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A Measure of Competition Based on 10-K Filings

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ABSTRACT

In this paper we develop a measure of competition based on management's disclosures in their 10-K filing and find that firms' rates of diminishing marginal returns on new and existing investment vary significantly with our measure. We show that these firm-level disclosures are related to existing industry-level measures of disclosure (e.g., Herfindahl index), but capture something distinctly new. In particular, we show that the measure has both across-industry variation and within-industry variation, and each is related to the firm's future rates of diminishing marginal returns. As such, our measure is a useful complement to existing measures of competition. We present a battery of specification tests designed to explore the boundaries of our measure

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The competition data is available for download: http://webuser.bus.umich.edu/feng/

and how it varies with the definition of industry and the presence of other measures of competition.

1. Introduction

In this paper we investigate the usefulness of management's discussion of competition in the 10-K. Financial statement analysis textbooks commonly recommend starting the evaluation process by considering the firm's competitive environment and its strategy for operating in its environment (Healy and Palepu [2007], Lundholm and Sloan [2007], Penman [2009]). Further, the Securities and Exchange Commission (SEC) recommends that the management discussion and analysis (MD&A) section of the firm's 10-K filing include a discussion of the firm's competitive position (Exchange Act Release No 34–48960). However, the SEC has recently expressed concern that many companies provide only boilerplate disclosures in the MD&A (Pozen [2008]).[1] This raises the question: is there information about the firm's competitive environment that can be gleaned directly from the firm's own disclosures? We develop a measure of competition based on statements made in the firm's 10-K and show how this new measure is related to future operating performance in ways that suggest it is a valid measure of competition. Further, we show that our construct captures variation in competition between firms in the same industry, as well as variation in competition across industries, and that both components are useful complements to existing measures of competition.

How managers perceive the firm's competitive environment can significantly influence their operating and investing decisions. For example, how they price their products depends on how they perceive the threat of substitutes from existing rivals or the threat of new entrants into their markets. How rapidly they invest in assets depends on whether they believe there are many or few rivals, and how contestable the investments are by those rivals. Furthermore, the realized level of competition has an obvious impact on the subsequent payoffs to these operating and investing decisions. A simple model that incorporates these ideas relates a firm's competitive environment to the rate of diminishing marginal returns on existing assets and on new investments. Economists have long held that competition causes these returns to mean revert. Stigler [1963, p. 54] states that, "There is no more important proposition in economic theory than that, under competition, the rate of return on investment tends toward equality in all industries. Entrepreneurs will seek to leave relatively unprofitable industries and enter relatively profitable industries." For this reason, our primary validity test

[1] Brown and Tucker [2011] investigate the extent of boilerplate discussion by comparing the annual changes in the MD&A to economic changes in the firm. They find that changes to the MD&A are positively associated with both economic changes in the firm and the magnitude of stock price reactions to MD&A filings.

for measuring competition is how well the variable conditions the rates of diminishing marginal returns on new and existing assets.

We find that a firm's return on net operating assets (RNOA) mean reverts more severely, and that returns on new investment in net operating assets (NOA) diminish faster, when management makes more references to competition in the 10-K. We show that these results are robust to different ways to construct our measure, including within matched size portfolios, and persist after controlling for a host of other competition measures. Further, the economic significance of the results is impressive. The coefficient of mean reversion on RNOA is –0.192 for the lowest decile of our competition measure but –0.278 for the highest decile of our measure. After controlling for the mean reversion effect, the rate of diminishing returns on new NOA is –0.086 for the lowest decile of our competition measure and –0.144 for the highest decile of our measure.

Our measure of a firm's competitive environment is surprisingly simple: we count the number of references to competition in the firm's 10-K filing, being careful to remove phrases such as "less competitive," and then scale by the total number of words in the document. Our intent is to capture the broadest notion of competition—the basic idea that more intense behavior from new and existing rivals diminishes a firm's ability to earn profits. Although many of the references to competition in the 10-K might be boilerplate, we find a surprising amount of variation in our measure. The first quartile value is 0.23 competition words per thousand 10-K words and the third quartile is 0.78 words per thousand. We provide anecdotes that illustrate how the word "competition" is used in discussions about product market competition, competition for labor and other inputs, and competition for investment opportunities.

We conduct a battery of specification checks to rule out various omitted-correlated variables. We find that our variable is significantly correlated with many other measures of competition found in the literature, but none of the correlations are particularly large. For instance, the Spearman correlation between our measure and the Herfindahl index is only 0.081. We also show that our competition measure is not proxying for the firm's current year performance, as might be the case if management blames poor performance on competition. We find that our measure is significant when constructed within size quintiles, so it is not proxying for a firm size effect, and is significant when alternative scaling variables are used. Finally, although the measure is very persistent through time, we find that its ability to condition the rate of diminishing marginal returns increases as we average it over more prior years, suggesting that we are eliminating noise in the measure and capturing a true level of persistent competition.

In microeconomics and particularly in industrial organization, competition is typically construed as an industry-level concept. Therefore, assessing the level of competition in an industry requires both a definition of industry boundaries and a measure of the competition taking place within those boundaries. By constructing a measure of competition from management disclosures, we allow both the industry boundary and the measure of competition to be determined endogenously by managers' perceptions. Besides sidestepping the issue of an industry definition, this approach has the advantage of capturing competition from many different sources that are hard to identify empirically, such as competition from private firms, foreign firms, and potential new entrants.

Although our measure does not require an industry definition, we also show that it can be combined with existing industry classification schemes to create an industry-level measure of competition. We find that this industry-average competition measure performs better than the firm-specific measure, and that the improvement increases with refinements in the definition of industry.[2] At the extreme, when we define a firm's industry as the collection of firms with similar product descriptions in their 10-K (as given in Hoberg and Phillips [2011]), the difference in the coefficient of mean reversion in RNOA between the lowest and highest deciles of our refined industry competition measure are approximately double the differences for the firm-specific measure. The fact that our measure works best when combined with the Hoberg-Phillips industry definitions suggests that it is a useful measure of competition within product markets. More generally, for a variety of industry definitions, our measure has both a significant across-industry component and a significant within-industry component, and both are related to future rates of diminishing returns.

An extensive literature in accounting establishes that a firm's disclosures can be influenced by concerns for what a rival firm may learn from the disclosure.[3] For most of our tests we take management's disclosures at face value and find that this results in a robust measure of competition. However, we also find some indirect evidence of strategic distortions. We posit that management is most likely to alter its disclosures away from an unbiased assessment when the threat of potential entrants is high and there are few existing rivals. Consistent with this, we find that our measure complements existing measures of competition the most in exactly the places where one might expect management to have the clearest insight and the least incentives to distort the disclosures: in industries with a high level of existing rivalry and a low threat of new entry, and in industries with very similar products.

In the next section we discuss our new measure of competition in more detail and develop our hypotheses in the context of the existing literature. We present the results from our tests in section 3 and conclude in section 4.

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[2] One possible explanation of our empirical findings is that our competition measure does not really capture competition; rather, it captures managers blaming competition for their firms' poor performance. To the extent that management's incentives to attribute poor performance to competition are firm specific, the fact that the industry-average of our measure leads to stronger results suggests that our empirical findings are not driven by this alternative explanation.

[3] For example, Wagenhofer [1990], Hayes and Lundholm [1996], Harris [1998], Leuz [2004], Berger and Hann [2007] is only a partial list of this literature.

2. *Measures and Hypotheses*

2.1 WHAT IS COMPETITION AND HOW DO WE MEASURE IT?

We present a new measure of competition based on textual analysis of a firm's 10-K filing. However, before discussing the construction of the measure, it is useful to consider what we could hope to capture with any measure of competition.

How competition affects firm performance is a central question in business and economics. Porter [1979] famously identifies five sources of competitive intensity in an industry that determine a firm's performance (barriers to entry, threat of substitutes, competitive rivalry, bargaining power of customers, and bargaining power of suppliers). Alternatively, a resource-based view of competition emphasizes limiting imitation from rivals by developing unique and rare resources (Barney [1986]). Consistent with this view, Brown and Kimbrough [2011] find that the degree to which a firm's earnings co-vary with industry earnings is negatively related to the firm's level of identifiable intangible assets (e.g., patents, copyrights, legal contracts). Another notion of competition, labeled "Red Queen" competition, describes how firms respond to innovation by rival firms with innovations of their own, resulting in a self-escalating system wherein performance is initially enhanced through innovation but later reduced by the responsive innovation of rivals (Barnett and McKendrick [2004]).[4] One can imagine that, in different firms and different contexts, management's discussion of its competitive environment might be in response to any of these concepts. But, as Barnett and McKendrick note, "A defining characteristic of competition is that one organization's solution becomes its rivals' problem" (p. 540). It is this broad construct that we wish to measure with our textual analysis of management's statements in the 10-K.

A more formal definition of competition pertains to the cross-elasticity of demand—competition is more intense if one firm's products are more ready substitutes for another firm's products. Empirical research has had some success in measuring product substitutability across various manufacturing industries (e.g., Syverson [2004a, b]). Particularly relevant to our study, these studies show that product substitutability differences arise *within* industries, caused by factors such as transportation costs and product differentiation.

The industrial organization literature views competition as an industry-wide construct where some industry factor, such as the concentration of production or the degree of product market differentiation, determines the industry's degree of competition. This view requires a definition of the

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[4] The name "Red Queen" competition comes from Lewis Carroll's *Through the Looking Glass* (Carroll [1960]). When Alice realizes that, although she is running as fast as she can, she doesn't seem to get anywhere, the Red Queen responds: "Here, you see, it takes all the running you can do, to keep in the same place."

industry boundaries and a measure of competition within those boundaries. So, for instance, a researcher might define the industry boundaries using the four-digit Standard Industrial Classification (SIC) code and the degree of competition using the Herfindahl index. Our measure is unique in that it does not require a definition of industry boundaries, although we show later that it can be used with industry groupings quite successfully.

Empirically, the most common measures of competition found in the literature are concentration ratios, either the Herfindahl index or the four-firm concentration ratio; both focus on the distribution of production across firms within an industry. Concentrated industries, where the bulk of production is done by a few firms, are thought to earn abnormal profits because barriers to entry thwart new entrants and the existing firms can more easily collude (i.e., there is little competitive rivalry).

Although industry concentration ratios have a rich history in economics, they lack precision when it comes to detecting how an individual firm's operating and investing decisions, and the financial consequences of those decisions, might be influenced by competition. Further, industry-based concentration measures are typically constructed using only the public firm data available in Compustat. Ali, Klasa, and Yeung [2009] and Bens, Berger, and Monahan [2011] find that failing to take private firms into account results in poor proxies for the actual industry concentration. Consistent with this, Dedman and Lennox [2009] survey private firm managers in the United Kingdom and find no relation between the managers' perceptions of their competitive environment and the industry concentration ratio. This latter result may accord well with the results of Syverson [2004b] in which he identified substantial competitive variation within a very specific industry—ready-mixed concrete—as a result of spatial boundaries.

There are a variety of fixed industry definitions used in the literature, ranging from the 48 industries in the Fama and French [1997] classification to the more than 1,000 industries found in the SIC four-digit classification system.[5] These definitions are relatively fixed in time and identify mutually exclusive sets of firms, and are thus subject to a number of criticisms. First, mutually exclusive sets are sometimes crude ways to group companies. For example, Apple competes with Microsoft in the software industry, Samsung and Nokia in the mobile phone industry, Amazon in the online retailing industry, and Google in both the hardware and software industries. More broadly, Rauh and Sufi [2012] offer large-sample evidence showing that SIC-code-based industry definitions bear little relation to the list of competitors that firms disclose in their proxy statements.

