ESSAYS IN CORPORATE DIVERSIFICATION

by

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(Under the Direction of Jeffry M. Netter)

ABSTRACT

This dissertation finds new evidence on the implications of corporate diversification on profitability, risk, and the information environment of firms. In the first essay, we focus on U.S. supplier firms with major corporate customers and examine how customer-base diversification affects firm profitability and distress risk. We propose and find that the relation between customer-base concentration and profitability is non-linear and dynamic. We show that customer concentration promotes operating efficiencies for profitable firms, but we find the opposite result for younger, less profitable firms. The reason for this dynamic relation is that firms who serve a few major customers make customer-specific investments that result in larger fixed costs and greater operating leverage. The first essay also analyzes whether a concentrated customer base increases the distress risk of the firm. We hypothesize and show that higher customer concentration is also associated with higher demand uncertainty as well as higher operating leverage. Due to higher operating leverage and demand uncertainty, firms with higher customer concentration are not able to reduce their expenses when the demand drops, leading to higher probability of default.

The second essay examines whether segment diversification leads to slower information processing by investors. We hypothesize that a more diversified revenue base should increase the complexity of a firm's earnings, which in turn should hamper investors' speed of information processing. We utilize the post-earnings-announcement drift (PEAD) to test this hypothesis. We propose to use firm complexity, a measure of corporate diversification, as a new limits-to-arbitrage variable. We show, using cross-sectional regressions, that PEAD is twice as strong for more diversified firms as it is for single segment firms. This is a surprising result because diversified firms are larger, more liquid, and more actively researched by investors. Unless firm complexity severely hampers the ability of investors to process information, one should expect to find weaker, not stronger, PEAD for diversified firms, because all other firm characteristics suggest that diversified firms should have lower limits to arbitrage.

INDEX WORDS: Customer Concentration, Customer-specific Investment, SG&A Expense, Profitability, Default Risk, Post-earnings-announcement Drift, Conglomerates, Mispricing, Limits to Arbitrage, Complicated Firms

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DEDICATION

To Eunbae, Quha, and my parents.

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CHAPTER 1

INTRODUCTION

Corporate diversification refers to the process of adding new businesses to the firm that are distinct from its established operations. In a broader sense, it can be interpreted as any corporate strategy that diversifies a firm's sources of revenue. Corporate diversification has been the subject of a great deal of research in many subfields in management. Industrial diversification is a major strategic management research topic, where the research is mainly influenced by resource-based theory. The theory posits that diversification can lead to superior firm performance because firms can maximize their resources across several businesses to realize additional returns (Wan, Hoskisson, Short and Yiu, 2011). Marketing literature has studied the benefits of a concentrated customer base and customer relationship management (Kalwani and Narayandas, 1995; Rauyruen and Miller, 2007). In accounting, the informativeness of segment disclosures has been emphasized as such disclosures are key sources of public information on firms' level of diversification (Ettredge, Kwon, Smith and Zarowin, 2005).

Corporate diversification is also an important area of research in finance. Much of the research in finance has studied the impact of corporate diversification on firm value (Lang and Stulz, 1994; Berger and Ofek, 1995; Campa and Kedia, 2002; Villalonga, 2004). This dissertation explores two novel issues related to corporate diversification. First, I seek to understand how diversification affects firms’ cost structure and variability of their revenues as well as their likelihood of default. Second, I analyze how corporate diversification affects the speed of information processing for investors.

In the first essay, we focus on U.S. supplier firms with major corporate customers and examine how customer-base diversification affects firm profitability and distress risk. Previous literature primarily has studied the impact of customer-base diversification on firm profitability and risk in the context of supplier firms' hold-up problems. In doing so one stream of the literature has studied the impact of customer firms' relative bargaining power over their supplier firms and how this has affected suppliers' gross margins. On the other hand others in this literature have studied the impact of relationship-specific investments undertaken by supplier firms and the potential improvements in firm efficiency attributable to these investments. One paper that investigates the hold-up problem is by Klein, Crawford and Alchian (1978) where the authors suggest that when a supplier firm undertakes relationship specific investments, the customer firm may act opportunistically and ask for concessions from the supplier firm. This paper is very much in line with Galbraith (1952) who also notes that a customer firm with significant bargaining power can demand price discounts from sellers. Furthermore, Williamson (1979, 1983) suggests that customer-specific investments can be site-specific, physical-asset-specific, or human-asset-specific and could expose the supplier firm to a hold-up problem. These seminal studies suggest that having a concentrated customer base is a risky choice that can lead to lower profitability. On the other hand, other researchers have emphasized the benefits of a concentrated customer base, such as higher overall effectiveness of selling expenditures, enhanced working capital management, and better coordination in pricing and production decisions (Carlton, 1978; Kalwani and Narayandas, 1995; Patatoukas, 2012).

It is an empirical question if the advantages of customer base concentration outweigh its disadvantages. Previous research has yielded mixed evidence on the effect of customer-base diversification on firm profitability (Lustgarten, 1975; Kalwani and Narayandas, 1995; Patatoukas, 2012). One of the main contributions of this dissertation is that we reconcile the mixed results documented in the literature within the context of a dynamic life cycle hypothesis. We propose and find that the relation between customer-base concentration and profitability is non-linear and dynamic. We show that customer concentration promotes operating efficiencies for profitable firms, but we find the opposite result for younger, less profitable firms. The reason for this dynamic relation is that firms who serve a few major customers make customer-specific investments that result in larger fixed costs and greater operating leverage, enhancing profitability in good periods and further reducing profitability in bad periods.

The first essay also analyzes whether a concentrated customer base increases the distress risk of the firm. Previous literature has shown both direct and indirect evidence that a concentrated customer base is associated with a higher level of distress risk. Banerjee, Dasgupta and Kim (2008) find that supplier firms maintain lower leverage if they are dependent on a few customers. They argue that it is because managers of supplier firms are aware of the additional risk associated with the relationship-specific investments. Similarly, Bae and Wang (2010) and Wang (2012) show that supplier firms in customer-supplier relationships hold more cash and pay less dividends, again recognizing their higher risk due to their reliance on relation-specific investments. Cardella (2012) find that supplier firms with exposure to major customers have lower credit ratings.

However, there has been little research studying the channel through which the level of customer-base diversification affects the distress risk in depth. In this essay, we document that high customer concentration is associated with higher operating leverage. Furthermore, we hypothesize and show that higher customer concentration is also associated with higher demand uncertainty. Due to higher operating leverage and demand uncertainty, firms with higher customer concentration are not able to reduce their expenses when the demand drops, leading to higher probabilities of default. The essay concludes that customer concentration is associated with higher operating leverage as well as higher demand uncertainty, significantly increasing a concentrated supplier's likelihood to default. Although previous studies have shown that operating leverage increases the risk of the firm (Lev, 1974; Mandelker and Rhee, 1984; García-Feijóo and Jorgensen, 2010; Novy-Marx, 2011), this essay is the first, to my knowledge, to relate higher customer base concentration to higher operating leverage as well as higher demand uncertainty and ultimately to higher default probability.

The second essay in this dissertation examines whether segment diversification leads to slower information processing by investors. We hypothesize that a more diversified revenue base should increase the complexity of a firm's earnings, which in turn should hamper investors' speed of information processing. We analyze the relationship between the post-earnings-announcement drift (PEAD) and firm complexity to test our hypothesis as higher PEAD is often interpreted as evidence of investors' underreaction to news related to earnings.

Since Ball and Brown's (1968) seminal study, many researchers have explored what causes PEAD and have found that the magnitude of PEAD is negatively related to firm size and positively related to measures of limits-to-arbitrage. Bernard and Thomas (1989) identify an inverse relationship between firm size and PEAD. Bhushan (1994) presents evidence indicating that PEAD is positively related to measures of costs of trading: stock price and trading volume. Chordia et al. (2009) document that PEAD occurs mainly in highly illiquid stocks. Mendenhall

(2004) find that PEAD is positively related to the idiosyncratic risk of a firm, which is a major risk faced by arbitrageurs.

In the second essay, we propose to use firm complexity, a measure of corporate diversification, as a new limits-to-arbitrage variable. We show, using cross-sectional regressions, that PEAD is twice as strong for more diversified firms as it is for single segment firms. This is a surprising result because diversified firms are larger, more liquid, and more actively researched by investors. Unless firm complexity severely hampers the ability of investors to process information, one should expect to find weaker, not stronger, PEAD for diversified firms, because all other firm characteristics suggest that diversified firms should have lower limits to arbitrage. We further show that our measure of firm diversification, a proxy for firm complexity, utilized in this essay is distinct from previously used measures of uncertainty and various proxies for information complexity, such as earnings quality, earnings persistence, and readability of the annual reports (Francis, Lanford, Olsson and Schipper, 2007; Chen, 2013; Li, 2008).

The remainder of this dissertation is organized as follows: Chapter 2 presents the manuscript entitled "Customer-base concentration, profitability and distress across the corporate life cycle," and Chapter 3 presents the manuscript entitled "Firm complexity and Post-Earnings-Announcement Drift." Chapter 2 is co-authored with Paul Irvine (Texas Christian University) and Çelim Yıldızhan (University of Georgia). Chapter 3 is co-authored with Alexander Barinov (University of Georgia) and Çelim Yıldızhan.

CHAPTER 2

CUSTOMER-BASE CONCENTRATION, PROFITABILITY AND DISTRESS ACROSS THE CORPORATE LIFE CYCLE

2.1 INTRODUCTION

Winning the business of a major customer is an exciting event in the life of the firm. Business from major customers can increase firm revenues markedly and permit efficiencies of scale in operations and delivery. Despite these advantages, economists have long warned of the danger of supplying a considerable fraction of firm output to a particular customer. Lustgarten (1975) credits Galbraith (1952) with the origin of the concept that large customers are threats to manufacturer's operating profits because, as important customers with significant bargaining power, they can demand price discounts from sellers. The problem with these major customers is that the margin improvements that the supplier firm can receive, through selling efficiencies or other economies of scale, do not necessarily accrue to the firm. Major customers recognize their bargaining power and can engage in ex-post renegotiation over the terms of the contract (Klein, Crawford and Alchian (1978), Williamson (1979)). Once the firm has committed resources to production for a major customer, these customer-specific investments represent costs that the firm cannot fully recover unless they can complete and deliver the order to the customer. Major customers can impair firm profitability by demanding price concessions, extended trade credit or other benefits. For example, Balakrishnan, Linsmeier and Venkatachalan (1996) argue that major customers are aware of the firm's cost savings from JIT adoption, and that customer demands for concessions subsequent to JIT adoption prevent the adopters from improving profitability.[1] In his empirical study of customer concentration, Lustgarten (1975) concludes that high customer concentration (at the industry level) reduces firm profitability.

Patatoukas (2012) challenges the conventional wisdom that customer concentration impairs firm profitability. Using SFAS 14 and SEC Reg S-K mandated disaggregated revenue disclosures available from Compustat, he creates a firm-specific measure of customer concentration and finds a positive relation between customer concentration and accounting rates of return. Taking advantage of a recent expansion in this data set, we extend his analysis to include firms with negative operating performance. We find that the relation between customer concentration and profitability is more complex than a simple positive or negative relation. While we find that many of Patatoukas' (2012) conclusions about profitable firms are correct, they are not generalizable to firms with negative operating performance. Such firms tend to be younger, their sales depend more on major customers, their costs are more inelastic with respect to sales, they encounter greater demand uncertainty, and they face a higher probability of financial distress. The strong effects of customer concentration on unprofitable firms produce a negative relation between customer concentration and firm profitability in the full sample. We conjecture that customer concentration increases operating leverage: if the supplier-customer relationship is successful, then firms with high levels of customer concentration are rewarded with high operating profits. However, if the relationship is not successful, firms that are dependent on major customers are less profitable and face greater probabilities of financial distress.

[1] Recently, Ng (2013) relates the example of Procter and Gamble who plan to extend the time they take to pay suppliers from 45 days to 75 days.

Following earlier studies on firm profitability (Fairfield and Yohn (2001), Soliman (2008)), Patatoukas (2012) focuses on firms with positive operating performance. While this sample selection criterion is often unavoidable in valuation research, such as the case where negative current earnings cannot be capitalized, the criterion can be avoided in a study of customer-supplier relations. We argue that unprofitable firms are more likely to reflect the negative effects of customer concentration such as major customers' demands for price concessions. We find that younger firms tend to have negative operating performance (and are thus excluded by Patatoukas (2012)), and among these firms we find a negative relation between customer concentration and profitability. Young firms with a concentrated customer base are at risk, in line with conventional wisdom. Our evidence suggests that only when a firm survives to a certain age does this negative relation recede and turn positive. Analyzing the full range of firm profitability allows us to reconcile the conventional wisdom with Patatoukas'(2012) results.

We examine the relation between customer concentration and firm profitability over the 1977-2007 period. Consistent with Patatoukas (2012) we find that customer concentration has a positive effect on the firm's cash conversion cycle and reduces inventory holdings, supporting Patatoukas' (2012) conclusion that customer concentration can promote operating efficiencies. However, for both young and unprofitable firms customer concentration reduces firm profitability. Investigating this result, we find that customer concentration is generally positively related to SG&A expenses. This relation is particularly strong for young and unprofitable firms. Since SG&A expenses constitute an important component of total firm costs, the relation between customer concentration and firm profitability is primarily attributable to the relation between customer concentration and SG&A expenses.

Motivated by Williamson (1979) who recognizes the central importance of customer-specific investments and by Anderson, Banker and Janakiraman's (2003) finding that SG&A costs can be sticky –responding asymmetrically to changes in firm sales: We hypothesize that SG&A elasticity across firms reflects the existence of customer-specific investments. Customer-specific SG&A expenses are, by definition, less transferable than general SG&A investments and thus cause SG&A costs to be stickier. Probing the nature of SG&A costs to explain the patterns we observe in customer concentration and firm profitability, we find that the elasticity of SG&A costs with respect to sales is lower in firms with higher customer concentration. This means SG&A costs are stickier for such firms. We argue that firms with higher customer concentration make more customer-specific SG&A expenses believing that such customer-specific investments will lead to the operating efficiencies documented in Patatoukas (2012).

However, as reflected in lower SG&A elasticity, customer-specific SG&A investments are predominantly fixed costs that are less transferable to other uses and so increase the firm's operating leverage. The effect of this increase in operating leverage on firm profitability varies with the firm's life cycle. We document that young firms with high customer concentration are more likely to face financial distress. These firms have a relatively high fixed-cost component in their SG&A expenses, and thus cannot reduce their costs significantly if demand drops. As the supplier-customer relationship matures, the risk of financial distress decreases; the mature firms in our sample are more likely to capture operating efficiencies that enhance profitability.

We also extend the Banker, Byzalov and Plehn-Dujowich (2012) hypothesis that cost elasticity is related to demand uncertainty by examining the effects of customer concentration on the relation between cost elasticity and demand uncertainty. Higher customer concentration is associated with higher demand uncertainty, exacerbating the operating leverage effect. Firms with only a few major customers have relatively undiversified sources of revenue, and their customer-specific investments prevent them from easily finding alternative sales when faced with declining demand from their major customers. Consistent with this argument, we find that demand uncertainty monotonically increases from firms in the lowest customer concentration quintile to the highest customer concentration quintile. The adverse impact of higher demand uncertainty for high customer concentration firms is especially pronounced for young firms.

We develop a dynamic life-cycle hypothesis about the effects of customer concentration on firm profitability that is able to synthesize our findings with Patatoukas (2012). We confirm Patatoukas' (2012) surprising result that, for profitable firms, customer concentration can lead to some operating efficiencies. However, we contend that these efficiencies come with a risk. For young firms, customer concentration is costly and only as the relationship matures does it lead to operating efficiencies that can significantly improve profitability. Early in the firm's life cycle, the high customer-specific costs associated with customer concentration lead to higher probabilities of delisting or default. A concentrated customer base is thus a risky choice for young firms. These firms face a trade-off between higher current distress probability and the possibility of improving operating efficiency and achieving higher profits in the future.

A major contribution of this paper is that it identifies the existence and magnitudes of both the costs and benefits of customer concentration. Knowledge of both the costs and benefits of customer concentration is important to managers making the crucial decision of whether to make customer-specific investments in the relationship between the firm and a major customer. Our ability to document the costs and benefits involved in this decision supports the usefulness of mandated disaggregated revenue disclosures and, as in Patatoukas (2012), highlights some of the benefits of improving disaggregated information about firms' operations.

2.2 HYPOTHESIS DEVELOPMENT

In contrast to the traditional view that major customers can extract benefits from the supplier firm and thus lower firm profitability, there are several reasons why major customers could be beneficial to the firm. All orders are different, in either their design, manufacture or logistical delivery. Meeting the demands of many small customers is expensive and firms can achieve economies of scale from dealing with a few major customers. Although a number of small orders can produce the same total sales as a single large order, the supplier faces the problem of customer retention and acquisition. Customer retention and acquisition can be expensive and by dealing with a few major customers, supplier firms can potentially reduce these costs. Cohen and Schmidt (2009) document some of the benefits of attracting large clients and Carlton (1978) outlines how a lower customer-per-firm ratio helps the firm coordinate pricing and production decisions. Costello (2013) and Fee, Hadlock and Thomas (2006) show how covenant restrictions and customer equity stakes can alleviate contracting problems that arise in the relationship. Volume discounts to large customers are common and reflect these economies.

Investigating the empirical evidence on customer concentration and firm profitability, Patatoukas (2012) cites two studies (Newmark (1989) and Kalwani and Narayandas (1995)) that challenge Lustgarten's (1975) finding that customer concentration reduces profitability. Faced with this mixed evidence, Patatoukas (2012) argues that whether major customers are beneficial or detrimental to the firm is ultimately an empirical issue. He answers that question in the affirmative by showing that customer concentration leads to improved profitability. Firms achieve this profitability through efficiencies in SG&A expenses, inventory turnover and cash conversion improvements. However, Patatoukas (2012) conditions his empirical tests on profitability, only firms with positive profits are analyzed. Although this choice is consistent with the literature on profitability, in this case the bargaining power of major customers could introduce an endogeneity bias into the analysis. Specifically, because granting concessions to major customers is costly, firms earning positive profits are likely to be less affected by customers demanding concessions than firms with operating losses. Focusing only on profitable firms could restrict the sample to those firms where the ability of major customers to obtain price concessions and other benefits is limited for some unobservable reason.

We conjecture that developing operating efficiencies from a major customer relationship is not a straight-line process. As suggested by Galbraith (1952), Lustgarten (1975), Balakrishnan et al. (1996), and Schloetzer (2012) major customers pose significant risks to supplier-firm profitability. We expect to see these risks occur in unprofitable firms, the sample unobserved in Patatoukas (2012). Since young firms tend to rely more on major customers and are more likely to be unprofitable, we expect the relation between customer concentration and firm profitability to vary with firm age. For young, unprofitable firms we expect the relation between customer concentration and profitability to be negative.

