’s financial statements. We evaluate conservative vs. aggressive reporting over four different samples. The first column reports our baseline specification, as described earlier in the paper.

We can see that in the main estimation sample, approximately two thirds of firms are
perceived as aggressive reporters. This fraction increases when moving to the restricted sample. However, firms with useful lives of one or two years are more likely to be classified as conservative if there is any measurement error, since almost all possible counterfactual depreciation policies would be more conservative. Dropping these firms in the third column of the table means that 86% of firms are classified as aggressive. Removing firms with effective useful lives at least as long as 18 years produces numbers in keeping with the restricted sample; this is not surprising given that only ten firms in the restricted sample fall into this category.

Table 2: This table shows the breakdown of firms by whether the market perceives them to be conservative or aggressive in their depreciation policy, according to our second stage estimation procedure. Within the aggressive category, optimal useful life of one corresponds to expensing and so is broken out separately. The main estimation sample contains all 559 firms for which the first stage estimation has explanatory power. The restricted sample of 220 firms requires that $R^2 > 0.5$ in the first stage of estimation, that $R^2 > 0.05$ in the second stage, and that the improvement in explanatory power of the optimally fitted earnings of firms over the counterfactual estimated earnings increase by 10%. The third column starts with the restricted sample and also requires an estimated useful life greater than two years, causing firms with the two fastest depreciation policies to be dropped, leaving 204 firms. In the fourth column, this added restriction is changed to an estimated useful life less than 18, so that firms with the two lengthiest depreciation policies are dropped and 210 firms are left. Note that neutral reporting firms are dropped by definition in the latter three samples, which is why neutral reporting is zero in those cases.

<table>
<thead>
<tr>
<th>Main Sample (firms)</th>
<th>Baseline</th>
<th>Restricted</th>
<th>Useful Life&gt;2</th>
<th>Useful Life&lt;18</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(559)</td>
<td>(220)</td>
<td>(204)</td>
<td>(210)</td>
</tr>
<tr>
<td>Conservative Reporting</td>
<td>.28</td>
<td>.18</td>
<td>.14</td>
<td>.19</td>
</tr>
<tr>
<td>Neutral Reporting</td>
<td>.07</td>
<td>—</td>
<td>—</td>
<td>—</td>
</tr>
<tr>
<td>Aggressive Reporting</td>
<td>.65</td>
<td>.82</td>
<td>.86</td>
<td>.81</td>
</tr>
<tr>
<td>Expense</td>
<td>.25</td>
<td>.35</td>
<td>.36</td>
<td>.36</td>
</tr>
</tbody>
</table>

A case of note within the aggressive reporting subset of firms is an optimal useful life of one, which corresponds to expensing treatment for investment. It is an interesting policy in the sense that expensing gives symmetric treatment across firms, regardless of the types of
investments they are making. Such a policy also throws out, as far as earnings are concerned, any information potentially revealed in the useful life, or, equivalently, the depreciation rate. Approximately 40% of the aggressive reporters fall into this category across each sample. In fact, this proportion is highest when restricting to an estimated useful life of at least three, which is striking since this restriction eliminates firms that were already relatively close to expensing. One might have expected that the expensing category would consist mostly of firms already using a relatively fast depreciation policy.

We assess the impact of a potential accounting reform mandating expensing by taking earnings and replacing depreciation over time with immediate expensing. Comparing this counterfactual policy with actual reported earnings yields higher earnings informativeness for 46% of firms. When we move to our restricted sample, value relevance is improved in 60% of cases. When instead comparing expensing to counterfactual earnings using the estimated depreciation policy, we see similar results. For the baseline sample, there is an improvement for 40% of firms, and for the restricted sample, for 61% of firms. In practice, there remains a large difference between expensing and common depreciation policies, so these improvements—particularly for the restricted sample—are unexpected. These results regarding expensing contribute to the vast literature following Ball and Brown [1968] on the relative informativeness of earnings and cash flows.

Our results clearly imply the value relevance of depreciation policy. Of course, the choice of depreciation, and in particular the assumed useful life, has consequences for financial statements beyond its effect on earnings. For example, proper measurement of plant assets on the balance sheet depends on the accuracy of this choice. Our earnings-focused approach necessarily leaves unmodeled such other functions of depreciation. Nonetheless, they have clear implications for accounting policy. To the extent there are non-earnings roles for depreciation, depreciation policy for these purposes could be decoupled from the choice of how capital expenditures are expensed over time. For example, GAAP could require expensing for some types of capital investment, with assumptions about useful lives disclosed.
in footnotes. The key idea coming out of our methodology, which transcends the debate about the relative value of the different roles for depreciation, is that as far as earnings are concerned, the market infers different depreciation expenses than are reported by the firm. At the very least, it is important to recognize the deleterious effect on earnings informativeness of having multiple objectives for depreciation policy.

