Product market competition and firms' disclosure of cross-segment differences in performance

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Roland Königsgruber[(a)]

Pietro Perotti[(b)]

Oliver Schinnerl[(c)]

Fanis Tsoligkas[(d)]

David Windisch[(e)]

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[(a)] SKEMA Business School – Université Côte d'Azur, Esplanade Mona Lisa, 92400 Courbevoie, roland.konigsgruber@skema.edu.

[(b)] School of Management, University of Bath, Claverton Down, BA2 7AY Bath, United Kingdom, p.perotti@bath.ac.uk.

[(c)] Institute of Accounting and Taxation, University of Graz, Universitaetsstrasse 15/G2, 8010 Graz, Austria, oliver.schinnerl@uni-graz.at.

[(d)] School of Management, University of Bath, Claverton Down, BA2 7AY Bath, United Kingdom, f.tsoligkas@bath.ac.uk, +44 (0) 1225 383076.

[(e)] University of Amsterdam, Plantage Muidergracht 12, 1018 TV Amsterdam, The Netherlands, d.w.windisch@uva.nl.

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Abstract:

This study examines how product market competition affects firms' disclosures of their individual segments' performance. We explicitly account for different types of product market competition by distinguishing between competitors who are already active in a particular market and potential competitors who are considering entering the market. Arguably, firms that are subject to intensive existing competition have lower incentives to conceal information because they are less likely to exhibit abnormal profitability. By contrast, a high level of potential competition constitutes a threat to profitability and hence provides incentives to conceal segment performance. In line with these proprietary cost arguments, we find that potential competition is negatively associated with the disclosure of cross-segment differences in performance, whereas existing competition is positively associated with the disclosure of cross-segment differences in performance. Our results remain robust to a number of sensitivity tests.

Keywords: Product Market Competition; Existing Competition; Potential Competition; Segment Reporting; Cross-Segment Differences.

JEL Classification: M41

Introduction

Information about the performance of a firm's individual segments is highly relevant to capital market participants (AIMR, 1993; AICPA, 1994; FAF, 2013; IASB, 2013), while segment disclosures can impose significant proprietary costs on the disclosing firms by revealing information to product market competitors (e.g., Sprouse, 1969; Ettredge *et al.*, 2002). These proprietary costs often serve as an explanation for why firms aggregate operating segments with different economic characteristics or shift revenues and costs among segments to conceal the underlying performance of their separate operations.[1] Several theoretical and empirical studies suggest that the relation between firm disclosure and proprietary costs, and consequently firms' disclosure decisions, depend on the nature of the product market competition (e.g., Healy and Palepu, 2001; Verrecchia, 2001; Li, 2010). Despite the extensive literature on segment reporting, no prior study has examined how different types of competition affect firms' segment disclosures. This lack of evidence as well as the importance of segment reporting to capital market participants serves as our motivation to examine the relation between two different types of product market competition—existing and potential—and firms' decisions to either disclose or conceal cross-segment differences in performance.

Building on theoretical arguments and empirical findings in prior segment disclosure literature, we expect that existing competition decreases firms' incentives to conceal segment performance. More specifically, if existing competition is high, the competitive harm from disclosing the performance of segments should be low (e.g., Harris, 1998; Botosan and Stanford, 2005) because abnormal profitability is more likely to occur in product markets with low existing competition (e.g., Bain, 1951). Conversely, we expect that potential competition

[1] See Hayes and Lundholm (1996), Nagarajan and Sridhar (1996), Harris (1998), Ettredge *et al.* (2006), Hann and Lu (2009), and Lail *et al.* (2014).

increases firms' incentives to conceal their segments' performance. If potential competition is more intense, for example due to low entry barriers, disclosing information on segment performance is more costly because competitors are more likely to enter the product market (e.g., Nagarajan and Sridhar, 1996).

We measure the extent to which firms disclose or conceal the performance of their segments by the cross-segment variability in profitability, which is calculated as the range of reported segment profitability (Ettredge *et al.*, 2006). This measure, which captures the degree to which segment disclosures reveal differences in the performance of a firm's segments, is based on the premise that segment disclosures provide information over and above firm-level disclosures to both capital market participants and product market competitors if there is heterogeneity between the segments. Any attempts to hide abnormal profitability, such as by aggregating operating segments or shifting revenues and costs among segments, would lead to a decline in the cross-segment variability in profitability and thus less disaggregated segment disclosures.

To measure both existing and potential competition, we follow Li's (2010) approach and employ nine commonly used proxies for measuring competition at the industry-level based on both firm- and segment-level data. We measure competition from potential entrants by (1) investment in property, plant, and equipment (PP&E), (2) research and development expenditures (R&D), (3) capital expenditures, and (4) product market size. Existing competition is captured using the (5) Herfindahl-Hirschman index, the (6) four-firm concentration ratio, the (7) total number of firms operating in an industry, and (8) product market size. To capture all aspects of competition, we also consider (9) industry profitability, which we measure using the industry return on assets (ROA) and the price-cost margin. Based on these nine competition variables, we conduct a principal component analysis and use the derived principal components as our measures of existing competition, potential competition, and industry profitability. The

key advantage of this approach is that it allows us to capture the different types of competition while reducing the number of variables for the empirical analysis.

We test our hypotheses using U.S. firm- and segment-level data from 1977 to 2018. Consistent with our expectations, we find that the cross-segment variability in profitability is positively associated with existing competition and negatively associated with potential competition. These findings not only suggest that both existing and potential product market competition are significantly associated with firms' segment performance disclosures but also that the direction of this association depends upon the nature of the competition. Our results remain robust when we consider alternative measures of cross-segment variability in profitability and an alternative definition of segment profitability.

Our study adds to the literature that examines the influence of competition on the disclosure of proprietary information by examining the association of both existing and potential competition with disclosures about the profitability of operations at the segment level. Prior empirical findings suggest that diversified firms hide segments to protect abnormal profits from competition (e.g., Harris, 1998; Botosan and Stanford, 2005; Berger and Hann, 2007). However, this literature does not consider both existing and potential competition simultaneously.

Moreover, prior studies often focus on the relation between competition and the number of segments disclosed (e.g., Harris, 1998; Botosan and Stanford, 2005). We differ from this stream of research by focusing on the cross-segment variability in profitability. The advantage of this measure compared with cross-sectional variation in the number of segments is that it also captures firms' efforts to conceal segment performance-related information by aggregating operations with different profitability or shifting revenues and costs among segments without changing the number of reported segments (Ettredge *et al.*, 2006).

Notably, our results contrast with results from previous studies that examine voluntary disclosure at the firm level, which typically find that existing competition reduces voluntary

disclosure, whereas potential competition increases voluntary disclosure (Li, 2010; Huang *et al.*, 2016). This suggests that the incentives to reveal or conceal information that play out at the segment and firm levels are substantially different.

Literature review and hypothesis development

Product market competition and disclosure

A primary purpose of corporate disclosures is to aid investors' and other firm outsiders' decision-making by providing information that allows a better assessment of a firm's future prospects. For diversified firms, segment disclosures provide important additional information over and above firm-level disclosures by revealing information about the firm's diversification strategy along with its different sources of operating performance. In line with these arguments, prior literature provides empirical evidence that more disaggregated segment disclosures improve the ability of investors, creditors, and analysts to assess a firm's performance (e.g., Aitken *et al.,* 1994; Ettredge *et al.*, 2005; Franco *et al.*, 2016; Kajüter and Nienhaus, 2017). Disclosing firms, in turn, benefit from lower expected cost of capital (e.g., Blanco *et al.*, 2015; Franco *et al.*, 2016).

However, segment reporting rules provide firms with considerable discretion. For example, firms can use the leeway in the aggregation criteria for defining reporting segments in SFAS 14 or shift sales and costs among segments under the management approach in SFAS 131 to conceal their segments' "true" performance (e.g., Berger and Hann, 2003; Ettredge *et al.*, 2006; Berger and Hann, 2007). This discretion entails a trade-off between the expected benefits of better informing firm outsiders and the associated costs of providing such disclosures. Regarding the latter, a key cost consideration is that competitors can use segment

information to assess a firm's weaknesses and opportunities to be exploited, which can impose proprietary costs on the disclosing firm.[2]

The analytical literature on firms' disclosure decisions on segments is fairly scarce. Hayes and Lundholm (1996) analytically show that, in the presence of fierce competition, firms maximize their market value by aggregating segments when segments perform differently. Arya *et al.* (2010) show that, if firms that are competing in multiple segments have an *ex-ante* desire to withhold information, and the segments are sufficiently similar, a partial disclosure equilibrium (aggregation) can be sustained. Schneider and Scholze (2015) show that segment disclosure under the management approach, as prescribed by SFAS 131 and IFRS 8, can discourage firms from gathering precise internal information to prevent the disclosure of disaggregated segment information to competitors. Overall, the findings in these models suggest that partial disclosure (aggregation) can be an equilibrium outcome.