In response to criticisms of traditional industry definitions, Hoberg and Phillips [2011] construct a measure of product similarity based on textual analysis of product descriptions in 10-K filings and then define industries as

[5] Other industry classification systems exist as well, such as the North American Industry Classification System (NAICS) and the Global Industry Classification Standard (GICS).

sets of sufficiently similar firms. These industry boundaries can vary across time and need not be mutually exclusive, with each firm having its own unique set of competitors. They find that using these industry boundaries more clearly defines where R&D or advertising expenditures create product market differentiation.[6] Although our primary analysis is on the firm-specific version of our measure, which does not require an industry definition, we also show that combining our measure of competition with the Hoberg-Phillips industry definition produces a very successful measure of industry-level competition.

We measure management's perceptions of the intensity of the competition they face using textual analysis of the firm's 10-K filing. We count the number of occurrences of "competition, competitor, competitive, compete, competing," including those words with an "s" appended, and then remove any case where "not," "less," "few," or "limited" precedes the word by three or fewer words. To control for 10-K length, we scale the number of competition-related words by the total number of words in the 10-K. The resulting measure of competition is

$$PCTCOMP = \frac{NCOMP}{NWORDS},$$

where *NCOMP* and *NWORDS* are the net number of occurrences of competition words and the total number of words in a 10-K, respectively. In the empirical analysis, we use the variable *COMP*, which is the decile-ranked value of *PCTCOMP*, computed each year, then scaled to be in [0,1]. In robustness checks, we also construct a within-size quintile version of *PCTCOMP*; report results using two different scalars, the firm's total assets and the firm's number of segments; and present results using the historical rolling average of *COMP*.

To illustrate the types of management statements our measure captures, appendix A gives six examples. The first example from Columbia Sportswear offers a rather standard reference to existing rivals. The second example from MHI Hospitality talks about how competition may limit investment opportunities when investments are contestable. The third example, also from Columbia Sportswear, refers to competition for inputs, in this case for employees. The fourth example from Open Text Corp. sounds exactly like "Red Queen" competition, describing a system of continual innovation in response to rivals' innovations.[7] The fifth example from First National Energy Corp illustrates why we remove references to competition

[6] This approach has also been successful in analyzing merger activity (Hoberg and Phillips [2010]) and financing activity (Hoberg, Phillips, and Prabhala [2013]).

[7] Open Text also illustrates why we use the whole 10-K filing rather than only the MD&A section. In their 2008 filing there were 74 competition references (of 61,290 words): 19 in Item 1 Description of Business, 29 in Item 1A Risk Factors, 3 in Item 7 MD&A, 1 in Item 10 Directors and Officers, and 22 in Item 11 Executive Compensation. Further, because companies do not use uniform descriptions of the required items in a 10-K filing, it would be difficult to design an algorithm that would cleanly isolate each section.

that are preceded by the words “no” or “limited.” Finally, comparing the fifth example with the sixth example from Oil Dri Corp. illustrates the subtlety of language and why no algorithm will be perfect. Oil Dri’s reference to competition should count, and yet it will wrongly be eliminated because it is preceded by “limited by.”[8]

Our approach is simple, parsimonious, and effective. It measures competition at the firm level and can respond to management’s concern about both private and public firms (unlike measures based on publicly available data). To capture the notion of competition in a more structured way would require much more detailed assumptions about the exact nature of competition, and the context and linguistic structure of the references to competition. However, more complicated methods in computational linguistics and natural language processing literature often lead to minimum improvement at significant costs (Berry [2004]). For instance, Turney [2002] uses a simple unsupervised learning algorithm to classify customer reviews of products on epinions.com into positive and negative categories and shows that a parsimonious approach performs equally well compared to more structured models.

Our measure assumes that managers have reasonably accurate perceptions of the relevant type of competition their firm faces and its “true” level, and that what they report in their 10-K filing is a reasonably unbiased representation of those perceptions. Absent an objective “true” measure of competition, we cannot distinguish between “true” competition and management’s perceptions or disclosures about it.[9] We do, however, offer some indirect evidence that some strategic distortion might be present in the disclosures about competition. We find that, at times when management might have the greatest motive to distort their disclosures about competition, our measure is less effective. These results are weak and indirect, but suggest that there might be a small amount of “strategic” distortion in our measure.

We assess the construct validity of our measure by correlating it with seven other measures of competition offered in Karuna [2007, 2010] and Li [2010]. These papers examine how industry-level competition influences management’s voluntary disclosures about future operating activities (e.g., management earnings forecasts, segment disclosures, research and development expenditures, order backlog). In contrast, we measure how

[8] As a practical matter, the part of the algorithm that eliminates competition references preceded by negative words has little impact on the results. An even simpler algorithm that counts only references to “competition” and “competitor” and these words with an “s” appended produces results that are extremely close to those reported here.

[9] Our approach of taking the 10-K disclosures at face value is consistent with other studies using textual analysis, including Hoberg and Phillips [2011], Li [2007], and Loughran and McDonald [2011]. Moreover, it is interesting to note that Johnston and Petacchi [2012] categorize a large sample of SEC comment letters and find that none of the SEC comments for 10-K filings relate to a firm’s discussion of its “Competitive Environment”—i.e., competition discussion does not appear to be a significant disclosure issue per the SEC.

management's disclosures about competition reveal information about future operating performance.

2.2 MANIFESTATIONS OF COMPETITION

To assess whether our measure based on management's references to competition in the 10-K is useful and valid, we examine how it conditions the rate of mean reversion in returns on existing assets and the rate of diminishing returns on new investments. There are a number of reasons to expect competition to affect these two rates. Consider a firm with no change to its asset base. Porter's five forces give a laundry list of reasons why firms with unusually high returns on existing assets will suffer declining returns as competition arrives to erode their competitive advantage. Similarly, firms with unusually low returns on existing assets will benefit from reduced competition as competitors leave their markets in search of higher asset returns elsewhere.[10]

Mean reversion in accounting rates of return is documented by considerable prior accounting research. Nissim and Penman [2001] find that return on equity mean reverts to an economy-wide average (about 12%), and Fairfield, Ramnath, and Yohn [2009] show that the return on equity mean reverts to an economy-wide rate and not an industry rate. Fama and French [2000] show that mean reversion is significant after controlling for cross-sectional correlation. Stigler [1968] and Lev [1983] find evidence of higher levels of earnings persistence in concentrated industries and industries with higher barriers to entry, respectively. Cheng [2005] finds that the rate of mean reversion in abnormal return on equity is slower for larger firms in concentrated industries with barriers to entry. Healy et al. [2011] find that international variation in measures of competition predict international variation in the rate of mean reversion in return on equity.[11] If our measure is a valid measure of competition, it should condition the rate of mean reversion in accounting returns. We hypothesize that:

H1: The coefficient of mean reversion in *RNOA* will become more negative as *COMP* increases.

Now consider how competition influences the return on new investments or divestments (i.e., a changing asset base). Absent any competitive forces, returns on investments typically diminish. For example, when growing, Starbucks opens stores at the most profitable locations first so that subsequent investments are necessarily less profitable. Similarly, when shrinking,

[10] See also Marx [1894] "The Tendency of the Rate of Profit to Fall," Chapter 3 of *Das Kapital*, Volume 3.

[11] Dickinson and Sommers [2012] study a number of variables that are hypothesized to proxy for "competitive effort," including inventory turnover, the ratio of operating liabilities to net operating assets, financial leverage, and net financial assets. They find that these variables help to predict next year's industry and risk-adjusted *RNOA* as main effects, but they find no evidence that the variables condition the rate of mean reversion in returns.

Starbucks closes the least profitable stores first so that the remaining assets are necessarily more profitable.[12] This intuition is formalized by Warusawitharana [2008]. He presents a model where diminishing marginal returns induce firms to invest or divest as their profitability changes. Effectively, the firm is attempting to adjust its size until its return on assets equals its cost of capital. Consistent with this, he finds that a firm's return on assets is a significant predictor of asset sales and purchases. We hypothesize that competition intensifies this effect, as it increases the rate of diminishing marginal returns. Real option theory maintains that, in the face of uncertain payoffs, a viable strategy is to wait and only invest when the expected return exceeds some threshold higher than the cost of capital. Grenadier [2002] shows that this threshold decreases in the presence of competition if rival firms can take contestable investment opportunities away from the firm. Simply put, Starbucks will have a lower threshold for investment when making store-opening decisions if there is a possibility that Caribou Coffee will claim the best locations while it waits. Empirically, Akdogu and McKay [2009] find that firms in competitive industries make large investments sooner than firms in monopolistic industries.

In accounting, diminishing marginal returns to changes in investment is studied in Fairfield, Whisenant, and Yohn [2003], who estimate the relation between future return on total assets (*ROA*), current *ROA*, and changes in *NOA*. They find that the future *ROA* is significantly decreasing in the changes in *NOA* after controlling for the current *ROA*. Richardson et al. [2005] find a similar result by regressing future *ROA* on current *ROA* and total accruals, where total accruals equals the change in *NOA* plus the change in noncash net financial assets (i.e., noncash financial assets less financial liabilities). They find that, after controlling for current *ROA*, future *ROA* is significantly decreasing in total accruals.[13] They then decompose total accruals and find that the diminishing rates of return are driven primarily by the changes in the *NOA*, as opposed to changes in the net financial assets.[14]

If our measure is a valid measure of competition, it should condition the rate of diminishing marginal return on investment. As a second test of our construct's validity, we hypothesize that:

H2: The coefficient of diminishing returns on *NOA* will become more negative as *COMP* increases.

[12] Smith [1776, p. 94] summarized this hypothesis with "It may be laid down as a maxim, that wherever a great deal can be made by the use of money, a great deal will commonly be given for the use of it; and that wherever little can be made by it, less will commonly be given for it."

[13] Curtis and Lewis [2010] find that the negative relation between future *ROA* and changes in *NOA* is due largely to firms with "old" assets.

[14] A different branch of the literature further decomposes return on asset measures into the profit margin times the asset turnover ratio, finding that changes in profit margin are more transitory than changes in asset turnover. See Nissim and Penman [2001], Fairfield and Yohn [2001], and Soliman [2008].

In sum, our paper furthers the existing financial statement analysis literature by conditioning the relations between future *RNOA*, current *RNOA*, and changes in *NOA*, on the level of competition, as measured by *COMP*. If both relations are more negative when our measure of competition is higher, this is consistent with *COMP* being a useful and valid measure of competition at the firm level.

Like prior research, we do not offer a dynamic model of how competition evolves over time. At any point in time a firm finds itself with some level of competition and this level conditions how the firm's return on new and existing assets will evolve in the future. One might expect that, as these returns change, so might the firm's competitive landscape, but we do not model or estimate this more complicated scenario. It is unlikely that "true" competition changes much from year to year and, not surprisingly, we find that *COMP* is quite persistent over time. We use this fact to create a slightly more precise measure of the level of competition, as discussed in the next section.

As with any cross-sectional model, it is tempting to ask how it would hold up in a changes specification. Note, however, that competition is not a main effect; it changes the rate that returns on new and existing assets diminish. A changes specification would have to specify how changes in competition produce changes in these rates. Further, because competition levels are likely to be very persistent from year to year, large changes in *COMP* are likely to be caused by noise, possibly because the firm underwent some large transaction during the prior or current year that required an unusual increase in the length of the 10-K to explain.[15]

3. Results

3.1 THE SAMPLE

We construct our sample based on the intersection of firm-years available on the EDGAR filings database, where we get the textual data on references to competition, and the Compustat annual file for years 1995–2009. Most EDGAR filings are not available before 1995. We merge these databases based on Compustat GVKEY and the SEC's Central Index Key and eliminate financial firms (SIC codes 6000–6999).