This prediction is based on the risk that arises from the customer-specific investments the firm makes to serve their major customers. The effects of these customer-specific investments should be particularly notable for SG&A expenses. Anderson, Banker and Janakiraman (2003) find that SG&A costs decrease less in response to falling sales than they increase with rising sales. They explain this "sticky-cost" phenomenon by arguing that managers delay cost reduction in times of weak demand if they expect demand to recover. We hypothesize that the nature of the firm's customer base affects SG&A cost stickiness. If a firm makes customer-specific investments in selling, general or administrative costs to capture operating efficiencies that come with major-customer relationships, then by definition these customer-specific investments are less transferable to other uses than more general investments. Firms with high customer concentration would thus tend to have a larger fixed cost component in their SG&A expenses. If this contention is true, then the elasticity of SG&A expenses with respect to sales should be lower the more concentrated the firm's customer base, as more inelastic SG&A expense reflects a greater proportion of fixed costs in the firm's cost structure.

The elasticity of SG&A expenses with respect to sales is the focus of a recent paper by Banker, Byzalov and Plehn-Dujowich (2012). These authors focus on understanding how demand uncertainty affects the firm's cost structure. Their surprising conclusion is that higher demand uncertainty is associated with a more rigid cost structure, with higher fixed and lower variable costs. They argue that this more rigid cost structure benefits firms facing high demand uncertainty because adjusting to positive demand shocks is relatively expensive without the fixed-cost structure in place to handle this demand. Thus, the firm without a large SG&A fixed-cost component cannot easily capture the profit potential arising from positive demand shocks.

Building on the arguments in Anderson et al. (2003), and Banker et al. (2012), we predict that customer concentration lowers the elasticity of SG&A expenses with respect to sales and that customer concentration leads to greater demand uncertainty. A firm with high customer concentration is more exposed to idiosyncratic demand shocks generated by major customers. When major customers receive their own demand shocks, they transfer this demand shock to their suppliers. Thus, higher demand uncertainty could complement the tendency for firms with high customer concentration to increase the fixed-cost component of their SG&A expenses.[2]

[2] Conversely, Matsen and Crocker (1985) suggest that take-or-pay contracts are sometimes used when the firm produces much of its output for a major customer. Take-or-pay clauses require the customer to pay for a contractually specified minimum quantity, even if delivery is not taken. Extensive use of take-or-pay contracts would reduce demand uncertainty.

Both cost-stickiness and the demand uncertainty associated with customer concentration increase operating leverage. Greater operating leverage increases the likelihood of financial distress in low-demand states of the world.

Anecdotally, young firms with a concentrated customer base are particularly at risk. The loss of a major customer can impose significant, often catastrophic, losses on a young firm. We test this idea by examining the effect of customer concentration on the probability of financial distress. We first replicate the IPO failure regressions in Demers and Joos (2007) to test whether customer concentration at the time of the IPO is a factor in determining whether a young firm encounters financial distress. In a more general setting, we replicate the Campbell, Hilscher and Szilagyi (2008) model of dynamic failure prediction. This test allows us to examine whether customer concentration contributes to financial distress across all firms, and it specifically allows us to test if the impact of customer concentration on the likelihood of firm failure changes with the age of the firm. Based on the analysis above, we predict that customer concentration should increase the likelihood of financial distress, but that this effect should attenuate as the relationship matures.

2.3 DATA

FASB accounting standards require all public companies to disclose the identities of their major customers representing more than 10% of their total sales. We extract the identities of each firm's major customers from the Compustat Customer Segment Files. We focus on the period between 1977 and 2007. Compustat Customer Segment Files provide for each firm the names of its major customers, revenue derived from sales to each major customer, and the type of each major customer.[3]

For each firm we determine whether its customers are listed in the CRSP/Compustat universe. If they are, then we assign them to the corresponding firm's PERMNO. Since the focus in this paper is on customer concentration and its impact on firms' operating and financial performance, even when the customer firm cannot be assigned a PERMNO, we still keep the supplier-customer link in the sample and identify the customer firm as a non CRSP/Compustat company.[4]

Following Patatoukas (2012), we construct our primary measure of customer concentration using the following formula:

$$CC_{i,t} = \sum_{j=1}^{n} \left(\frac{Sales\ to\ Customer\ j_{\ i,j,t}}{Total\ Sales_{i,t}} \right)^2$$

If firm *i* has *n* major customers in year *t*, the measure of customer concentration ($CC_{i;t}$) of the firm is defined as the sum of the squares of the sales shares to each major customer. The sales share to each customer *j* in year *t* is calculated as the ratio of firm *i*'s sales to customer *j* in year *t* scaled by firm *i*'s total sales in year *t*. Patatoukas (2012) constructs his customer concentration measure in the spirit of the Herfindahl-Hirschman index, and suggests that the measure captures two elements of customer concentration: the number of major customers and the relative importance of each major customer. By definition, the customer concentration (*CC*) is bounded

[3] The dataset groups customers into three broad categories based on their type: “company”(COMPANY), “domestic government”(GOVDOM), and “foreign government”(GOVFRN). We exclude information on customers that are identified as domestic or foreign governments, even if they may be major customers for a certain supplier firm.

[4] Cohen and Frazzini (2008) report that the Compustat Customer Segment files report the names of customer companies but often fail to provide company identification codes such as customer firms' PERMNO's. For these firms, we use a phonetic string matching algorithm to generate a list of potential matches to the customer name. We then hand-match the customer to the corresponding PERMNO based on the firm's name, segment, and SIC code.

between 0 and 1 as *CC* is equal to 1 if the firm earns all of its revenue from a single customer and as the customer base diversifies *CC* tends to 0.

As in Patatoukas (2012), we exclude financial services firms from the sample. Our sample consists of all firms listed in the CRSP-Compustat database with non-negative book values of equity, non-missing values of customer concentration (*CC*), market value of equity (*MV*), annual percentage sales growth (*GROWTH*), and accounting rates of return at the fiscal year-end when we can identify major customers.[5] After imposing these restrictions, we are left with 49,760 supplier firm-year observations between 1977 and 2007.

Our sample differs from the sample used in Patatoukas (2012). Patatoukas (2012) focuses on the subsample of firm-year observations with positive operating margins, whereas we include firm-year observations with operating losses. Of the 49,760 firm-year observations in our sample, 10,836 have operating losses (21.8 percent). Excluding this significant subset of the sample limits understanding of the impact of customer concentration on firm profitability. Furthermore, over a comparable period we have significantly more firm-year observations with positive operating margins (38,924) than Patatoukas' (2012) 25,389.[6] To alleviate concerns regarding our sample, we repeat all analyses using only the set of firm-year observations with positive operating margins and find results qualitatively similar to Patatoukas (2012).

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[5] Including firms with both negative earnings and negative book values confounds a direct interpretation of higher ROE as a good outcome. We drop negative book value firms to avoid this confusion. In unreported analysis, we include negative book value firms and find consistent results.

[6] Hoechle, Schmid, Walter and Yermack (2012) report a temporary deletion of valid Compustat segment file observations during 2007-2008. This problem, as well as periodic updates to the Compustat segment files, can account for the difference in sample sizes between our paper and Patatoukas (2012).

2.3.1 DESCRIPTIVE STATISTICS

Figure 2.1 presents the time series of average customer concentration from 1977 to 2007 as reported in the Compustat customer segment files. We first note that customer concentration exhibits a marked increase from the early years of the sample through 1997, a period coincident with a general increase in the number of listed firms. The number of firms reporting customer concentration fell from a high of close to 3,500 in 1997 to what appears to be a steady state of just over 2,000 for the 2002-2007 period. Consistent with Patatoukas (2012), median customer concentration reveals a generally increasing trend over time, from a low of 0.03 in 1977 and 1978 to a high of over 0.06 in 2007.

Table 2.1 lists our variable definitions, grouped into four categories: (i) Supplier-firm characteristics, (ii) Customer-firm characteristics, (iii) IPO failure prediction variables that follow the definitions in Demers and Joos (2007) for easy comparison of their results to our tests, and (iv) Default prediction variables used in our extension of the Campbell, Hilscher and Szilagyi (2008) default prediction model. *CC* is the basic measure of customer concentration described in Equation (1) and *ΔCC* measures the year over year change in *CC*.

Table 2.2 presents summary statistics for several key variables for the full sample (Panel A), for positive and negative profitability subsamples (Panel B), and for mature versus young subsamples (Panel C). The variables *MV*, *AGE*, and *GROWTH* define the basic characteristics of supplier firms. *MV* measures the firm's market value of equity in millions of dollars, *AGE* is the firm's age in years, measured from the time of its Initial Public Offering (IPO). *GROWTH* is the supplier firm's annual sales growth rate.

ROA, *ROE*, and *SGA* define key operating characteristics of supplier firms. *ROA* is the ratio of income before extraordinary items to the beginning of year book value of total assets for the firm. *ROE* is the ratio of income before extraordinary items to the beginning of year book value of equity for the firm. *SGA* is the ratio of selling, general, and administrative expenses to sales. *IHLD* is the ratio of inventory to the book value of total assets for the firm. *TLMTA* and *CASHMTA* are variables defined in Campbell et al. (2008) as total liabilities scaled by the market value of total assets and firm cash holdings scaled by the market value of total assets, respectively. Following Patatoukas (2012), we also include weighted averages of major customers' characteristics. Every year, each customer characteristic is weighed by the supplying firm's percent of sales to that customer relative to their total revenues from all major customers. *CMV* is the weighted average market value of equity for a firm's major customers, in millions of dollars. *CAGE* is the weighted average age of firms' major customers. *CCSALES* is the percentage of firm sales that go to identifiable major customers. *CSG* is the weighted average annual percentage sales growth for a firm's identifiable major customers.

Panel A of Table 2.2 reports the mean, standard deviation, skewness, median, 25th, and 75th percentile values for the variables used in this study. On average, each supplier has 1.89 major customers and generates 33 percent of its annual sales from these customers (*CCSALES*). *CC* averages 10.1% for the 49,760 observations in the sample with a standard of deviation of 14.7%. The latter statistic suggests that there is large cross-sectional variation in firms' dependence on their major customers for revenues. Our sample is considerably larger than the restricted sample in Patatoukas (2012), but mean *CC* is close to the mean in Patatoukas (2012). This fact shows that any differing results due to our expansion of the sample is not attributable to radical differences in customer concentration. Changes in customer concentration are also similar to those in Patatoukas (2012). On average each firm accounts for only 2% of their customer's cost of goods sold. While these summary statistics are similar to Patatoukas (2012) and further verify the asymmetric relation between suppliers and customers, our sample firms are younger and smaller than those in Patatoukas (2012). Firms in our sample average only 10.3 years of age compared to 14.8 in Patatoukas (2012) with a market cap of $806 million relative to Patatoukas' (2012) $1,206 million. Because we do not censor on profitability, the average *ROA* and *ROE* are lower at -0.01 (Patatoukas (2012), 0.06) and -0.03 (0.13), respectively. In only 6% of our sample do suppliers and customers operate in the same 4-digit SIC industry.[7] Three of our main dependent variables, *ROA*, *ROE* and *SGA*, and the key explanatory variable, *CC*, are all significantly skewed. In order to mitigate the effect of skewness, we use the decile rank of *CC* (*ΔCC*) instead of *CC* (*ΔCC*), as in Patatoukas (2012), in our regression analyses.

Panel B of Table 2.2 separates the sample into positive and negative operating margin groups. For each group, we report the mean, median, and standard deviation of key variables and report the differences in means across the two groups. Positive operating margin firms dominate the composition of the sample by a ratio of almost 4:1. The differences between these two groups are striking and almost always statistically and economically significant. Negative operating margin (*OM*) firms have a mean customer concentration of 14.2%, compared to 9.0% for positive *OM* firms (t-statistic of the difference = -27.6). They are also younger, averaging only 7.3 years compared to 11.1 years for the positive *OM* subsample (t-statistic of the difference = 48.6). Total liabilities to market assets averages 0.30 for the negative *OM* firms and 0.36 for positive *OM* firms. Negative *OM* firms have more cash to total assets (*CASHMTA*) at 0.17 relative to the 0.09 cash holdings of positive *OM* firms. We note that by inspection positive *OM*

[7] When we use the Fama-French (1997) 49 industry group classification model to identify a firm's industry affiliation, we find that 27% of supplier-customer relationships are between supplier firms and customer firms that operate in the same industry.

firms have more debt and less cash, but both types of firms have significant debt in their capital structure and these high average debt levels could lead to economically significant distress risk. Firms that are not profitable are, on average, younger, smaller in size, and more reliant on their major customers for their revenues. Furthermore, firms with negative operating margins have significantly higher SG&A expenses as a percentage of their sales than profitable firms.

Motivated by the significant difference in firm age between positive and negative *OM* firms, Panel C of Table 2.2 examines the characteristics of the sample firms by age. The median firm age is 7, so we define young firms as those that have been public for at most 7 years. This definition splits the sample into two similar-sized groups of 24,628 mature firm-year observations and 25,132 young firm-year observations. The customer concentration measure (*CC*) is higher for young firms (11.3%) relative to mature firms (8.9%), but the difference is not as great as that between the positive and negative *OM* subsamples. As expected, young firms are smaller than mature firms and they are growing faster. Illustrating the connection between firm age and profitability, young firms are significantly less profitable than mature firms. Young firms have a mean *ROA* of -0.05 and a mean *ROE* of -0.08 compared to the mean *ROA* of 0.02 and the mean *ROE* of 0.03 for mature firms. These differences are statistically significant. Young firms have higher SG&A expenses than mature firms, but relatively less debt and more cash. The latter facts indicate that there is nothing about the average capital structure of young firms that renders them more likely to experience financial distress.

The statistically significant differences in the characteristics of customer concentration in both Panels B and C are not strikingly large. The positive *OM* firms in Panel B have slightly larger and older customers than those of the negative *OM* firms. Positive *OM* firms have customers that are growing slightly faster; averaging 12% for positive *OM* firms relative to 10%

for negative *OM* firms. In Panel C, the mature firms have, not surprisingly, somewhat larger and older customers, but the young firms' customers are growing marginally faster; 12% for the young firms relative to 11% for the mature firms.

In the rest of the paper we try to understand the differences between firms with positive operating margins and firms with negative operating margins and determine whether firm age is a key driver of these differences. Furthermore we analyze the impact of customer concentration on firm profitability for the full sample of firms.

2.4 RESULTS

2.4.1 CUSTOMER CONCENTRATION AND FIRM PERFORMANCE

2.4.1.1 CORRELATION ANALYSIS

Table 2.3 presents Pearson and Spearman correlations across the full sample (Panel A), the positive operating margin subsample (Panel B) and the negative operating margin subsample (Panel C). By analyzing these correlations, we can get an initial idea of how the relation between customer concentration and firm profitability depends on the sign of operating profitability. In the full sample, customer concentration is negatively related to *ROA* and *ROE* with correlation coefficients of -0.11 and -0.08, respectively. In the positive *OM* subsample, the correlations are positive for *ROA* at 0.03 and *ROE* at 0.01. In the negative *OM* subsample, the signs of these correlations reverse. Here, the correlation between customer concentration and *ROA* is -0.07 and -0.02 for *ROE*.[8] The correlation between customer concentration and *SGA*, a key measure of

[8] Note that the skewed distribution of *CC* can cause the subsample correlations to fail to bracket the full sample correlation, an illustration of Simpson's paradox.

operating efficiency in Patatoukas (2012), is positive in the full sample, indicating that customer concentration is not generally associated with cost savings. Nevertheless, in the positive *OM* subsample, the correlations are negative (-0.04), consistent with the findings in Patatoukas (2012). In the negative *OM* subsample, the sign of the correlation is reversed and relatively large at 0.23. Customer concentration is negatively correlated with firm age in all three panels, supporting the inference from Table 2 Panel B, that younger firms tend to have higher customer concentration.

Why is the effect of customer concentration so different across positive and negative *OM* firms? We illustrate how firm profitability varies by customer concentration and firm age in Figure 2.2. Panel A of Figure 2.2 shows the non-linear U-shaped relation between customer concentration and profitability. The lowest profitability firms have high customer concentration and as profitability increases customer concentration declines. As profitability continues to climb customer concentration increases again. We identify graphically how the exclusion of the lowest profitability firms likely masks the non-linear relation between customer concentration and profitability. Figure 2.2 also identifies how the lowest profitability deciles tend to be younger firms. Profitability generally increases in firm age until it turns down again in the highest profitability deciles.

These initial findings are consistent with our dynamic life-cycle hypothesis about how customer concentration relates to firm profitability over the life of the firm. We confirm Patatoukas' (2012) surprising result that customer concentration can be positively related to profitability and that operating efficiencies associated with customer concentration are a plausible cause for the increased profitability in already profitable firms. Despite these potential efficiencies, we contend that newly-public firms face significant risks from customer concentration. For young firms, a concentrated customer base is costly and only as the relationship matures does it lead to operating efficiencies that significantly improve profitability. The cost structure facing young firms can lead to greater probabilities of financial distress and delisting, a contention we investigate below.

2.4.1.2 SORTING ON CUSTOMER CONCENTRATION AND FIRM AGE

To test our hypothesis on the dynamic nature of customer concentration and its effects on firms' operating efficiency, we first do a simple sorting procedure presented in Table 2.4. We first separate the sample into two groups, and analyze the full sample in Panel A and just the firms with positive operating margins (as in Patatoukas (2012)) in Panel B. Then for each panel we sort the firms into young and mature firms using the median age of 7 years reported earlier as our breakpoint. We then sort young and mature firms into quintiles based on customer concentration and examine the means and medians of the key operating variables, *ROE*, *ROA*, and *SGA* across the quintiles.

For the full sample in Panel A we see a marked difference in operating performance across customer concentration quintiles. *ROA* and *ROE* monotonically decline as customer concentration increases. This pattern is particularly strong for young firms. In the lowest customer concentration quintile *ROA* is -0.68% for young firms but *ROA* declines to -8.86% for young firms in the highest customer concentration quintile. A similar pattern is observed for *ROE*, as *ROE* monotonically declines from -0.53% in the lowest customer concentration quintile to -14.4% in the highest quintile. SG&A expenses as a percentage of sales monotonically increase with customer concentration from 37.9% in the lowest *CC* quintile to 69.4% in the highest. Similar patterns are observed for the mature firms in the full sample, but these firms tend to be profitable, particularly in the low customer concentration quintiles. For mature firms SG&A expenses also increase with customer concentration from 26.1% in the lowest *CC* quintile to 37.1% in the highest quintile. In the full sample, particularly for young firms, customer concentration is related to higher SG&A expenses and lower profitability.