Prior empirical literature shows that firms are more likely to conceal (disclose) segments when existing competition is low (high), with competition typically defined as industry concentration, where high concentration is interpreted as indicative of low existing competition. Harris (1998), for example, provides empirical evidence that firms are more likely to conceal operations in less competitive industries that are earning higher rates of return. Botosan and Stanford (2005), using the retroactive segment disclosures that are required by SFAS 131, also find that firms are hiding profitable segments in less competitive industries under SFAS 14; yet, they do not find that firms are hiding poorly performing segments. For an international sample of firms disclosing under IAS 14, the predecessor of IFRS 8, Nichols and Street (2007) document a negative association between firms' decisions to separately disclose

[2] Another consideration is agency costs. Specifically, firms may attempt to withhold information about a segment's poor performance to avoid external scrutiny. For instance, Berger and Hann (2003) and Bens *et al.* (2011) show that proprietary cost motives exist along with agency cost motives to aggregate segment information. Bugeja *et al.* (2015) reach similar conclusions using a sample of Australian firms that report under AASB 114 (similar to IAS14R and subsequently IFRS 8). Therefore, we control for agency costs in our models.

a business segment and ROA in excess of the industry average. Their results support the idea that firms hide more profitable segments.

Most of the literature to date focuses on the empirical relation between competition and the number of segments that a firm discloses, which does not capture firms' reporting decisions on the performance of its segments, particularly when there is no change in the number of reported segments. To overcome this limitation, Ettredge *et al.* (2006) employ the range of reported segment earnings, which measures cross-segment earnings variability, to show that firms conceal differences in segment profitability when industry concentration is high (i.e., existing competition is low). Their findings imply that firms tend to disclose more disaggregated segment information when existing competition is high. Wang *et al.* (2011) report similar evidence with respect to cross-segment differences in earnings growth rates. In line with the argument of competitive harm, Ettredge *et al.* (2002) show that firms that were expected to suffer the most competitive harm from the adoption of SFAS 131 experienced negative returns on the disclosure dates of new information about the content of SFAS 131 before its introduction.

Overall, the empirical evidence in the literature suggests that firms have proprietary cost incentives to conceal differences in segment profitability, and these incentives are stronger when existing competition is low.

In contrast to existing competitors, potential competitors face entry costs that are sunk costs to existing competitors. Therefore, competitors' decisions to enter the product market depend on the magnitude of the entry costs relative to the expected payoffs, whereas existing competitors' decisions to stay in a product market are only based upon the expected payoffs. Regarding potential competition, Wang *et al.* (2011) show that the revelation of cross-segment differences in earnings growth is positively associated with capital intensity—a proxy that is typically used for entry barriers. Their evidence indicates that firms are more likely to reveal

cross-segment differences in segment performance when entry costs are high. However, Wang *et al.* (2011) do not focus on the effects of different types of product market competition on firms' segment disclosure decisions.

Hypotheses development

Product market competition is a multidimensional construct (Karuna, 2007), with an important conceptual distinction between existing and potential competition. In this paper, we define them as follows: existing competition is a firm's competitors that already operate in the same industry and may offer similar types of goods or services, and potential competition is the threat of new firms entering an incumbent firm's product market.

Prior literature on existing competition finds that firms are more likely to conceal information about their operations in less competitive industries. A typical explanation for this is that less competitive industries are more likely to allow for abnormal profits (e.g., Bain, 1951) and thus are more likely to be protected (e.g., Harris, 1998; Botosan and Stanford, 2005). Diversified firms can protect abnormal segment profits from being disclosed to competitors by aggregating segments with different economic characteristics or by shifting revenues and costs among segments (e.g., Hayes and Lundholm, 1996; Ettredge *et al.*, 2006; Lail *et al.*, 2014). However, as existing competition increases and more firms compete in the same market, the opportunities for abnormal profits decrease (e.g., Bain, 1951). Consequently, the competitive harm of segment disclosures in more competitive industries is expected to be lower (i.e., high existing competition reduces a firm's incentives to conceal the profitability of its separate operations). Given the evidence that more disaggregated segment disclosures provide capital-market benefits, such as lower expected cost of capital (e.g., Blanco *et al.*, 2015; Franco *et al.*, 2016), we expect the cross-segment variability in profitability to be higher for firms that are facing high existing competition. Therefore, we formulate the following testable hypothesis:

H1. The cross-segment variability in profitability is positively associated with the level of *existing* competition.

In contrast to existing competitors, potential competitors face entry costs, which are sunk costs to existing competitors, and they may also be less informed about the attractiveness of a particular product market. Therefore, competitors' decisions to enter the product market depend on the magnitude of the entry costs relative to the expected payoffs. Consequently, incumbent firms have incentives to conceal their segments' profitability when entry costs are low.[3] Following this argumentation, and given that more disclosure provides capital-market benefits, we expect that firms that face high potential competition are less likely to provide more disaggregated segment disclosures. Thus, we formulate the following testable hypothesis:

H2. The cross-segment variability in profitability is negatively associated with the level of *potential* competition.

Data and methodology

Data and sample selection

We obtain financial statement information at the firm level from the Compustat Fundamentals Annual database and at the segment level from the Compustat Historical Segments database. As sufficient segment data is available starting from 1977, we consider a 42-year period (1977–2018), for our analysis.[4] To construct our sample, we eliminate all firms that are incorporated outside the United States and do not report data in USD in the Compustat Fundamentals Annual database. In addition, we eliminate all firm-year observations with

[3] Hayes and Lundholm (1996) show that, if entry costs are sufficiently small, a competitor would enter all of an incumbent firm's product markets.

[4] SEC Regulation S-K and SFAS 14 required publicly-traded firms to report information on their business segments for fiscal years ending after December 15, 1977. Therefore, our sample period begins with all December year-end firms in 1977.

missing or negative firm-level sales. Our main analyses are based on all firms with multiple line-of-business segments (Compustat *STYPE* is "BUSSEG" or "OPSEG") with sufficient data to compute the cross-segment variability in profitability, our competition measures, and the control variables. The final sample consists of 32,627 firm-year observations from 5,964 unique firms with multiple line-of-business segments. Table 1 gives a detailed description of the sample selection process.

===== Insert Table 1 about here =====

Measuring product market competition

Several different proxies have been suggested in the literature for capturing various aspects of competition (e.g., Karuna, 2007; Li, 2010; Li, 2013). However, any one measure might not completely describe the nature of competition in the industry (Karuna, 2007). Furthermore, taken individually, several of these measures can be interpreted ambiguously. For example, a high cost margin may be indicative of low existing competition (allowing for higher prices), but it can also indicate an attractive market and therefore high potential competition. Similarly, Ali *et al.* (2014) argue that industry concentration can be interpreted as either low or high industry competition. To circumvent these problems, we follow Li's (2010) approach and calculate nine different proxies for competition using firm- and segment-level data. Subsequently, we categorize these competition variables into two groups based on the aspect of competition with which they are most likely associated. Specifically, we measure competition from potential entrants at the industry level using PP&E, R&D, capital expenditures, and product market size. Further, we measure competition from existing competitors at the industry level using the Herfindahl-Hirschman index, the four-firm

concentration ratio, the total number of firms operating in an industry, and product market size. To capture all aspects of competition, we also consider industry profitability, which we measure using the industry ROA and the price-cost margin. All variables are defined in Appendix A. Similar to Li (2010), we conduct a principal component analysis, which allows us to reduce the number of variables for our regression analysis while ensuring that we "obtain maximum variance from [the] original variables" (Li, 2010, p. 696).

We perform the principal component analysis with all nine competition variables, which are measured at the industry-year level using single-segment firms from the Compustat Fundamentals Annual database and line-of-business segments from the Compustat Historical Segments database. An industry is defined by its four-digit SIC code. We summarize this sample selection process in Appendix B, Table B1 and present details on the principal component analysis in Appendix B, Table B2.[5] From the principal component analysis of the nine variables, we focus on the first three components with eigenvalues ≥ 1 (Kaiser, 1960), which are used as our industry-year-specific measures of competition. Specifically, the negative of the first principal component (PC1), which is denoted by *ExistingComp_Ind*, measures competition from existing competitors; the negative of the second principal component (PC2), which is denoted by *PotentialComp_Ind*, measures the threat of potential entrants; and the third principal component (PC3), which is denoted by *IndustProf_Ind*, measures industry profitability.[6] We present the descriptive statistics for all competition measures that are used in the principal component analysis and the three identified components

[5] The loadings of the variables indicate that the first principal component reflects competition from existing competitors, the second component reflects competition from potential entrants, and the third component reflects industry profitability; accordingly, Li (2010) suggests using the first three principal components as measures of the different aspects of competition. Specifically, the first principal component is loaded by IND-MKTS (product market size), IND-CON4 (the four-firm concentration ratio), IND-HHI (the Herfindahl-Hirschman index), and IND-NUM (the number of firms in an industry); the second principal component is loaded by IND-PPE (PPE intensity), IND-R&D (R&D intensity), IND-CPX (capital intensity), and IND-MKTS; and the third principal component is loaded by IND-MGN (price-cost margin) and IND-ROA (return on assets).