5 Robustness and Extensions

In this section we consider the robustness and validity of our methodology and findings. We first study the bias which noise\textsuperscript{14} may introduce in our results. To do this, we allow for firms to be assigned randomly to market-inferred depreciation policies and show that our measures of relative conservatism/aggressiveness are unlikely to be obtained by chance. Next, we use alternative specifications in our second stage returns regressions—first adjusting for amortization expense and then controlling separately for book value and net property, plant, and equipment. These robustness checks leave our results on relative aggressiveness essentially unchanged. Finally, we describe a simple external validity test for our conservatism measure by comparing reporting quality on this margin to the likelihood of financial restatements. We find that firms with larger deviations between market-inferred and actual policies are more likely to issue restatements.

5.1 Survivorship Bias

We select firms such that there is sufficient data to perform our estimation. This requires that we have depreciation expense, capital expenditures and earnings before extraordinary items in each year from 1980 to 2007. Such a large sample leaves out many shorter-lived firms, and there could be concern that this would bias our results. We find that the depreciation policy used by firms is on average three years longer than the value relevance preferred

\textsuperscript{14}By noise, we mean the numerical biases introduced in our modeling procedure.
policy, meaning that markets value earnings as though capital expenditures are expensed more quickly than they actually are. This relationship could be due to something idiosyncratic about long-lived firms, meaning we might not observe this phenomenon for younger or expiring firms, if we were to have the data—this concern, if valid, would not necessarily undermine our results, but would cast doubt on their external validity.

To investigate this issue, we construct a measure of firm age using the number of years that the firm is included in Compustat. Given that this database begins in 1950 and our investigation ends in 2007, firm age runs from 28 to 58. If survivorship bias were to be a concern, we would expect our results to vary according to this variable. Comparing the difference between actual and inferred depreciation policies for firms above and below the median firm age, we get -2.82 for “old” firms and -2.68 for “young” firms. This difference is not close to statistically significant, with a p-value of 0.8215; a similar result obtains using a test of medians across the two groups. Putting this reporting difference and firm age in a simple linear regression framework again reveals no statistically significant relationship. The fact that there seems to be no relationship between our results and firm age in sample alleviates concern about such a relationship outside of the sample.

5.2 Noise as a Benchmark

It would be concerning if it were possible to obtain our results even in the absence of an effect of depreciation policy on the informativeness of earnings. We use sparse regressions to model earnings informativeness firm by firm, and thus there remains ample unexplained variation. By chance, depreciation policy could be correlated with unobservable drivers of earnings informativeness, leading to spurious conclusions about accounting conservatism as perceived by the market. In principle, a computational procedure could bias in either direction: in favor of finding conservatism results, or in favor of finding aggressiveness. If a computational procedure were to bias in favor of conservatism, then our findings regarding aggressiveness would be strengthened. If, however, the converse were true, then one might
be concerned about the validity of our results. Below, using pure noise as a benchmark for the numerical bias of our method, we show that our computational procedure favors results which are conservative, biasing against our findings of aggressiveness, and underlining the robustness of our results.

For each firm, we denote by $\tau^*$ the firm’s estimated depreciation policy. Given the $T$ years investigated by our procedure, for each firm there are $T$ possible market-inferred depreciation policies, $\tau^{**} = 1, \ldots, T$. Hence, the likelihood that the two policies match, $\tau^{**} = \tau^*$, by pure chance is just $\frac{1}{T}$ for each estimated depreciation policy. Similarly, the likelihood of $\tau^{**} > \tau^*$—where the firm depreciates at a faster rate than the market perceives, or conservatism—is $\frac{T - \tau^*}{T}$, and the likelihood of $\tau^{**} < \tau^*$—where the firm uses slower depreciation than inferred by the market, or aggressiveness—is $\frac{\tau^* - 1}{T}$. We consider a firm with $\tau^* = 8$ (as the mean of our sample is 8.3 years), for illustration, meaning there are seven potential policies which involve depreciating investment more quickly ($1, \ldots, 7$), and eleven potential policies which depreciate less quickly ($9, \ldots, 19$). Given our particular $T = 19$, and our data, matching would occur in 5.3% ($\frac{1}{19}$) of cases. The noise benchmark would also yield seven policies out of 19 (36.8%—38.7% in our sample) as denoting aggressive reporting (for $\tau^{**} = 1, \ldots, 7$), and eleven out of 19 (57.9%—56.1% in our sample) as denoting conservative reporting (for $\tau^{**} = 9, \ldots, 19$). In fact, the mean is a sufficient statistic for the direction of any pure noise-induced bias. We conclude that plausible estimation-induced noise would mechanically bias against our results.