This pattern of customer concentration leading to deteriorating operating performance is masked when we only look at the young firms with positive operating performance in Panel B. For young firms with positive operating performance, *ROE* and *ROA* show no overall pattern in customer concentration, though profitability of the highest customer concentration quintile is higher than that of the lowest customer concentration quintile. Consistent with Patatoukas' (2012) results we find that SG&A expenses decline with customer concentration for profitable firms. However, analyzing only the profitable firms introduces an endogeneity bias; as the mere fact that these firms are profitable could simply mean that they do not face significant adverse effects from customer concentration. In general, the effects of customer concentration are smaller for mature firms than they are for young firms, but the different patterns between the full sample and the positive *OM* subsample illustrate how examining only positive *OM* firms is incomplete and inferences about positive *OM* firms don't apply to negative *OM* firms.

The different patterns across positive and negative OM samples are outlined in the graphs in Figure 2.3. Figure 2.3 graphs *ROA* in two dimensions: by *CC* quintile and *AGE* quintile. In the full sample in Panel A, profitability is clearly higher for all firm ages in the lowest customer concentration quintile, and much lower for young firms that have the highest customer concentration. In the positive *OM* subsample graph presented in Panel B, the profitability differences are much smaller across both *AGE* and *CC* quintiles, and *ROA* is marginally higher in the highest *CC* quintile in four of five *AGE* quintiles.

2.4.1.3 REGRESSION ANALYSES

We verify the net effect of customer concentration on profitability and costs in Table 2.5 which presents the average coefficients of Fama-MacBeth regressions using six firm operating characteristics as the dependent variables. Following Patatoukas (2012) the independent variables we use are customer concentration rank *Rank(CC)* and control variables for market value (*MV*), firm age (*AGE*), sales growth (*GROWTH*), an indicator variable for firms having more than one line of business (*CONGLO*), and financial leverage (*FLEV*). The full sample results in Panel A show that inclusion of negative operating margin firms has a profound effect on the empirical evidence about the relation between customer concentration and firm operations. Unlike Patatoukas' (2012, 373) results, customer concentration is negatively related to both *ROA* and *ROE* in the full sample. Customer concentration is also negatively related to asset turnover (*ATO*) and positively related to SG&A expenses. These results show how Patatoukas' (2012) results do not generalize to firms with operating losses and illustrate that the endogeneity of profitability can mask the full effect of customer concentration on firm profitability.

Panel B of Table 2.5 presents the same analysis for profitable firms only. For these firms and using the same set of control variables, we generally can confirm many of the findings in Patatoukas (2012). Customer concentration is positively related to *ROA* and *ROE* as well as profit margin (*PM*), but we do not confirm, in our larger sample of positive *OM* firms, that customer concentration has beneficial effects on asset turnover. In line with Patatoukas (2012) and arguments on the impact of customer power in Kelly and Gosman (2000), we find that suppliers with more concentrated customer bases report significantly lower gross margins. Patatoukas (2012) argues that the negative effects on gross margins can be offset if high *CC* firms spend less on SG&A expenses. As in Patatoukas (2012) we find this offsetting effect exists in this subsample. Positive operating margin firms with higher customer concentration tend to spend significantly less on SG&A expenses.

When we examine firms with negative operating margins in Panel C of Table 2.5, we can see that the relation between customer concentration and firm operating characteristics is markedly different than it is for firms with positive operating margins. In Panel C, we find that customer concentration has a negative effect on *ROE*, *ROA*, and profit margins (*PM*). Unlike the results for positive operating margin firms in Panel B, the negative impact of customer concentration on gross margins is not offset by lower SG&A expenses. In the SGA regression reported in Column 8, the coefficient on customer concentration is significantly positive.

To summarize, we expand upon one of the main tables in Patatoukas (2012, Table 2, Panel A) in Table 2.5. While we find generally consistent results regarding the effects of customer concentration in the subsample of positive operating margin firms, we find contrary results in the subsample of firms with negative operating margins. Furthermore, the coefficients on the rank of customer concentration in the negative operating margin subsample are larger in magnitude and of the opposite sign to those in the subsample of positive operating margin firms. When we decompose the sample by firm age in Panels D and E we find results that are generally consistent with our contention that removing negative operating margin firms from the full sample tends to filter the sample by firm age. In Panel E, we find that customer concentration adversely affects the profitability of young firms. Customer concentration is negatively related to *ROA* and *ROE* and positively related to SG&A expenses for young firms. For mature firms (Panel D) the effects of customer concentration on *ROA*, *ROE* and *SGA* are insignificant. The adverse effects of customer concentration on young firms tend to dominate the full sample estimates. We specifically examine the effects of customer concentration and financial distress for young firms below in Section 2.4.3.1.

2.4.1.4 CHANGES IN CUSTOMER CONCENTRATION

To test the causal relation between customer concentration and operating characteristics, we regress changes in *ROA* and *SGA* on changes in customer concentration and the set of control variables in Patatoukas (2012). These results are presented in Table 2.6. As in Patatoukas (2012) we calculate the effects of changes in the rank of customer concentration to better define the direction of causality between customer concentration and firm operating characteristics. Patatoukas (2012) finds that changes in customer concentration, *Rank(ΔCC)*, have a significantly positive effect on changes in *ROA* (*ΔROA*), and a significantly negative effect on changes in SG&A expenses (*ΔSGA*) for firms with positive operating margins.[9] Panel A of Table 2.6 estimates regressions using our full sample and finds results that contradict those in Patatoukas (2012). Specifically, changes in customer concentration rank are significantly negatively related to changes in ROA and significantly positively related to changes in SG&A expenses. These results generally confirm the contentions that we derive on customer concentration and firm performance from the static analysis in Tables 2.4 and 2.5.

We next support our ideas on the life-cycle effects of customer concentration on firm performance by splitting the sample into young and mature firms and examining the two subsamples separately. First, in Panel B, we examine the young firms in the sample and find causal results similar to those in the full sample. *Rank(ΔCC)* adversely impacts future operating

[9] Patatoukas (2012) also finds a positive relation between changes in customer concentration and changes in *ROE*. We do not include *ROE* changes as the specification in Patatoukas (2012) contains no leverage control. When we estimate the Table 6 regressions for changes in *ROE* with a leverage control variable, the coefficients on changes in customer concentration are insignificantly negative.

performance (*ΔROA*) for young firms. The evidence suggests that one of the major drivers of this deteriorating operating performance is an increase in SG&A expenses. We suggest, and in the next section provide evidence that, Patatoukas (2012) is correct in that eventually in the life-cycle of the firm, operating efficiencies can be achieved from customer concentration. However, these gains do not seem to be as direct as those illustrated in Patatoukas'(2012) sample. In particular, young firms seem to face greater costs adjusting to a concentrated customer base. The coefficients of *Rank(ΔCC)* for mature firms (Panel C) are statistically insignificant. Thus, we do not claim that the negative effects of customer concentration on firm performance are universal across all firms. Rather, as illustrated by the size of the coefficients on the variable *Rank(ΔCC)* in Panel B, the effects seem to be concentrated in younger firms.

The results in Tables 2.4, 2.5, and 2.6 show that customer concentration doesn't always improve firm performance. Rather, customer concentration adversely impacts firm operating performance in the full sample. Our results suggest that the negative impact of customer concentration on firm performance manifests itself most severely on firms with negative operating margins and on younger firms.

2.4.2 CUSTOMER CONCENTRATION AND FIRM COST STRUCTURE

2.4.2.1 OPERATING PERFORMANCE OF YOUNG FIRMS

To better understand how customer concentration affects the operations of young firms, we replicate another Patatoukas (2012) test and examine the effect of customer concentration on specific operating efficiency measures. Panel A of Table 2.7 examines the effect of customer concentration on young firms' inventory, asset turnover components, advertising, and SG&A

expenses while controlling for firm size, age, sales growth, lines of business and financial leverage. In Panel A, we find that Patatoukas' (2012) conclusions about operating efficiency are generally correct. Having large and important customers allows suppliers to reduce inventory holding costs (*IHLD*) and improve inventory turnover. The ties that develop between the firm and its major customers allow the firm to effectively manage its inventory. This finding still leaves the firm susceptible to an undiversified customer base, in that lower demand from major customers may not be offset by countervailing increases in demand from other customers. However, it does suggest that once an order from a major customer has been received, the firm can fulfill the order relatively efficiently. With the exception of cash turnover, the other components of asset turnover are either consistent with the contention that customer concentration improves operating efficiency or insignificant. However, customer concentration has a significantly negative effect on cash turnover.[10]

We also find, consistent with Patatoukas (2012), that young firms' advertising expenses as a percentage of sales are negatively related to customer concentration. Although a relatively small component of firm costs, examining the effects of customer concentration on advertising expenses is interesting because the argument is so intuitive. Having developed a relationship with major customers, it makes sense that the firm spends relatively less trying to attract new customers. However, the reduction in advertising expenses is not the driver of the customer concentration – SG&A expense relation. Patatoukas (2012) finds, as we do, advertising expense is too small to explain the customer concentration – SG&A expense relation in his sample of positive operating margin firms. While we agree that advertising costs are relatively unimportant, we add a specification using *SGA* as the dependent variable to highlight the fact that the

[10] In unreported results we find that cash holdings increase with customer-base concentration. This finding is consistent with high customer concentration firms holding higher precautionary cash balances, which impairs their cash turnover.

customer concentration – SG&A expense relation is very different for young firms than it is for positive operating margin firms. Customer concentration can help elements of young firms' operations, but having a concentrated customer base results in significantly higher costs for these firms, a finding that we explore in more detail below.

In Panel B of Table 2.7 we examine the effect of customer concentration on young firms' cash management and receivables. We construct this analysis to show how some of the conclusions in Patatoukas (2012) do generalize to younger, less profitable firms, yet others do not. We examine the effects of customer concentration on the ratio of accounts receivable to sales (*DAYS_RCVBLE*), the ratio of accounts payable to cost of goods sold (*DAYS_PAYABLE*), the ratio of inventory to cost of goods sold (*DAYS_INVT*), the total of the cash conversion elements measured as receivables less payables plus inventory (*TOTCYCLE*), and the provision for doubtful accounts relative to accounts receivable (*DOUBTFUL*). We find that customer concentration increases days receivable, increases days payable, and is not significantly related to days of inventory. Overall, the effects of customer concentration on young firms' cash management components are different from those in Patatoukas' (2012) sample of positive operating margin firms. However, the total effect (*TOTCYCLE*) is negative, consistent with Patatoukas (2012). We also find that doing business with large customers reduces the provision for doubtful accounts.

Our examination of specific components of young firms' operating performance often produces results that are consistent with the surprising findings in Patatoukas (2012), that customer concentration can lead to operating efficiencies. Despite the overall adverse effects of customer concentration on young firms, we find that young firms accrue certain benefits from their relationships with major customers, particularly in their working capital management.

Nevertheless, we find that customer concentration so adversely affects SG&A expenses, an important component of operating expenses, that neither the reductions in advertising costs nor the improvements in working capital management offset the high SG&A expenses that come with customer concentration. We next proceed to examine the effects of customer concentration on the economics of the major components of firm costs below.

2.4.2.2 ELASTICITY OF OPERATING EXPENSES, OPERATING LEVERAGE, AND DEMAND UNCERTAINTY

In Section 2.2 we develop contentions regarding how a firm's customer base affects its cost structure, particularly, given the focus on operating efficiency, on the patterns of cost-stickiness in SG&A expenses. We show in Panel A of Table 2.8 how operating expenses break down for the average firm in our sample. Cost of goods sold average 64.4% of sales and SG&A expenses average 39.1%. As a component of SG&A expenses, advertising expense averages only 1.0% of sales. This figure indicates why the improvements in advertising expenses customer concentration allows do not necessarily translate into operating profitability.

Panel B of Table 2.8 examines the elasticity with respect to sales for the two major components of firm operating costs, cost of goods sold and SG&A expenses, across five different quintiles of customer concentration. Our examination of cost elasticity is derived from the cost-stickiness arguments of Anderson et al. (2003) and Baumgarten, Bonenkamp and Homburg (2010). Cost elasticity with respect to sales measures the percentage variation in costs relative to percentage variation in firm sales. We find that for all firms, costs are inelastic, varying less than one-to-one with sales variation. We also find a distinct pattern in cost elasticity: the higher a firm's customer concentration, the lower its cost elasticity. The differences are significant across the concentration quintiles, and particularly dramatic for SG&A elasticity. All SG&A costs are sticky in the sense that they are inelastic and thus tend to be less variable than firm sales. SG&A cost elasticity is 0.79 for firms in the lowest customer concentration quintile falling to 0.56 in the highest customer concentration quintile. Economically, we infer from this data that firms with higher customer concentration make greater investments in customer-specific SG&A expenses. They do this to capture the potential operating efficiencies documented in Section 4.2.1. Such investments allow firms to more easily expand their operations when major customers increase their demand (Banker et al. 2012). However, when demand falls, these customer-specific investments are less transferable to other customers than more general costs.

We contend that high customer concentration firms make customer-specific investments that can lead to greater operating profitability should the relationship succeed. However, such firms may face greater risks should sales to major customers decline. To understand how sales risk varies with customer concentration we examine demand uncertainty. Banker et al. (2012) postulate that demand uncertainty, measured by the volatility of sales, can lead to lower cost elasticity. They argue that firms facing high demand uncertainty make greater fixed-cost investments in order to capitalize in high-demand states. Firms that do not make such investments would, due to high short-term adjustment costs, not be able to capitalize on the high profits available in high demand states. Their arguments would dovetail into our findings on cost elasticity and customer concentration if demand uncertainty increases with customer concentration.

When we examine demand uncertainty across customer concentration quintiles in Panel C of Table 2.8, we find that demand uncertainty significantly increases from the lowest customer concentration quintile (0.19) to the highest customer concentration quintile (0.32). If one considers firm sales in a portfolio context, then this finding makes sense. Firms with a few major customers are relatively undiversified in sales and thus, customer-specific demand shocks are more likely to impact sales compared to the impact of customer-specific demand shocks on the revenues of firms with diversified customer bases. The monotonically increasing relation we find between customer concentration and demand uncertainty complements the arguments of both Patatoukas (2012) and Banker et al. (2012). If the firm –major customer relationship encourages firms to make customer-specific investments, they will have more inelastic cost structures and potentially higher profits should the relationship succeed. However, the higher fixed costs for firms with concentrated customer bases could also lead to a greater probability of financial distress for these firms. We investigate this issue in our final empirical tests below.

2.4.3 CUSTOMER CONCENTRATION AND FIRM FAILURE

Having observed that customer concentration in young, unprofitable firms implies that such firms have higher demand uncertainty and lower cost elasticity, we next investigate the relation between customer concentration (*CC*) and probability of failure at different stages of a firm's life. For this purpose we conduct two types of analyses, both follow established methods to highlight the incremental power of customer concentration to explain financial distress. Section 2.4.3.1 replicates the IPO failure model of Demers and Joos (2007) while Section 2.4.3.2 replicates the firm failure model of Campbell et al. (2008).

2.4.3.1 IPO FAILURE

Earlier we speculate that customer concentration could be risky for young firms. In this section we support this contention by analyzing whether our measure of customer concentration *Rank(CC)* is related to the probability of firm failure. Our first test is a replication of the determinants of IPO failure procedure in Demers and Joos (2007). To estimate the failure probability for IPOs, we use the 1980-2000 data from Demers and Joos (2007) and calculate the probability of failure for 2,431 IPOs over the next 5 years (to match the Demers and Joos (2007) framework) and the next 7 years (to correspond to our definition of young firms). To do this we use the same CRSP delisting classification codes used in their paper. Therefore, the dependent variable in Table 2.9 is a discrete dependent variable that takes on a value of 1 if the IPO fails within 5 or 7 years after the firm goes public.

We then merge the Demers and Joos (2007) data with our customer concentration data. Because not all firms in the Demers and Joos (2007) sample have customer concentration data, our sample is smaller than that in Demers and Joos (2007) consisting of 2,431 firms with customer concentration data relative to their 3,574 firms. By extending the definition of IPO failure by an additional two years, we find that a total of 415 firms in our sample fail within 7 years after their IPO, compared to 292 that fail within 5 years of going public. Our 7 year failure rate is 2.44% per year, slightly lower than the annual failure rate of 2.70% in Demers and Joos (2007).

Demers and Joos (2007) define failure using the CRSP delisting codes for liquidation (400) and delistings (500) with exclusions for firms that switch exchanges (501) or delist at the firm's request (503). IPO failure is thus defined as firm liquidation or involuntary failure to maintain a listing. Besides default, failure to maintain listing could occur for several reasons including deficiencies in market maker participation or the number of shareholders. The price of the issue could also fall below the exchange minimum or the firm could be delisted because it is delinquent in filing required documents or paying exchange fees.

Following Demers and Joos (2007), the variables we use for static IPO failure prediction are the following: *UNDERWRITER* is the Carter-Manaster underwriter reputation ranking. *INC_AGE* is the natural log of the age of the firm measured from the date of incorporation. We use age from incorporation in this analysis, rather than *AGE* of the firm as a public entity to conform with the definitions in Demers and Joos (2007).[11] *VC* is an indicator variable set equal to 1 if the firm is venture-capital-backed at the time of IPO. *AUDITOR* is an indicator variable set equal to 1 if the firm has a Big 8 or a national firm auditor. *IPO_MARKET* is the average initial return to all IPOs in the 90 days prior to the firm's IPO. *FIRSTDAYRET* is the first-day initial return: closing price on the IPO date less offer price as percentage of the offer price. *OFFERPRICE* is the CPI-adjusted IPO offer price. *IPO_LEV* is equal to total liabilities divided by the sum of total assets plus the proceeds raised at the date of IPO. *RD* is the natural log of one plus R&D expense at the time of IPO. *LSGA* is the natural log of selling, general, and administrative expenses at the time of IPO. *GM* is the gross margin ratio at the time of IPO. *DEFICIT* is the negative log of retained earnings if the firm is in a deficit position, 0 otherwise. *SALES* is the natural log of one plus sales at the time of IPO.

A hypothesis of this paper is that young firms, such as recently-public IPOs, face greater risk from customer concentration than more mature firms. In Table 2.7 we show that customer concentration can, in some ways, improve the operating efficiency of the firm. However, this operating efficiency improvement comes at the cost of greater customer-specific investments.

[11] Their choice is undoubtedly driven by the fact that, as all IPOs start as newly-public firms, *AGE* does not vary across firms.

These investments, by definition, are less transferable to other customers should the relationship with a major customer fail. This risk could result in the liquidation or delisting of the firm due to financial distress. Thus, we contend that young firms face a trade-off between the efficiency gains that can arise from customer concentration and a higher likelihood of financial distress. To test this contention, we replicate the Demers and Joos (2007) failure prediction model.