[6] Thus, higher values reflect more competition from existing competitors, potential entrants, and industry profitability, respectively.

for our sample period (1977–2018) in Appendix B, Table B3.[7] We note that the descriptive statistics for our measures of competition are generally consistent with those that are presented in Li (2010). However, slight differences arise due to additional restrictions on segment data (see Appendix B, Table B1) and an extended time period.[8]

Finally, we measure an individual firm's exposure to existing and potential competition as the weighted average of the respective type of competition in its segments. Specifically, in our main analysis, we use firm-year-specific measures of competition, which are denoted by *ExistingComp*, *PotentialComp*, and *IndustProf* computed as the weighted average of our industry-year-specific competition measures *ExistingComp_Ind*, *PotentialComp_Ind*, and *IndustProf_Ind*, with the contribution of segment-level sales to firm-level sales as a weight. This is important because our analysis is restricted to firms that report multiple line-of-business segments, and these firms are likely to operate in different product markets with differing competitive environments. Therefore, their individual firm-level exposure to competition is likely to depend upon the composition of their business and the relative importance of their respective segments. Notably, a limitation of using aggregate measures of competition at the firm level is that, if competition in smaller segments drives the firm-level segment disclosure decisions, we would underestimate a firm's overall competitive pressures. However, as this limitation would add noise to our measures and reduce the power of our tests, it would work against finding a significant association between our variables of interest.[9] Moreover, to assess the potential influence of small segments on our results, in our additional analyses, we repeat our analysis after dropping the smallest segment of every firm in our sample.

[7] An untabulated comparison of the descriptive statistics for our competition measures using the same time period as in Li (2010) without our sample modifications shows similar results.
[8] Li's (2010) sample covers the period 1977–2007.
[9] We thank an anonymous reviewer for pointing this out.

Measuring the cross-segment variability in profitability

Segment reporting provides additional information about firm performance over and above what can be seen from firm-level reporting if segments exhibit heterogeneity in profitability (Chen and Zhang, 2003). If all segments show identical profitability, then segment reporting contains no new information. When firms have incentives to conceal "true" segment profitability, they can aggregate operating segments with different profitability (e.g., Berger and Hann, 2003) or exploit their discretion in allocating sales, costs, and corporate overheads (e.g., Chen and Zhang, 2003; Hann and Lu, 2009; Lail *et al.*, 2014; Wang and Ettredge, 2015). Such behavior will result in a deviation from the "true" cross-segment variability in segment profitability, which we use as our measure to capture the extent to which multi-segment firms conceal (or reveal) different sources of operating performance.

Similar to Ettredge *et al.* (2006), we measure cross-segment variability in profitability by a firm's range of profitability across all its reported segments in a given year. Segment profitability is measured by return on sales (ROS) calculated as reported segment operating profit divided by segment sales.[10] Our main measure, *RoSRange*, is defined as the difference between the highest and the lowest segment ROS. Because operating profit margins vary across industries, there are cross-sectional differences in the inherent cross-segment variability in ROS, depending on the firms' business composition. Therefore, we include a measure of inherent cross-segment variability in ROS, *InhRoSRange*, in our regression model. Following Ettredge *et al.* (2006), we compute this measure using the average industry-year ROS of single-segment firms in the corresponding four-digit SIC code segments.

[10] Ettredge *et al.* (2006) and Wang *et al.* (2011) also employ ROS as a measure of segment profitability, whereas André *et al.* (2016) and Troberg *et al.* (2010) use ROA. We obtain similar results when we use ROA (see Table 6).

To assess the robustness of our results, we measure the cross-segment variability in profitability using a number of alternative definitions. We discuss the construction of these variables and the results in our results section.

Competition and cross-segment variability in profitability

To test our hypotheses, we employ an ordinary least squares regression, where the dependent variable is the cross-segment variability in profitability. The independent variables capture the different types of competition. Furthermore, we include a number of control variables that potentially affect the cross-segment variability in profitability which we draw from prior literature. Thus, we employ the following regression model:

$$RoSRange_{i,t} = \beta_0 + \beta_1 ExistingComp_{i,t} + \beta_2 PotentialComp_{i,t} + \sum \beta_k \, Controls + \varepsilon_{i,t} \qquad (1)$$

where *RoSRange* is our firm-level measure of cross-segment variability in profitability, and *ExistingComp* and *PotentialComp* are our firm-level measures of existing competition and potential competition, respectively.

Hypothesis H1 predicts that existing competition is positively associated with the cross-segment variability in profitability, and H2 predicts that potential competition is negatively associated with the cross-segment variability in profitability. Hence, we expect coefficient β_1 to be positive and coefficient β_2 to be negative.

To capture all aspects of competition, we follow Li (2010) and include *IndustProf* as a control variable, which measures industry profitability. Furthermore, we control for other variables that prior literature finds relevant in the context of our study. Following Ettredge *et al.* (2006), we include *InhRoSRange*, which measures the inherent cross-segment variability in profitability and is calculated using the range of the means of ROS for single-segment firms in all four-digit SIC code industries that a firm reports as segments, which are weighted using the relative size (identified by sales) of the segments. *Diverse* is the number of two-digit SIC

industries in which the firm operates, capturing the diversity of a firm's operations, and can be seen as another proxy for inherent variability (Ettredge *et al.*, 2006).[11] *SFAS131* controls for the effect of SFAS131 on segment information revelation; it is a dummy variable that equals one for fiscal years beginning after December 15, 1997. *Size* is the natural logarithm of total assets; *NSegm* is the number of reported segments, and *SegmAgg* indicates the level of segment aggregation, which is obtained by the number of four-digit SIC codes that are assigned to the firm, divided by the number of reported segments. Following Wang *et al.* (2011), we include proxies for agency cost incentives to conceal segment information. Specifically, we include free cash flows (*FreeCF*) and abnormal accruals (*Accruals*) in our regression model. Firms with higher free cash flows (*FreeCF*) have more opportunities to waste money on organizational inefficiencies (Jensen, 1986), whereas abnormal accruals may indicate poor monitoring and thus more severe agency problems. Following André *et al.* (2016), we include dummy variables for firms that are involved in mergers and acquisitions (*M&A*), report a loss (*Loss*), and are audited by a big 4 auditor (*Big4*), as well as the book-to-market ratio (*BtM*) as an inverse proxy of growth opportunities. In addition, we include the amount of equity and debt that are issued during the year, scaled by the total assets (*ExtFin*) at the beginning of the year. Finally, we include year-fixed effects to account for variations in the cross-segment variability in profitability over time.

Results

Descriptive statistics and cross-correlations

The sample with sufficient data for our main analyses comprises 32,627 firm-year observations from 1977 to 2018. Descriptive statistics are reported in Table 2, and the

[11] Given the mixed findings on its association with *RosRange*, Ettredge *et al.* (2006, p. 109) note that *Diverse* is a "less useful proxy for inherent variance." Nevertheless, we include *Diverse* to ensure consistency with prior literature. Untabulated analyses show that our results remain unchanged when we exclude *Diverse*.

correlation matrix is in Table 3. The mean and median of *RoSRange* are 0.936 and 0.157, respectively, which indicates that *RoSRange* is right skewed. Therefore, we also examine the results' sensitivity using the natural logarithm of *RoSRange* as the dependent variable.[12] The mean (median) *ExistingComp* is 2.621 (2.401), and the mean (median) *PotentialComp* is -1.165 (-0.139). The correlation table in Table 3 shows that *RoSRange* is positively correlated with *ExistingComp* (Pearson 0.057, Spearman 0.177) and negatively correlated with *PotentialComp* (Pearson -0.088, Spearman -0.188). All sets of correlations are significantly different from zero at the 1% level.[13]

===== Insert Table 2 about here =====

===== Insert Table 3 about here =====

Multiple regression analysis

This section reports the findings of the multiple regression analyses for our hypotheses concerning the effect of different types of product market competition on the cross-segment variability in profitability.

===== Insert Table 4 about here =====

Our main results (Table 4, column 1) show that the coefficient of *ExistingComp* is positive and highly significant (0.075, t-value 3.913), whereas the coefficient of *PotentialComp* is negative and highly significant (-0.081, t-value -3.464). Table 4, column 2 shows that the

[12] Ettredge *et al.* (2006), Wang *et al.* (2011), and André *et al.* (2016) also document the skewness in *RoSRange*.
[13] The individual correlations must be interpreted with caution because they can be confounded by time trends and other economic variables. For example, the significantly negative Pearson correlation between *Diverse* and *InhRoSRange*—two variables that can both be seen as proxies for inherent variability (Ettredge *et al.*, 2006)—becomes insignificant after accounting for year-fixed effects. Reflecting on this issue, we have also performed yearly regressions and our conclusions remain unchanged.

results, using the logarithmically transformed dependent variable *RoSRange*, are consistent. Again, the coefficient of *ExistingComp* has a positive and significant coefficient (0.125, t-value 13.098), whereas the coefficient *PotentialComp* is negative and highly significant (-0.052, t-value -6.233). These findings indicate that cross-segment variability in profitability is positively associated with existing competition and negatively associated with potential competition, which are consistent with our H1 and H2, respectively. In other words, high existing competition is associated with increased disclosure of differences in the profitability of segments, whereas high potential competition is associated with decreased disclosure of such differences. Overall, our results indicate that proprietary cost motives have a strong and significant association with firms' disclosures of the profitability of their segments. Most importantly, this association is fundamentally different for potential and existing competition.