It is also possible to formally test whether our results are statistically different from a noise benchmark for the particular case of the restricted sample.\textsuperscript{15} We use this sample because of the better fit and the associated binary categorization into conservative or aggressive. For this sample of 220 firms, 40 firms (18%) are categorized as conservative, whereas pure chance would yield 130 (59%). To test whether this difference is statistically significant, let $x \sim B(n, p)$—binomially distributed—with $n = 220$ and $p = 0.592$. We get $p$ from averaging\textsuperscript{15} Where we require a good fit in the first stage and second stage. The minimum $R^2$ in the first stage is 0.5; in the second stage it is .05. Also, we require a change from $\tau^*$ to $\tau^{**}$.
over firms in the restricted sample using calculations as described above. We want to find
the probability of getting \( x \leq 40 \) firms, or the likelihood we could obtain our results from
noise alone. To evaluate this probability, we use the normal approximation to the binomial
distribution, \( \tilde{x} \sim N(np, np(1 - p)) \). From this,

\[
Prob(\tilde{x} \leq 40) = Prob\left(z \leq -\frac{(130.22 - 40)}{7.29}\right) \approx 10^{-35}
\]

or more than 12 standard deviations away from the mean of the normal distribution. We
reject the hypothesis that a simple noise benchmark could explain our results.

5.3 Alternative Specifications

In our Stage 1 analysis, which involves modeling the relationship between capital expendi-
tures and depreciation, we want our data on depreciation to reflect exactly the depreciation
of the capital assets derived from the same capital expenditures. For a variety of institutional
and data collection issues, the primary measure of depreciation available in Compustat com-
bines reported depreciation with amortization of intangible assets. The simplest correction
for this issue would be to use a measure of the latter to disentangle the true depreciation
by year, for each firm. Amortization of intangibles appears not to have been collected for
all firms in the Compustat universe, especially for earlier years. This causes measurement
error in estimating depreciation policy. In our primary analysis, we have avoided correcting
for amortization because it is missing for so many firm years. Our sample would be much
smaller, unless we were to impute zeros for the missing data. While our fit is somewhat
improved by using this imputation, an important distortion is introduced because there is a
bias in data availability across firms and over time. In Table 3, we re-estimate our results on
reporting conservatism using the correction for amortization. We find that our results are
similar in both the main sample and the restricted sample. It appears that any measure-
ment error induced by including amortization in our baseline specification does not have a meaningful impact.

Table 3: This table shows the breakdown of firms by whether the market perceives them to be conservative or aggressive in their depreciation policy, according to our second stage estimation procedure. The main estimation sample contains all 559 firms for which the first stage estimation has explanatory power. The restricted sample of 220 firms requires that $R^2 > 0.5$ in the first stage of estimation, that $R^2 > 0.05$ in the second stage, and that the improvement in explanatory power of the optimally fitted earnings of firms over the counterfactual estimated earnings increase by 10%. The majority of firms are perceived as aggressive in their depreciation policy, and this only increases as the sample is restricted. Note that neutral reporting firms are dropped by definition in the restricted sample, which is why neutral reporting is zero for that sample in each case. The first column shows the reporting distribution for the noise benchmark, while the second column reproduces the baseline results of Table 2. The third column corrects depreciation with data on amortization and the last columns add book value and net property, plant and equipment to the earnings regressions, respectively.

<table>
<thead>
<tr>
<th>Main Sample (firms)</th>
<th>Noise (559)</th>
<th>Baseline (559)</th>
<th>Amortization (611)</th>
<th>Book Value (559)</th>
<th>Net PPE (559)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Conservative Reporting</td>
<td>.56</td>
<td>.28</td>
<td>.26</td>
<td>.25</td>
<td>.26</td>
</tr>
<tr>
<td>Neutral Reporting</td>
<td>.05</td>
<td>.07</td>
<td>.06</td>
<td>.07</td>
<td>.09</td>
</tr>
<tr>
<td>Aggressive Reporting</td>
<td>.39</td>
<td>.65</td>
<td>.68</td>
<td>.68</td>
<td>.65</td>
</tr>
<tr>
<td>Restricted Sample (firms)</td>
<td>(220)</td>
<td>(220)</td>
<td>(247)</td>
<td>(152)</td>
<td>(138)</td>
</tr>
<tr>
<td>Conservative Reporting</td>
<td>.59</td>
<td>.18</td>
<td>.20</td>
<td>.20</td>
<td>.13</td>
</tr>
<tr>
<td>Neutral Reporting</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
<td>–</td>
</tr>
<tr>
<td>Aggressive Reporting</td>
<td>.41</td>
<td>.82</td>
<td>.80</td>
<td>.80</td>
<td>.87</td>
</tr>
</tbody>
</table>