We require that the firm have sufficient financial data to compute the *RNOA*, *ROA*, the change in *NOA*, and the change in total assets. We also eliminate firms with sales, *NOA*, or total assets that are less than zero, or if their market value (*MV*) is less than $1 million. Finally, consistent with prior studies, we eliminate firms with extreme financial ratios. Specifically, we eliminate firms with *RNOA* greater than 100% or less than –100%, and eliminate firms with sales growth less than –100% or greater than 1,000%.

[15] This notion is confirmed when we find that using *COMP* averaged over time produces larger economic results as we discuss in section 3.4.

The final sample is 33,492 firm-years. All variables are winsorized at the 1% and 99% level.

3.2 DESCRIPTIVE STATISTICS FOR *PCTCOMP*

Summary statistics for *PCTCOMP* are given by industry in table 1. To establish a benchmark, the grand mean of *PCTCOMP* is 0.583 words per thousand words in the 10-K, shown at the bottom of the table. To put this in some perspective, the sample-wide median number of competition words is 27 and the median number of total words is 59,870. Both have increased steadily over our sample period. Table 1 is sorted by the average *PCTCOMP* within each industry (as defined in Fama and French [1997]), with Electronic Equipment at the top with 0.780 competition words per thousand and Precious Metals at the bottom with 0.174.[16] Note that, although we have rank ordered table 1 by Fama-French industries, this is only for broad descriptive purposes; our measure does not require an industry definition. Nonetheless, table 1 shows that there is substantial variation in *PCTCOMP* both across and within industries. In fact, the within-industry variation is typically about half the mean. Later we show that both sources of variation add significantly to our model.

Table 1 also reports the Herfindahl index (*HHI*) and the number of firms in each industry. It is clear that *PCTCOMP* measures something quite different from the Herfindahl index, even when it is averaged over all the firms in the industry. *PCTCOMP* appears more closely related to the number of firms in the industry, although by no means perfectly so. We quantify these relations in table 2.

Although *PCTCOMP* varies significantly across firms in the same industry, it does not vary much for a single firm through time. Figure 1 plots *COMP* (the deciled version of *PCTCOMP*) for the year before and year after the sort. The figure shows some mean reversion in the tails, as almost any measure does when sorted, but in no case does the average value change by 2 deciles, and the relative order of the 10 deciles is maintained from the year before through the year after the sort.

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[16] It is interesting to observe that several commodity industries (e.g., coal, petroleum, mining, metals) have the lowest reported level of competition based on our measure. Given that these firms compete in markets with relatively homogenous products, low levels of competition may seem anomalous. We suggest two possibilities: (1) As Hayek [1948, p. 95] and others have noted, producing homogenous products is not a sufficient condition for perfect competition—"free entry into the market" and "complete knowledge of the relevant factors on the part of all participants in the market" are also essential elements. A distinct possibility, then, is that these industries have substantial barriers to entry, in particular, which is reflected in the relatively few firms that compete in these industries (with perhaps the exception of petroleum). (2) At the other extreme possibility, competition in these commodity-based industries reflects perfect competition and competition is so obvious that mention of this fact in the annual report is superfluous. The fact that both of these possibilities exist leads us to conduct robustness tests in which we exclude firms with extreme levels of competition discussion.

TABLE 1

Competition Measure by Fama-French Industry

Fama-French Industry	Mean	Median	Std. Dev.	*HHI*	*n*
Electronic Equipment	0.780	0.692	0.408	0.16	211
Telecommunications	0.758	0.678	0.398	0.12	127
Computers	0.752	0.648	0.374	0.23	120
Measuring and Control Equip	0.724	0.652	0.375	0.21	86
Electrical Equipment	0.721	0.670	0.423	0.27	73
Medical Equipment	0.671	0.607	0.332	0.19	113
Alcoholic Beverages	0.660	0.606	0.278	0.27	8
Business Services	0.651	0.585	0.359	0.18	466
Recreational Products	0.634	0.557	0.373	0.35	33
Retail	0.623	0.563	0.334	0.29	85
Miscellaneous	0.614	0.530	0.287	0.24	15
Pharmaceutical Products	0.606	0.589	0.215	0.11	113
Wholesale	0.586	0.518	0.271	0.33	169
Textiles	0.573	0.507	0.277	0.41	9
Machinery	0.561	0.482	0.355	0.29	138
Steel Works, Etc.	0.544	0.492	0.252	0.26	65
Shipbuilding, Railroad Eq	0.539	0.425	0.344	0.22	6
Food Products	0.537	0.444	0.357	0.51	37
Rubber and Plastic Products	0.535	0.505	0.307	0.32	29
Automobiles and Trucks	0.523	0.481	0.295	0.21	59
Construction Materials	0.521	0.494	0.214	0.35	61
Business Supplies	0.520	0.446	0.284	0.29	43
Printing and Publishing	0.518	0.553	0.207	0.22	28
Healthcare	0.505	0.432	0.257	0.29	85
Consumer Goods	0.502	0.431	0.247	0.33	56
Entertainment	0.501	0.411	0.272	0.24	61
Construction	0.497	0.431	0.302	0.24	55
Aircraft	0.496	0.407	0.214	0.26	12
Apparel	0.493	0.478	0.215	0.48	34
Defense	0.477	0.451	0.214	0.37	11
Candy and Soda	0.476	0.478	0.173	0.52	10
Personal Services	0.470	0.437	0.287	0.43	40
Transportation	0.467	0.443	0.231	0.19	122
Fabricated Products	0.460	0.420	0.237	0.40	14
Chemicals	0.453	0.427	0.215	0.27	76
Utilities	0.449	0.373	0.291	0.14	147
Restaurants, Hotel, Motel	0.403	0.368	0.223	0.15	35
Agriculture	0.396	0.408	0.109	0.74	8
Shipping Containers	0.395	0.492	0.183	0.37	7
Coal	0.349	0.265	0.265	0.20	7
Petroleum and Natural Gas	0.336	0.297	0.199	0.09	180
Nonmetallic Mines	0.307	0.293	0.191	0.40	10
Precious Metals	0.174	0.144	0.171	0.18	11
Total	0.583	0.513	0.337	0.23	3,060

This table presents the industry mean, median, and standard deviation for *PCTCOMP*. To calculate the industry mean, the mean of *PCTCOMP* is calculated for each firm with at least five years of data and the industry statistics are calculated from the firm means for each industry with at least five firms. *HHI* is the average Herfindahl index over the time period and *n* is the number of firms in the industry with a minimum of five years of data.

TABLE 2

Relation Between PCTCOMP, Industry-Level Competition, and Product Similarity

Panel A: By *PCTCOMP* Quintile

	Potential Entrants				Existing Rivals			Product Similarity
PCTCOMP Quintile	*IND-PPE* ↓	*IND-R&D* ↓	*IND-CPX* ↓	*IND-MKTS* ↓	*IND-HHI* ↓	*IND-CON4* ↓	*IND-NUM* ↑	*SIM* ↑
Least competitive: 1	5,946.5	117.1	628.6	9.85	0.244	0.678	44.34	265.3
2	4,502.7	171.2	464.7	9.77	0.242	0.683	45.81	278.1
3	4,140.3	225.4	433.2	9.82	0.232	0.675	49.82	289.6
4	4,063.8	275.4	441.1	9.87	0.224	0.665	54.22	305.5
Most competitive: 5	4,606.3	349.9	521.6	10.11	0.209	0.646	62.56	333.9
Diff (5) − (1)	−1,340.2***	232.7***	−106.9***	0.27***	−0.035***	−0.032***	18.22***	68.62***
t-stat	[−11.55]	[40.28]	[−7.68]	[8.84]	[−9.95]	[−8.26]	[24.41]	[13.01]
Relation consistent with arrow?	Y	N	Y	N	Y	Y	Y	Y

Panel B: Correlation Coefficients Between *PCTCOMP* and Other Measures

	Potential Entrants				Existing Rivals			Product Similarity
Correlation	*IND-PPE* ↓	*IND-R&D* ↓	*IND-CPX* ↓	*IND-MKTS* ↓	*IND-HHI* ↓	*IND-CON4* ↓	*IND-NUM* ↑	*SIM* ↑
Pearson	−0.079	0.129	−0.042	0.015	−0.096	−0.098	0.167	0.104
Spearman	−0.120	0.132	−0.064	−0.027	−0.081	−0.091	0.152	0.101

This table presents the relation between *PCTCOMP* and various industry-level competition and product similarity measures. The sample size is 36,958 firm-years for the industry-level competition measures and 32,812 firm-years for the similarity measure (the similarity measure is not available for years 1995 or 2009, which is the main reason for the difference in sample size). Panel A presents the results by quintile of *PCTCOMP*. The arrows indicate the expected direction of the relation between *PCTCOMP* and each measure. Difference in means tests between the means of quintiles (5) and (1) are presented at the bottom of each column. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Panel B presents univariate correlations. We follow Li [2010] in defining the industry competition variables: *IND-PPE*, *IND-R&D*, and *IND-CPX* are the weighted average of property, plant, and equipment, research and development, and capital expenditures in the industry, respectively. To calculate each industry measure, each firm's value is weighted by a ratio of its sales to the total industry sales. We use firm segment data to calculate these values. *IND-MKTS* is the natural log of aggregate industry sales, *IND-CON4* is the sum of the market shares of the four largest firms in the industry, *IND-HHI* is the sum of the squared market shares of all firms in the industry, and *IND-NUM* is the total number of firms in the industry. *SIM* is the total product similarity measure (*TNIC3TSIMM*) downloaded from the Hoberg-Phillips data library Web site (http://www.rhsmith.umd.edu/industrydata/industryconcen.htm), calculated by comparing the product descriptions from firms' 10-K reports.

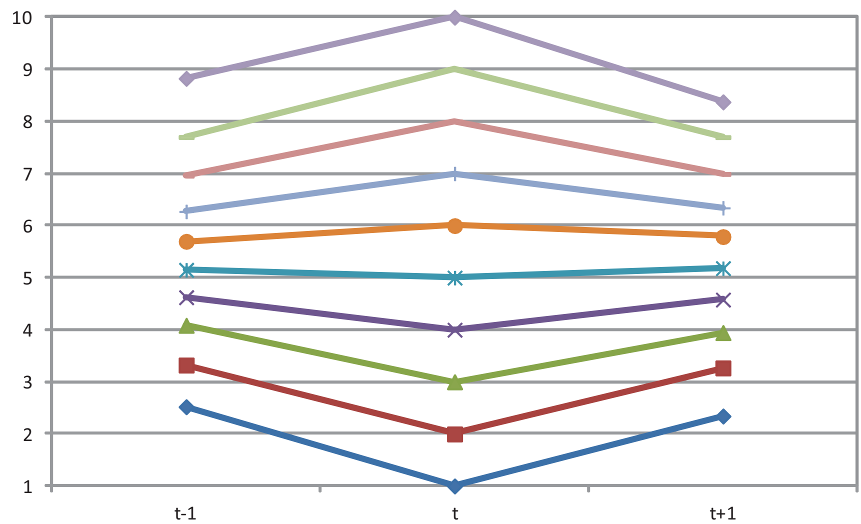

FIG. 1.—Persistence of Competition Disclosure. The average decile is plotted for years $t-1$, t, and $t+1$ for deciles of *PCTCOMP* created in year t.