Table 2.9 presents the logistic estimation of IPO failure risk. We regress the qualitative variable for IPO failure over the next 5 and 7 years against the set of Demers and Joos (2007) predictive variables in Columns (1) and (3). Within our subsample we find results that are consistent with Demers and Joos (2007) who find that research and development expenses and sales are significantly negatively related to IPO failure. In addition, leverage and SG&A expenses are positively related to the probability of failure. The finding that failure is positively related to SG&A expenses is significant given our evidence that customer concentration in young firms is related to higher customer-specific SG&A expenses. Columns (2) and (4) of Table 2.9 include our measure of customer concentration, *Rank(CC)*, as a regressor. Customer concentration is significantly positively related to the probability that an IPO firm fails over the next 5 and 7 years. Thus, the disclosure of customer information is useful in predicting firm distress risk. Young firms with higher customer concentration are more likely to face financial distress, a result we attribute to the greater customer-specific investments made by these firms. Note that both the coefficient size and statistical significance of *Rank(CC)* is less in the 7 year regression compared to the 5 year failure prediction regression. This finding is consistent with our conjecture that customer concentration is particularly risky for young firms, but as the relationship matures, the relationship can yield the operational efficiencies documented in Patatoukas (2012).

2.4.3.2 BROAD FAILURE

The analysis in Table 2.9 is a static analysis that predicts only if an IPO eventually fails over the next 5 or 7 years. We can get a better idea of the impact of customer concentration on failure risk by analyzing our full sample on a year-by-year basis. To accomplish this we run a dynamic model predicting firm failure for all firms over the period between 1980 and 2007. The dependent variable is the dichotomous outcome variable: firm failure or no failure in a particular firm-year. To predict failure we start with the framework in Campbell, Hilscher, and Szilagyi (2008) who use financial and market variables to predict default. We use their nomenclature for the set of predictive variables: total liabilities to the market value of assets (*TLMTA*), net income to market value of assets (*NIMTA*), the standard deviation of stock returns over the previous three months (*SIGMA*), market to book ratio (*MB*), relative size of the firm as measured by the log of the market value of the firm relative to the log of market value of the S&P 500 Index (*RSIZE*), the ratio of firm cash holdings to the market value of total assets (*CASHMTA*), and the prior month's stock returns relative to the S&P 500 Index returns over the same time period (*EXRET*).[12]

Campbell et al. (2008) find that this set of independent variables is able to predict default. We examine this finding for our sample in Column (1) of Table 2.10. In this specification, we use the independent variables proposed by Campbell et al. (2008) to estimate the failure probability for 48,948 firm-year observations. For our sample of firms with customer concentration data, we find results that confirm the Campbell et al. (2008) model of failure predictability. The model has a psuedo-R^2 of 20.9% and all of the independent variables are significant with the expected sign.

[12] All financial variables are observable 12 months prior to the failure event to avoid endogenous relations being recorded between the predictive variables and the failure event.

In Column (2) of Table 2.10 we add the measure of customer concentration, *Rank(CC)*, to the regression. In Column (3) of Table 2.10 we include the interaction variable *AGE* × *Rank(CC)* to test our contention that if a young firm survives, it can successfully manage the relationship with major customers, eventually improving operating performance and lowering failure risk.

We find significant results from including the customer concentration variables. The coefficient on *Rank(CC)* in Column (2) is positive and significant. This result demonstrates that customer concentration captures failure-related information that is not already reflected in the existing predictors of firm failure. In Column (3) we find that increasing customer concentration significantly increases the risk of failure for all firms, but that this effect declines as the firm ages. Column (4) estimates the effects of the customer concentration variables without using the Campbell et al. (2008) control variables to demonstrate that interactions between customer concentration and the control variables are not driving our conclusions.

Overall, the results in Tables 2.9 and 2.10 support our hypothesis that the relation between customer concentration and firm profitability is dynamic and entails significant failure risk for young firms. Young firms with higher customer concentration exhibit weaker operating performance and incur a significant increase in failure risk. However, if the firm survives these risky early years then, consistent with Patatoukas (2012), customer concentration can improve the firm's operations. To fully understand the effects of customer concentration on firm operations, we need to recognize that observing only firms with positive operating margins, censors many younger firms that are not yet profitable and face significant failure risk from customer concentration.

2.5 CONCLUSION

All supplier firms face the dilemma of whether to cater to a few dominant customers or whether to seek a more diversified customer base. A long line of research dating back to Galbraith (1952) suggests that major customers are threats to firms' operating profits because, as important customers with significant bargaining power, they can demand price discounts and other concessions from suppliers. In a recent study, Patatoukas (2012) challenges this view. Rather than looking at industry-level concentration, as in previous studies, he creates a firm-specific measure of customer concentration and finds that profitable firms with high customer concentration benefit from the customer-specific investments they have undertaken through improved operating efficiencies and reduced SG&A expenses.

In this paper we use a recently expanded data set of sales to major customers to study the economics of supplier firms. By examining all such firms, whether profitable or not, we outline a dynamic life-cycle hypothesis wherein young unprofitable firms face considerable profitability and financial distress risks from their relationships with their major customers. However, if the relationship survives, these firms can eventually benefit from some of the operating efficiencies documented in Patatoukas (2012). We find that in the subsample of firms with positive operating margins, the correlation between *ROA* and customer concentration is positive, while the correlation between SG&A expenses and customer concentration is negative. However, in the subsample of firms with negative operating margins the relations reverse as the correlation between *ROA* and customer concentration is negative, while the correlation between SG&A expenses and customer concentration is positive. The adverse impact of customer concentration on profits is particularly dramatic for young firms, who tend to be less profitable. The exclusion of firms with negative operating margins from an analysis investigating the impact of customer concentration on the operations of firms thus introduces a bias. Firms with positive operating margins appear to be the set of firms where customer concentration effects are benign or favorable, while the adverse effects of customer concentration are strongly evident in young and unprofitable firms.

We find that many of the operational efficiencies documented in Patatoukas (2012) exist, even for young firms, but these benefits are outweighed by the negative impact of customer concentration on SG&A expenses. We conjecture that young firms with major customers make customer-specific investments, particularly in SG&A expenses, and these customer-specific investments are harder to transfer to other customers should the customer-supplier relationship deteriorate. We find that firms with higher customer concentration have more inelastic SG&A expenses and costs of goods sold, a finding which supports our conjecture regarding customer-specific investments.

Firms with higher customer concentration also face greater demand uncertainty as they are more exposed to idiosyncratic demand shocks from their major customers. Banker et al. (2012) theorize that firms facing higher demand uncertainty will make investments that enable them to make greater profits during high demand states of the world. However, these investments are harder to transfer to alternative customers, and though they can produce operating efficiencies should the relationship be successful, we find that they can increase the risk of financial distress, particularly for young firms. As the relationship between young firms and major customers successfully matures, these risks diminish and greater operating efficiencies have the potential to be realized.

Customer concentration gives rise to customer-specific investments that cause costs to be "sticky" or inelastic, increasing operating leverage. This operating leverage effect enhances profitability in profitable periods while increasing the firm's losses in unprofitable periods, consequently increases the risk of financial distress. Customer concentration brings both costs and benefits to the firm. Identifying these costs, by analyzing the full range of firm profitability, allows us to reconcile the conventional wisdom with Patatoukas' (2012) results.

Table 2.1: Variable definitions

Table 2.1 describes the main variables used in this study. Supplier and customer firm characteristics are defined as in Patatoukas (2012). The customer-base concentration variable (CC) measures the extent to which a firm's customer base is more or less concentrated. In addition to describing supplier firms' characteristics we also summarize their major customers' firm level attributes. In order to do so, we calculate weighted averages of the respective characteristics for each supplier firm's major customers, using sales shares as the weights. CMV is the weighted-average market value of identifiable major customers, CAGE is the weighted-average age of a supplier's major customers and CSG is the weighted-average sales growth of identifiable major customers. Supplier-customer relationships are obtained from the COMPUSTAT Customer Segment files. Market equity prices, accounting profitability measures and other financial statement items are from the CSRP-COMPUSTAT merged database. In this paper we also run two sets of failure prediction regressions. In Table 2.9, we replicate Demers and Joos (2007) to assess the impact of customer base concentration on IPO failure. Variables used in predicting IPO failures with the Demers and Joos (2007) logistic model are defined as in Demers and Joos (2007). In Table 2.10, we run dynamic logistic regressions as in Campbell, Hilscher and Szilagyi (2008) (hereafter CHS (2008)). Variables used in predicting firm failures with the dynamic CHS (2008) failure model are defined as in CHS (2008).

Variable	Definition
Supplier Firm Characteristics as defined in Patatoukas (2012)	
CC	Customer-base concentration measure ($0 \leq CC \leq 1$)
ΔCC	Annual change in CC
MV	Market value of equity
AGE	Firm age of the supplier firm, measured from the time of the firm's Initial Public Offering (IPO)
GROWTH	Annual sales growth
ROA	Income before extraordinary items / Beginning of year book value of assets
ROE	Income before extraordinary items / Beginning of year book value of equity
SGA	Selling, general, and administrative expenses / Sales
GM	Gross margin of the supplier firm: (Sales - Cost of goods sold) / Sales
PM	Profit margin of the supplier firm: Income before extraordinary items / Sales
IHLD	Inventory / Beginning of year book value of assets
ATO	Asset turnover of the supplier firm: Sales / Beginning of year book value of assets
FLEV	Beginning of year book value of assets / Beginning of year book value of equity
CONGLO	An indicator variable equal to 1 if the supplier firm reports at least two business segments
Customer Firm Characteristics as defined in Patatoukas (2012)	
CMV	Weighted average market value of equity of identifiable customers
CAGE	Weighted average firm age of identifiable customers
CCSALES	Sales to major customers / Total sales of the supplier firm
CSG	Weighted average annual sales growth of identifiable customers
Default Prediction Variables Used in Table 2.9, as defined in Demers and Joos (2007)	
RANK(CC)	Decile rank of the firm at the time of its IPO based on the customer-base concentration score
VC	An indicator variable equal to 1 if the firm is venture capital backed
UNDERWRITER	Carter-Manaster underwriter reputation ranking
AUDITOR	An indicator variable equal to 1 if the firm has Big 8 or a national firm auditor, 0 otherwise
IPO_MARKET	Initial return to all IPOs in the 90 days prior to the firm's IPO
OFFERPRICE	Inflation-adjusted IPO offer price
FIRSTDAYRET	First-day initial return: closing price on the IPO date less offer price as % of offer price
INC_AGE	Natural log of one plus the firm age, where firm age is measured from the time of incorporation

RD	Natural log of one plus R&D expense
LSGA	Natural log of selling, general, and administrative expenses
DEFICIT	Negative natural log of retained earnings if the firm is in a deficit position, 0 otherwise
SALES	Natural log of (1+Sales)
IPO_LEV	Total liabilities / (Total assets + the proceeds raised at the time of IPO)
Default Prediction Variables Used in Table 2.10, as defined in Campbell Hilscher and Szilagyi (2008)	
TLMTA	Total liabilities / Market value of total assets*
CASHMTA	Cash and short-term assets / Market value of total assets*
SIGMA	Standard deviation of the firm's daily stock returns over the past 3 months
MB	Market-to-Book ratio
RSIZE	Log ratio of market capitalization to S&P 500 index
PRICE	Log price per share
EXRET	Monthly log excess return on equity relative to S&P 500 index

*We follow CHS (2008) and adjust the market value of total assets. Adjusted market value of total assets is equal to the book value of total assets as measured in Compustat quarterly (data item: ATQ) plus ten percent of the difference between the market and book values of equity. The procedure increases total asset values that are extremely small and are likely mismeasured.

Table 2.2: Descriptive statistics for the main variables

Table 2.2 reports the mean, standard deviation, skewness, median, 25th percentile, and 75th percentile values of the main variables used in this study. MV and CMV are in millions of US dollars while AGE and CAGE are in years. The descriptive statistics are based on the sample used in the regression analyses. Our sample includes firms from 1977 to 2007. We only include non-financial firms which have non-missing customer-base concentration measures, non-missing accounting profitability measures, and non-negative book values of equity. Panel A describes our full sample of 49,760 supplier firm year observations. Panel B divides the full sample into two groups: supplier firm year observations with positive operating margins and supplier firm year observations with negative operating margins. The mean differences between the two groups and the corresponding t-statistics are reported on the right-hand side of Panel B. Panel C divides the full sample into two groups: supplier firm year observations where the firm age is less than or equal to seven years and supplier firm year observations where the firm age is greater than seven years. The mean differences between the two groups and the corresponding t-statistics are reported on the right-hand side of Panel C.

Panel A: Full sample

Variable	Observations	Mean	Std. Dev.	Skewness	25th Percent.	Median	75th Percent.
CC	49,760	0.101	0.147	2.930	0.014	0.046	0.125
ΔCC	43,048	-0.003	0.094	-0.534	-0.018	0.000	0.015
MV	49,335	805.6	3,886.7	12.0	16.5	65.7	318.6
AGE	49,760	10.3	9.0	1.3	3.0	7.0	15.0
GROWTH	49,667	0.22	0.62	4.60	-0.03	0.10	0.29
ROA	49,760	-0.01	0.22	-2.77	-0.05	0.03	0.09
ROE	49,760	-0.03	0.51	-2.90	-0.10	0.07	0.18
SGA	49,760	0.39	0.63	6.12	0.14	0.24	0.40
IHLD	49,410	0.16	0.15	0.83	0.03	0.14	0.26
TLMTA	49,256	0.35	0.24	0.51	0.15	0.31	0.52
CASHMTA	49,254	0.11	0.14	2.72	0.02	0.06	0.14
CMV	20,714	37,121	57,333	2.7	3,338	14,414	43,453
CAGE	20,762	22.1	10.9	-0.2	15.0	23.0	30.0
CCSALES	49,760	0.33	0.24	0.81	0.13	0.27	0.49
CSG	20,508	0.11	0.21	2.94	0.02	0.09	0.17

Panel B: Profitable firm years (positive-OM sample) vs. unprofitable firm years (negative-OM sample)

	Positive OM sample				Negative OM sample				Mean	
Variable	Observations	Mean	Std. Dev.	Median	Observations	Mean	Std. Dev.	Median	differences	(t-stat)
CC	38,924	0.090	0.133	0.040	10,836	0.142	0.184	0.072	-0.052	(-27.63)
ΔCC	33,841	-0.001	0.078	0.000	9,207	-0.010	0.136	-0.002	0.009	(5.85)
MV	38,589	990.2	4,344.9	91.9	10,746	143.0	999.0	23.2	847.2	(35.11)
AGE	38,924	11.1	9.4	8.0	10,836	7.3	6.7	5.0	3.9	(48.63)
GROWTH	38,902	0.22	0.49	0.12	10,765	0.21	0.93	-0.03	0.01	(0.92)
ROA	38,924	0.06	0.10	0.05	10,836	-0.28	0.29	-0.20	0.34	(120.82)
ROE	38,924	0.11	0.31	0.11	10,836	-0.51	0.74	-0.34	0.63	(86.44)
SGA	38,924	0.23	0.15	0.20	10,836	0.96	1.15	0.60	-0.73	(-65.67)
IHLD	38,627	0.17	0.15	0.15	10,783	0.14	0.15	0.10	0.02	(15.16)
TLMTA	38,534	0.36	0.23	0.33	10,722	0.30	0.24	0.24	0.06	(22.81)
CASHMTA	38,532	0.09	0.11	0.05	10,722	0.17	0.21	0.09	-0.08	(-38.58)
CMV	16,527	38,193	58,279	14,759	4,187	32,889	53,231	12,317	5,303	(5.65)
CAGE	16,560	22.5	10.7	23.0	4,202	21.0	11.4	22.0	1.5	(7.68)
CCSALES	38,924	0.31	0.24	0.25	10,836	0.40	0.26	0.35	-0.09	(-32.18)
CSG	16,368	0.12	0.20	0.09	4,140	0.10	0.24	0.08	0.02	(3.86)

Panel C: Mature firms vs. young firms

Variable	Mature firms sample				Young firms sample				Mean	
	Observations	Mean	Std. Dev.	Median	Observations	Mean	Std. Dev.	Median	differences	(t-stat)
CC	24,628	0.089	0.135	0.039	25,132	0.113	0.157	0.053	-0.024	(-18.53)
ΔCC	21,442	0.001	0.078	0.000	21,606	-0.007	0.107	0.000	0.008	(8.58)
MV	24,476	1,108.7	4,678.3	87.0	24,859	507.2	2,872.5	50.1	601.6	(17.18)
AGE	24,628	17.1	8.3	15.0	25,132	3.6	2.0	3.0	13.4	(246.57)
GROWTH	24,607	0.13	0.42	0.08	25,060	0.31	0.75	0.15	-0.18	(-33.61)
ROA	24,628	0.02	0.16	0.04	25,132	-0.05	0.26	0.02	0.06	(32.64)
ROE	24,628	0.03	0.42	0.09	25,132	-0.08	0.58	0.05	0.11	(24.57)
SGA	24,628	0.29	0.44	0.21	25,132	0.49	0.76	0.28	-0.19	(-34.24)
IHLD	24,492	0.18	0.14	0.16	24,918	0.15	0.15	0.11	0.03	(22.27)
TLMTA	24,430	0.38	0.23	0.35	24,826	0.33	0.24	0.27	0.05	(23.51)
CASHMTA	24,428	0.10	0.13	0.05	24,826	0.12	0.16	0.06	-0.02	(-14.31)
CMV	10,769	40,337	58,619	16,246	9,945	33,638	55,701	11,767	6,699	(8.43)
CAGE	10,790	23.5	10.7	24.0	9,972	20.6	10.8	22.0	2.9	(19.38)
CCSALES	24,628	0.31	0.23	0.25	25,132	0.35	0.25	0.30	-0.05	(-20.82)
CSG	10,694	0.11	0.18	0.09	9,814	0.12	0.23	0.09	-0.02	(-6.38)

Table 2.3: Pearson (Spearman) correlations above (below) the main diagonal

Table 2.3 reports the Pearson and Spearman correlation coefficients for the main variables used in our study. Panel A employs the full sample, whereas Panels B and C report the correlations for firms with positive operating margins and firms with negative operating margins, respectively. All correlation coefficients are statistically significant at the one percent level (significant at $p < 0.01$) except for the correlations denoted by "a" (significant at $p < 0.05$) and the ones denoted by "b" (statistically insignificant).