Our Stage 2 analysis involves a standard earnings informativeness regression as in Lev and Zarowin [1999], in which we include a constant, earnings, and change in earnings. We are modeling earnings informativeness on a firm by firm basis, so we are interested in the most direct effects of earnings informativeness. However, there are some clear controls that we could use in our modeling of earnings informativeness. The first alternative specification we test uses book value as an additional control. We find that the categorization of firms in each sample is consistent with our baseline specification. This indicates the robustness of
our baseline results. Further, book value controls make our results slightly more conservative in the main sample. It is important to note that the restricted samples and estimated useful life restriction samples are now smaller (152 vs. 220). This is due to our requirement in this restricted sample that the explanatory power increase considerably when compared to earnings with the estimated useful life. Book value is collinear, to a degree, with earnings, and so reduces the incremental explanatory power, while leaving similar the direction of change in policies.

An alternative control which could be included in the returns regressions, given its relation to depreciation is net property, plant, and equipment. Including this control variable, we find that our results on conservatism are the same for the main sample as from the more parsimonious baseline model. The sample size decreases when moving to the restricted sample, though this is similarly explained by collinearity of net PPE to earnings, and the effect of the 10% $R^2$ restriction in the presence of a model with more explanatory power. If anything, in the restricted sample, aggressive reporting is actually more common.

Our conservatism and aggressiveness measure is quite stable. However, this similarity may hide differences in the distribution of market-inferred policies across specifications. In Figure 9 we reproduce the distribution of differences between optimally fitted and estimated useful life using our baseline specification for all 559 firms, and then overlay the same histogram for the specification controlling for book value in the returns regressions. This figure shows the conservative (positive) vs. aggressive (negative) reporting and the number of firms by which the market’s interpretation differs. The distributions appear very similar. In fact, a pairwise t-test, where the null hypothesis is that the distributions are the same, yields a p-value of 0.35, while the Kolmogorov-Smirnov test, which employs sensitivities to both location and shape, finds a p-value of 0.867; these results mean we cannot reject the null hypothesis that the two distributions are the same.
Figure 9: This figure shows the estimated effective useful life subtracted from the optimally fitted effective useful life for the 559 firms in our sample for both our baseline specification and when controlling for book value in our Stage 2 estimates. In our baseline specification, optimally fitted effective useful life is the effective useful life which produces earnings numbers which best describe returns in a simple earnings informativeness regression. In our book value control, we use book value as an additional covariate in our earnings informativeness regressions. The estimated useful life is the number of years as fitted using a straight line depreciation schedule. On the horizontal axis is the difference in years. On the vertical axis is the number of firms binned into each year differential. 0 would mean that the optimally fitted and estimated effective useful lives coincide. A negative number depicts aggressiveness in accounting, and a positive number depicts conservatism. The median and modal difference is -3 years and the mean is -2.7 years for the baseline specification. Controlling for book value gives us a median and modal difference of -3 years, and a mean difference of -3 years. Both specifications indicate most firms exhibit aggressiveness in their depreciation policy.

5.4 Reporting Quality and Financial Restatements

Our measure of accounting conservatism uses market responses to financial reports to identify not only aggressiveness and conservatism, but the degree by which the market must
reinterpret effective useful life—when compared to accounting data—to effectively price the firm. We refer to this difference as the *reporting quality* of a firm. Specifically, we take the absolute value of the difference between the optimal life inferred by the market and the estimated life. We then say that a firm which exhibits a concordance between financial statement disclosures and the information inferred by the market is of high quality in a reporting sense.