Interestingly, our results contrast with some prior studies that examine the effect of competition on *voluntary* management disclosures (e.g., Li, 2010; Huang *et al.*, 2016). The difference regarding the effect of potential competition on segment- and firm-level disclosures may be explained by the mandatory nature of segment reporting or the higher value of segment-level information for competitors. Specifically, segment disclosures are mandatory and can reveal the profitability of specific product markets, whereas management forecasts are voluntary and only provide information about the aggregated operations of a firm. This is important because the disclosure of multiple activities, as is the case for segment disclosures, causes competitors to shift their attention to the firm's most profitable activity.

For our control variables, Table 4 shows that the coefficient of *IndustProf* is negative (positive) in our main regression model (log model) but insignificant. Our measure that captures the inherent cross-segment variability in profitability (*InhRoSRange*), which reflects the variability that is inherent to the business and beyond the control of the firm, is positively associated with firms' cross-segment variability in profitability (Ettredge *et al.*, 2006). The

number of unique segments (*Diverse*) captures the diversity of industries in which firms operate and can also be seen as a proxy for inherent variability (Ettredge *et al.*, 2006); we consistently observe a significantly positive coefficient. The dummy variable *SFAS131* has a positive and significant coefficient; consistent with Ettredge *et al.* (2006), we interpret the result as SFAS 131 providing generally more diverse segment information. The coefficient of *Size* (measured as the natural logarithm of total assets) is negative and significant. Prior literature explains this result by the greater ability of larger firms to conceal differences in profitability across segments (see Ettredge *et al.*, 2006; managers' responses to the Exposure Draft preceding SFAS 131 in Financial Accounting Standards Board, 1996). The number of segments (*NSegm*) is positively and significantly associated with cross-segment variability in profitability. Harris (1998) argues that firms choose to disclose fewer segments to reduce proprietary costs; hence, the choice of the number of segments to report may be positively associated with the choice to report differences in the profitability across segments. The coefficient on segment aggregation (*SegmAgg*) is insignificant in the standard regression model and significantly positive in the log specification. In line with prior literature (e.g., Wang *et al.*, 2011; André *et al.*, 2016), we find that agency costs are negatively related to the cross-segment variability in profitability, indicating the existence of agency cost motives to conceal segment profitability (see also Berger and Hann, 2007). More specifically, the coefficients on free cash flow (*FreeCF*) and abnormal accruals (*Accruals*), which are used as proxies for agency costs, are both negative and statistically significant. Furthermore, using the book-to-market ratio (*BtM*) as an inverse proxy for growth opportunities, we find growth firms have more cross-segment variability in profitability.[14] This finding contrasts the argument that growth firms have more incentives to hide profitable segments (e.g., Prencipe, 2004) and aligns more with literature that argues that

[14] When we use the market-to-book ratio (e.g., Gao and Sidhu, 2018; Kurt, 2018) instead of the book-to-market ratio, we obtain positive coefficients that are consistent with the results presented here.

disclosure, as a means to reduce information asymmetry, is more important for riskier high-growth firms (e.g., Core, 2001; Hope *et al.*, 2006). M&A firms have less cross-segment variability in profitability, whereas loss-making firms have more variation in segment profitability than profit-making firms. The *Big4* dummy variable has no significant association with *RoSRange*. Finally, we find that firms that have issued more debt and/or equity during the year appear to disclose larger differences in the profitability of their segments, as indicated by the positive and significant coefficient of *ExtFin*. This finding is in line with prior literature (e.g., Ettredge *et al.*, 2006; Wang *et al.*, 2011) and suggests that firms that have capital market incentives provide more transparent segment disclosures.

Additional tests

We conduct a series of additional analyses to test whether our findings are robust to alternative definitions of key variables. We present and discuss our findings in this section.

Alternative measures of cross-segment variability in profitability

In this section, we closely follow Ettredge *et al.* (2006) and examine four alternative measures of cross-segment variability in profitability. These modifications are guided by the possibility that firms' efforts to conceal segment differences have different motivations. For example, a firm may have stronger incentives to conceal a profitable segment when it contributes significantly more to a firm's overall profitability. More specifically, we firstly consider three alternative ways to estimate the variability in profitability across segments. (1) *RoSRangeLrgAvg* is defined, for each year, as the difference between the ROS of the largest segment (identified by sales) and the average segment ROS of the firm; notably, this variable can have negative values because the ROS of the largest segment may be less than the average segment's ROS. (2) *RoSRangeXsml* is the range of a firm's segment ROS after dropping the

smallest segment, as identified by sales. (3) *RoSRangeTr1* is the range of a firm's segment ROS, with truncation at one if the value is greater than one.

The extent to which financial statements reflect the variability of growth across different segments is an important issue in assessing cross-segment variability in profitability. Prior literature emphasizes the importance of information on firm-level earnings growth (e.g., Easton and Harris, 1991; Baber *et al.*, 1999; Easton *et al.*, 2009) and segment-level earnings growth (e.g., Chen and Zhang, 2003; Hirshleifer and Teoh, 2003; Hope and Thomas, 2008; Wang *et al.* 2011). Accordingly, the fourth alternative measure of cross-segment variability in profitability is variability in earnings growth, which we estimate across segments (*RoSGrRange*), following Wang *et al.* (2011). *RoSGrRange* is the range of earnings growth, which is calculated as earnings growth for the fastest growing segment minus earnings growth for the slowest growing segment; earnings growth is defined as change (from year *t-1* to year *t*) in a segment's operating profits, scaled by segment sales for the prior year.

===== Insert Table 5 about here =====

The results of our alternative measures (Table 5) show a consistent association between existing and potential competition and the variability in segment performance. These alternative analyses reinforce our findings that the propensity of firms to reveal differences in the profitability of their segments is positively associated with existing competition and negatively associated with potential competition.

Further analysis

Table 6 includes four additional analyses. (1) We firstly use only firm-year observations that apply the segment reporting standard of SFAS 131 (now ASC 280). With the introduction of SFAS 131 in 1997, segment reporting changed from an industry-based to a management-based

approach. While the new SFAS 131 was expected to reduce firms' ability to aggregate operating segments with different economic characteristics, flexibility under the management approach allows for a wide range of possibilities to conceal segments' profitability (Ettredge *et al.*, 2006). Prior literature demonstrates that the adoption of SFAS 131 resulted in more disaggregated segment information and in a greater cross-segment variability in profitability (e.g., Berger and Hann, 2003; Ettredge *et al.*, 2006; Hann and Lu, 2009). (2) In our next analysis, we examine whether the introduction of the management approach moderates firms' incentives (and possibilities) to conceal or reveal information on the cross-segment performance that arises from existing and potential competition. Therefore, we introduce two interaction terms between *SFAS131*, a dummy variable equal to 1 for periods after 1997, with existing and potential competition. In this case, the main effects of existing and potential competition capture the association of product competition with the cross-segment disclosure on segment performance prior to the adoption of SFAS 131. The interaction terms capture the incremental association after the adoption of SFAS 131. (3) We then define segment profitability using ROA instead of ROS. This is motivated by recent work in the segment literature (e.g., Troberg *et al.*, 2010; André *et al.*, 2016), which employs ROA instead of ROS as a measure of segment profitability. (4) Finally, we follow Ettredge *et al.* (2006) and Wang *et al.* (2011) and redefine external financing needs in a more forward-looking manner. This mitigates possible concerns that firms may time segment reporting incentives and reveal information in advance of a debt or equity issue. Importantly, the sample size for this analysis is lower because we require data for two years ahead.

===== Insert Table 6 about here =====

Per our analyses (Table 6), our basic results and conclusions remain the same: the coefficient of existing competition is positive, whereas the coefficient of potential competition

is negative. However, where we examine the effect of the SFAS 131's adoption, we find that the interaction term between *SFAS131* and *PotentialComp* is significantly negative (-0.069, t-value -2.166). The effect on *PotentialComp* itself is negative but insignificant. This suggests that firms' efforts to conceal information in the face of potential competition are mainly driven by the period after the adoption of SFAS 131.

Conclusions

In this paper, we address how competition from both existing and potential competitors affects firms' decisions regarding segment disclosures. Most importantly, we distinguish among different types of product market competition. This is important because the incentives to reveal or conceal information on segments' performance may differ between existing and potential competition. Using the variability of profitability among segments as our measure of the disclosure of cross-segment differences in performance, we find that existing competition is positively associated with cross-segment variability in profitability, whereas potential competition is negatively associated with cross-segment variability in profitability.

Our findings are in line with proprietary cost motives, suggesting that firms conceal operations in cases where competitive harm is more likely to be stronger and dominant. As existing competition increases and more firms compete in the same market, the opportunities for abnormal profits decrease, and proprietary costs that arise from disclosing segment information decrease. Conversely, as potential competition increases, it is more costly to disclose information on segments' performance because competitors are more likely to enter the product market. Our results remain robust to a number of sensitivity tests. Overall, our results are consistent with the predictions of Hayes and Lundholm (1996) and Arya *et al.* (2010), who analytically show that partial disclosure equilibria exist in the face of competition.

The disclosure of greater diversity in operating profitability across segments improves the transparency of segment disclosures. Transparent and high-quality segment reporting information is of paramount importance to investors and analysts to better understand the nature of past and current cash flows and risks in diversified firms and to predict future cash flows (AIMR, 1993). Thus, our findings inform capital market participants, such as investors and financial analysts, about the effect of different types of competition on the transparency of diversified firms' reported segment profitability.