As our first evidence that *COMP* is picking up the broadly defined construct "competition," in table 2 we relate it to the seven other measures of competition offered in Li [2010], and with the Hoberg-Phillips measure of firm similarity (*SIM*).[17] Li's measures are (1) the weighted average of property, plant, and equipment in the industry (*IND-PPE*); (2) the weighted average of research and development in the industry (*IND-R&D*); (3) the weighted average of capital expenditures in the industry (*IND-CPX*). For these three weighted average measures, each firm's amount is weighted by the ratio of its segment sales to industry aggregate sales, creating a "representative firm" measure for each industry. The other measures are (4) the product market size (*IND-MKTS*), measured as the natural log of industry aggregate sales; (5) the four-firm concentration ratio (*IND-CON4*), measured as the sum of market shares of the four largest firms in an industry; (6) the Herfindahl-Hirschman index (*IND-HHI*), measured as the sum of squared market shares of all firms in an industry; and (7) the total number of firms in the industry (*IND-NUM*). The first four measures are commonly considered to measure competition from new rivals, and measures five to

[17] See the discussion in Li [2010] for references to the accounting and economics literature that originally proposed each of these measures, and for precise definitions of the computations of the measures. We do not tabulate two of Li's measures because they are not clearly measures of exiting rivalry or potential entrants (industry *ROA* and industry profit margin). Industry *ROA* is not significantly related to our measure and industry profit margin is weakly related, with a Spearman correlation of –0.088. See Hoberg and Phillips [2011] for a complete description of their measure.

seven are considered measures of competition from existing rivals. Other than *IND-NUM*, all constructs are predicted to be decreasing as competition increases. Note also that, consistent with the industrial organization view of competition, all seven measures are defined at the industry level. The *SIM* measure of product similarity is the sum of the pairwise similarity scores between a firm and all other firms on Compustat with EDGAR data (above a certain similarity threshold), where a pairwise similarity score is based on the number of similar words in the product description section of the 10-K, and ranges from zero to one.

Panel A of table 2 gives the value of each alternative competition measure sorted by quintiles of *PCTCOMP*, along with *t*-statistics for the difference in means between the top and bottom quintile. Panel B gives the Pearson and Spearman correlations. As table 2 shows, *PCTCOMP* is weakly related to most of the other proxies for competitive intensity, including the Hoberg-Phillips measure of product similarity. Two measures have the wrong sign, *IND-R&D* and *IND-MKTS*, although the Spearman correlation between *IND-MKTS* and *PCTCOMP* is insignificantly positive. Of particular note, based on the *t*-statistic size in panel A, are *IND-PPE*, *IND-R&D*, *IND-NUM*, and *SIM*.

Firms in industries with larger PP&E levels reference competition in their 10-K significantly less than firms in industries with smaller PP&E levels, consistent with the idea that the required investment in these industries creates barriers to entry, and so competitors pose a less significant threat to them. Firms in industries with more member firms (*IND-NUM*) or that have a high number of competitors with similar products (*SIM*) reference competition more frequently, consistent with the idea that they experience more competition from existing rivals and, hence, reference competition more frequently. All three effects are economically significant; firms in the lowest quintile of *PCTCOMP* have 29% more *PPE*, 29% fewer firms in their industry, and 21% lower similarity score than firms in the highest quintile of *PCTCOMP*.

The variable that appears the most anomalous in table 2 is *IND-R&D*, which is increasing with *PCTCOMP* when the prediction is that it should be decreasing. The argument, based on a resource model of competition given in Barney [1986] or Peteraf [1993], is that firms create barriers to entry with R&D expenditures, and yet we find that the firms with the largest R&D expenditures discuss competition the most in their 10-K. However, Brown and Kimbrough [2011] argue and find empirical support for the idea that R&D expenditures only create barriers to entry when they are associated with a recognized intangible asset, such as a patent, copyright, or other legal contract. Similarly, Ellis, Fee, and Thomas [2012] find that firms with greater R&D expenditures are less likely to specifically list large customers by name in their 10-K. Finally, R&D expenditures may represent "Red Queen" competition, and the management's discussion is in response to the need to make continuous innovations in response to rivals' innovations (as the example of Open Text Corp. in appendix A illustrated).

In sum, *PCTCOMP* appears to be a valid measure of competition insofar as it is correlated with other well-known measures, but the relatively low correlations imply that the *PCTCOMP* has substantial unique variation. It is also weakly related to the amount of product market similarity a firm has with other firms, but clearly measures something quite different. Moreover, we show in the next section that our measure is significant in the presence of these other measures, implying that it is not simply a noisy version of another construct.

3.3 OTHER VARIABLE DEFINITIONS AND DESCRIPTIVE STATISTICS

The remaining variable definitions follow the definitions used in the prior literature (the Xpressfeed codes are italicized in parentheses—see appendix B for additional description of the variable definitions). Financial statement variables without a time subscript are measured as of the end of the current fiscal year *t*. *RNOA* is defined as operating income after depreciation (*oiadp*) divided by the average *NOA*, where *NOA* is defined as net accounts receivable (*rect*) + inventories (*invt*) + all other current assets (*aco*) + net property, plant and equipment (*ppent*) + intangibles (*intan*) + all other assets (*ao*) – accounts payable (*ap*) – all other current liabilities (*lco*) – all other liabilities (*lo*). This construction of *NOA* follows Fairfield, Whisenant, and Yohn [2003]. Our object of prediction is the one-year-ahead change in *RNOA*, denoted as D_RNOA_{t+1}.

We focus on *RNOA* rather than *ROA* because diminishing returns to investment apply primarily to operating assets.[18] Consistent with this, in untabulated tests we find similar but weaker evidence based on the *ROA*, defined as operating income after depreciation divided by average total assets (*at*).

Other financial variables used as descriptive measures, or as controls in various regressions, are as follows. *MV* is calculated as the natural log of the *MV* of equity at the end of the fiscal year (price [*prc*] × shares outstanding [*shrout*]). Sales growth is defined as the year-over-year percentage change in sales (*sales*).

Table 3 gives descriptive statistics for the variables in the study. *RNOA* has a median of 0.12, consistent with prior studies. Next year's change, D_RNOA_{t+1}, has a small negative mean and a median value of zero. This is the benchmark prediction our model will try to improve upon. The first and third quartiles for *RNOA* are 0.04 and 0.22, respectively, so there is a significant amount of variation available to explain. The change in *NOA*, *D_NOA*, is scaled by total assets at the beginning of the period. Although the change in *NOA* is no longer a percent change, this is consistent with

[18] Financial assets and liabilities may exhibit diminishing returns for sufficiently large changes. However, the rate of return on investments in financial assets does not generally vary with the size of the investment until the investment is completely owned and the next best financial investment is made. Similarly, the rate of interest charged on a financial obligation does not vary within a debt issue, but may increase when a new issue is made.

TABLE 3
Summary Statistics

Variable	Mean	p25	Median	p75	*SD*	*n*
PCTCOMP	0.58	0.23	0.44	0.78	0.49	33,379
COMP	0.50	0.22	0.44	0.78	0.32	33,379
D_NOA	0.07	−0.03	0.04	0.13	0.20	33,379
RNOA	0.11	0.04	0.12	0.22	0.25	33,379
D_RNOA_{t+1}	−0.01	−0.06	0.00	0.04	0.17	33,379
MV	5.70	4.20	5.64	7.08	2.08	33,379
TOTAL ASSETS	2,199	83	304	1,288	5,844	33,379
SGROWTH	0.18	−0.01	0.09	0.24	0.53	33,379

This table presents the summary statistics for the variables used in this paper. Observations with $RNOA >$ 1; $RNOA < -1$; $MV < 0$ (i.e., market value of equity <\$1 million); $SGROWTH < -1$; or $SGROWTH > 10$ have been eliminated. All other variables, except *PCTCOMP*, *COMP*, *fCOMP*, *iCOMP*, and *MV*, have been winsorized at the 1% and 99% level. See appendix B for variable definitions.

TABLE 4
Pearson Correlations

$n = 33{,}379$	*COMP*	*D_NOA*	*RNOA*	D_RNOA_{t+1}	*MV*	*TOTAL ASSETS*
D_NOA	−0.01					
RNOA	**−0.04**	**0.17**				
D_RNOA_{t+1}	**−0.03**	**−0.17**	**−0.37**			
MV	**−0.15**	**0.13**	**0.32**	**−0.02**		
TOTAL ASSETS	**−0.15**	−0.01	**0.08**	**0.02**	**0.60**	
SGROWTH	**0.02**	**0.43**	**0.05**	**−0.08**	**0.06**	**−0.03**

This table presents pairwise Pearson correlations between the variables of interest in this study. All boldfaced correlation coefficients are significant at the 5% level or higher. See appendix B for variable definitions.

the definition in Fairfield, Whisenant, and Yohn [2003] and Richardson et al. [2005]. Because *NOA* can be very small, scaling by total assets keeps the variable from becoming too extreme. The change in *NOA* is 0.04 at the median indicating the median firm is modestly growing.

Table 4 gives the Pearson correlations between the main variables in the study. In terms of our variable of interest, *COMP* (the decile-ranked value of *PCTCOMP*), the most extreme correlation is with size, measured either as total assets or *MV*; bigger firms report relatively less competition than smaller firms. In terms of D_RNOA_{t+1}, the two main effects of diminishing marginal returns are present; the future change in *RNOA* has a negative correlation with the current period's level (*RNOA*) and a negative correlation with the current period's change in operating assets (*D_NOA*). Further, the economic magnitude of the relation between D_RNOA_{t+1} and firm size, as measured by *MV* or total assets, is immaterial.

3.4 THE INFLUENCE OF REPORTED COMPETITION ON FUTURE PERFORMANCE

To assess the impact of reported competition on the rate of diminishing returns on current and new investments, we estimate variations on the following two regressions:

$$D\_RNOA_{\mathrm{i,t+1}} = \Sigma\beta_t I_t + \beta_1 * RNOA_{i,t} + \beta_2 * D\_NOA_{i,t} + e_{i,t+1} \tag{1}$$

and

$$\begin{aligned} D\_RNOA_{i,t+1} = {} & \Sigma\beta_t I_{\mathrm{t}} + \beta_1 * RNOA_{i,t} + \beta_2 * D\_NOA_{i,t} + \beta_3 * COMP_{i,t} \\ & + \beta_4 * RNOA_{i,t} * COMP_{i,t} + \beta_5 * D\_NOA_{i,t} * COMP_{i,t} + e_{i,t+1}. \end{aligned} \tag{2}$$

The first regression gives the estimated diminishing marginal return relations before any consideration of reported competition and the second regression fully interacts all the variables in the first regression with *COMP* (recall that *COMP* is scaled such that it is zero in the lowest decile and one in the highest decile). In equation (1), β_1 measures the rate of mean reversion in *RNOA* controlling for any change in *NOA*; as such, it measures the diminishing marginal rate of return on existing assets. Controlling for the mean reversion in *RNOA*, the coefficient β_2 estimates the diminishing marginal rate of return on changes in *NOA*. Both β_1 and β_2 are hypothesized to be negative. In equation (2), these effects are conditioned on the level of *COMP*, as measured by the coefficients β_4 and β_5, both of which are hypothesized to be negative. Both regressions have year fixed effects, denoted by $\Sigma\beta_t I_{\mathrm{t}}$ (in the tables we report only the average of the yearly fixed effects). We include year fixed effects to control for a common period effect across all firms in a year. In addition, all *t*-statistics are computed with standard errors clustered at the industry level to control for unspecified correlation between observations for the same industry in different years.[19]

Consistent with prior research (Fairfield and Yohn [2001], Soliman [2008], Curtis and Lewis [2010]), the sample for the diminishing marginal return regressions in table 5 is limited to firms with positive operating income (reducing the sample to 26,823 observations). Although *RNOA* mean reverts for a loss firm, the rate of mean reversion is likely not the same as the rate for profit firms (Fama and French [2000]); the earnings of loss firms are more transitory than the earnings of gain firms (Li [2011]). Further, the rate of mean reversion toward profit is not necessarily increasing in competition, which is what equation (2) would predict for loss firms. Nevertheless, for completeness, in table 6 we give the results with loss firms included.