In this section, our goal is to validate the results of our two stage procedure and to show an additional application of its output without commenting broadly or specifically on the reporting quality literature. To facilitate evaluation of our measure, we obtain data on restatement announcements due to financial reporting fraud or accounting errors. These data come from the Government Accountability Office’s Financial Restatement Database compiled using Lexis-Nexis and cover publicly traded U.S. companies from July 1, 2002 to June 30, 2006. We merge restatement announcements with our sample, firm by firm, and find at least one restatement for 18% of the firms. In our restricted sample, this proportion rises to 20%. While these restatements are typically not concerned with depreciation *per se*, it seems reasonable that a mismatch in depreciation policies between the market and the financial statements reflects a broader issue of reporting quality.

Given a large divergence between the market inferred depreciation policy and the estimated actual policy, we would conclude lower reporting quality—and hence a greater likelihood of making a restatement. On the other hand, with a small divergence between the market inferred depreciation policy and the estimated policy, we would conclude a higher reporting quality—and hence a smaller likelihood of making a restatement. Accordingly, our measure of *reporting quality* should be negatively correlated with the likelihood of making a restatement.

Table 4 shows the results of comparing our measure of reporting quality with the prevalence of restatements. In the main estimation sample, the difference in the median reporting quality for firms is six years for those firms making restatements, and five years for those
Table 4: This table shows our measure of reporting quality for firms which made restatements and for firms which did not. We measure reporting quality as the absolute value of the difference between the market’s perception of the accounting policy (depreciation) and the actual accounting policy. A lower number means higher reporting quality. The median reporting quality is statistically significantly worse for firms making restatements. When moving to the restricted sample, the results are both larger and more precisely estimated. Looking at means of the measure produce similar relative numbers and statistical conclusions.

<table>
<thead>
<tr>
<th>Reporting Quality</th>
<th>Non-Restaters</th>
<th>Restaters</th>
<th>Equality p-value</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Median</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Main Sample</td>
<td>5</td>
<td>6</td>
<td>.042</td>
</tr>
<tr>
<td>Restricted Sample</td>
<td>5</td>
<td>8</td>
<td>.003</td>
</tr>
<tr>
<td><strong>Mean</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Main Sample</td>
<td>5.9</td>
<td>6.9</td>
<td>.062</td>
</tr>
<tr>
<td>Restricted Sample</td>
<td>6.1</td>
<td>8.0</td>
<td>.006</td>
</tr>
</tbody>
</table>

firms not making restatements. This difference is in the expected direction and is statistically significant (p-value of .042) using a K-sample equality-of-medians test. Moving to the restricted sample, the results are stronger. This is as expected because the sample restrictions imply stronger confidence by the market in its inference about financial reporting quality. In fact, the differences between restaters and non-restaters increases to three, with a p-value of .005. When we compare the mean reporting quality across groups, we obtain similar results. Hence, we conclude that firms which issued restatements appear to engage in depreciation policies which are more different from perceived depreciation policies than firms which did not issue any restatements during the time of our sample. This shows that our measure has explanatory power in separating out firms for which the market perceives a large gap between the most informative depreciation policy and that reflected in a company’s actual financial statements.
6 Conclusion

Earnings informativeness is an important issue within the framework of value relevance. Earnings are affected by many factors, but depreciation policy is one over which managers can certainly exercise discretion. We use a two-stage structural model to reveal the market’s perception of depreciation policy as conservative or aggressive through the lens of earnings informativeness. In the first stage, we estimate a two parameter model of depreciation, including the effective useful life of an investment, and the depreciable fraction—the fraction of investment to be depreciated. This model has explanatory power for 559 out of the 892 firms in our sample (63%). The median effective useful life is seven years, while most firms have a depreciable fraction close to unity.

In the second stage, we use a standard earnings informativeness regression at the individual firm level. We uncover the value relevance preferred policy by calculating counterfactual earnings using different depreciation policies and choose the policy which maximizes earnings informativeness. Comparing this policy with that estimated in the first stage allows us to categorize firms as either conservative or aggressive in their financial reporting. A significant portion of firms fall into the aggressive reporting category across all samples and specifications. In fact, a wholesale change to mandatory expensing would yield an increase in the informativeness of earnings for a majority of firms in our restricted sample. This is unexpected, given the perceived conservatism imposed by GAAP. However, since depreciation policy is an area where auditor oversight is of relatively limited efficacy, accounting standards may then be stricter in other areas as a counterweight.