Our results also inform accounting regulators and governing bodies in the financial reporting process, such as auditors and supervisory boards. For instance, recent post-implementation reviews of SFAS 131 and IFRS 8—the current standards regulating segment reporting in the US and under the IFRS—indicate that firms are still concerned about competitive harm that is related to segment reporting, while many investors complain that segments are uninformative because of improper aggregation (FAF, 2013; IASB, 2013). Therefore, proprietary cost motives may reduce the transparency of segment disclosures and thus could jeopardize the effectiveness of the standards. Our results are consistent with this premise and show that, although the adoption of SFAS 131 has increased transparency, it has been less effective in affecting firms' motives that arise from competition to disclose information about the performance of a firm's individual segments.

Future research can examine specific events that lead to an exogenous change in the competitive situation. For instance, deregulation of many industries may provide settings in which high entry barriers have disappeared, leading to a sudden increase in potential competition. The expiry of important patents and technological changes can provide similar settings for natural experiments.

References

American Institute of Certified Public Accountants (AICPA) (1994), *Improving Business Reporting—A Customer Focus: Meeting the Information Needs of Investors and Creditors, Comprehensive Report of the Special Committee on Financial Reporting*. AICPA: New York, NY.

Aitken, M. J., R. M. Czernkowski, and C. G. Hooper (1994), "The information content of segment disclosures: Australian evidence", *Abacus*, Vol. 30, No. 1, pp. 65–77.

Ali, A., S. Klasa, and E. Yeung (2014), "Industry concentration and corporate disclosure policy", *Journal of Accounting and Economics,* Vol. 58, Nos 2–3, pp. 240–264.

André, P., A. Filip, and R. Moldovan (2016), "Segment disclosure quantity and quality under IFRS 8: Determinants and the effect on financial analysts' earnings forecast errors", *The International Journal of Accounting,* Vol. 51, No. 4, pp. 443–461.

Arya, A., H. Frimor, and B. Mittendorf (2010), "Discretionary disclosure of proprietary information in a multisegment firm". *Management Science,* Vol. 56, No. 4, 645–658.

Association for Investment Management and Research (AIMR) (1993), *Financial Reporting in the 1990's and Beyond*. AIMR: Charlottesville, VA.

Baber, W. R., S.-H. Kang, and K. R. Kumar (1999), "The explanatory power of earnings levels vs. earnings changes in the context of executive compensation", *The Accounting Review,* Vol. 74, No. 4, pp. 459–472.

Bain, J. S. (1951), "Relation of profit rate to industry concentration: American manufacturing, 1936–1940". *The Quarterly Journal of Economics,* Vol. 65, No. 3, pp. 293–324.

Bens, D. A., P. G. Berger, and S. J. Monahan (2011), "Discretionary disclosure in financial reporting: An examination comparing internal firm data to externally reported segment data", *The Accounting Review,* Vol. 86, No. 2, pp. 417–449.

Berger, P. G. and R. Hann (2003), "The impact of SFAS No. 131 on information and monitoring", *Journal of Accounting Research,* Vol. 41, No. 2, pp. 163–223.

Berger, P. G. and R. N. Hann (2007), "Segment profitability and the proprietary and agency costs of disclosure", *The Accounting Review,* Vol. 82, No. 4, pp. 869–906.

Blanco, B., G. Lara, M. Juan, and J. A. Tribo (2015), "Segment disclosure and cost of capital", *Journal of Business Finance & Accounting,* Vol. 42, Nos 3–4, pp. 367–411.

Botosan, C. A. and M. Stanford (2005), "Managers' motives to withhold segment disclosures and the effect of SFAS No. 131 on analysts' information environment", *The Accounting Review,* Vol. 80, No. 3, pp. 751–772.

Bugeja, M., R. Czernkowski, and D. Moran. (2015), "The impact of the management approach on segment reporting", *Journal of Business Finance & Accounting,* Vol. 42, Nos 3–4 pp. 310–366.

Chen, P. F. and G. Zhang (2003), "Heterogeneous investment opportunities in multiple-segment firms and the incremental value relevance of segment accounting data", *The Accounting Review,* Vol. 78, No. 2, pp. 397–428.

Core, J. E. (2001), "A review of the empirical disclosure literature: Discussion", *Journal of Accounting and Economics*, Vol. 31, Nos 1–3, pp. 441–456.

Easton, P. D. and T. S. Harris (1991), "Earnings as an explanatory variable for returns", *Journal of Accounting Research*, Vol. 29, No. 1, pp. 19–36.

Easton, P. D., S. J. Monahan, and F. P. Vasvari (2009), "Initial evidence on the role of accounting earnings in the bond market", *Journal of Accounting Research,* Vol. 47, No. 3, pp. 721–766.

Ettredge, M. L., S. Y. Kwon, and D. B. Smith (2002), "Competitive harm and companies' positions on SFAS No. 131", *Journal of Accounting, Auditing, and Finance*, Vol. 17, No. 2, pp. 93–109.

Ettredge, M. L., S. Y. Kwon, D. B. Smith, and M. S. Stone (2006), "The effect of SFAS No. 131 on the cross-segment variability of profits reported by multiple segment firms", *Review of Accounting Studies,* Vol. 11, No. 1, pp. 91–117.

Ettredge, M. L., S. Y. Kwon, D. B. Smith, and P. A. Zarowin (2005), "The impact of SFAS No. 131 business segment data on the market's ability to anticipate future earnings", *The Accounting Review,* Vol. 80, No. 3, pp. 773–804.

Financial Accounting Foundation (FAF) (2013), *Post-Implementation Review: SFAS 131*. FAF: Norwalk, CT.

Financial Accounting Standards Board (1996), *Exposure draft: Proposed statement of financial accounting standards: Reporting disaggregated information about a business enterprise*. Financial Accounting Series. FASB: Norwalk, CT.

Franco, F., O. Urcan, and F. P. Vasvari (2016), "Corporate diversification and the cost of debt: The role of segment disclosures". *The Accounting Review,* Vol. 91, pp. 1139–1165.

Gao, R. and B. K. Sidhu (2018), "The impact of mandatory international financial reporting standards adoption on investment efficiency: Standards, enforcement, and reporting incentives", *Abacus*, Vol. 54, No. 3, pp. 277–318.

Hann, R. N. and Y. Y. Lu (2009), *Earnings management at the segment level*, Working Paper*,* University of Maryland.

Harris, M. S. (1998), "The association between competition and managers' business segment reporting decisions", *Journal of Accounting Research,* Vol. 36, No. 1, pp. 111–128.

Hayes, R. M. and R. Lundholm (1996), "Segment reporting to the capital market in the presence of a competitor", *Journal of Accounting Research*, Vol. 34, No. 2, pp. 261–279.

Healy, P. M. and K. G. Palepu (2001), Information asymmetry, corporate disclosure, and the capital markets: A review of the empirical disclosure literature", *Journal of Accounting and Economics,* Vol. 33, Nos 1–3, pp. 405–440.

Hirshleifer, D. and S. H. Teoh (2003), "Limited attention, information disclosure, and financial reporting", *Journal of Accounting and Economics,* Vol. 36, Nos 1–3, pp. 337–386.

Hope, O. K. and W. B. Thomas (2008), "Managerial empire building and firm disclosure", *Journal of Accounting Research,* Vol. 46, No. 3, pp. 591–626.

Hope, O. K., W. B. Thomas, and G. Winterbotham (2006), "The impact of nondisclosure of geographic segment earnings on earnings predictability", *Journal of Accounting, Auditing & Finance*, Vol. 21, No. 3, pp. 323–346.

Huang, Y., R. Jennings, and Y. Yu (2016), "Product market competition and managerial disclosure of earnings forecasts: Evidence from import tariff rate reductions", *The Accounting Review,* Vol. 92, No. 3, pp. 185–207.

International Accounting Standard Board (IASB) (2013), Post-Implementation Review: IFRS 8 Operating Segments, IASB: London, UK.

Jensen, M. C. (1986), Agency cost of free cash flow, corporate finance, and takeovers, *American Economic Review,* Vol. 76, No. 2, pp. 323–329.

Kaiser, H. F. (1960), "The application of electronic computers to factor analysis", *Educational and Psychological Measurement*, Vol. 20, No. 1, pp. 141–151.

Kajüter, P. and M. Nienhaus (2017), "The impact of IFRS 8 adoption on the usefulness of segment reports", *Abacus,* Vol. 53, No. 1, pp. 28–58.