[19] In our setting, we expect that the correlations within industries are more significant than cross-sectional correlations. We follow Petersen [2009], who argues that panel regressions with appropriate fixed effects and clustered standard errors are more general than a Fama–MacBeth approach. Specifically, we include time-fixed effects in the regressions to control for the nonstochastic component of the cross-sectional effects, and calculate and report standard errors clustered at the industry-level; when we do not include the year-fixed effects, our results are calculated using two-way clustering on industry and year, which accounts for both cross-sectional and temporal dependence.

TABLE 5

Pooled Regressions of Changes in Return on Net Operating Assets and Competition

	Dependent Variable: D_RNOA_{t+1}			
Independent Variables	(1)	(2)	(3)	(4)
	−0.112***	−0.086***	−0.092***	−0.084***
D_NOA	[−16.59]	[−9.19]	[−8.53]	
RNOA	−0.244***	−0.192***	−0.192***	
	[−14.60]	[−11.25]	[−7.94]	
ATO				−0.010***
				[−6.44]
PM				−0.169***
				[−9.69]
COMP		−0.002	−0.001	0.011
		[−0.39]	[−0.16]	[1.21]
COMP * *D_NOA*		−0.058***	−0.059**	−0.074***
		[−3.46]	[−2.31]	[−4.61]
COMP * *RNOA*		−0.086***	−0.089**	
		[−2.99]	[−2.26]	
COMP * *ATO*				−0.009***
				[−2.81]
COMP * *PM*				−0.136***
				[−2.68]
Avg. Year FE/Intercept	0.026***	0.026***	0.025***	0.035***
Year FE?	Y	Y	N	Y
SE clustered by industry?	Y	Y	Y	Y
SE clustered by year?	N	N	Y	N
Adj. R^2	0.169	0.173	0.113	0.141
N	26,823	26,823	26,823	26,823

This table presents the results of a pooled OLS regression of future changes in *RNOA* on (1) contemporaneous *D_NOA* and *RNOA* with year fixed effects, (2) including *COMP* and interactions, (3) including *COMP* and interactions without year fixed effects but with standard errors clustered at the industry and year level, and (4) *D_NOA* and components of *RNOA* (*ATO* and *PM*). Firms with negative *RNOA* in year *t* have been deleted for this analysis. See appendix B for variable definitions. Models with year fixed effects report the average of the intercept coefficients. Standard errors are clustered at the industry (four-digit SIC) level when year fixed effects are included and are clustered at both the industry and year levels when year fixed effects are not included in column (3); *t*-statistics are reported in brackets below the coefficient estimates. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

The first column in table 5 shows significant diminishing marginal returns. The coefficient of –0.112 on *D_NOA* means *RNOA* is estimated to decrease next year by over 10% of the increase in *NOA*, all else equal. The mean reversion coefficient of –0.244 on *RNOA* implies that *RNOA* next year is estimated to decrease by almost a quarter of the current year's *RNOA*. These coefficient estimates are consistent with prior studies. Column 2 in table 5 reports the model when our measure of competition is interacted with all the variables in column 1. The significant negative coefficients on *COMP∗D_NOA* and *COMP∗RNOA* show that competition accelerates the rate of diminishing returns on new investments and existing assets, respectively. And the economic magnitude is impressive. The mean reversion coefficient on *RNOA* is –0.192 when competition is in the lowest decile and is –0.192 to 0.086 = –0.278 when competition is in the highest decile. Similarly, the coefficient on *D_NOA* is –0.086 when competition is in the lowest

TABLE 6
Using Industry-Adjusted Return on Net Operating Assets

	Dependent Variable: $ADJ\_D\_RNOA_{t+1}$		
Independent Variables	(1) All Firms	(2) Above Industry Mean	(3) Below Industry Mean
D_NOA	−0.074***	−0.107***	−0.034***
	[−7.97]	[−7.83]	[−3.49]
ADJ_RNOA	−0.217***	−0.255***	−0.212***
	[−12.27]	[−10.14]	[−3.94]
COMP	−0.007**	−0.001	−0.001
	[−2.02]	[−0.12]	[−0.10]
*COMP * D_NOA*	−0.060***	−0.059**	−0.048**
	[−3.36]	[−2.49]	[−2.18]
*COMP * ADJ_RNOA*	−0.114***	−0.122***	0.158
	[−3.09]	[−2.61]	[1.33]
Avg. Year FE/Intercept	0.005**	0.017***	−0.002
Year FE?	Y	Y	Y
SE clustered by industry?	Y	Y	Y
Adj. R^2	0.153	0.192	0.016
N	26,823	17,841	8,982

This table presents the results of a pooled OLS regression of future changes in industry-adjusted *RNOA* on *D_NOA* and industry-adjusted *RNOA* and interactions with *COMP*. Column (1) includes all firms, column (2) includes only those firms above the industry mean, and column (3) includes only those firms below the industry mean. Firms with negative *RNOA* in year *t* have been deleted for this analysis. See appendix B for variable definitions. Models with year fixed effects report the average of the intercept coefficients. Standard errors are clustered at the industry (four-digit SIC) level; *t*-statistics are reported in brackets below the coefficient estimates. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

decile and –0.086 to 0.058 = –0.144 when competition is in the highest decile.[20] As an alternative specification of the error structure, the regression reported in column 3 includes a single intercept rather than yearly fixed effects, and clusters standard errors at both the year and industry levels. The results for all variables are very similar to those reported in column 2.

The last column in table 5 replaces the current period *RNOA* with net operating margin (*PM*) and net operating asset turnover (*ATO*). This is exploratory because we do not have a hypothesis for why reported competition might affect margins or turnovers differently. For a given level of operating assets, competition could reduce sales, and hence *ATO*, and for a given level of sales, competition could reduce profit, and hence *PM*. What we see in the third column of table 5 is that both effects are significant. Further, the expected impact on the dependent variable is similar for the two components of *RNOA*. Multiplying the coefficient on *PM*∗*COMP* with the median value of *PM* (0.094) results in a –0.013 incremental effect and

[20] The adjusted R^2 has a small increase from column (1) (16.9%) to column (2) (17.3%). We do not expect a substantially higher R^2 here because the dependent variable (future change in *ROA*) is time-varying and our key independent variable is an interaction of current *ROA* and investment and a relatively persistent variable (competition). Given this, our focus is not on the increase in R^2, but on the economic magnitude of the interaction term.

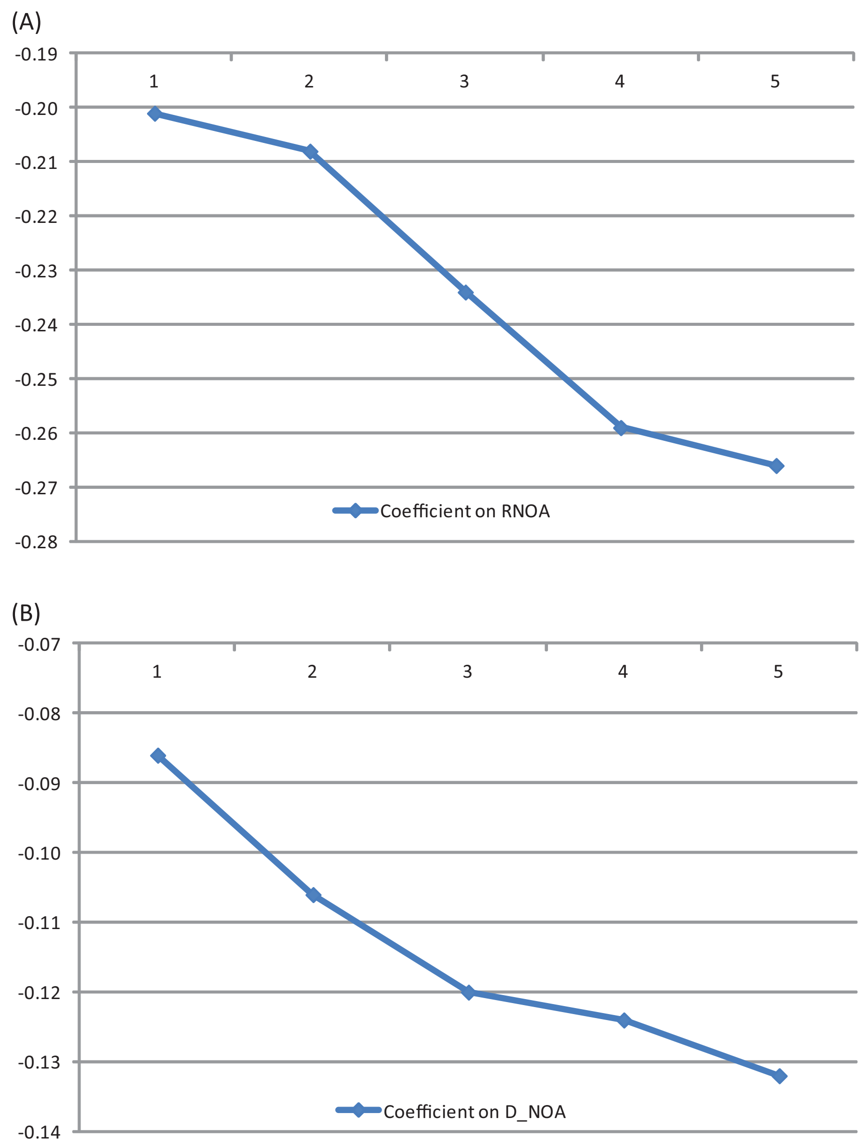

FIG. 2.—(A) Coefficient β_1 by *PCTCOMP* Quintile in: $D\_RNOA_{t+1} = \beta_0 + \beta_1 *RNOA + \beta_2 *D\_NOA$. (B) Coefficient β_2 by *PCTCOMP* Quintile in: $D\_RNOA_{t+1} = \beta_0 + \beta_1 *RNOA + \beta_2 *D\_NOA$.

multiplying the coefficient on *ATO*∗*COMP* with the median value of *ATO* (1.786) results in a –0.016 incremental effect.

To illustrate the effect of competition on the return on existing assets and new investments, figures 2(A) and (B) graph the estimated coefficients from equation (1) within each quintile of *PCTCOMP*. As both figures show, as our measure of competition increases, the rates of diminishing returns become more negative. The biggest effect on the rate of mean reversion in *RNOA* comes in quintiles three and four of *PCTCOMP*, although the biggest effect on the rate of diminishing returns on new investment comes in quintiles two and three.

Table 6 presents the first of many specification checks. In this table we create the variables *ADJ_D_RNOA* and *ADJ_RNOA* by subtracting the industry mean from the current and future *RNOA* (using the Fama-French industry definitions).[21] The idea is that *RNOA* is more likely to mean-revert toward an industry average than toward zero (as table 5 implicitly assumes). The downside to this specification is that it requires an industry definition. As seen in column 1, the coefficients on the interactions with *COMP* remain significant and are actually slightly more negative than those reported in table 5. To examine this further, we divide the sample between firms whose current *RNOA* is above industry mean or below the industry mean (where the industry mean is computed before the loss firms are eliminated). Comparing columns 2 and 3, we see that the coefficients on *COMP*D_NOA* are relatively similar across the two samples, but the coefficients on *COMP*ADJ_RNOA* are very different. Consistent with the hypothesis that competition accelerates the mean reversion of abnormally high *RNOA* but impedes the mean reversion from below the mean, we find opposite signs on the *COMP*ADJ_RNOA* coefficients. However, only the negative coefficient for firms above the mean is statistically significant.