This paper makes a contribution not only to the modeling of managerial discretion in financial statements, but more generally to the study of conservatism and reporting quality in financial accounting. We generate a new measure of conservatism, using a two-step approach which uses market reactions to identify the value relevance preferred depreciation policy. Extensions to both stages of our model could be contemplated. In the first stage, the modeling of depreciation could be further enriched, as well as expanded to consider other
accounting policies involving managerial discretion. In the second stage, the study of counterfactuals could incorporate more elaborate variation in parameters, or a mechanism other than value relevance to uncover how the market interprets accounting policies. We leave these, and other extensions, to future research.
References


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A Estimation Procedure

A.1 Stage 1

For each firm, we calculate a structural depreciation schedule according to capital expenditures. Here, \( \text{Dep}_{i,t}^{0} \) represents actual depreciation for firm \( i \) in year \( t \), \( \text{CapX}_{i,t} \) represents capital expenditure by firm \( i \) in year \( t \), whereas \( \text{Dep}_{i,t}(\tau, \lambda) \) represents the structural depreciation schedule for firm \( i \) in year \( t \), which is to be estimated. In this last expression, \( \tau \) is the useful life of capital assets, and \( \lambda \) is the depreciable fraction (or the fraction of investment to be depreciated). The latter captures both nonzero residual values for depreciable investment as well as a positive fraction of investment in nondepreciable assets, such as land. This second category can also be thought of as representing a separate type of investment with a very long but finite useful life, and so having a low rate of depreciation, such as for power plants or other utilities, which may be assumed to operate for upwards of 50 years.

We calculate \( \text{Dep}_{i,t}(\tau, \lambda) \) as,

\[
\text{Dep}_{i,t}(\tau, \lambda) = \lambda \left[ \frac{\text{CapX}_{i,t}}{\tau} + \frac{\text{CapX}_{i,t-1}}{\tau} + \cdots + \frac{\text{CapX}_{i,t-\tau+1}}{\tau} \right]
\]

(3)

Essentially, \( \text{Dep}_{i,t}(\tau, \lambda) \) represents \( \frac{1}{\tau} \) of capital expenditures in the previous \( \tau \) years, beginning with capital expenditures this year, with the remaining portion of capital expenditures \( \tau - 1 \) years ago being the remaining capital vintage to be depreciated. The depreciable fraction, \( \lambda \), is the part of capital which is depreciated. For \( T \) years in the sample, \( t = \text{Begin Year}, \text{Begin Year} + 1, \ldots, \text{End Year} \), the structural depreciation schedule is calculated for \( \tau = 1, 2, \ldots, \tau^{\text{MAX}} - 1 \) years of effective useful life.\(^{18}\) If \( T \) is the total number of years in the sample, normalizing \( t = 1 \) as the beginning year in the sample, the fit of

\(^{16}\)Our parameterization, using both effective useful life, \( \tau \), and a depreciable fraction, \( \lambda \), has approximation issues. Namely, our data limits the number of years that we can go back in terms of looking at capital investment. Given a \( \tau^{\text{MAX}} \), the maximum number of years we allow for in depreciating capital assets, some firms’ depreciation policies will be approximated as shorter than they otherwise would. This biases against our result of aggressive reporting because some firms’ policies will be measured in the first stage as more conservative than they actually are.

\(^{17}\)Begin Year represents the first year to be used in calculating the fit of the structural depreciation schedule. However, the sample must include data going back \( \tau^{\text{MAX}} \) years.

\(^{18}\)\( \tau^{\text{MAX}} \) represents the total number of years used in calculating possible effective useful life.
Dep_{i,t}(\tau, \lambda) to Dep_{i,t}^0 for i = 1, \ldots, \tau is,

\[ R^2_{i,\tau,\lambda} = 1 - \frac{\sum_{t=1}^{T} (\text{Dep}_{i,t}^0 - \text{Dep}_{i,t}(\tau, \lambda))^2}{\sum_{t=1}^{T} (\text{Dep}_{i,t}^0 - \overline{\text{Dep}_{i,t}})^2} \quad (4) \]