Karuna, C. (2007), "Industry product market competition and managerial incentives", *Journal of Accounting and Economics,* Vol. 43, Nos 2–3, pp. 275–297.
Kothari, S. P., A. J. Leone and C. E. Wasley (2005), "Performance matched discretionary accrual measures", *Journal of Accounting and Economics,* Vol. 39, No. 1, pp. 163–197.
Kurt, A. C. (2018), "How do financial constraints relate to financial reporting quality? Evidence from seasoned equity offerings", *European Accounting Review*, Vol. 27, No. 3, pp. 527–557.
Lail, B., W. Thomas, and G. Winterbotham (2014), "Classification shifting using the corporate/other segment", *Accounting Horizons,* Vol. 28, No. 3, pp. 455–477.
Li, E. X. (2013), "Revealing future prospects without forecasts: The case of accelerating material contract filings", *The Accounting Review,* Vol. 88, No. 5, pp. 1769–1804.
Li, X. (2010), "The impacts of product market competition on the quantity and quality of voluntary disclosures", *Review of Accounting Studies,* Vol. 15, No. 3, pp. 663–711.
Nagarajan, N. J. and S. S. Sridhar (1996), "Corporate responses to segment disclosure requirements", *Journal of Accounting and Economics*, Vol. 21, No. 2, pp. 253–275.
Nichols, N. B. and D. L. Street (2007), "The relationship between competition and business segment reporting decisions under the management approach of IAS 14 Revised", *Journal of International Accounting, Auditing and Taxation,* Vol. 16, No. 1, pp. 51–68.
Prencipe, A. (2004), "Proprietary costs and determinants of voluntary segment disclosure: Evidence from Italian listed companies, *European Accounting Review,* Vol. 13, No. 2, pp. 319–340.
Schneider, G. T. and A. Scholze (2015), "Mandatory disclosure, generation of decision-relevant information, and market entry", *Contemporary Accounting Research*, Vol. 32, No. 4, pp. 1353–1372.
Sprouse, R. T. (1969), "Diversified views about diversified companies", *Journal of Accounting Research*, Vol. 7, No. 1, pp. 137–159.
Troberg, P., J. Kinnunen, and H. J. Seppänen (2010), "What drives cross-segment diversity in returns and risks? Evidence from Japanese and US firms", *The International Journal of Accounting,* Vol. 45, No. 1, pp. 44–76.
Verrecchia, R. E. (2001), "Essays on disclosure", *Journal of Accounting and Economics,* Vol. 32, Nos 1–3, pp. 97–180.
Wang, Q. and M. Ettredge (2015), "Discretionary allocation of corporate income to segments", *Research in Accounting Regulation,* Vol. 27, No. 1, pp. 1–13.
Wang, Q., M. Ettredge, Y. Huang, and L. Sun (2011), "Strategic revelation of differences in segment earnings growth", *Journal of Accounting and Public Policy,* Vol. 30, No. 4, pp. 383–392.

Appendix A: Variables definition

Competition measures

IND-PPE	Weighted average of property, plant, and equipment (PPE) of all firms in an industry-year. We use a firm's market share, calculated as the ratio of its sales to industry aggregate sales, as its weight. A multi-segment firm's segment PPE is allocated to its segments according to the segment-to-firm-level sales ratio.
IND-R&D	Weighted average of R&D of all firms in an industry. We use a firm's market share, calculated as the ratio of its sales to industry aggregate sales, as its weight. If a multi-segment firm's segment R&D is missing, it is replaced by the firm-level R&D multiplied with the segment-to-firm-level sales ratio. If a firm's segment R&D is still missing, it is replaced by zero.
IND-CPX	Weighted average of capital expenditures (CPX) of all firms in an industry. We use a firm's market share, calculated as the ratio of its sales to industry aggregate sales, as its weight. If a multi-segment firm's segment CPX is missing, it is replaced by the firm-level CPX multiplied with the segment-to-firm-level sales ratio.
IND-MKTS	Size of the product market, measured as the natural logarithm of industry aggregate sales.
IND-CON4	Four-firm concentration ratio, measured as the sum of market shares of the four largest firms in an industry.
IND-HHI	Herfindahl-Hirschman Index, calculated by summing the squares of the market shares of all firms in an industry.
IND-NUM	Total number of firms in an industry.
IND-MGN	Price-cost margin, measured as industry aggregate sales to industry aggregate operating costs ratio. If a multi-segment firm's segment operating costs are missing, they are replaced by the segment sales divided by the firm's price-cost margin.
IND-ROA	Return on assets (ROA), measured as industry aggregate EBITDA divided by industry aggregate total assets. If a multisegment firm's segment EBITDA is missing, it is replaced by segment assets multiplied by the firm's return on assets. If segment total assets are missing, they are replaced by segment EBITDA divided by the firm's ROA. If both segment EBITDA and segment total assets are missing, they are replaced by firm-level ROA multiplied by the segment-to-firm-level sales ratio.

Extracted components from a principal component analysis – industry level

ExistingComp_Ind	Existing competition is computed as the negative of Comp1 retained from the PCA. It measures competition from existing competitors and is loaded by *IND-HHI*, *IND-CON4*, *IND-NUM,* and *IND-MKTS*.
PotentialComp_Ind	Potential competition is computed as the negative of Comp2 retained from the PCA. It measures the threat of potential entrants and is loaded by *IND-PPE*, *IND-R&D*, *IND-CPX* and *IND-MKTS*.
IndustProf_Ind	Industry profitability resembles Comp3 retained from the PCA. It is loaded by *IND-MGN* and *IND-ROA*.

Extracted components from a principal component analysis – firm level

ExistingComp	The measure for existing competition is computed at the firm-level as the weighted average of the industry-level competition measure *ExistingComp_Ind* with the contribution of segment sales to firm sales as a weight.
PotentialComp	The measure for potential competition is computed at the firm-level as the weighted average of the industry-level competition measure *PotentialComp_Ind* with the contribution of segment sales to firm sales as a weight.
IndustProf	Industry profitability is computed at the firm-level as the weighted average of the industry-level profitability measure *IndustProf_Ind* with the contribution of segment sales to firm sales as a weight.

Cross-segment variability in profitability

RoSRange	Difference between the highest and the lowest segment return on sales (ROS). ROS is calculated as reported segment operating income divided by segment sales.
LnRoSRange	Natural logarithm of RoSRange.
RoSRangeLrgAvg	Difference, for each year, between the ROS of the largest segment (identified by sales) and the average of segment ROS.
RoSRangeXsml	Range in a firm's segment ROS for each year after dropping the smallest segment (identified by sales).
RoSRangeTr1	Range is a firm's segment ROS for each year with truncation at 1 if the value is greater than 1.
RoSGrRange	Range of earnings growth, calculated as earnings growth for the fastest growing segment minus earnings growth for the slowest growing segment; earnings growth is defined as change (from year *t-1* to year *t*) in a segment's operating profits, scaled by net segment sales for the prior year.
RoARange	Difference between the highest and the lowest segment return on assets (ROA). ROA is calculated as reported segment operating income divided by segment assets.

Control variables

InhRoSRange	Range of mean ROS for single-segment firms in all four-digit SIC code industries reported as segments, weighted by the relative size (identified by sales) of the segments
Diverse	Number of two-digit SIC industries in which the firm operates
SFAS131	Dummy variable for fiscal years beginning after December 15, 1997
Size	Natural logarithm of total assets (*AT*)
NSegm	Number of reported segments
SegmAgg	Number of four-digit SIC codes assigned to a firm, divided by the number of reported segments
FreeCF	Free cash flow defined as cash flow from operations (*OANCF*) less dividends (*DV*) less capital expenditures (*CAPX*) scaled by lagged total assets (*AT*). For periods prior to 1988, and when *OANCF* is missing, cash flow is calculated using the balance sheet approach, i.e., $IB - \Delta ACT - \Delta LCT - \Delta CHE + \Delta DLC + \Delta TXP - DP$
Accruals	Performance-adjusted discretionary accruals computed based on Kothari *et al.* (2005)
M&A	Dummy variable for the presence of mergers and acquisition during the year (*ACQMETH* is not missing or *ACQ* is non-zero)
Loss	Dummy variable if a company reports a loss ($IB < 0$)
Big4	Dummy variable if a company is audited by a big 4 audit firm (*AU* is 4, 5, 6, or 7)
BtM	Book to market ratio ($SEQ/PRCC\_F \times CSHO$)
ExtFin	External financing. This equals the sum of net equity and debt financing scaled by lagged total assets (*TA*). Net equity financing is $SSTK - PRSTKC - DV$ and net debt financing is $DLTIS - DLTR + DLCCH$. *DLCCH* is replaced with 0 if missing.

Notes: All continuous variables are winsorized at the 1st and 99th percentile.

Appendix B: Calculation of competition measures

Table B1: Sample selection procedure for product market competition measures

	#firm-years
All firms in the Compustat Fundamentals Annual database from 12/1977 to 05/2018	421,203
Less observations that are incorporated outside the United States (*FIC* is not "USA") or do not have data available in US dollars (*CURCD* is not "USD")	343,065
	#segment-years
Sample of individual segments and single-segment firms after matching the Compustat Fundamentals Annual database with the Compustat Historical Segment database	1,062,983
Less segments other than line-of-business segments (*STYPE* is "BUSSEG" or "OPSEG")	-506,303
Less non-operating segments (e.g., corporate overheads, intersegment eliminations), which are typically not part of a firm's core operations[15], and discontinued/divested segments[16]	-35,565
Less observations with missing data on SIC industry codes and/or missing or non-positive segment- or firm-level sales	-77,031
Less observations with missing data for one of our nine competition variables. If a firm has multiple segments operating in the same four-digit SIC industry, these segments are merged into a single segment.	-74,756
Final sample of individual segments and single-segment firms used for the computation of our nine product market competition measures	369,328
Final sample of product market competition measures by industry-year	34,682

[15] Following Hann and Lu (2009), we classify a business segment as non-operating if the Compustat segment ID is 99 or the textual segment description refers to a non-operating segment. Specifically, we screen out the textual segment descriptions for the words: "corporate", "reconciliation", "eliminations", "reclassification", "headquarter", "intercompany", "intersegment", "unallocated", "overhead", "parent", and different misspellings of these expressions.