Table 7 presents nine additional robustness tests. In column 1 we force the competition measure to capture only variation unrelated to the size of the firm. To construct this measure we create deciles of *PCTCOMP* within-size quintiles, where size is measured as total assets. The concern is that the weak negative correlation between *PCTCOMP* and size is causing *PCTCOMP* to proxy for an underlying size effect. Of course, bigger firms could legitimately face less competition, so this version of our measure might well throw out legitimate variation. The results in column 1 are weaker than the results in table 5 but the coefficients on *COMP*D_NOA* and *COMP*RNOA* are still significant.[22] In the next two models we explore size as it impacts the scale of our measure.

For the main tests we scale *PCTCOMP* by the total number of words in the 10-K and then sort into deciles to construct *COMP*. To rule out the possibility that the scalar is somehow impacting our results, we use total assets and the number of business segments as two alternative scalars. We use total assets because it is the most common measure of the scale and scope of a firm's operations, and we use the number of segments because the MD&A section of the 10-K specifically requires a discussion by business segment.

[21] Similar inferences are obtained using four-digit SIC definitions of industry.

[22] In untabulated results, we also include firm size and industry-fixed effects in the regression and our results are very similar.

TABLE 7

Robustness Tests of Changes in Return on Net Operating Assets and Competition

	Dependent Variable: D_RNOA_{t+1}									
Independent Variables	(1) Size Adjusted *COMP*	(2) Scaled by Total Assets	(3) Scaled by Number of Segments	(4) Rolling Average *COMP*	(5) Including *D_RNOA*	(6) Excluding High *RNOA*	(7) Excluding Low *PCTCOMP*	(8) Excluding High *PCTCOMP*	(9) Including Loss Firms	
D_NOA	−0.091***	−0.080***	−0.088***	−0.078***	−0.083***	−0.083***	−0.090***	−0.090***	−0.085***	β_1
	[−9.00]	[−8.66]	[−9.48]	[−7.48]	[−8.68]	[−8.37]	[−9.29]	[−9.32]	[−9.04]	
RNOA	−0.212***	−0.127***	−0.143***	−0.186***	−0.196***	−0.127***	−0.184***	−0.191***	−0.191***	β_2
	[−12.74]	[−7.06]	[−9.44]	[−9.04]	[−11.57]	[−7.84]	[−8.58]	[−11.09]	[−11.23]	
D_RNOA					0.041***					
					[3.69]					
COMP	0.002	−0.015**	0.013***	−0.005	−0.002	−0.004	−0.002	0.004	−0.002	β_3
	[0.46]	[−2.49]	[2.71]	[−0.88]	[−0.44]	[−0.85]	[−0.38]	[0.64]	[−0.42]	
*COMP * D_NOA*	−0.044**	−0.047**	−0.039**	−0.072***	−0.052***	−0.049***	−0.051***	−0.043**	−0.057***	β_4
	[−2.53]	[−2.56]	[−2.20]	[−3.58]	[−3.16]	[−2.72]	[−2.89]	[−2.50]	[−3.46]	
*COMP * RNOA*	−0.054*	−0.214***	−0.180***	−0.094**	−0.084***	−0.077**	−0.096***	−0.090**	−0.086***	β_5
	[−1.91]	[−6.79]	[−5.84]	[−2.53]	[−2.94]	[−2.13]	[−2.90]	[−2.32]	[−2.99]	
LOSS									−0.016*	β_6
									[−1.93]	
*LOSS * D_NOA*									0.028	β_7
									[0.93]	
*LOSS * RNOA*									−0.137***	β_8
									[−2.96]	
*LOSS * COMP*									−0.030**	β_9
									[−2.26]	

(Continued)

TABLE 7 — *Continued*

Independent Variables	(1) Size Adjusted *COMP*	(2) Scaled by Total Assets	(3) Scaled by Number of Segments	(4) Rolling Average *COMP*	(5) Including *D_RNOA*	(6) Excluding High *RNOA*	(7) Excluding Low *PCTCOMP*	(8) Excluding High *PCTCOMP*	(9) Including Loss Firms	
	Dependent Variable: D_RNOA_{t+1}									
*LOSS * COMP * D_NOA*									0.072	β_{10}
									[1.58]	
*LOSS * COMP * RNOA*									0.087	β_{11}
									[1.51]	
Avg. Year FE	0.025***	0.028***	0.017***	0.027***	0.026***	0.016***	0.026***	0.024***	0.026***	
Year FE?	Y	Y	Y	Y	Y	Y	Y	Y	Y	
SE clustered by industry?	Y	Y	Y	Y	Y	Y	Y	Y	Y	
Adj. R^2	0.170	0.191	0.176	0.173	0.175	0.108		0.165	0.173	
N	26,823	26,823	26,823	26,823	26,823	25,349	23,841	24,467	33,379	
Coefficients for Loss Firms:										
D_NOA	$(\beta_1 + \beta_7)$								-0.058^{+++}	
RNOA	$(\beta_2 + \beta_8)$								-0.328^{+++}	
*COMP * D_NOA*	$(\beta_4 + \beta_{10})$								0.015	
*COMP * RNOA*	$(\beta_5 + \beta_{11})$								0.001	

This table presents various robustness checks of the main results in table 5. Column (1) presents results after size-adjusting *PCTCOMP*. *PCTCOMP* is size-adjusted by creating the *COMP* deciles of *PCTCOMP* within year and total assets size quintile (rather than just year). Columns (2) and (3) present the results after scaling the number of competition words by average total assets and number of reported business segments, respectively (rather than scaling by the total number of words in the 10-K). Column (4) presents the results using the historical rolling average of *COMP* for each firm-year. To generate the rolling average, we average across the annual observations of *COMP* for as many lags as are available, up to a maximum of 10 years. Column (5) presents the results after including current year change in *RNOA* (i.e., D_RNOA_t). Column (6) excludes firm years with an $RNOA_t$ more than two standard deviations larger than the mean of *RNOA*t. Column (7) excludes firms in the bottom decile of *PCTCOMP*. Column (8) excludes firms in the top decile of *PCTCOMP*. Column (9) includes firms with $RNOA_t < 0$. See appendix B for variable definitions. Year-fixed effects are included and the average of these coefficients is reported. Heteroscedasticity robust *t*-statistics clustered at the industry (four-digit SIC) level are presented in brackets below the coefficient estimates. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. $^{+++}$denotes significance at the 1% level based on the *F*-test.

The results are shown in columns 2 and 3 in table 7. Both models yield similar results. When *COMP* is constructed using either scalar, the coefficient on *COMP*∗*D_NOA* is slightly smaller than in table 5, although still significant, and the coefficient on *COMP*∗*RNOA* is considerably larger, and considerably more significant. We believe that scaling by the number of words in the document is the most natural way to identify management's concern about competition, but alternative scalars yield even stronger results.

As was seen in figure 1, our *COMP* measure is very persistent through time. If *COMP* is a noisy measure of "true" competition, and if "true" competition is also very persistent through time, then averaging our measure over many prior periods should average out some of the noise and result in a better measure of "true" competition. In column 4 of table 7, we report the results when *COMP* is averaged over up to 10 prior years (i.e., years $t-9$ to t). The results are consistent with a reduction in noise in that both mean reversion coefficients increase relative to the results in table 5.

The model in column 5 of table 7 includes the current year change in *RNOA* (*D_RNOA*) in the regression to account for any correlation between contemporaneous performance and management's discussion of competition. If, for example, management tends to blame a decline in performance on competition and this decline persists, then our competition measure may simply be picking up information that is already included in the financial results. The results in column 5 indicate that, although changes in performance persist (i.e., the coefficient on *D_RNOA* is significantly positive, consistent with Fairfield and Yohn [2001]), this has little effect on the magnitude of the coefficients on *COMP*∗*RNOA* and *COMP*∗*D_NOA*.

Columns 6, 7, and 8 of table 7 explore the impact of nonlinearities on our main results. Prior studies find that mean reversion occurs more severely for extreme performance firms. In column 6 we exclude firms with current *RNOA* more than two standard deviations above the mean to see if *COMP* is simply identifying these extreme observations. The results show that both interactions with *COMP* remain significant, and the coefficients are only slightly smaller than those reported in column 2 of table 5. In column 7 we exclude observations in the bottom decile of *PCTCOMP* ($COMP = 0$). Here the concern is that firms with extremely high competition may not discuss it in their 10-K because everybody already knows that this is the case; consequently, they will wrongly measure as having low levels of competition. The results in column 7 are very similar to the results in table 5 column 2. The coefficient on *COMP*∗*D_NOA* is slightly smaller but the coefficient on *COMP*∗*RNOA* is slightly bigger. In column 8 we explore the opposite possibility that the effect is primarily driven by a few firms, which discuss competition extensively. We remove those observations in the most extreme top decile of *PCTCOMP* ($COMP = 1$) and again find similar results. It thus appears that the nonlinear aspects of the data are not driving the results.

Finally, in column 9 of table 7 we estimate equation (2) on the full sample that includes loss firms (approximately 19% of the sample) with an interacted dummy variable (*LOSS*) for loss firms that allows them to have different coefficients from profit firms. The very bottom of the table provides the coefficient estimates for the loss firms. The coefficient of the main effect of diminishing marginal returns ($\beta_1 + \beta_7$) is significant and of comparable magnitude to the profit sample value (i.e., β_7 is insignificant), but the estimated coefficient of mean reversion ($\beta_2 + \beta_8$) is significantly larger than for the profit sample. This is consistent with Fama and French [2000], who find that mean reversion occurs much faster for poorly performing firms. Moreover, we find that conditioning on the extent of competition provides no incremental explanatory power for loss firms (i.e., $\beta_4 + \beta_{10}$ and $\beta_5 + \beta_{11}$ are insignificantly different from zero). This provides useful confirmatory evidence of the suggestion in Brooks and Buckmaster [1976] and Fama and French [2000] that accounting conservatism—rather than competition per se—plays a significant role in the earnings mean reversion of loss firms (i.e., earnings with significant write-downs in year t empirically mean revert more quickly in $t + 1$).

In table 3 we validated our measure by showing that it was weakly correlated with other accepted measures of competition. Table 8 shows that our results are not due to an omitted-correlated variable problem where *PCT-COMP* is only a proxy for one of these other effects. For each of the seven alternative competition measures, and for the product similarity measure, we estimate the following equation, where *IND-COMP* is replaced with the particular alternative measure in question:

$$\begin{aligned} D\_RNOA_{i,t+1} = {} & \Sigma\beta_t I_t + \beta_1 * RNOA_{i,t} + \beta_2 * D\_NOA_{i,t} + \beta_3 * COMP_{i,t} \\ & + \beta_4 * RNOA_{i,t} * COMP_{i,t} + \beta_5 * D\_NOA_{i,t} * COMP_{i,t} \\ & + \beta_3 * IND\_COMP_{i,t} + \beta_4 * RNOA_{i,t} * IND\_COMP_{i,t} \\ & + \beta_5 * D\_NOA_{i,t} * IND\_COMP_{i,t} + e_{i,t+1}. \end{aligned} \tag{3}$$

If our measure *COMP* is simply a noisy proxy for one of the *IND-COMP* measures, then including them both in the same regression will cause *COMP*'s interactions with *RNOA* and *D_NOA* to become insignificant. To make the alternative measures comparable to *COMP*, we sorted each into deciles, and then scaled them to be between zero and one. Theoretically, competition is decreasing in the first six measures, so the sign on the interaction should be positive (thus making the sum of coefficients less negative), and is increasing in *IND-NUM* and *SIM*, so the sign on these interactions should be negative. Table 8 gives the results. Looking across the row for *COMP***RNOA* and *COMP***D_NOA* shows that all the interactions remain significant in the presence of all eight alternative proxies for competition.[23] Further, the coefficient magnitudes generally remain comparable to the levels in table 5. The coefficients on the first four *IND-COMP* variables