Panel A: Full sample

	CC	*MV*	*AGE*	*GROWTH*	*ROA*	*ROE*	*SGA*	*TLMTA*	*CASHMTA*
CC		-0.11	-0.10	0.08	-0.11	-0.08	0.18	-0.12	0.10
MV	-0.13		0.19	0.06	0.25	0.22	-0.11	-0.28	-0.13
AGE	-0.11	0.18		-0.21	0.16	0.12	-0.18	0.14	-0.08
GROWTH	0.00[b]	0.18	-0.18		-0.04	-0.02	0.07	-0.14	-0.07
ROA	-0.10	0.34	0.12	0.32		0.75	-0.56	-0.03	-0.09
ROE	-0.11	0.34	0.12	0.31	0.92		-0.38	-0.05	-0.05
SGA	0.05	-0.19	-0.21	-0.06	-0.36	-0.37		-0.40	0.28
TLMTA	-0.14	-0.27	0.15	-0.21	-0.23	-0.15	-0.25		-0.20
CASHMTA	0.11	-0.05	-0.05	-0.08	-0.04	-0.09	0.21	-0.27	

Panel B: Positive-OM sample

	CC	*MV*	*AGE*	*GROWTH*	*ROA*	*ROE*	*SGA*	*TLMTA*	*CASHMTA*
CC		-0.10	-0.09	0.08	0.03	0.01	-0.04	-0.09	0.10
MV	-0.12		0.17	0.04	0.21	0.15	-0.05	-0.31	-0.12
AGE	-0.09	0.17		-0.21	-0.04	0.00[b]	-0.12	0.11	-0.02
GROWTH	0.03	0.12	-0.23		0.16	0.11	0.02	-0.13	-0.06
ROA	0.01[a]	0.24	-0.03	0.35		0.63	-0.05	-0.44	0.03
ROE	-0.02	0.25	-0.01	0.34	0.89		-0.06	-0.23	-0.01[b]
SGA	-0.07	-0.09	-0.11	0.02	-0.01[a]	-0.09		-0.37	0.24
TLMTA	-0.10	-0.29	0.12	-0.24	-0.52	-0.33	-0.35		-0.22
CASHMTA	0.10	-0.05	-0.02	-0.04	0.09	-0.02	0.24	-0.28	

Panel C: Negative-OM sample

	CC	*MV*	*AGE*	*GROWTH*	*ROA*	*ROE*	*SGA*	*TLMTA*	*CASHMTA*
CC		0.01[b]	-0.06	0.09	-0.07	-0.02[a]	0.23	-0.16	0.01[b]
MV	0.01[b]		0.03	0.12	-0.04	0.01[b]	0.09	-0.42	0.03
AGE	-0.06	0.03		-0.24	0.19	0.10	-0.19	0.18	-0.08
GROWTH	0.00[b]	0.19	-0.20		-0.22	-0.13	0.11	-0.17	-0.08
ROA	-0.09	0.00[b]	0.22	-0.09		0.65	-0.45	0.19	0.12
ROE	-0.03	0.07	0.14	-0.05	0.84		-0.23	0.01[b]	0.16
SGA	0.17	0.14	-0.26	0.05	-0.49	-0.30		-0.51	0.22
TLMTA	-0.18	-0.43	0.18	-0.21	0.17	-0.06	-0.34		-0.13
CASHMTA	0.04	0.14	-0.05	-0.08	0.12	0.24	0.12	-0.15	

Table 2.4: Customer-base concentration sorts in different age and profitability groups

Table 2.4 reports time series averages for return on assets (ROA), return on equity (ROE) and selling, general and administrative expenses scaled by sales (SGA) for customer-base concentration portfolios. We sort stocks into quintiles each December from December 1977 to December 2007 based on their customer-base concentration values, obtained at the end of the previous year. We compute the mean (median) returns on assets (ROA), returns on equity (ROE) and selling, general and administrative expenses scaled by sales (SGA) for these quintile portfolios on an annual basis. We report the time series averages for ROA, ROE and SGA for all the quintiles for young and mature firms separately. H-L is the time series average of the difference between the highest customer-base concentration portfolio and the lowest customer-base concentration portfolio for each variable. Young firms are those that are aged less than or equal to seven years, and mature firms are those that are aged greater than seven years. Panel A reports results for all observations in CRSP-COMPUSTAT while Panel B reports results for only firms with positive operating margins. H-L time series averages that are statistically significant at the one percent level (significant at $p < 0.01$) are denoted with ***, those that are statistically significant at the five percent level (significant at $p < 0.05$) are denoted with **, and those that are statistically significant at the ten percent level (significant at $p < 0.10$) are denoted with *. H-L time series averages that are statistically insignificant are not marked.

Panel A: Full sample								**Panel B: Positive-OM sample**							
		Lowest CC	2	3	4	*Highest CC*	H-L			*Lowest CC*	2	3	4	*Highest CC*	H-L
Young Firms (AGE ≤ 7)	*ROA*	-0.68%	-3.23%	-4.40%	-5.61%	-8.86%	-8.18%***	Young Firms (AGE ≤ 7)	*ROA*	6.00%	6.14%	5.81%	5.85%	6.94%	0.94%***
		(3.42%)	(2.58%)	(2.10%)	(1.67%)	(0.61%)	(-2.81%)***			(5.31%)	(5.40%)	(5.42%)	(5.48%)	(6.14%)	(0.82%)***
	ROE	-0.53%	-6.41%	-8.83%	-10.16%	-14.36%	-13.83%***		*ROE*	11.26%	11.30%	10.06%	9.54%	12.58%	1.32%*
		(7.49%)	(5.26%)	(4.04%)	(3.59%)	(1.31%)	(-6.17%)***			(11.39%)	(11.19%)	(10.68%)	(10.62%)	(12.11%)	(0.72%)
	SGA	37.93%	42.41%	44.73%	48.11%	69.36%	31.43%***		*SGA*	26.08%	26.32%	25.76%	23.93%	22.72%	-3.36%***
		(26.42%)	(27.97%)	(28.64%)	(27.15%)	(29.04%)	(2.62%)***			(22.52%)	(23.43%)	(22.37%)	(21.23%)	(19.12%)	(-3.40%)***
Mature Firms (AGE > 7)	*ROA*	3.40%	2.71%	1.62%	1.18%	-0.53%	-3.93%***	Mature Firms (AGE > 7)	*ROA*	5.75%	6.17%	5.74%	5.66%	6.19%	0.44%**
		(4.75%)	(4.59%)	(4.08%)	(3.82%)	(3.31%)	(-1.44%)***			(5.50%)	(5.57%)	(5.26%)	(5.25%)	(5.47%)	(-0.03%)
	ROE	6.93%	5.13%	3.11%	1.79%	-1.52%	-8.45%***		*ROE*	11.62%	12.22%	10.97%	10.93%	10.26%	-1.36%**
		(10.75%)	(9.58%)	(8.50%)	(7.96%)	(6.53%)	(-4.22%)***			(12.15%)	(11.49%)	(10.81%)	(10.87%)	(10.46%)	(-1.70%)***
	SGA	26.07%	27.33%	28.49%	28.27%	37.11%	11.04%***		*SGA*	22.81%	22.33%	22.03%	20.91%	20.19%	-2.63%***
		(20.96%)	(21.62%)	(21.35%)	(19.92%)	(19.70%)	(-1.27%)*			(19.91%)	(19.91%)	(19.60%)	(18.28%)	(16.46%)	(-3.45%)***

Table 2.5: Customer-base concentration and supplier firm performance

Table 2.5 reports the results for Fama–MacBeth regressions. We run yearly cross-sectional regressions of accounting performance measures on the decile rank of customer-base concentration and control variables. Our sample includes firms from 1977 to 2007. We only include non-financial firms which have non-missing customer-base concentration measures, non-missing accounting profitability measures, and non-negative book value of equity. Panel A reports results for the full sample which includes both profitable and unprofitable firms, while Panel B reports results for the subset of firms that have positive operating margins, and Panel C reports the results for firms with negative operating margins. Panels D and E report the results using the samples of mature firms (AGE > 7) and young firms (AGE ≤ 7), respectively. We average the coefficients over time and report the means in the first rows and the corresponding Newey-West-adjusted t-statistics in the rows below in parentheses. Following Patatoukas (2012), we calculate the customer-base concentration measure (CC) as the sum of the squares of the sales shares of a supplier firm's major customers. The dependent variables include (1) return on assets (ROA), (2) return on equity (ROE), (3) asset turnover (ATO), (4) profit margin (PM), (5) gross margin (GM), and (6) the ratio of selling, general and administrative expenses to sales (SGA). Other control variables include the log of market value of equity (MV), the log of firm age (AGE), annual sales growth rate (GROWTH), the indicator variable that equals 1 if the firm reports at least two business segments (CONGLO), and the leverage ratio defined as book value of assets divided by book value of equity (FLEV). N is the number of firm-year observations used in the regression.

Panel A: Full sample

	(1) *ROA*	(2) *ROE*	(3) *ATO*	(4) *PM*	(5) *GM*	(6) *SGA*
Intercept	-0.158	-0.343	1.038	-1.104	0.274	0.987
	(-5.01)	(-3.46)	(3.57)	(-7.11)	(5.26)	(13.13)
Rank(CC)	-0.022	-0.039	-0.131	-0.245	-0.055	0.109
	(-3.85)	(-3.34)	(-8.90)	(-4.65)	(-7.82)	(3.84)
MV	0.030	0.058	-0.019	0.057	0.020	-0.034
	(11.69)	(13.69)	(-2.45)	(4.80)	(10.31)	(-4.64)
AGE	0.016	0.028	0.070	0.098	-0.014	-0.073
	(3.10)	(3.47)	(12.32)	(3.39)	(-2.08)	(-11.42)
GROWTH	0.006	0.033	0.372	0.010	0.024	0.027
	(0.53)	(1.30)	(7.76)	(0.56)	(3.87)	(2.59)
CONGLO	-0.004	-0.005	0.001	0.055	-0.054	-0.081
	(-1.61)	(-2.24)	(0.14)	(5.10)	(-20.61)	(-9.00)
FLEV	-0.002	-0.010	0.011	0.009	-0.005	-0.013
	(-2.12)	(-1.33)	(2.01)	(3.33)	(-8.00)	(-7.08)
Industry F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Avg. R^2	0.197	0.166	0.323	0.131	0.201	0.195
N	49,118	49,118	49,118	49,118	49,118	49,118

Panel B: Positive-OM sample

	(1) *ROA*	(2) *ROE*	(3) *ATO*	(4) *PM*	(5) *GM*	(6) *SGA*
Intercept	0.018	-0.095	1.374	-0.007	0.385	0.330
	(1.20)	(-0.20)	(5.72)	(-1.40)	(-6.56)	(-10.98)
Rank(CC)	0.017	0.033	-0.045	0.017	-0.014	-0.047
	(6.56)	(4.80)	(-2.22)	(15.00)	(-1.69)	(-5.46)
MV	0.014	0.030	-0.051	0.015	0.015	-0.007
	(11.61)	(10.68)	(-5.19)	(9.64)	(-7.64)	(-4.34)
AGE	-0.005	-0.006	0.041	-0.002	-0.024	-0.014
	(-1.42)	(-0.87)	(5.42)	(-0.72)	(-4.89)	(-4.79)
GROWTH	0.040	0.097	0.508	0.021	0.015	0.000
	(6.52)	(5.17)	(16.00)	(6.63)	(-3.26)	(-0.20)
CONGLO	-0.016	-0.028	-0.012	-0.013	-0.063	-0.036
	(-11.53)	(-13.74)	(-2.23)	(-10.84)	(-32.46)	(-27.95)
FLEV	-0.004	0.017	0.006	-0.004	-0.006	-0.005
	(-8.77)	(2.50)	(1.31)	(-12.82)	(-9.30)	(-9.34)
Industry F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Avg. R^2	0.219	0.175	0.366	0.174	0.383	0.322
N	38,542	38,542	38,542	38,542	38,542	38,542

Panel C: Negative-OM sample

	(1) *ROA*	(2) *ROE*	(3) *ATO*	(4) *PM*	(5) *GM*	(6) *SGA*
Intercept	-0.312	0.073	0.984	-1.584	0.168	0.984
	(-6.68)	(0.37)	(3.97)	(-3.27)	(2.30)	(4.89)
Rank(CC)	-0.062	-0.108	-0.378	-0.824	-0.139	0.454
	(-4.86)	(-3.52)	(-2.66)	(-8.13)	(-6.46)	(10.26)
MV	0.008	0.015	-0.029	-0.011	-0.002	0.008
	(2.18)	(2.50)	(-1.42)	(-0.51)	(-0.29)	(0.72)
AGE	0.040	0.062	0.047	0.305	0.008	-0.169
	(10.75)	(6.32)	(1.34)	(7.14)	(1.07)	(-9.99)
GROWTH	-0.035	-0.059	0.166	0.041	0.038	0.049
	(-3.03)	(-2.61)	(2.64)	(0.82)	(2.53)	(1.66)
CONGLO	0.023	0.055	0.053	0.257	-0.032	-0.240
	(3.19)	(2.60)	(0.80)	(4.86)	(-2.01)	(-7.20)
FLEV	0.001	-0.152	-0.006	0.038	-0.003	-0.025
	(0.47)	(-15.65)	(-0.29)	(3.44)	(-0.89)	(-2.56)
Industry F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Avg. R^2	0.288	0.452	0.42	0.278	0.279	0.326
N	10,572	10,572	10,572	10,572	10,572	10,572

Panel D: Mature firms (*AGE*>7)

	(1) *ROA*	(2) *ROE*	(3) *ATO*	(4) *PM*	(5) *GM*	(6) *SGA*
Intercept	-0.088	-0.226	1.203	-0.523	0.408	0.629
	(-1.34)	(-1.47)	(15.30)	(-2.81)	(18.57)	(8.73)
Rank(CC)	-0.004	-0.011	-0.071	-0.112	-0.043	0.023
	(-0.75)	(-0.90)	(-1.67)	(-2.63)	(-3.40)	(0.60)
MV	0.021	0.043	-0.029	0.032	0.020	-0.017
	(13.69)	(32.75)	(-5.31)	(4.12)	(10.78)	(-3.19)
AGE	0.010	0.017	0.106	0.074	-0.050	-0.084
	(1.03)	(0.61)	(11.28)	(3.58)	(-6.03)	(-8.58)
GROWTH	0.044	0.115	0.531	0.095	0.041	-0.017
	(3.70)	(5.10)	(9.60)	(5.71)	(4.96)	(-2.42)
CONGLO	-0.008	-0.018	-0.039	0.012	-0.041	-0.040
	(-5.11)	(-9.13)	(-1.72)	(2.36)	(-6.02)	(-5.05)
FLEV	-0.003	0.002	0.004	0.001	-0.004	-0.007
	(-3.61)	(0.37)	(0.54)	(0.80)	(-4.29)	(-4.27)
Industry F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Avg. R^2	0.234	0.208	0.393	0.166	0.280	0.239
N	24,455	24,455	24,455	24,455	24,455	24,455

Panel E: Young firms (*AGE*≤7)

	(1) *ROA*	(2) *ROE*	(3) *ATO*	(4) *PM*	(5) *GM*	(6) *SGA*
Intercept	-0.160	-0.335	1.132	-1.062	0.289	0.979
	(-4.70)	(-3.20)	(3.62)	(-7.27)	(5.22)	(11.70)
Rank(CC)	-0.038	-0.062	-0.184	-0.368	-0.067	0.179
	(-3.84)	(-3.64)	(-11.38)	(-4.93)	(-4.91)	(5.88)
MV	0.043	0.081	-0.009	0.093	0.024	-0.058
	(8.81)	(8.96)	(-0.81)	(3.93)	(10.49)	(-4.08)
AGE	0.014	0.019	0.056	0.138	0.011	-0.077
	(3.60)	(2.46)	(2.77)	(4.72)	(1.72)	(-8.91)
GROWTH	-0.006	0.005	0.342	-0.020	0.016	0.034
	(-0.39)	(0.16)	(5.61)	(-0.46)	(3.27)	(2.05)
CONGLO	0.005	0.016	0.041	0.114	-0.059	-0.134
	(1.20)	(3.39)	(1.91)	(5.70)	(-11.86)	(-7.71)
FLEV	-0.001	-0.024	0.016	0.017	-0.006	-0.018
	(-0.88)	(-3.14)	(1.92)	(2.45)	(-7.03)	(-4.53)
Industry F.E.	Yes	Yes	Yes	Yes	Yes	Yes
Avg. R^2	0.237	0.210	0.343	0.161	0.213	0.220
N	24,663	24,663	24,663	24,663	24,663	24,663

Table 2.6: Changes in customer-base concentration and changes in supplier firm performance

Table 2.6 reports the results for Fama–MacBeth regressions. Changes in return on assets (*ROA*) and SG&A costs (*SGA*) are calculated in year t+1, whereas the decile rank of the annual change in customer-base concentration and control variables are calculated in year t. We run annual regressions of year t to year t+1 changes in ROA and SGA on the decile rank of annual change in customer-base concentration from year t-1 to year t and on year t values of a list of control variables. Our sample includes firms from 1977 to 2007. We only include non-financial firms with non-missing customer-base concentration firm-year observations, non-missing accounting profitability measures, and non-negative book value of equity. Panel A reports results for the full sample of firm year observations, while Panels B and C report results for the sub-samples of young (AGE$\leq$ 7) and mature firms (AGE > 7), respectively. In all panels, we average the coefficients over time and report the means in the first rows and the corresponding Newey-West-adjusted t-statistics in the rows below in parentheses. The dependent variables are (1) one-year ahead change in return on assets (ΔROA_{t+1}) and (2) one-year ahead change in the ratio of selling, general and administrative expenses to sales (ΔSGA_{t+1}). Rank(ΔCC_t) is the decile rank of annual change in customer-base concentration scaled to be bounded between 0 and 1. Other control variables are profit margin (PM_t), asset turnover (ATO_t), annual change in profit margin (ΔPM_t) and annual change in asset turnover (ΔATO_t). N is the number of firm-year observations used in the regression.