[16] Identified by the words "discontinued" or "divested" in the textual segment description.

Table B2: Results of the principal component analysis

Panel A: Eigenvalues of the principal component analysis				
Principal component	Eigenvalue	Difference in Eigenvalue	Variance explained	Cumulative variance
Comp1	3.364	1.648	0.374	0.374
Comp2	1.716	0.514	0.191	0.564
Comp3	1.202	0.273	0.134	0.698
Comp4	0.929	0.249	0.103	0.801
Comp5	0.680	0.223	0.076	0.877
Comp6	0.457	0.148	0.051	0.927
Comp7	0.309	0.117	0.034	0.962
Comp8	0.192	0.039	0.021	0.983
Comp9	0.153	.	0.017	1.000

Panel B: Scoring coefficients for orthogonal varimax rotation			
Raw variable	Comp1	Comp2	Comp3
IND-PPE	0.035	0.618	-0.078
IND-R&D	-0.015	0.407	0.146
IND-CPX	0.024	0.615	-0.030
IND-MKTS	-0.342	0.242	0.135
IND-CON4	0.580	0.070	0.048
IND-HHI	0.539	0.075	0.006
IND-NUM	-0.503	0.059	-0.009
IND-MGN	0.030	0.008	0.655
IND-ROA	-0.004	-0.046	0.723

Notes: This table presents the principal component analysis of our nine competition measures based on data obtained from the Compustat Historical Segments database and the Compustat Fundamentals Annual database. The sample consists of 34,682 industry-year observations from 1977 to 2018. Four-digit SIC codes are used to identify the industry. Comp1 to Comp3 are three principal components with eigenvalues ≥ 1, extracted from the analysis using the orthogonal rotation method. IND-PPE, IND-R&D, IND-CPX, IND-MKTS, IND-CON4, IND-HHI, IND-NUM, IND-MGN, and IND-ROA are the original competition variables measured at the industry-year level.

Table B3: Descriptive statistics for competition variables

Variable	N	Mean	Min	Q1	Median	Q3	Max	SD
IND-PPE	34,682	1039.782	0.092	24.691	117.692	541.225	23692.810	3216.838
IND-R&D	34,682	27.256	0.000	0.000	0.129	6.474	762.954	101.032
IND-CPX	34,682	112.874	0.000	3.564	16.922	69.949	2430.179	325.721
IND-MKTS	34,682	6.809	-0.402	5.349	7.024	8.466	12.126	2.489
IND-CON4	34,682	0.912	0.356	0.887	1.000	1.000	1.000	0.154
IND-HHI	34,682	0.556	0.054	0.277	0.502	0.932	1.000	0.320
IND-NUM	34,682	10.320	1.000	2.000	4.000	10.000	118.000	17.992
IND-MGN	34,682	1.537	0.980	1.267	1.411	1.630	4.258	0.484
IND-ROA	34,682	0.125	-0.307	0.087	0.128	0.171	0.377	0.092
ExistingComp_Ind	34,682	0.000	-1.409	-0.732	-0.226	0.446	3.438	1.000
PotentialComp_Ind	34,682	0.000	-5.767	0.043	0.295	0.438	0.722	1.000
IndustProf_Ind	34,682	0.000	-3.278	-0.514	-0.072	0.438	3.422	1.000

Notes: The sample for the computation of the competition variables consist of 34,682 industry-year observations from 1977 to 2018. All variables are winsorized at the 1% percentile.

Table 1: Sample selection process

	#firm-years
All firm-year observations of firms incorporated in the United States in the Compustat Fundamentals Annual database from 1977 to 2018	**343,065**
Less:	
Observations with missing or non-positive firm-level sales	-65,437
Single-segment firm-year observations	-191,876
Observations with missing data for RoSRange	-27,763
Observations with missing data for the control variables	-25,362
Final sample	**32,627**

Table 2: Descriptive statistics for the main variables

Variable	N	Mean	Min	Q1	Median	Q3	Max	SD
RoSRange	32,627	0.936	0.003	0.068	0.157	0.378	32.154	3.801
ExistingComp	32,627	2.621	-1.550	1.227	2.401	3.846	6.688	1.819
PotentialComp	32,627	-1.165	-12.371	-1.515	-0.139	0.343	0.975	2.484
IndustProf	32,627	0.258	-4.432	-0.321	0.048	0.556	5.074	0.977
InhRoSRange	32,627	2.418	0.002	0.050	0.168	1.122	51.161	7.203
Diverse	32,627	1.891	1.000	1.000	2.000	2.000	9.000	0.860
SFAS131	32,627	0.464	0.000	0.000	0.000	1.000	1.000	0.499
Size	32,627	5.529	-3.772	3.799	5.530	7.203	13.004	2.301
NSegm	32,627	2.755	2.000	2.000	2.000	3.000	13.000	1.022
SegmAgg	32,627	0.835	0.083	0.667	1.000	1.000	1.000	0.245
FreeCF	32,627	0.180	-0.761	-0.020	0.048	0.332	1.411	0.379
Accruals	32,627	0.018	-0.755	-0.058	0.014	0.098	0.629	0.203
M&A	32,627	0.395	0.000	0.000	0.000	1.000	1.000	0.489
Loss	32,627	0.268	0.000	0.000	0.000	1.000	1.000	0.443
Big4	32,627	0.591	0.000	0.000	1.000	1.000	1.000	0.492
BtM	32,627	0.707	-3.630	0.331	0.588	0.976	3.997	0.850
ExtFin	32,627	0.051	-0.293	-0.047	-0.007	0.053	1.583	0.250

Notes: The sample for the main analysis consists of 32,627 firm-year observations from 1977 to 2018. All variables are defined in Appendix A. Continuous variables are winsorized at the 1% percentile.

Table 3: Correlation matrix of main variables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)
(1) RoSRange	1.000	0.177*	-0.188*	0.034*	0.255*	0.111*	0.129*	-0.068*	0.284*	-0.097*	-0.170*	-0.036*	-0.043*	0.250*	-0.046*	-0.116*	0.076*
(2) Existing Comp	0.057*	1.000	-0.412*	0.002	0.267*	-0.109*	-0.018*	0.067*	-0.009	-0.059*	-0.055*	0.032*	-0.065*	0.014	-0.041*	-0.014	0.055*
(3) PotentialComp	-0.088*	-0.345*	1.000	-0.239*	-0.335*	0.197*	-0.475*	-0.400*	-0.074*	0.266*	0.344*	0.083*	-0.079*	-0.050*	-0.137*	0.175*	0.005
(4) IndustProf	0.035*	0.131*	-0.378*	1.000	0.233*	-0.146*	0.166*	-0.025*	0.003	-0.160*	0.036*	-0.055*	0.103*	-0.022*	0.061*	-0.223*	-0.059*
(5) InhRos Range	0.085*	0.140*	-0.213*	0.255*	1.000	-0.006	0.257*	-0.007	0.031*	-0.015*	-0.169*	-0.048*	0.059*	0.122*	0.020*	-0.191*	0.043*
(6) Diverse	0.030*	-0.117*	0.171*	-0.182*	-0.074*	1.000	-0.318*	-0.054*	0.361*	0.528*	0.113*	0.064*	-0.023*	-0.053*	-0.095*	0.108*	0.017*
(7) SFAS131	0.102*	-0.011	-0.384*	0.219*	0.218*	-0.299*	1.000	0.284*	0.055*	-0.490*	-0.360*	-0.136*	0.182*	0.107*	0.261*	-0.211*	-0.038*
(8) Size	-0.077*	0.079*	-0.302*	0.016*	0.002	-0.006	0.280*	1.000	0.314*	-0.227*	-0.101*	-0.067*	0.265*	-0.265*	0.377*	-0.111*	-0.145*
(9) NSegm	0.065*	-0.019*	-0.058*	0.000	-0.020*	0.453*	0.057*	0.321*	1.000	-0.264*	0.030*	0.018*	0.133*	-0.106*	0.111*	0.002	-0.056*
(10) SegmAgg	-0.038*	-0.066*	0.270*	-0.226*	-0.070*	0.481*	-0.490*	-0.216*	-0.252*	1.000	0.152*	0.086*	-0.135*	-0.035*	-0.190*	0.144*	0.038*
(11) FreeCF	-0.126*	-0.078*	0.258*	-0.075*	-0.139*	0.162*	-0.444*	-0.189*	0.011	0.212*	1.000	-0.134*	-0.062*	-0.289*	-0.080*	0.149*	-0.242*
(12) Accruals	-0.044*	0.024*	0.047*	-0.038*	-0.025*	0.056*	-0.088*	-0.009	0.032*	0.050*	-0.218*	1.000	-0.073*	-0.082*	-0.068*	0.163*	0.080*
(13) M&A	-0.021*	-0.069*	-0.056*	0.094*	0.050*	-0.004	0.182*	0.264*	0.135*	-0.131*	-0.119*	-0.044*	1.000	-0.084*	0.156*	-0.142*	0.133*
(14) Loss	0.160*	0.009	-0.053*	-0.001	0.089*	-0.061*	0.107*	-0.273*	-0.099*	-0.036*	-0.198*	-0.087*	-0.084*	1.000	-0.091*	-0.021*	0.155*
(15) Big4	-0.024*	-0.045*	-0.128*	0.064*	0.023*	-0.084*	0.261*	0.377*	0.108*	-0.190*	-0.137*	-0.024*	0.156*	-0.091*	1.000	-0.095*	-0.099*
(16) BtM	-0.054*	-0.008	0.101*	-0.126*	-0.063*	0.071*	-0.153*	-0.084*	-0.004	0.092*	0.163*	0.126*	-0.092*	-0.034*	-0.081*	1.000	-0.042*
(17) ExtFin	0.112*	0.025*	0.000	-0.014	0.040*	-0.022*	-0.012	-0.163*	-0.071*	0.022*	-0.209*	-0.016*	0.138*	0.161*	-0.095*	-0.094*	1.000

Notes: The sample for the main analysis consists of 32,627 firm-year observations from 1977 to 2018. The Pearson (Spearman) correlation coefficients are presented below (above) the diagonal. All the variables are defined in Appendix A. * indicates statistical significance at the 1% level.