[23] In untabulated results we also examined two other competition measures from Li [2010], the industry *ROA* and the industry profit level. Our *COMP* interactions are virtually unchanged. We also construct industry concentration measures based on the Global Industry Classification Standard (GICS)—a classification scheme that may better explain stock return

TABLE 8

Tests of Changes in Return on Net Operating Assets Controlling for Industry-Level Competition and Product Similarity

	Dependent Variable: D_RNOA_{t+1}							
Independent Variables	(1) *IND-PPE*	(2) *IND-R&D*	(3) *IND-CAPX*	(4) *IND-MKTS*	(5) *IND-CON4*	(6) *IND-HHI*	(7) *IND-NUM*	(8) *SIM*
D_NOA	−0.074***	−0.048***	−0.074***	−0.059***	−0.094***	−0.097***	−0.061***	−0.069***
	[−6.40]	[−4.34]	[−6.38]	[−5.10]	[−5.72]	[−5.77]	[−5.39]	[−5.47]
RNOA	−0.170***	−0.140***	−0.154***	−0.154***	−0.263***	−0.255***	−0.144***	−0.166***
	[−7.17]	[−6.00]	[−6.38]	[−6.21]	[−7.67]	[−7.61]	[−6.45]	[−7.61]
COMP	−0.002	−0.005	−0.003	−0.003	−0.004	−0.004	−0.005	−0.007
	[−0.48]	[−1.18]	[−0.60]	[−0.70]	[−0.81]	[−0.75]	[−1.06]	[−1.28]
*COMP * D_NOA*	−0.059***	−0.037**	−0.059***	−0.058***	−0.059***	−0.060***	−0.057***	−0.063***
	[−3.62]	[−2.24]	[−3.64]	[−3.57]	[−3.67]	[−3.69]	[−3.47]	[−3.63]
*COMP * RNOA*	−0.082***	−0.052**	−0.077***	−0.072***	−0.065**	−0.068**	−0.049*	−0.053*
	[−2.91]	[−2.04]	[−2.82]	[−2.69]	[−2.47]	[−2.55]	[−1.87]	[−1.90]
IND-COMP	0.004	0.011*	0.005	0.005	−0.010	−0.009	0.002	0.006
	[0.66]	[1.72]	[0.90]	[0.70]	[−1.39]	[−1.22]	[0.29]	[0.93]
*IND-COMP * D_NOA*	−0.022	−0.109***	−0.021	−0.054**	0.023	0.028	−0.049**	−0.026
	[−1.09]	[−5.04]	[−1.02]	[−2.35]	[1.02]	[1.22]	[−2.02]	[−1.06]
*IND-COMP * RNOA*	−0.053	−0.119***	−0.088**	−0.087*	0.126***	0.112**	−0.127***	−0.091**
	[−1.42]	[−2.77]	[−2.17]	[−1.81]	[2.65]	[2.42]	[−2.83]	[−2.36]
Avg. Year FE	0.025***	0.021***	0.024***	0.024***	0.031***	0.030***	0.025***	0.020***
Year FE?	Y	Y	Y	Y	Y	Y	Y	Y
SE clustered by industry?	Y	Y	Y	Y	Y	Y	Y	Y
Adj. R^2	0.174	0.178	0.175	0.175	0.176	0.176	0.178	0.179
N	26,665	26,665	26,665	26,665	26,665	26,665	26,665	23,582

This table presents the results of a pooled OLS regression of future changes in *RNOA* (*D_RNOA*) on the current level of *RNOA*, *D_*NOA, and *COMP* after controlling for industry-level competition and product similarity. We follow Li [2010] for the definition of the industry competition measures and use the data from Hoberg and Phillips [2011] for the product similarity measure (see table 3 for details). Theoretically, all industry competition measures except *IND-NUM* are decreasing in the level of competition. To be consistent with the calculation of *COMP*, we use deciles of the industry competition and product similarity measures, scaled between 0 and 1. See appendix B for other variable definitions. Year-fixed effects are included and the average of these coefficients is reported. Heteroscedasticity robust *t*-statistics clustered at the industry (four-digit SIC) level are presented in brackets below the coefficient estimates. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

are sometimes significant but all have the wrong sign when interacted with *RNOA*. Including *IND-R&D* has the largest impact on our coefficients of interest, although the signs on the interactions with *IND-R&D* are positive, which is inconsistent with the theory that R&D intensity reduces competition.

In contrast to the first four columns of table 8, columns 5 through 8 show that the two concentration ratios, the number of firms in the industry, and the Hoberg-Phillips product similarity measure all have significant interactions with *RNOA* (and in the predicted direction). The continued significance of the interactions between *COMP* and *D_NOA* and *RNOA* indicates that our measure is a useful complement to certain industry-based measures of competition. For instance, the difference in the rate of mean reversion in *RNOA* between the top and bottom deciles of *COMP* is –0.068 as seen in column 6; if we also take the difference between the top and bottom deciles of *IND-HHI* this increases threefold to –0.068 to 0.112 = –0.180 (recall that higher levels of *HHI* indicate lower levels of competition).

We have emphasized that *COMP* does not require a definition of industry boundaries. Nonetheless, any discussion of competition begs the question "competition with whom?" and industries are a natural way to think about the set of relevant firms. For this reason, we examine an industry-level version of our measure. In particular, we create the variable *iCOMP* by averaging *PCTCOMP* over the firm's industry each year (excluding the firm itself), forming deciles, and then scaling the ranks to be between zero and one. We use four different industry definitions; the Fama-French 48 industries, which average 162 firms per industry; the SIC3 and SIC4 definitions, which average 62 and 21 firms per industry, respectively; and the Hoberg-Phillips Text-Based Network Industry Classification (TNIC) metric, which averages 43.9 firms per industry.[24] Recall that the first three definitions have relatively little temporal variation and create mutually exclusive sets of industries although the Hoberg-Phillips measure is dynamic and does not impose exclusivity on the sets of industries.

Table 9 gives the results for regressions that add *iCOMP* and interactions with *D_NOA* and *RNOA* to equation (2).[25] Beginning with the Fama-French industry definition in column 1, we see that both the interactions with *COMP* and the interactions with *iCOMP* are significant. For *D_NOA*, the interaction with *COMP* has a coefficient of –0.045 and the interaction with

co-movements (see Bhojraj, Lee, and Oler [2003])—and find that our results are virtually identical.

[24] The Hoberg-Phillips text-based industries were developed to have a distribution similar to that of SIC3 in terms of number of firms. We note that the medians for SIC3 and Hoberg-Phillips TNIC are very similar. Moreover, the mean number of firms we report in table 9 are only for the subsample of firms that we analyze, not the full sample.

[25] In previous versions of the paper, we also report the results of a purely "within-" industry constructed version of *COMP*, wherein *PCTCOMP* was ranked within industry-year (rather than just year). The results of this variable are very similar to those of *COMP* reported in table 9 in which *COMP* is conditioned on *iCOMP* in the regression.

TABLE 9
Examining Within and Between Industry Competition

	Dependent Variable: D_RNOA_{t+1}			
Independent Variables	(1) FF 48	(2) SIC-3	(3) SIC-4	(4) H-P TNIC
D_NOA	−0.069***	−0.066***	−0.070***	−0.062***
	[−4.93]	[−4.35]	[−4.62]	[−4.22]
RNOA	−0.145***	−0.143***	−0.142***	−0.128***
	[−6.18]	[−5.88]	[−5.97]	[−5.25]
COMP	−0.004	−0.003	−0.004	−0.008
	[−0.77]	[−0.60]	[−0.84]	[−1.54]
*COMP * D_NOA*	−0.045***	−0.036**	−0.037**	−0.027
	[−2.73]	[−2.16]	[−2.14]	[−1.52]
*COMP * RNOA*	−0.060**	−0.063**	−0.050*	−0.013
	[−2.07]	[−2.16]	[−1.72]	[−0.47]
iCOMP	0.005	0.004	0.005	0.009
	[0.79]	[0.71]	[0.88]	[1.41]
*iCOMP * D_NOA*	−0.048**	−0.068***	−0.059**	−0.081***
	[−2.18]	[−2.74]	[−2.43]	[−3.29]
*iCOMP * RNOA*	−0.101***	−0.101**	−0.121***	−0.176***
	[−2.60]	[−2.49]	[−3.16]	[−4.60]
Avg. Year FE/Intercept	0.022***	0.022***	0.023***	0.016***
Year FE?	Y	Y	Y	Y
SE clustered by industry?	Y	Y	Y	Y
Adj. R^2	0.176	0.177	0.181	0.185
N	26,823	26,102	24,001	23,001
Mean firms per industry	162.0	62.0	21.0	43.9
Mean coefficient of variation of *PCTCOMP* within industry	0.70	0.67	0.66	0.66

This table presents the results of a pooled OLS regression of future changes in *RNOA* on firm level variation (*COMP*) and industry level variation (*iCOMP*) in competition. *iCOMP* is calculated for firm i in industry k by averaging *PCTCOMP* over all firms j in industry k in year t, where $i \neq j$ (i.e., the firm's own *PCTCOMP* is excluded from the average). Consistent with the calculation of *COMP*, we create deciles of this variable across all firms each year and transform the decile values between 0 and 1. Each column calculates *iCOMP* based on different industry definitions as indicated by the column header. The sample size decreases as the industry definition becomes more specific because an increasing number of industries include only one firm and are eliminated from the sample. The decrease in sample size for *HP-TNIC* is mainly caused by a loss of the first and last years of the sample in which these industry definitions are unavailable. Firms with negative *RNOA* in year t have been deleted for this analysis. See appendix B for variable definitions. Models with year fixed effects report the average of the intercept coefficients. Standard errors are clustered at the industry (four-digit SIC) level; t-statistics are reported in brackets below the coefficient estimates. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

iCOMP has a coefficient of –0.048. Both the firm- and industry-level competition measures contribute to the description of diminishing returns on new assets. Similarly, for *RNOA* the interaction with *COMP* has a coefficient of –0.060 and the interaction with *iCOMP* has a coefficient of –0.101. Both the firm- and industry-level measures contribute to the description of diminishing returns on existing assets. The results are similar for the SIC3 and SIC4 classifications, as seen in columns 2 and 3. The most interesting results arise when we use the Hoberg-Phillips industry definitions. In column 4, the interactions with *COMP* are no longer significant although the interactions with *iCOMP* are significant and have notably larger coefficients than those reported in columns 1, 2, and 3. For instance, the difference in the rate of mean reversion in *RNOA* between the top and bottom deciles of *iCOMP* is –0.176, almost three times larger than the original coefficient on *COMP∗RNOA* reported in column 2 of table 5. These results suggest that, as the industry classification scheme improves, the power of our competition measure to identify different levels of industry competitiveness also improves.[26]

The results in table 9 also help mitigate the concern about an alternative explanation of our main results in the paper. One possible explanation of our empirical findings is that our competition measure does not really capture competition; rather, it captures managers' blaming competition for their firms' poor performance. Under this alternative explanation, our measure reflects the excuses of managers for their poor performance, rather than the true competition. To the extent that management's incentives to attribute poor performance to competition are firm specific, the result in table 9 that the industry-average of our measure leads to stronger results suggests that our empirical findings are not driven by this alternative explanation.

Our final set of tests looks for any evidence of strategic manipulation of the disclosures in the 10-K to influence rival firms. Our maintained assumptions are that managers have a reasonably accurate perception of the "true" amount of competition they face, whatever its form, and that their disclosures about competition in the 10-K filing are a reasonably accurate reflection of these perceptions. Absent an observable measure of "true" competition, we cannot directly assess these maintained assumptions, so any evidence we offer is necessarily circumstantial. Our approach is to identify firms that, based on other measures of competition, might face the greatest incentives to distort their disclosures about competition, or simply have an inaccurate perception of their competitive threats, and then compare these with firms who face the least incentives to distort their disclosures.