Panel A: Full sample			**Panel B: Young firms (AGE$\leq$ 7)**			**Panel C: Mature firms (*AGE*> 7)**		
	(1)	(2)		(1)	(2)		(1)	(2)
	ΔROA_{t+1}	ΔSGA_{t+1}		ΔROA_{t+1}	ΔSGA_{t+1}		ΔROA_{t+1}	ΔSGA_{t+1}
Intercept	0.012	-0.034	Intercept	0.029	0.085	Intercept	0.016	0.014
	(0.22)	(0.80)		(0.20)	(0.89)		(0.36)	(0.84)
$Rank_t(\Delta CC)$	-0.007	0.017	$Rank_t(\Delta CC)$	-0.009	0.020	$Rank_t(\Delta CC)$	-0.005	0.006
	(-2.22)	(6.07)		(-2.02)	(2.03)		(-1.05)	(1.03)
PM_t	-0.076	0.047	PM_t	-0.070	0.045	PM_t	-0.079	0.052
	(-1.50)	(1.86)		(-1.58)	(1.19)		(-1.59)	(2.68)
ATO_t	-0.010	-0.002	ATO_t	-0.014	0.001	ATO_t	-0.010	-0.004
	(-12.71)	(-1.04)		(-9.15)	(0.16)		(-7.06)	(-1.36)
ΔPM_t	0.021	0.024	ΔPM_t	0.021	0.024	ΔPM_t	-0.010	0.022
	(0.78)	(0.97)		(0.88)	(0.69)		(-1.82)	(1.15)
ΔATO_t	0.003	0.000	ΔATO_t	0.007	0.001	ΔATO_t	0.008	0.001
	(1.10)	(0.08)		(1.37)	(0.17)		(1.09)	(1.41)
Industry F.E.	Yes	Yes	Industry F.E.	Yes	Yes	Industry F.E.	Yes	Yes
Avg. R^2	0.120	0.191	Avg. R^2	0.159	0.236	Avg. R^2	0.167	0.279
N	35,668	35,419	N	15,672	15,525	N	19,996	19,894

Table 2.7: Operating performance drivers for young firms

In Table 2.7 we analyze the impact of customer-base concentration on the operating performance of young firms (AGE ≤ 7). Our sample includes firm year observations from 1977 to 2007. In Panel A, the dependent variables include asset turnover components as well as selling, general and administrative expenses: (1) IHLD: the ratio of inventory to the book value of total assets, (2) INVT: inventory turnover, (3) RCVBLE: account receivables turnover, (4) NPP&E: net PP&E turnover, (5) INTANG: intangible asset turnover, (6) CASH: cash turnover, (7) ADVERT: advertising expense to sales, and (8) SGA: the ratio of selling, general and administrative expenses to sales. In Panel B, we analyze working capital efficiencies for young firms using the following dependent variables: (1) DAYS_RCVBLE: days' receivables measured as the ratio of accounts receivable to sales multiplied by 365, (2) DAYS_PAYBLE: days' payables measured as the ratio of accounts payable to cost of goods sold multiplied by 365, (3) DAYS_INVT: days' inventory measured as the ratio of inventory to cost of goods sold multiplied by 365, (4) TOTCYCLE: total cash conversion cycle measured as days' receivables minus days' payables plus days' inventory, and (5) DOUBTFUL: provisions for doubtful accounts; measured as the ratio of estimated doubtful accounts receivable to total accounts receivable. The main independent variable is *Rank(*CC*)*, the corresponding decile rank of the firm based on its customer-base concentration score. Other control variables include the log of market value of equity (MV), the log of firm age (AGE), annual sales growth rate (GROWTH), the indicator variable that equals 1 if the firm reports at least two business segments (CONGLO), and the leverage ratio defined as book value of assets divided by book value of equity (FLEV). N is the number of firm-year observations used in the regression.

Panel A: Asset turnover components, advertising expenses and SG&A per dollar of sales

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
		Asset turnover components						
	IHLD	INVT	RCVBLE	NPP&E	INTANG	CASH	ADVERT	SGA
Intercept	0.186	37.394	17.643	22.442	200.137	21.876	0.021	0.979
	(5.18)	(1.64)	(2.65)	(3.72)	(1.87)	(1.34)	(4.96)	(11.70)
Rank(CC)	-0.037	3.771	0.871	-0.138	-1.844	-18.327	-0.003	0.179
	(-4.45)	(1.77)	(3.64)	(-0.14)	(-0.07)	(-5.93)	(-2.33)	(5.88)
MV	-0.013	0.317	0.063	-1.089	3.433	-3.088	-0.001	-0.058
	(-21.64)	(0.80)	(0.60)	(-3.10)	(0.51)	(-3.47)	(-3.19)	(-4.08)
AGE	0.010	-2.476	-0.261	-1.695	-29.993	10.662	-0.002	-0.077
	(2.93)	(-2.17)	(-0.78)	(-1.45)	(-2.07)	(4.07)	(-3.14)	(-8.91)
GROWTH	-0.003	11.781	7.083	10.831	10.436	4.039	0.002	0.034
	(-1.95)	(5.34)	(23.56)	(6.31)	(0.93)	(1.95)	(2.47)	(2.05)
CONGLO	-0.004	2.003	-0.530	-3.076	-27.639	-5.724	-0.004	-0.134
	(-0.66)	(1.41)	(-1.22)	(-2.71)	(-1.46)	(-1.03)	(-8.84)	(-7.71)
FLEV	0.002	-0.293	-0.036	0.555	0.088	5.847	-0.001	-0.018
	(3.71)	(-0.78)	(-0.37)	(1.58)	(0.04)	(4.12)	(-6.18)	(-4.53)
Industry F.E.	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Avg. R^2	0.468	0.310	0.289	0.202	0.166	0.187	0.146	0.220
N	24,451	19,998	24,459	24,640	11,362	24,442	24,662	24,663

Panel B: Cash conversion cycle components and collectability of accounts receivable

	(1)	(2)	(3)	(4)	(5)
	Cash conversion cycle				
	DAYS_ RCVBLE	DAYS_ PAYBLE	DAYS_ INVT	TOTCYCLE	DOUBTFUL
Intercept	98.122	36.173	100.487	197.551	0.070
	(7.33)	(0.68)	(9.23)	(2.94)	(5.25)
Rank(CC)	20.064	56.234	-3.752	-24.775	-0.005
	(5.89)	(5.73)	(-1.26)	(-2.84)	(-2.83)
MV	-3.476	-6.477	-4.558	-1.870	-0.006
	(-6.22)	(-1.95)	(-7.21)	(-1.31)	(-18.63)
AGE	-3.854	-15.640	2.054	14.173	0.003
	(-2.23)	(-1.94)	(1.54)	(2.53)	(2.35)
GROWTH	-31.484	-11.731	-23.387	-43.188	0.000
	(-16.09)	(-1.90)	(-8.89)	(-11.39)	(0.05)
CONGLO	-4.814	-45.238	-12.862	23.127	-0.004
	(-1.59)	(-6.16)	(-7.08)	(6.38)	(-4.13)
FLEV	1.001	10.432	-0.601	-9.961	0.001
	(1.18)	(2.41)	(-1.41)	(-2.34)	(1.58)
Industry F.E.	Yes	Yes	Yes	Yes	Yes
Avg. R^2	0.184	0.150	0.258	0.194	0.171
Obs.	24,569	24,647	24,452	24,368	18,251

Table 2.8: Elasticity of operating expenses with respect to sales and demand uncertainty in customer base concentration quintiles

Panel A of Table 2.8 reports panel data means of operating expenses as a percentage of sales. Panel B of Table 2.8 reports the mean and median elasticity values of costs of goods sold (COGS) and selling, general and administrative expenses (SG&A) with respect to sales. Panel C of Table 2.8 reports the mean and median values of demand uncertainty for each customer-base concentration quintile. The marginal elasticity of COGS (SG&A expense) with respect to sales of firm i in year t is calculated as the change in log-COGS (SG&A expense) for firm i from year t-1 to year t , $\Delta lnCOGS_{i,t}$ ($\Delta lnSG\&A_{i,t}$), divided by the change in log-sales for firm i from year t-1 to year t ($\Delta lnSales_{i,t}$). The demand uncertainty for firm i is defined as the standard deviation of annual changes in log-sales. Following Banker et al. (2012), we estimate demand uncertainty on a rolling basis, using the data for the most recent 5 years. H-L column reports the cross-sectional differences between the mean and median COGS elasticity, SG&A elasticity and demand uncertainty estimations of the highest and lowest customer-base concentration quintiles. N is the number of firm-year observations. H-L cross-sectional differences that are statistically significant at the one percent level (significant at $p < 0.01$) are denoted with ***, those that are statistically significant at the five percent level (significant at $p < 0.05$) are denoted with **, and those that are statistically significant at the ten percent level (significant at $p < 0.10$) are denoted with *. H-L cross-sectional differences that are statistically insignificant are not marked.

Panel A: Operating expenses

Item	% of Sales
Cost of Goods Sold	64.4%
SG&A Expenses	39.1%
Advertising Expense	1.0%
Non-advertising SG&A Expenses	38.1%

Panel B: Customer base concentration and elasticity of operating expenses with respect to sales

Customer-base Concentration	COGS Elasticity			SG&A Elasticity		
	N	Mean	Median	N	Mean	Median
Lowest	9,867	0.97	0.98	9,867	0.79	0.83
2	9,889	0.95	0.97	9,889	0.72	0.74
3	9,889	0.91	0.96	9,889	0.69	0.7
4	9,843	0.92	0.96	9,845	0.66	0.65
Highest	9,727	0.87	0.96	9,727	0.56	0.52
H - L		-0.10***	-0.02***		-0.23***	-0.31***

Panel C: Customer base concentration and demand uncertainty

Customer-base Concentration	Demand Uncertainty		
	N	Mean	Median
Lowest	7,030	0.19	0.13
2	7,024	0.22	0.15
3	6,722	0.24	0.17
4	6,282	0.26	0.19
Highest	5,838	0.32	0.22
H - L		0.12^{***}	0.09^{***}

Table 2.9: Determinants of firm failure within five (seven) years of initial public offering

Table 2.9 shows the logistic failure regression estimates for all firms with an initial public offering (IPO) date between 1980 and 2000. The dependent variable used in columns (1) and (2) is a dummy variable equal to one if the firm fails within five years of its IPO, following Demers and Joos (2007). The dependent variable used in columns (3) and (4) is a dummy variable equal to one if the firm fails within seven years of its IPO, following our definition of young (AGE $\leq$ 7) firms. Each year firms are sorted into ten portfolios based on their customer-base concentration measure (*CC*), which is described in detail in Table 2.1. *Rank(*CC*)* is the corresponding decile rank of the firm at the time of its IPO based on the CC score. UNDERWRITER is the Carter-Manaster underwriter reputation ranking. VC indicator variable is set equal to 1 if the firm is venture capital backed. AUDITOR indicator variable is equal to 1 if the firm has Big 8 or a national firm auditor. IPO_MARKET is the initial return to all IPOs in the 90 days prior to the firm's IPO. FIRSTDAYRET is the first-day initial returns: closing price on the IPO date less offer price as a percentage of the offer price. OFFERPRICE is the inflation-adjusted IPO offer price. INC_AGE is the natural log of one plus firm age measured in years from the date of incorporation and is different from the variable AGE used in Tables 2.1 through 2.6. IPO_LEV is equal to total liabilities divided by the sum of total assets plus the proceeds raised at the time of IPO. RD is the natural log of one plus R&D expense. LSGA is the natural log of selling, general, and administrative expenses. GM is the ratio of sales minus cost of goods sold to sales. DEFICIT is the negative log of retained earnings if the firm is in a deficit position, 0 otherwise. SALE is the log of one plus sales in millions generated for the year prior to the IPO. All independent variables are measured at the time of IPO. Values of *z-statistics* are reported in parentheses below coefficient estimates. *N* is the total number of firm-IPO-years in the sample and *# of Failures* is the number of failure events observed in the entirety of the sample. McFadden pseudo R^2 values are reported for each regression.

	Failure within 5 years of IPO		Failure within 7 years of IPO	
	(1)	(2)	(3)	(4)
Intercept	1.160	0.796	1.658	1.411
	(3.90)	(2.35)	(6.16)	(4.65)
Rank(CC)		0.512		0.347
		(2.24)		(1.76)
UNDERWRITER	-0.158	-0.160	-0.134	-0.136
	(-4.02)	(-4.07)	(-3.97)	(-4.02)
VC	-0.067	-0.062	-0.148	-0.144
	(-0.37)	(-0.35)	(-0.98)	(-0.95)
AUDITOR	-0.273	-0.270	-0.351	-0.350
	(-1.36)	(-1.34)	(-1.94)	(-1.94)
IPO_MARKET	1.883	1.870	1.151	1.135
	(3.88)	(3.85)	(2.58)	(2.54)
FIRSTDAYRET	-0.281	-0.291	-0.135	-0.142
	(-1.04)	(-1.07)	(-0.59)	(-0.62)
OFFERPRICE	-0.061	-0.062	-0.034	-0.034
	(-3.68)	(-3.70)	(-2.75)	(-2.75)
INC_AGE	-0.323	-0.325	-0.295	-0.295
	(-3.78)	(-3.79)	(-4.03)	(-4.02)
IPO_LEV	2.186	2.205	1.932	1.946
	(4.88)	(4.92)	(4.92)	(4.96)
RD	-0.675	-0.696	-0.390	-0.404
	(-4.71)	(-4.84)	(-3.43)	(-3.54)
LSGA	0.444	0.471	0.243	0.262
	(2.88)	(3.06)	(1.88)	(2.03)
GM	-0.993	-0.944	-1.281	-1.238
	(-2.97)	(-2.82)	(-4.38)	(-4.22)
DEFICIT	-0.082	-0.075	-0.022	-0.018
	(-1.10)	(-1.02)	(-0.35)	(-0.28)
SALES	-0.560	-0.545	-0.495	-0.487
	(-5.65)	(-5.51)	(-5.87)	(-5.78)
# of Failures	292	292	415	415
N	2,431	2,431	2,431	2,431
Pseudo R^2	0.222	0.224	0.186	0.188

Table 2.10: Dynamic failure prediction

Table 2.10 reports results from dynamic logistic regressions of the failure indicator on the predictor variables for all firms in CRSP-COMPUSTAT between the years of 1980 and 2007. The dependent variable is a dummy variable equal to one if the firm fails in a given year, where failure is defined in the spirit of Demers and Joos (2007). The data are constructed such that all independent variables are observable 12 months before the failure event. Each year firms are sorted into ten portfolios based on their customer-base concentration measure (*CC*), which is described in detail in Table 1. *Rank(*CC*)* is the corresponding decile rank of the firm in a given year based on its customer-base concentration score. Firm age (AGE) is measured in years from the time of IPO. TLMTA is the ratio of total liabilities to the market value of total assets and is used as a measure of leverage. NIMTA is the ratio of net income to the market value of total assets, and is used as a measure of profitability. SIGMA is the standard deviation of daily stock returns over the previous three months. MB is the market-to-book ratio. RSIZE is the log ratio of market capitalization to the market value of the S&P 500 index. CASHMTA is the ratio of cash to the market value of total assets. EXRET is the monthly log excess stock return relative to the S&P 500 index. Values of *z-statistics* are reported in parentheses below coefficient estimates. *N* is the total number of firm-year observations in the sample and *# of Failures* is the number of failure events observed in the entirety of the sample. McFadden pseudo R^2 values are reported for each regression.

	(1)	(2)	(3)	(4)
	Failure	Failure	Failure	Failure
Intercept	-14.040	-14.159	-14.172	-4.450
	(-31.70)	(-31.75)	(-31.67)	(-61.66)
Rank(CC)		0.401	0.520	0.948
		(3.21)	(3.71)	(7.63)
*AGE * Rank(CC)*			-0.015	-0.037
			(-1.79)	(-4.56)
TLMTA	2.380	2.456	2.482	
	(13.79)	(14.08)	(14.18)	
NIMTA	-21.716	-21.560	-21.482	
	(-13.48)	(-13.38)	(-13.31)	
SIGMA	0.457	0.454	0.426	
	(3.87)	(3.84)	(3.57)	
MB	0.291	0.286	0.284	
	(10.24)	(10.05)	(9.94)	
RSIZE	-0.675	-0.666	-0.669	
	(-18.68)	(-18.33)	(-18.33)	
CASHMTA	-1.251	-1.302	-1.347	
	(-3.57)	(-3.71)	(-3.83)	
EXRET	-4.123	-4.097	-3.999	
	(-5.33)	(-5.30)	(-5.16)	
# of Failures	771	771	771	771
N	48,948	48,948	48,948	48,948
Pseudo R^2	0.209	0.210	0.211	0.008

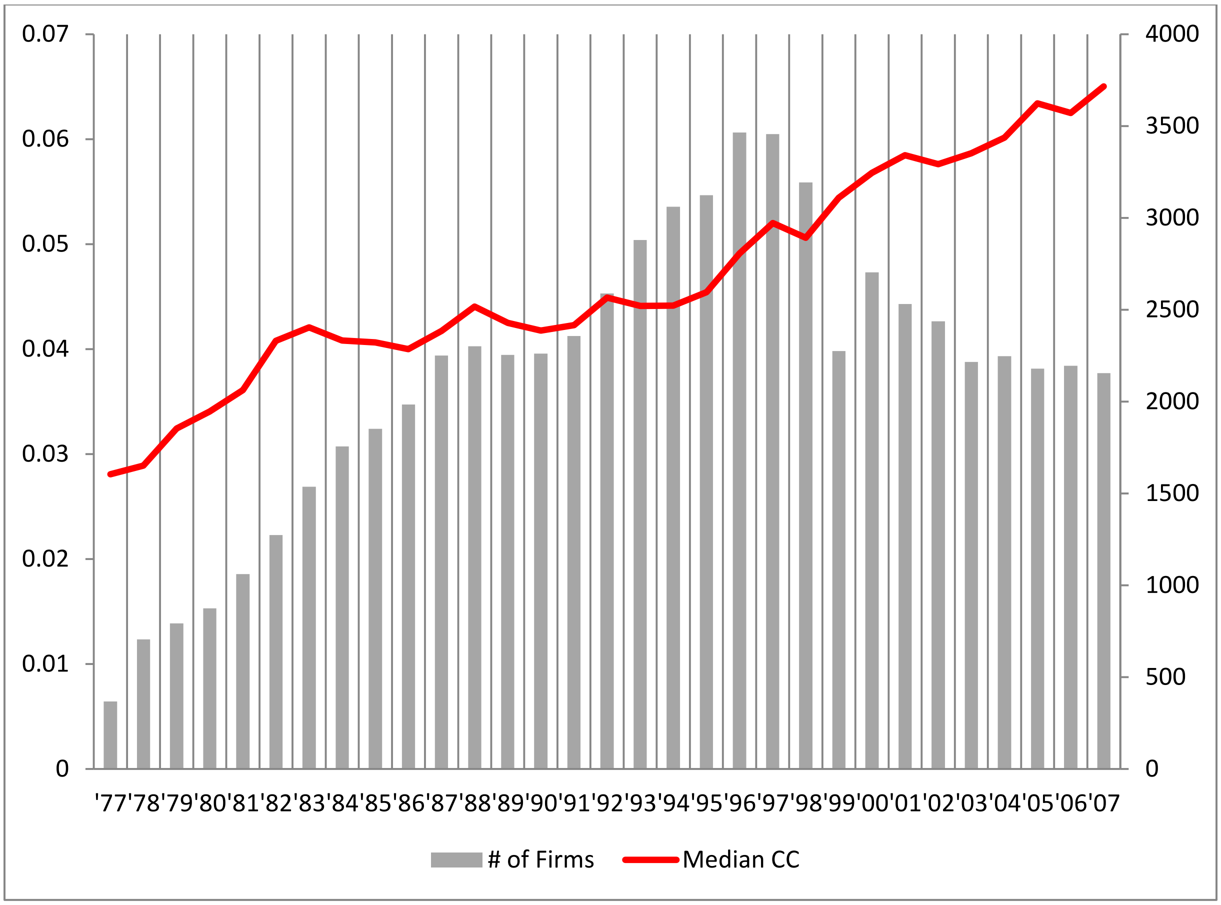
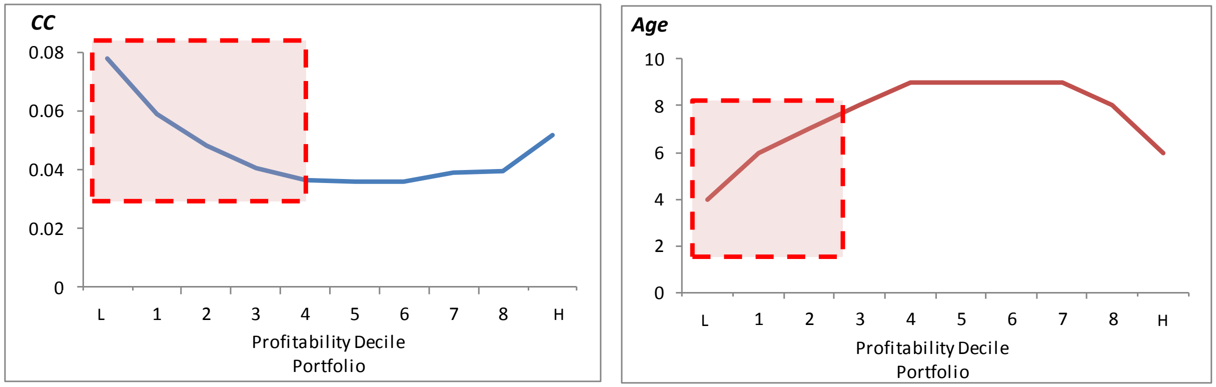


Figure 2.1: Time-series trend of customer-base concentration

Figure 2.1 plots the time series of the cross sectional median of customer-base concentration over the 1977-2007 period. The line chart shows the time-series trend of the yearly median customer-base concentration measure (CC) and the bar chart shows the number of supplier firms that report their major customers in COMPUSTAT customer segment files.