Table 4: Product market competition and the cross-segment variability in profitability

	RoSRange	Ln(RoSRange)
ExistingComp	0.075***	0.125***
	[3.913]	[13.098]
PotentialComp	-0.081***	-0.052***
	[-3.464]	[-6.233]
IndustProf	-0.034	0.022
	[-0.605]	[1.122]
InhRoSRange	0.019***	0.007***
	[3.318]	[3.613]
Diverse	0.144***	0.109***
	[2.843]	[4.097]
SFAS131	0.363***	0.175***
	[12.460]	[19.300]
Size	-0.201***	-0.136***
	[-9.696]	[-17.330]
NSegm	0.399***	0.503***
	[8.264]	[21.195]
SegmAgg	0.303	0.217**
	[1.623]	[2.407]
FreeCF	-1.933***	-0.914***
	[-5.291]	[-11.141]
Accruals	-1.682***	-0.779***
	[-6.285]	[-11.076]
M&A	-0.214***	-0.171***
	[-3.505]	[-7.643]
Loss	0.688***	0.574***
	[9.116]	[16.800]
Big4	0.019	-0.033
	[0.310]	[-1.072]
BtM	-0.106***	-0.089***
	[-2.949]	[-5.243]
ExtFin	0.715***	0.287***
	[3.993]	[5.531]
Constant	0.234	-3.129***
	[0.947]	[-28.498]
N	32,627	32,627
Adjusted R^2	0.077	0.252

Notes: The table shows the association between product market competition and the cross-segment variability in profitability measured as *RoSRange*. The first column presents the results using *RoSRange* as the dependent variable. The second column presents the results using the natural logarithm of *RoSRange* as the dependent variable. All the variables are defined in Appendix A. All models include year-fixed effects. Reported t-values in brackets are calculated using two-way clustered standard errors, clustered by year and firm. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Table 5

Alternative measures of the cross-segment variability in profitability and growth

	RoSRangeLrgAvg	*RoSRangeXsml*	*RoSRangeTr1*	*RoSGrRange*
ExistingComp	0.021***	0.023***	0.025***	0.042***
	[3.176]	[9.101]	[12.804]	[5.569]
PotentialComp	-0.015**	-0.012***	-0.012***	-0.045***
	[-2.092]	[-4.740]	[-6.653]	[-4.475]
IndustProf	0.008	-0.000	-0.002	-0.030
	[0.427]	[-0.040]	[-0.403]	[-1.466]
InhRoSRange	0.006***	0.003***	0.001***	0.004*
	[2.843]	[2.890]	[3.382]	[1.980]
Diverse	0.036**	0.008	0.025***	0.063***
	[2.152]	[1.321]	[4.860]	[3.052]
SFAS131	0.075***	0.054***	0.026***	0.181***
	[7.170]	[8.324]	[11.986]	[13.725]
Size	-0.063***	-0.030***	-0.031***	-0.101***
	[-9.394]	[-10.310]	[-18.763]	[-14.270]
NSegm	0.069***	0.092***	0.086***	0.160***
	[5.598]	[11.792]	[16.857]	[7.935]
SegmAgg	0.058	0.068***	0.028	0.024
	[0.990]	[2.755]	[1.622]	[0.320]
FreeCF	-0.595***	-0.242***	-0.172***	-0.721***
	[-5.193]	[-5.647]	[-10.296]	[-5.527]
Accruals	-0.543***	-0.192***	-0.157***	-0.553***
	[-6.241]	[-6.177]	[-11.739]	[-4.878]
M&A	-0.050**	-0.014**	-0.030***	-0.037
	[-2.536]	[-2.353]	[-6.572]	[-1.312]
Loss	0.223***	0.129***	0.122***	0.344***
	[8.758]	[10.793]	[16.696]	[10.127]
Big4	0.005	-0.004	-0.006	-0.010
	[0.268]	[-0.418]	[-0.922]	[-0.445]
BtM	-0.030**	-0.026***	-0.016***	-0.061***
	[-2.270]	[-4.125]	[-4.432]	[-3.491]
ExtFin	0.229***	0.047*	0.059***	0.613***
	[3.522]	[1.805]	[5.403]	[8.125]
Constant	0.242***	-0.065*	0.078***	0.312***
	[3.295]	[-1.969]	[3.561]	[3.741]
N	32,627	15,410	32,627	26,835
Adjusted R^2	0.061	0.196	0.250	0.082

Notes: The table shows the association between product market competition and alternative measures of cross-segment variability in profitability. The models with *RoSRangeXsml* and *RoSGrRange* as dependent variables contain fewer observations, because *RoSRangeXsml* is only available for firms with more than two segments and *RoSGrRange* is calculated as the change from year *t*-1 to year *t*, and thus requires consecutive observations on *RoS*. All the variables are defined in Appendix A. All models include year-fixed effects. Reported t-values in brackets are calculated using two-way clustered standard errors, clustered by year and firm. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.

Table 6: Further analysis

	SFAS 131 Firms Only	Effect of SFAS 131 adoption	RoARange	Alternative ExtFin
ExistingComp	0.101**	0.083***	0.022***	0.071***
	[2.747]	[4.815]	[3.786]	[3.383]
ExistingComp*SFAS131		0.020		
		[0.555]		
PotentialComp	-0.081**	-0.014	-0.016***	-0.088***
	[-2.819]	[-0.668]	[-2.719]	[-3.150]
PotentialComp*SFAS131		-0.083**		
		[-2.562]		
IndustProf	0.003	-0.046	0.039***	-0.039
	[0.036]	[-0.816]	[3.162]	[-0.647]
InhRoSRange/InhRoARange	0.016**	0.018***	0.021	0.019***
	[2.427]	[3.073]	[0.749]	[3.053]
Diverse	0.294**	0.130**	0.038**	0.146***
	[2.450]	[2.585]	[2.128]	[2.754]
SFAS131		0.464***	0.091***	0.242***
		[3.509]	[6.770]	[7.575]
Size	-0.197***	-0.194***	-0.128***	-0.175***
	[-4.790]	[-8.344]	[-18.191]	[-7.912]
NSegm	0.485***	0.414***	0.185***	0.363***
	[6.873]	[8.502]	[11.619]	[6.829]
SegmAgg	0.199	0.385**	-0.063	0.098
	[0.753]	[2.109]	[-1.154]	[0.472]
FreeCF	-4.949***	-0.900***	-0.324***	-1.624***
	[-6.266]	[-5.573]	[-4.095]	[-4.654]
Accruals	-1.838***	-1.000***	-0.435***	-1.566***
	[-3.710]	[-5.394]	[-5.708]	[-5.224]
M&A	-0.215*	-0.248***	-0.092***	-0.186***
	[-1.836]	[-4.122]	[-7.811]	[-2.973]
Loss	0.530***	0.769***	0.179***	0.691***
	[4.128]	[9.471]	[8.119]	[7.382]
Big4	0.057	-0.041	-0.010	0.027
	[0.414]	[-0.700]	[-0.540]	[0.410]
BtM	-0.103	-0.102***	-0.101***	-0.116**
	[-1.639]	[-2.773]	[-7.573]	[-2.659]
ExtFin	0.490	1.012***	0.049	0.456***
	[1.537]	[4.936]	[1.319]	[3.361]
Constant	0.015	-0.173	0.649***	0.319
	[0.039]	[-0.702]	[9.113]	[1.147]
N	15,132	32,627	29,539	25,360
Adjusted R^2	0.080	0.072	0.149	0.069

Notes: The table shows further analyses. In the first column, we eliminate observations prior to SFAS 131 adoption. In the second column, we include interaction terms to examine the incremental effect of SFAS 131 adoption on the association between our measures of product market competition and the cross-segment variability in profitability. In the third column, we use return on assets instead of return on sales to calculate our proxy of cross-segment variability in profitability. In this case, the sample is reduced because segment assets are not reported in Compustat as frequently as profits or sales. In the last column, we redefine *EXTFIN* following Ettredge *et al.* (2006) and Wang *et al.* (2011) as the net equity and debt financing two years after year t. All the variables are defined in Appendix A. All models except the SFAS 131 adoption model in the second column include year-fixed effects. Reported t-values in brackets are calculated using two-way clustered standard errors, clustered by year and firm. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels, respectively.