where \( \overline{\text{Dep}_{i,t}} = \frac{1}{T} \sum_{t=1}^{T} \text{Dep}_{i,t}^0 \). Using the objects \( \text{Dep}_{i,t}(\tau, \lambda) \) and \( R^2_{i,\tau,\lambda} \), we find the best fitting expected useful life using a naive algorithm. We first calculate \( \text{Dep}_{i,t}(\tau, \lambda) \) for \( t = 1, \ldots, T \) and \( \tau = 1, 2, \ldots, \tau^{MAX} \), using least squares to fit \( \lambda_i^*(\tau) \) using \( \text{Dep}_{i,t}(\tau, \lambda_i(\tau)) \) fitted to \( \text{Dep}_{i,t}^0 \), for \( t = 1, \ldots, T \).\(^{19}\) Next, for \( \tau = 1, 2, \ldots, \tau^{MAX} \), and using all years in the sample, we calculate \( R^2_{i,\tau,\lambda_i^*(\tau)} \). This means we can find our best fits for the two parameter model, choosing \( \tau_i^* = \arg\max_{\tau=1,2,\ldots,\tau^{MAX}} R^2_{i,\tau,\lambda_i^*(\tau)} \), and \( \lambda_i^* = \lambda_i^*(\tau^*) \). We repeat this procedure firm by firm for all firms in the sample. This means that \( \text{Dep}_i(\tau^*, \lambda_i^*) = [\text{Dep}_{i,1}(\tau^*, \lambda_i^*), \ldots, \text{Dep}_{i,T}(\tau^*, \lambda_i^*)] \) is the best fit for \( \text{Dep}_i^0 = [\text{Dep}_{i,1}^0, \ldots, \text{Dep}_{i,T}^0] \), and so we have our structural parameters \( \tau_i^* \), the effective useful life, \( \lambda_i^* \), the depreciable fraction, as well as the fit \( R^2_{i,\tau^*,\lambda_i^*} \).

A.2 Stage 2

Using capital expenditures and varying the expected useful life \( \tau = 1, \ldots, \tau^{MAX} \), we can calculate structural depreciation schedules as in equation 3,

\[ \text{Dep}_{i,t}(\tau, \lambda_{i,t}^*) = \lambda_{i,t}^* \left[ \frac{\text{CapX}_{i,t}}{\tau} + \frac{\text{CapX}_{i,t-1}}{\tau} + \cdots + \frac{\text{CapX}_{i,t-\tau+1}}{\tau} \right] \quad (5) \]

Which represents the counterfactual depreciation by firm \( i \) in year \( t \) using \( \tau \) as the effective useful life of depreciable assets.\(^{20}\) By restricting depreciation in this way, we can calculate counterfactual earnings according to any given useful life. Let \( E_{i,t}(\tau) \) be the counterfactual earnings in year \( t \) using a structural depreciation schedule \( \text{Dep}_{i,t}(\tau, \lambda_{i,t}^*) \). As earlier, \( \text{Dep}_{i,t}^0 \) represents actual depreciation by firm \( i \) in year \( t \). Then we calculate,

\[ E_{i,t}(\tau) = E_{i,t}^0 + \text{Dep}_{i,t}^0 - \text{Dep}_{i,t}(\tau, \lambda_{i,t}^*) \quad (6) \]

We use \( E_{i,t}(\tau) \) to calculate \( \Delta E_{i,t,t-1}(\tau) = E_{i,t}(\tau) - E_{i,t-1}(\tau) \), the change in counterfactual earnings from year \( t - 1 \) to year \( t \) for the particular useful life \( \tau \). We now have the pieces

\(^{19}\)\( \tau^{MAX} \) remains an artificial limit on effective useful lives. The reasoning is that a longer effective useful life can be approximated using a smaller depreciable fraction.

\(^{20}\)Here we assume that \( \lambda = \lambda_{i,t}^* \), found in Stage 1, for best fitting \( \tau^* \).
necessary to perform the counterfactual earnings informativeness regression,

\[ \text{Return}_{i,t}(\tau) = \alpha_{i,\tau} + \beta_{i,1,\tau} E_{i,t}(\tau) + \beta_{i,2,\tau} \Delta E_{i,t,t-1}(\tau) \]  

(7)

We run this regression for \( \tau = 1, \ldots, \tau^{\text{MAX}} \), obtaining the \( R^2 \) for each possible effective useful life. We choose the \( \tau \) such that the regression of returns on counterfactual earnings explains the most variation. This means we find for each firm \( i \),

\[ \tau_{i}^{**} = \arg \max_{\tau=1,\ldots,\tau^{\text{MAX}}} R^2_{i,\tau} \]  

(8)

There are two obvious earnings benchmarks which could be used when measuring the informativeness of counterfactual depreciation policies: \( E_i^0 = [E_{i,1}, \ldots, E_{i,T}] \), the actual, observed earnings, or \( E_i(\tau^*) = [E_{i,1}(\tau^*), \ldots, E_{i,T}(\tau^*)] \), earnings computed using the best fitting two parameter depreciation policy from the Stage 1 estimation. The first case would seem to present a higher hurdle for our procedure since removing the information contained in \( \text{Dep}_i^0 \) and replacing it with a structural depreciation schedule \( D_i(\tau^*, \lambda^*) \) could reduce the explanatory power of earnings with respect to earnings. The second case may be more apt for comparison purposes when considering the counterfactual depreciation policies.