Panel A: Full sample



Panel B: Positive-OM sample

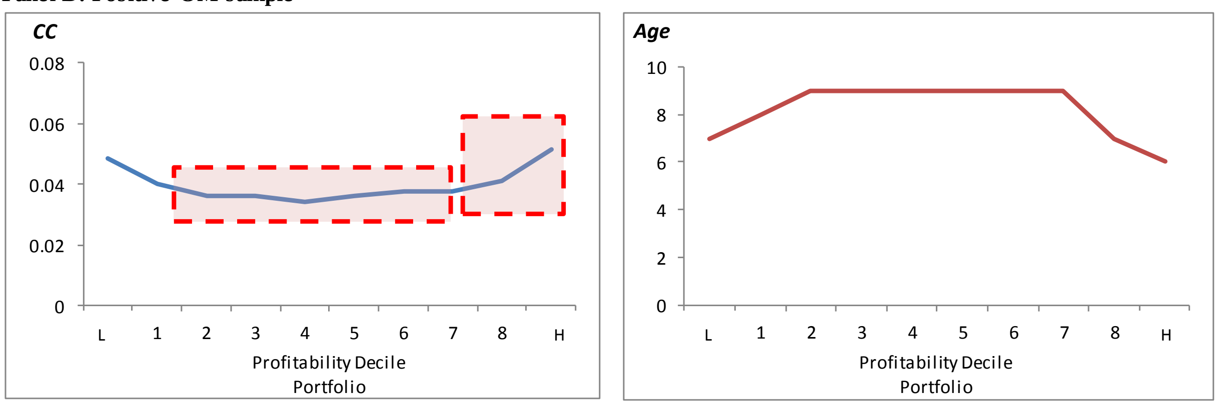
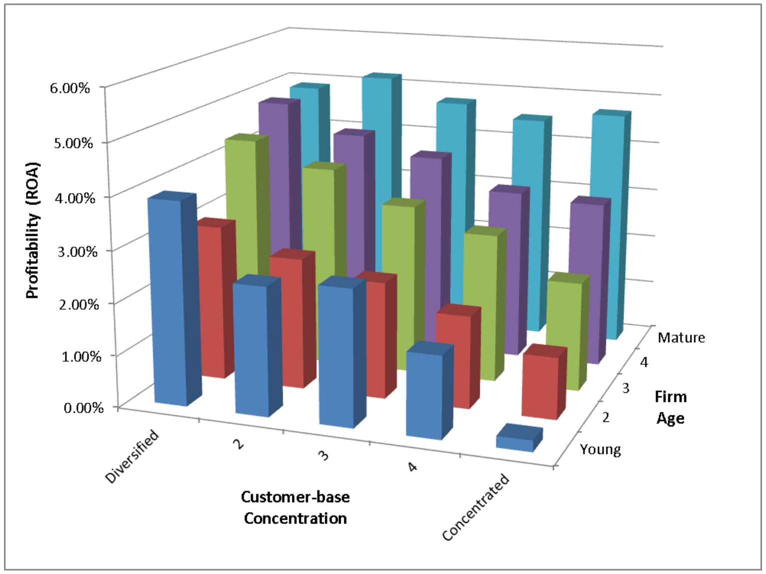


Figure 2.2: Median customer-base concentration and firm age in profitability deciles

Figure 2.2 illustrates how two supplier firm characteristics, the median customer-base concentration measure (CC) and the median firm age (AGE), correlate with supplier firm profitability. We sort the supplier firm universe into ten deciles based on return on assets (ROA). The horizontal axis reports each portfolio's ROA decile. Portfolio 0 (9) is the decile portfolio for the firms with the lowest (highest) ROA. The vertical axis reports the median CC for each ROA portfolio in the figures on the left hand side and the median firm age in the figures on the right side. Panel A illustrates the results for the full sample while Panel B describes the results for the subset of firms with positive operating margins.

Panel A: Full sample



Panel B: Positive-OM sample

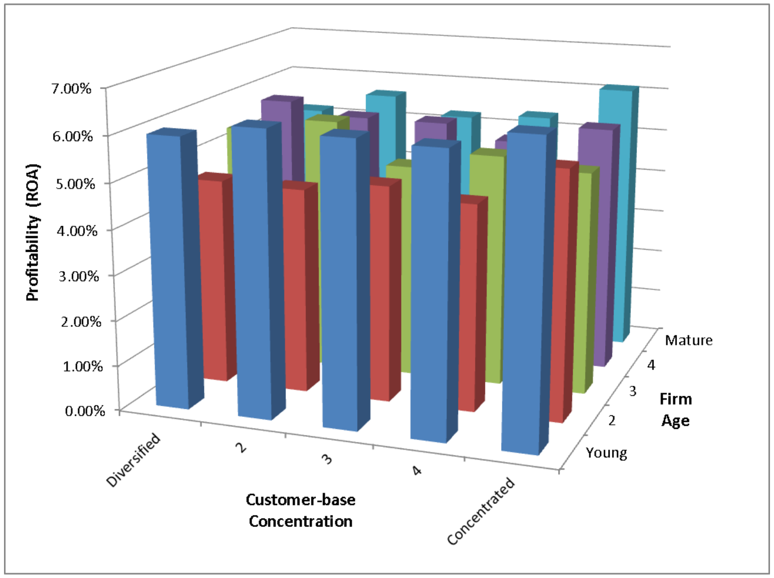


Figure 2.3: Median of return on assets in customer-base concentration and age groups

Figure 2.3 illustrates how return on assets (*ROA*) changes with customer base concentration (*CC*) and firm age (*AGE*). We perform a two-way independent sort of firm-year observations into 5 × 5 = 25 groups based upon customer-base concentration and firm age, where age is measured from the time of the firm's IPO. The vertical axis reports the median ROA for each group. One of the horizontal axes ranks the groups based upon customer-base concentration while the other horizontal axis ranks the groups based upon firm age. Panel A illustrates the results for the full sample while Panel B describes the results for the subset of firms with positive operating margins.

CHAPTER 3

FIRM COMPLEXITY AND POST-EARNINGS-ANNOUNCEMENT DRIFT

3.1 INTRODUCTION

In a recent paper, Cohen and Lou (2012) find that investors take longer to process value-relevant information about conglomerates. In particular, Cohen and Lou find that pseudo-conglomerate returns significantly predict the returns to the real conglomerates one month ahead, which indicates that conglomerates take an extra month to incorporate industry-wide shocks into their prices.[13]

We take a different approach in relating firm complexity to the speed of information processing by considering complexity as a limits-to-arbitrage variable. We hypothesize that complex firms (conglomerates) should have stronger post-earnings-announcement drifts (PEAD). We use three measures of complexity - a dummy variable for conglomerates, the number of business segments, and sales concentration based on the Herfindahl index - and find in cross-sectional regressions that PEAD is twice as strong for complex firms as it is for single-segment firms.

Stronger PEAD for more complex firms is a surprising result, because firm complexity is positively related to size. Furthermore, complex firms are more liquid, are less volatile and have

[13] For each conglomerate firm, a pseudo-conglomerate consists of a portfolio of the conglomerate firm's segments made up using only stand-alone firms from the respective industries. For each portfolio that corresponds to a specific segment of the conglomerate firm an equal-weighted return is calculated. Returns corresponding to each segment are then value-weighted according to that segment's contribution to the conglomerate firm's total revenues in order to calculate a corresponding pseudo conglomerate return.

better coverage by financial analysts and institutions. Unless firm complexity severely hampers the ability of investors to process information, one should expect to find weaker, not stronger post-earnings-announcement drifts for complex firms, because all other firm characteristics suggest that complex firms should have lower limits to arbitrage. We verify in the data that conglomerates indeed have lower limits to arbitrage, and controlling for the relation between PEAD and limits to arbitrage, the relation between PEAD and complexity becomes even stronger.

Further analysis of the relation between PEAD and firm complexity reveals that PEAD increases monotonically with complexity. While we observe a noticeable increase in PEAD as we go from single-segment firms to even the least complex conglomerates (the ones with one dominant segment or the ones with only two segments), PEAD increases with complexity in the conglomerate-only sample as well. PEAD in more complex conglomerates is triple that of the PEAD observed in single-segment firms.

We find that the relation between PEAD and complexity persists for at least two months. The duration of the return predictability attributable to PEAD for complex firms is longer than the duration of the return predictability documented in Cohen and Lou (2012) which lasts only for one month. We conclude that investors of complex firms have even greater trouble interpreting earnings-related information than they do interpreting industry-wide shocks.

While all proxies for limits to arbitrage we consider are negatively related to firm complexity and therefore cannot explain our finding that PEAD is stronger for complex firms, it is still possible that complexity (conglomerate status in particular) is related to a certain unknown variable that also affects the strength of PEAD. In an effort to understand if investors really have difficulty interpreting information related to more complicated firms we focus on periods during which firm complexity increases. If the level of firm complexity (conglomerate status) is related to a certain unknown variable that also drives PEAD, then new conglomerates would likely have little exposure to this variable and one would expect new conglomerates to have low levels of PEAD. Under our hypothesis, however, investors should have the greatest confusion when interpreting earnings announcements of new conglomerates, due to the significant and recent change in their complexity level.

We show that our hypothesis is correct. First, we verify that PEAD is higher for all conglomerates by showing that PEAD of existing conglomerates (firms that have been conglomerates for more than two years) is twice as strong as the PEAD of single-segment firms. Second, we show that PEAD is significantly stronger for new conglomerates than it is not only for single-segment firms but also for existing conglomerates. Specifically we find that PEAD for new conglomerates is double that of existing conglomerates and more than four times that of single-segment firms. To sum up, the increase in complexity (defined either as an increase in the number of segments or as the change in the conglomerate status) is associated with a large increase in PEAD, consistent with our hypothesis that it is firm complexity (and not any other characteristic common to conglomerates) that leads to stronger PEAD. We also find that investors are most confused about firms that expand from within (firms that expand from within are those firms that add new lines of business without being involved in M&A activity).

Turning to the potential causes of the relation between PEAD and firm complexity, we first control for the predictability of conglomerate returns documented in Cohen and Lou (2012). Indeed, if earnings announcements are pre-dated by relevant news about the industries the conglomerate operates in and vice versa, pseudo-conglomerate returns could predict the magnitude of PEAD for conglomerates, and this extra return predictability for conglomerates might lead to stronger PEADs in the conglomerate subsample. We find no evidence of overlap between our result and the Cohen and Lou result.

We also analyze the relation between the earnings announcement effect and complexity and find that the sensitivity of the earnings announcement return to earnings surprise is about 25% stronger for complex firms. We conclude that, per unit of earnings surprise, earnings announcements of complex firms have more information for investors to digest. However, the fact that for conglomerates, 25% more information at the announcement leads to twice as strong PEAD subsequently suggests that investors also have difficulty interpreting information related to complicated firms.

Finally, we compare the analyst coverage of simple and complex firms in more depth and find that firm complexity is detrimental to the quantity and quality of analyst coverage. Although on average complicated firms have more analyst coverage than single-segment firms, once we compare multi-segment firms to single-segment firms of similar size, we find that complex firms are followed by a smaller number of analysts, these analysts have less industry expertise and make larger errors in their earnings forecasts. We also document that in general lower analyst coverage and coverage of lower quality are both associated with stronger PEAD, a finding that is new to the literature to the best of our knowledge. Controlling for the relation between PEAD and analyst coverage (adjusted for size) weakens the link between PEAD and firm complexity, which suggests that lower analyst coverage could be one of the many reasons why complex firms have stronger PEADs. We document that controlling for the impact of analyst coverage on PEAD can account for at most 30% of the additional PEAD experienced by complex firms.

We show that up to a half of the additional PEAD experienced by complex firms is due to two separate but complementary reasons: First, we find that a unit of SUE carries more information for complicated firms; second the quantity and quality of the analyst coverage is much lower for complicated firms. Finally, we conclude that the remaining half of the additional PEAD experienced by complex firms seems to be purely attributable to firm complexity per se.

3.2 DATA

We use three measures of firm complexity. The first measure, Conglo, is the conglomerate dummy, equal to 1 if the firm is a conglomerate and 0 otherwise. The firm is deemed to be a conglomerate if it has business divisions in two or more different industries, according to Compustat segment files. Industries are defined using two-digit SIC codes. The second measure of complexity, NSeg, is the number of divisions with different two-digit SIC codes. The third measure, Complexity, is a continuous variable based on sales concentration. Complexity equals 1-HHI, where HHI is the sum of sales shares of each division squared, $HHI = \sum_{i=1}^{NSeg} s_i^2$, where sales share, s_i, for each division is the fraction of total sales generated by that division. According to the third definition of complexity, a firm with sales in a single segment would have a Complexity measure of 0, whereas a firm with sales in a large number of industries could achieve a Complexity score close to 1.

Our measure of PEAD is the slope from the Fama-MacBeth (1973) regression of cumulative post-announcement returns on earnings surprises. Post-announcement cumulative abnormal returns (CARs) are cumulated between trading day 2 and trading day 60 after the earnings announcement. CARs are size and book-to-market adjusted following Daniel et al. (1997) (also known as DGTW). Earnings announcement dates are from COMPUSTAT, and daily returns are from CRSP daily files.

We measure earnings surprise as standardized unexpected earnings (SUE), defined as the difference between earnings per share in the current quarter and earnings per share in the same quarter of the previous year, scaled by the share price for the current quarter.[14] Since we calculate SUE and PEAD values as in Livnat and Mendenhall (2006) we use the same sample selection criteria. In doing so, we restrict the sample to firm-quarter observations with price per share greater than $1 as of the end of quarter t in an effort to reduce noise caused by small SUE deflators. We also keep only those observations with non-negative book value of equity at the end of quarter t-1, while excluding those observations with market value of equity less than $5 million at the end of quarter t-1.

Our sample period is determined by the availability of the segment data and lasts from January 1977 to December 2010.

All other variables are defined in the Data Appendix.

3.3 DESCRIPTIVE STATISTICS

Our paper uses firm complexity as a new proxy for limits to arbitrage. This challenges the established perception about multi-segment firms. Complex firms tend to be larger, more liquid, less volatile, and more transparent and as such they are expected to have lower limits to arbitrage. In this section, we empirically verify the relationship between firm complexity and the traditional measures of limits to arbitrage in an effort to emphasize the distinctiveness of our measure.

Panel A of Table 3.1 reports the full distribution of SUE, Complexity=1-HHI, and number of segments for all firms and for conglomerates only. A few numbers are particularly

[14] Using alternative specifications of SUE, such as calculating SUE as the deviation from consensus analyst forecasts, yields results that are qualitatively and quantitatively similar.

noteworthy. First, since our focus is “PEAD per unit of SUE”, it is important to note that SUE changes by 0.139=0.064-(-0.075) between the 95th and the 5th percentiles and by 0.273=0.129-(-0.145) between the 97.5th and the 2.5th SUE percentiles. Thus “PEAD per unit of SUE” has to be divided by 7 to measure the spread in CARs between firms with SUEs in the 95th and the 5th percentiles, suggesting that the spread in CARs between firms with SUEs in the 97.5th and the 2.5th percentiles will be roughly double that.

Second, we notice that most firms in our sample are not conglomerates (the median number of segments in the full sample is 1) and most conglomerates have two segments (the median number of segments for conglomerates is 2 except for a few years early in the sample).[15] A relatively large number of conglomerates report three segments and some have four segments, whereas conglomerates with five or more segments make up less than 2.5% of the sample.

Third, the distribution of complexity suggests that there is a significant number of low-complexity firms. For example, a two-segment firm where one segment accounts for 95% of the revenues would have a complexity measure of 0.095. This level of complexity is comparable to the 10th complexity percentile in our sample which is only 0.079. A two-segment firm where one segment accounts for 90% of sales has the complexity measure of 0.18. This level of complexity is comparable to the 25th complexity percentile in the sample of conglomerates only. These observations suggest that even small segments are reported in Compustat, and that we are not lumping together single-segment firms with conglomerates that have a lot of small segments.

The rest of Table 3.1 compares the firm characteristics of single-segment firms, multi-segment firms (conglomerates), and all Compustat firms. Multi-segment firms are firms that have business segments with more than one two-digit SIC code, according to Compustat segment

[15] In untabulated results, we find that 27% of firms in the sample are conglomerates. This number varies from 47% in the late 1970s to 17% in the late 1990s back to 25% in the 2000s.

files. Single-segment firms are those firms that are classified in Compustat segment files and operate in a single industry. "All Compustat firms" in the table does not refer to the aggregation of single-segment and multi-segment firms, but rather refers to all firms with non-missing quarterly earnings.[16]

In Panel B, we summarize earnings surprises (SUE) and announcement returns (CAR(-1;+1)) for the three types of firms specified as above. CAR(-1;+1) is size and book-to-market adjusted as in DGTW. Panel B1 reports the mean CAR values, in an attempt to assess whether conglomerates, on average, have more positive earnings surprises, and Panel B2 reports the means of absolute values of CAR(-1;+1), testing whether earnings surprises experienced by conglomerates are different in magnitude.

We find in Panel B that conglomerates experience earnings surprises that are comparable to full sample means, but significantly smaller in magnitude than the earnings surprises experienced by single-segment firms. Panel B1 reveals that SUEs and announcement CARs of all three firm groups (single-segment, multi segment, all firms) are, on average, positive at 15.6 bp, 15.5 and 16 bp, respectively, and that conglomerates have somewhat more positive SUEs, but the difference is never statistically significant.