Li [2010] studies how competition influences a firm's likelihood of providing earnings or capital expenditure guidance to analysts, finding that firms in industries facing a high threat of entry or a low level of rivalry among existing firms disclose less than firms in industries facing a low threat of entry or high rivalry among existing firms. For our first set of tests we hypothesize that this same distinction will influence how truthfully firms talk about competition in their 10-K filing. To identify the type of competitive threat faced by the firm, we use the industry competition variables from Li [2010] discussed in tables 2 and 8.

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[26] In untabulated results we also add interactions between the Herfindahl index (HHI) and *D_NOA* and *RNOA* to the regression shown in column 4 of table 9. Unlike the results in table 8 column 6, the interactions with the Herfindahl index are no longer significant (i.e., when industries are defined using Hoberg-Phillips, and competition is measured at the industry level using *iCOMP*, the Herfindahl index is no longer significant).

Li [2010] uses the first four variables (*IND-PPE*, *IND-R&D*, *IND-CAPX*, and *IND-MKTS*) as proxies for the threat of potential entry by new rivals and uses the next three (*IND-CON4*, *IND-HHI*, and *IND-NUM*) as proxies for the threat from existing rivals. To mitigate the noise in any one of the variables relative to its underlying construct, we create two new variables, *POTENTIAL* and *EXISTING*, by averaging over the decile ranks of each of the variables within the particular competition construct. We then identify two sets of firms. The firms in the first set have low levels of *POTENTIAL* and high levels of *EXISTING*, and are hypothesized to have little reason to distort their disclosures about competition. These firms already face stiff competition from existing firms and do not fear entry from new firms. The firms in the second set have high levels of *POTENTIAL* and low levels of *EXISTING*, and are hypothesized to have the greatest reason to distort their disclosures about competition. These firms want to deter entry from new firms and keep existing rivals from altering their behavior. We use the median of *POTENTIAL* and *EXISTING* to identify high and low values of each construct.

The results from estimating equation (2) on the two sets of firms are given in columns 1 and 2 in table 10. Both models show diminishing returns on new and existing investments, as seen by the significantly negative coefficients on *D_NOA* and *RNOA*. However, the amount that our measure of competition conditions these rates is considerably greater for the first set of firms (who have less incentive to distort disclosures) than for the second set of firms (who have more incentive to distort disclosures). The coefficient on *COMP*∗*D_NOA* is –0.084 in the first model and –0.052 in the second model; both are significant. The coefficient on *COMP*∗*RNOA* is –0.101 in the first model and only –0.014 in the second model, and this last value is insignificant. Although the evidence is indirect, the lower coefficients on the interactions with *COMP* in the second model are what we would expect if the *COMP* measure is being distorted by firms in industries with a high threat of entry and low rivalry among existing firms.

For our second set of tests we perform the same exercise using the Hoberg-Phillips *SIM* variable to separate firms into two groups (using the sample median *SIM* score to divide firms into groups of high- and low-product similarity). The idea here is that variation in management's discussion of competition is more meaningful for firms who face many rivals with similar products because such firms have a clearer view of competitive threats. The rival firms and rival products already exist, and they are either successfully or unsuccessfully competing with these rivals. On the other hand, a firm with a low *SIM* score may have a harder time assessing the competitive landscape and so variation in *COMP* for these firms is less accurate. The results in columns 3 and 4 support this hypothesis. The coefficients on the interaction terms *COMP*∗*D_NOA* and *COMP*∗*RNOA* are –0.080 and –0.087, respectively, when the *SIM* score is above the median and only –0.039 and –0.023, respectively, when the *SIM* score is below

TABLE 10

Interaction with Other Competition Measures

	Dependent Variable: D_RNOA_{t+1}			
Independent Variables	(1) Low Potential Entrant Threat and High Existing Rivalry	(2) High Potential Entrant Threat and Low Existing Rivalry	(3) High Product Similarity	(4) Low Product Similarity
D_NOA	−0.090***	−0.083***	−0.076***	−0.092***
	[−4.33]	[−7.26]	[−5.00]	[−7.70]
RNOA	−0.219***	−0.169***	−0.213***	−0.202***
	[−7.57]	[−6.99]	[−7.83]	[−7.77]
COMP	0.002	−0.001	−0.007	−0.006
	[0.30]	[−0.20]	[−0.94]	[−0.79]
*COMP * D_NOA*	−0.081**	−0.050**	−0.080***	−0.037
	[−2.29]	[−2.30]	[−2.99]	[−1.59]
*COMP * RNOA*	−0.103**	−0.021	−0.087**	−0.025
	[−2.53]	[−0.55]	[−2.26]	[−0.59]
Avg. Year FE	0.024***	0.021***	0.025***	0.024***
Year FE?	Y	Y	Y	Y
SE clustered by industry?	Y	Y	Y	Y
Adj. R^2	0.213	0.133	0.190	0.165
N	8,882	9,930	11,098	12,484

This table presents the main results from table 5 after conditioning on the type and level of industry competition and the extent of competition based on product similarity. For industry competition, we identify firms in industries with a low threat of potential entry and a high level of existing rivalry (column 1) and firms in industries with a high threat of potential entry and a low level of existing rivalry (column 2). We average across the deciles of the industry measures *IND-PPE*, *IND-R&D*, *IND-CAPX*, and *IND-MKTS* as a proxy for the threat of entry and *IND-CON4*, *IND-HHI*, and *IND-NUM* as a proxy for the level of existing rivalry. If a firm is below the median for the potential threat proxy and above the median for the existing rivalry, the firm-year will be included in column 1. Likewise, if a firm is above the median for the potential threat proxy and below the median for the existing rivalry, the firm-year will be included in column 2. The sample size does not equal that of table 5 because some firms are in the high/high and low/low categories. In columns (3) and (4) we portion the sample based on the Hoberg and Phillips [2011] total product similarity measure (*TNIC3TSIMM*—see table 3 for details). After identifying the separate subsamples for each of the columns, we repeat the regression from column 2 of table 5. See appendix B for variable definitions. Models with year fixed effects report the average of the intercept coefficients. Standard errors are clustered at the industry (four-digit SIC) level; *t*-statistics are reported in brackets below the coefficient estimates. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

the median.[27] We believe that the results in table 10 not only help us understand the strategic disclosure aspects of our proposed measure, but also reinforce the complementarity of our disclosure-based variable with traditional industry measures of competition.

[27] To examine the complementarity of *competitors'* reported competition with a firm's own report of competition, we also partition the sample based on the level of *iCOMP* (using the Hoberg-Phillips TNIC definition). In untabulated results, we find that the *COMP* interactions with *D_NOA* and *RNOA* are more negative in the high *iCOMP* partition compared to the low *iCOMP* partition (where neither coefficient is significant). This result reinforces the complementarity notion of considering both the firm and its competitors.

4. *Conclusion*

By simply counting the number of times a firm refers to competition in its regulatory 10-K, we measure a firm's competitive environment in a simple yet novel way. We show that this measure is only weakly related to industry concentration and other existing measures of competition, and can be used as a stand-alone measure of competition or to construct an industry-level measure. Further, our results show that the measure behaves as if it is measuring "true" competition, in that higher levels correspond to greater rates of mean reversion on the firm's *RNOA* and greater rates of diminishing returns to new investment. Conditioning a forecast of next year's *RNOA* by the level of competition results in a significant and economically meaningful difference between firms with high versus low levels of competition. These results suggest that the disclosures management makes in the 10-K filing about competition are useful for financial statement analysis.

APPENDIX A

Competition References

1) "The markets for sportswear, outerwear, footwear, and related accessories and equipment are highly competitive. In each of our geographic markets, we face significant competition from numerous and varying competitors. Some of our large wholesale customers also pose a significant competitive threat by marketing apparel, footwear and equipment under their own private labels." Columbia Sportswear Co., 2-27-2009.
2) "We compete for investment opportunities with entities that have substantially greater financial resources than we do. These entities generally may be able to accept more risk than we can prudently manage. This competition may generally limit the number of suitable investment opportunities offered to us. This competition may also increase the bargaining power of property owners seeking to sell to us, making it more difficult for us to acquire new properties on attractive terms." MHI Hospitality Corp, 3-25-2009.
3) "Our future success will also depend on our ability to attract and retain key managers, designers, sales people and others. We face intense competition for these individuals worldwide, and there is a significant concentration of well-funded apparel and footwear competitors in and around Portland, Oregon." Columbia Sportswear Co. 2-27-2009.
4) "The markets for our products are intensely competitive, and are subject to rapid technological change and other pressures created by changes in our industry. We expect competition to increase and intensify in the future as the pace of technological change and adaptation quickens and as additional companies enter into each of our markets.

Numerous releases of competitive products have occurred in recent history and may be expected to continue in the near future." Open Text Corp, 8-26-2008.

5) "We believe that there is currently no or limited competition in the markets we plan to pursue, and there is an increasing demand due to the rising levels of installed wind energy capacity worldwide." First National Energy Corp, 1-4-2011.
6) "Our ability to acquire additional reserves in the future could be limited by competition from other companies for attractive properties." Oil Dri Corp, 10–12-2010.

APPENDIX B

Variable Definitions

Variable	Description
NWORDS	The total number of words in the 10-K.
NCOMP	The number of times "competition, competitor, competitive, compete, competing," occurs in the 10-K, including those words with an "s" appended. Cases where "not," "less," "few," or "limited" precedes the word by three or fewer words were removed.
PCTCOMP	Number of occurrences of competition-related words (*NCOMP*) per 1,000 total words in the 10-K (*NWORDS*). In table 2 only, we de-trended this variable by subtracting the mean for all firms in year t from firm i's *PCTCOMP* value (creating variable *PCTCOMP_ DETREND*).
COMP	A transformation of *PCTCOMP*, scaled between 0 and 1, calculated by forming decile rank portfolios of *PCTCOMP* each year, subtracting 1 from the decile rank and dividing by 9.
RET	The 12-month buy and hold return calculated by compounding the 12 monthly returns beginning the first month after the 10-K filing date and adjusting the return by subtracting the corresponding 12-month buy and hold return from the same NYSE/AMEX/NASDAQ decile size portfolio.
RNOA	Return on net operating assets calculated by dividing operating income after depreciation ($oiadp_{i,t}$) by the average net operating assets ($(NOA_{i,t} + NOA_{i,t-1})/2$). D_RNOA_{t+1} is the change in this variable from year t to year $t + 1$.
NOA	Net operating assets calculated as net accounts receivable (*rect*) + inventories (*invt*) + all other current assets (*aco*) + net property, plant and equipment (*ppent*) + intangibles (*intan*) + all other assets (*ao*) – accounts payable (*ap*) – all other current liabilities (*lco*) – all other liabilities (*lo*). *D_NOA* is the change in this variable from year $t - 1$ to year t scaled by average total assets.
ROA	Return on assets calculated by dividing operating income after depreciation ($oiadp_{i,t}$) by the average total assets ($(at_{i,t-1} + at_{i,t})/2$).
TA	Total assets ($at_{i,t}$). *D_TA* is the change in this variable from year $t - 1$ to year t scaled by the average total assets.
MV	*MV_$* is market value of equity at the end of the fiscal year (price (*prc*) × shares outstanding (*shrout*)). *MV* is the natural log of *MV_$*. Firms with market values less than $1 million have been deleted.
SGROWTH	Year-over-year percentage change in sales calculated as $(Sale_{i,t} - Sale_{i,t-1})/Sale_{i,t-1}$.

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