### B Accelerated Depreciation

Jackson et al. [2009] find, looking from 1988 to 2006, that 80% of firms use straight line depreciation exclusively. The authors also show that this number has increased monotonically over time, to 86%. Additionally, their categorization excludes all firms which use accelerated depreciation for any of their assets. Of the 20% in the accelerated category, 84% use a combination of straight line and accelerated. The authors also find that straight line depreciation is the predominant method in most industries. Regardless, some firms do use accelerated depreciation. In our main specifications, we do not explicitly allow for any use of accelerated methods. We investigate here whether this restriction could be adding a significant bias to our results.

If firms are indeed using a significant amount of accelerated depreciation, our main concern is that this would bias our results in favor of finding aggressiveness, and so undermine the conclusions of the paper. As we discussed in Section 5.2, such a bias could come from a fundamental misestimation of the effective useful lives employed by firms. We show below that when accounting for some accelerated depreciation by firms, the distribution of \( \tau^* \), the effective useful life of depreciable assets, remains unchanged.
Accelerating the depreciation process entails front loading the depreciation schedule such that much of the expense for a capitalized asset occurs in the first several years. We allow for some use of accelerated methods in a simple way—by imposing expensing for a fraction of capital. While this change affects all firms uniformly, it allows us to account for possible bias in our estimation of effective useful life. In Figure 10, we show the median model fit $R^2$ for all firms for which we can explain some of the variation across different accelerated fractions, from 0% to 15% in 1% increments. We also show the number of firms that are fitted. Naturally, the number of firms we can fit goes down, but so does the median $R^2$ as the accelerated fraction increases. This is striking as we are removing firms at the 0 and still get a decreasing median $R^2$. We cannot argue that allowing for acceleration improves the fit of our model.

![Median R² and Firm Count by Accelerated Percentage](image)

**Figure 10:** This figure shows the median $R^2$ fit and number of firms explained while incorporating 0% to 15% accelerated depreciation in 1% increments. On the horizontal axis is the level of % accelerated depreciation of capital expenditures. On the left vertical axis is the median $R^2$ for firms for which we can explain some variation and on the right vertical axis is the number of firms that can be modeled. The median $R^2$ is 0.72 for 0% accelerated depreciation, and is 0.66 for 15% accelerated. The total sample size is begins at 559 for 0% accelerated depreciation (our baseline specification) and decreases to 492 for 15% accelerated.

Further, we present histograms comparing our baseline specification to accelerating 1%, 5%, and 10%, respectively in Figure 11, Figure 12, and Figure 13. Each table shows only
those firms for which the accelerated sample produced $R^2$ estimates greater than zero, meaning that the sample is reduced from 559. For 1% we only lose one firm, but the sample decreases to 545 and 519, respectively for 5% and 10%. It is clear that the results are similar for effective useful lives, regardless of the degree of accelerated depreciation employed. Not including accelerated depreciation in the first stage does not significantly alter our results, although with accelerated depreciation, our estimation procedure yields small decreases in effective useful lives. The number falls to 8.31, 8.10, and 8.02 for 1%, 5%, and 10%, respectively. We therefore find that using straight-line depreciation has a negligible effect on estimated effective useful lives and so our results as a whole.

![Estimated Effective Useful Life: Baseline vs. 1% Accelerated](image)

**Figure 11:** This figure shows the estimated effective useful life for firms, $\tau^*$, incorporating 1% accelerated depreciation. On the horizontal axis is the level of $\tau^*$ in years and on the vertical axis is the number of firms which fit into each year bin. The total sample size is 558. In blue is the baseline, and in outlined black is the accelerated. The mean for baseline is 8.35 and the mean for 1% 8.31.
**Figure 12:** This figure shows the estimated effective useful life for firms, $\tau^*$, incorporating 5% accelerated depreciation. On the horizontal axis is the level of $\tau^*$ in years and on the vertical axis is the number of firms which fit into each year bin. The total sample size is 545. In blue is the baseline, and in outlined black is the accelerated. The mean for baseline is 8.35 and the mean for 5% 8.10.

**Figure 13:** This figure shows the estimated effective useful life for firms, $\tau^*$, incorporating 10% accelerated depreciation. On the horizontal axis is the level of $\tau^*$ in years and on the vertical axis is the number of firms which fit into each year bin. The total sample size is 519. In blue is the baseline, and in outlined black is the accelerated. The mean for baseline is 8.35 and the mean for 10% 8.02.