Panel B2 shows that the magnitude of the announcement CARs is significantly smaller for conglomerates than it is for single-segment firms or all Compustat firms, whereas the average absolute magnitude of SUE is similar for all three groups of firms.

Panel C summarizes the median values of several liquidity measures for single-segment firms, multi-segment firms, and all Compustat firms. The first three - the Gibbs measure (Hasbrouck, 2009), the Roll (1984) measure, and the effective spread estimate of Corwin and

[16] The number of firms in quarterly Compustat files is about twice as large as the number of firms reported in Compustat segment files, because single-segment firms and firms with relatively small segments do not have to report segment data.

Schultz (2012) estimate the effective bid-ask spread. We find that the bid-ask spread of a representative conglomerate is roughly one-third to two-thirds lower than the bid-ask spread of a representative single-segment firm and roughly one-quarter to one-third lower than the bid-ask spread of a representative Compustat firm.

The fourth liquidity measure, the Amihud (2002) measure, estimates the price impact and shows that conglomerates experience 50% less price impact when compared to a representative single-segment firm and 40% less price impact when compared to a representative Compustat firm.

The last measure is a catch-all trading cost measure from Lesmond et al. (1999). This measure calculates the fraction of zero-return days in each firm-year and assumes that stocks are not traded when the trading costs are higher than the expected profit from trading. Thus, a greater fraction of zero-return days is synonymous with higher trading costs. We find that for conglomerates the median number of zero-return days is 11.8% , as opposed to 14.1% for single-segment firms and 13.7% for the full sample (all differences are statistically significant).

In summary, all liquidity measures in Panel C strongly suggest that conglomerates are significantly more liquid than single-segment firms and other firms in Compustat with missing segment files. Thus, the liquidity measures suggest that if the link between PEAD and complexity were driven by liquidity effects, then PEAD would be stronger for simpler firms, contrary to our hypothesis. This observation also suggests that, controlling for the interaction between PEAD and liquidity should make the relation between PEAD and complexity economically even more significant.

In Panel D, we consider several characteristics of the information environment. We find that conglomerates have significantly lower idiosyncratic volatility (defined as the volatility of

Fama-French model residuals) when compared to single-segment firms and other firms on Compustat, and slightly lower turnover, which can also be interpreted as a measure of uncertainty. Panel D also shows that a representative conglomerate is twice the size of a representative single-segment firm, has significantly larger analyst following and also has significantly more institutional ownership.

We conclude that a representative conglomerate enjoys a more transparent information environment, receives more attention from investors and is more actively studied when compared to a representative single-segment firm. Analysis of traditional proxies for liquidity and information transparency suggest that conglomerates should have significantly lower limits to arbitrage.

3.4 FIRM COMPLEXITY AND PEAD

3.4.1 COMPLEX FIRMS HAVE STRONGER PEAD

Table 3.2 presents our main results, as we study the relation between PEAD and firm complexity. We perform Fama-MacBeth (1973) regressions with post-announcement cumulative abnormal returns (CAR(2;60)) on the left-hand side and earnings surprise (SUE) and its interaction with alternative measures of firm complexity on the right-hand side. Our measure of PEAD is the (positive) slope on SUE. Higher values of complexity measures utilized in this study correspond to a higher degree of complexity by construction. In this context observing a stronger PEAD for complex firms is associated with finding a positive coefficient on the interaction of SUE and complexity.

A caveat is in order: our definition of PEAD is the extra drift per unit of SUE. Complex firms experience higher levels of PEAD than single-segment firms when both types of firms are exposed to the same amount of SUE. That does not necessarily imply that if we divide the sample into two sub-samples composed of simple firms and complex firms, a straight-forward trading strategy based on PEAD (buying firms in the top SUE decile while shorting firms in the bottom SUE decile) will be more profitable for complex firms, since complex firms can well have (and do have, see Panel A2 of Table 3.1) smaller magnitudes of earnings surprises. However, in order to understand whether investors take longer to process the same amount of information when they are confronted with more complex firms, one should compare PEAD per comparable units of earnings surprise.[17]

The literature on price momentum (see, e.g., Lee and Swaminathan, 2000, Lesmond et al., 2004, Zhang, 2006, and others) finds a puzzling absence of momentum for microcaps (stocks in the lowest NYSE/AMEX market cap quintile). Consequently, all results that momentum is stronger for firms with higher limits to arbitrage hold only in the sample with microcaps excluded. Since PEAD and price momentum are two related anomalies, we choose to exclude microcaps from our analysis as well. Another benefit of excluding microcaps is that microcaps are dominated by single-segment firms, and our regression analysis that compares PEAD for single-segment firms and conglomerates would have virtually no basis for such a comparison among microcaps.[18]

The first column in Table 3.2 estimates PEAD in the pairwise regression of CAR(2;60) on SUE. The regression estimates that the difference in SUE between the 95th and the 5th

[17] A stronger PEAD per unit of SUE in cross-sectional regressions also implies a profitable trading strategy, as described in Fama (1976), who shows in Chapter 9 that slopes from Fama-MacBeth regressions are returns to tradable, albeit relatively difficult to construct portfolios.
[18] Table 3, discussed in the next subsection, presents, among other things, our main results with small caps included back into the sample.

(97.5th and 2.5th) SUE percentiles implies a CAR of 1.64% (3.23%) in the three months following the announcement. The second column adds the Amihud measure and its interaction with SUE. We find that PEAD is significantly stronger for firms with higher values of the Amihud measure (firms with higher price impact).[19]

In the third column, we perform the first test of our main hypothesis by regressing CARs on SUE, the conglomerate dummy, and the interaction of SUE and the conglomerate dummy. The interaction of the conglomerate dummy and SUE is highly significant and suggests that for conglomerates PEAD is 2.3% (1.17%) greater per three months than it is for single-segment firms when we estimate the difference in the PEADs by using the SUE differential between the 97.5th and the 2.5th (95th and 5th) SUE percentiles.

The fourth column combines columns two and three and estimates the relation between PEAD and conglomerate status controlling for the interaction between PEAD and price impact. We find that controlling for the product of PEAD and price impact increases the loading on the interaction term between PEAD and the conglomerate dummy approximately by 25%.

Columns five and six repeat the analyses conducted in columns three and four, and replace the conglomerate dummy with the continuous complexity measure, 1-HHI. The results in columns five and six are qualitatively similar to the results in columns three and four: more complex firms have significantly stronger PEAD per unit of SUE, and this relation increases in magnitude when we control for the product of SUE and the Amihud measure. The magnitude of the coefficient on the product of SUE and complexity suggests that the effect of the interaction term on PEAD is roughly equal to the impact estimated in columns three and four: the median

[19] In untabulated results, we tried other measures of trading costs and limits to arbitrage from Panels B and C of Table 3.1 and could not find a reliable relation between PEAD and any of them. However, the fact that there is no relation between, say, PEAD and size in Fama-MacBeth regressions does not imply that a PEAD-based trading strategy will not be more profitable for small firms, because the regression measures PEAD as “CAR per unit of SUE", and smaller firms may well (and do) witness more extreme SUEs.

level of the complexity variable for conglomerates is about 0.37[20], thus the slope of 0.184 in column five would estimate the difference in PEADs of a representative single-segment firm and a representative conglomerate at 1.81% (0.94%) when the SUE differential between the 97.5th and the 2.5th (95th and 5th) percentiles is used in the estimation.

Columns seven and eight use the number of segments (with different two-digit SIC codes) as a proxy for complexity. Once again, the interaction term between PEAD and complexity is statistically significant even prior to controlling for the confounding effects of other limits to arbitrage proxies. Furthermore the economic significance of the interaction term increases after controlling for the relation between PEAD and price impact, and is qualitatively similar to the effect documented in columns three to six.

3.4.2 DEGREE OF COMPLEXITY MATTERS

In Table 3.3, we test whether more complex conglomerates have stronger PEADs. While the evidence in Table 3.2 (columns 5 to 8) suggests that they do, we acknowledge that both Complexity=1-HHI and NSeg have a huge mass at 0 and 1, respectively, and the positive relation between those two variables and the strength of PEAD might be solely attributable to the difference between conglomerates and single-segment firms.

In Table 3.3, we get rid of the mass at 0 (or 1) by restricting the sample to conglomerate firms only and by re-running the regressions from Table 3.2 in this conglomerate only sample. For Table 3.3 only, we include the firms with market cap below the 20th NYSE/AMEX size percentile back in the sample for two reasons. First, since we are restricting our attention to

[20] Complexity of 0.37, or HHI=0.63 roughly corresponds to a two-segment firm with one segment taking slightly over 75% of sales, or to a three-segment firm with one segment taking 78% of sales and the other two taking 12% and 10% respectively.

conglomerates only, we are no longer worried about the fact that there are few conglomerates among small firms, a fact that makes comparing single-segment and conglomerate PEADs in Table 3.2 more challenging but has no relevance for Table 3.3. Second, the number of conglomerates is relatively small (roughly 1,000 per year, or a quarter of our full sample), and the number of conglomerates with non-missing market caps above the 20th NYSE/AMEX size percentile is even smaller, and thus we need all the observations we can have to make our tests more powerful.

In column one, we re-run the regression from column five of Table 3.2 in the full sample with small firms included and confirm that PEAD is indeed significantly stronger for complex firms in this sample. The coefficient on the product of SUE and complexity is expectedly smaller than that in Table 3.2, but is still both statistically and economically significant. The regression coefficients suggest that the difference in PEADs of a representative conglomerate and a representative single-segment firm is 1.28%.

In column two, we perform the regression from column one using only conglomerates with complexity below the median. First, we observe that the slope on SUE, which now measures PEAD for conglomerates with the lowest degree of complexity, is about a third greater than the slope on SUE in column one, which measures PEAD for single-segment firms. We conclude that there is indeed a significant jump in PEAD based upon the conglomerate status: even the least complicated conglomerates have between 44 and 86 basis points stronger PEAD than single-segment firms.[21]

[21] The estimates were obtained by multiplying the difference in the slopes in columns 2 and 1, (0.131-0.099) · 100% = 3.2%, by the difference between the 97.5th and the 2.5th SUE percentiles (0.129-(-0.145)=0.273). Alternative values are obtained by using the spread between the 95th and the 5th SUE percentiles (0.064-(-0.075)=0.139). The spreads between SUE percentiles are from Panel A1 of Table 1.

Second, the slope on the product of SUE and complexity in column two suggests a statistically and economically significant difference between the PEADs of conglomerates with the lowest complexity and the PEADs of conglomerates with median complexity. Since the median complexity is 0.37 (see Panel A2 in Table 1), the PEAD for conglomerates with median complexity is more than twice the PEAD for conglomerates with the lowest complexity. For example, plugging in the spread in SUE between the 95th and the 5th percentiles, we estimate the PEAD for conglomerates with the lowest complexity at 1.82%, and the PEAD for conglomerates with median complexity at 4.11% (both figures are abnormal returns over three months, or 59 trading days, after the earnings announcement).

In column three, we re-estimate the same regression only for conglomerates with complexity above the median and observe that the relation between PEAD and complexity has almost the same strength in this sub-sample as in column two, which deals with low-complexity conglomerates.

In column four, we use an alternative approach to measuring the relation between PEAD and the degree of complexity. We create two dummy variables: one for conglomerates with complexity measures below the median (CompLow) and another for conglomerates with complexity measures above the median (CompHigh). The slopes on the interactions of the dummy variables with the SUE variable estimate the additional PEAD experienced by low-complexity and high-complexity conglomerates respectively as compared to single-segment firms. The coefficients suggest that PEAD is roughly 1.5% (per three months) stronger for low-complexity firms than it is for single-segment firms and an additional 1.5% stronger for high-complexity firms.

In the next three columns, we utilize the number of segments (NSeg) as an alternative measure of complexity. In the fifth column of Table 3.3, we repeat our baseline regression utilizing the number of segments as our measure of complexity (similar to column seven of Table 3.2) in the conglomerate-only sample that includes the smallest conglomerates. In the fifth column of Table 3.3, we observe a somewhat weaker, but still statistically and economically significant relation between the strength of PEAD and the number of segments and conclude that this relation is robust to including the smallest conglomerates into the sample.[22]

Since the median number of segments for conglomerate firms is two, we cannot analyze the interaction of PEAD and complexity separately for low- and high-complexity firms by equating complexity to the number of segments (low-complexity group would then have no variation in complexity, since all firms with the number of segments below the median have two segments). Therefore, in column six we repeat the regression from column five for all multi-segment firms. We find that the relation between PEAD and the number of segments remains economically significant, but loses statistical significance.

On the surface, column six seems to suggest that the relation between PEAD and number of segments in the full sample is attributable primarily to the fact that NSeg variable has a mass at one, and that while conglomerates are different from single-segment firms in terms of PEAD, two-segment firms are not that different from four (or more) segment firms in this regard. However, further analysis reveals that, first, the problem of "mass at the lowest value" is not alleviated by excluding single-segment firms, since two-segment conglomerates are as numerous as all other conglomerates, three-segment conglomerates are as numerous as four-and-more-

[22] The slope on the product of SUE and NSeg in column five of Table 3 suggests that PEAD increases by 0.5% to 1% per each additional segment in the conglomerate only sample which includes the smallest conglomerates. The impact of additional business segments on PEAD is smaller in the conglomerate only sample as PEAD increases between 0.67% and 1.32% for every additional segment in the sample that includes single segment firms (but excludes the smallest size quintile), as evidenced in column seven of Table 2.

segment conglomerates, etc., and second, that conglomerates with more than five segments add more noise than information.

Analysis conducted in column seven of Table 3.3 improves our understanding of the impact of the degree of firm complexity on PEAD in the conglomerate only sample. We construct two dummies, one for two-segment conglomerates (SegLow), and one for all other conglomerates (SegHigh). The use of these dummies eliminates the assumption that the difference in PEAD between two- and three-segment firms will be the same as the difference in PEAD between seven- and eight-segment firms. Furthermore the use of SegLow and SegHigh dummies also allows us to treat two-segment firms as a separate class, since two-segment conglomerates are as numerous as all other conglomerates put together.

The estimates in column seven provide strong evidence that single-segment firms have lower PEADs than two-segment firms, and two-segment firms have lower PEADs than firms with more than two segments, as the coefficients on the interaction terms of SUE with both dummies are economically large and statistically significant. Using the spread in SUE between the 95th and the 5th percentiles, we can use the coefficients in column seven to estimate PEAD at 1.31% (per three months) for single-segment firms, 2.32% for two-segment firms, and 3.55% for firms with more than two segments. Looking at the spread in SUE between the 97.5th and the 2.5th percentiles will roughly double those estimates.

To sum up, Table 3.3 presents evidence that PEAD is stronger for more complex conglomerates than for less complex conglomerates, and hence the relation between PEAD and complexity is richer than just the link between PEAD and the conglomerate status. We find that PEAD increases roughly monotonically as the complexity of a conglomerate increases.

3.4.3 PEAD AND COMPLEXITY IN EVENT TIME

Cohen and Lou (2012) find that returns to pseudo-conglomerates, made up of single-segment firms, predict the returns to conglomerates in the next month and conclude that firm complexity slows down investors' reaction to industry-wide news. The industry-wide news is first reflected in the prices of simple firms and then the prices of complicated firms move in the same direction. Cohen and Lou find that the predictability is limited to only one month: it takes the investors in complicated firms only one extra month to process the industry-wide shocks and set the prices of conglomerates roughly right, or at least make them unpredictable using returns to single-segment firms.

As this paper shows, earnings-related information is another type of information investors in conglomerates have trouble digesting. Thus, it is interesting to find out whether reacting to earnings related information also takes investors in multi-segment firms a month, as in the related example documented in Cohen and Lou, or longer.

To this end, in Table 3.4 we disaggregate post-announcement CARs into three pieces - CAR(2;20), CAR(21;40), and CAR(41;60) - each approximately a month long and re-run the regressions from Table 3.2 for each subperiod CAR separately.

The first column of Table 3.4 repeats our main analysis in Table 3.2. The next three columns conducts the same regression, by utilizing alternative complexity measures. Each column is labeled with the complexity measure used in that column. We find that the dependence of PEAD on firm complexity stays visible for two months, being, if anything, stronger in the second month. In the third month, the interaction between SUE and complexity loses statistical significance, while remaining economically significant. On the other hand, in the third month, PEAD is insignificant for single-segment firms, too, and the (point estimate of the) ratio of PEAD for simple and complicated firms does not seem to change much with time.

We conclude therefore that it takes investors in complicated firms longer to process earnings related information than it takes them to process industry-wide shocks studied by Cohen and Lou (2012). The difference in PEADs between simple and complicated firms lasts for at least two months.

3.4.4 NEW CONGLOMERATES HAVE STRONGER PEAD THAN OLD ONES

While all proxies for limits to arbitrage we considered are negatively related to complexity and therefore cannot explain our finding that PEAD is stronger for complex firms, it is still possible that complexity and conglomerate status in particular are related to a certain unknown variable that in turn affects the strength of PEAD.

In an effort to understand if investors really have difficulty interpreting information related to more complicated firms we focus on periods during which firm complexity increases. If the level of firm complexity (conglomerate status) is related to a certain unknown variable that also drives PEAD, then new conglomerates would likely have little exposure to this variable and one would expect new conglomerates to have low levels of PEAD. Under our hypothesis, however, investors should have the greatest confusion when interpreting earnings announcements of new conglomerates, due to the significant and recent change to their complexity level.

In Panel A of Table 3.5, we use a dummy variable for the change in the conglomerate status called NewConglo. NewConglo is set to one in the year after the firm switches from having one segment to having more than a single segment, continues to be one for another year, and becomes zero afterwards. NewConglo is also zero in all years when the firm has only one segment. In an average year, we have about 5,000 firms with segment data, about 1,300 conglomerates, and 120-200 new conglomerates, for which NewConglo is 1. Thus, new conglomerates comprise 2.5-4% of our sample and 10-15% of all conglomerates.

The first column of Panel A presents our baseline regression from column three of Table 3.2 (post-announcement CAR on SUE, the Conglo dummy, and the product of SUE and Conglo) with the NewConglo dummy and its interaction with SUE added. The slope on the product of SUE and NewConglo estimates the extra PEAD experienced by new conglomerates as compared to existing conglomerates, since Conglo is, by construction, always 1 when NewConglo is 1.

We make two important observations based on the analysis conducted in the first column of Panel A in Table 3.5. First, PEAD experienced by existing conglomerates (firms that have been conglomerates for more than two years) is more than twice the PEAD experienced by single-segment firms. The regression estimates suggest that PEAD is 1.1% (per three months after the announcement) for single-segment firms and 2.5% for existing conglomerates when we use the difference between the 95th and the 5th percentiles of SUE to calculate differences in PEAD.[23] We conclude that controlling for the effect of new conglomerates does not reduce the significance of the interaction term between PEAD and the conglomerate dummy. The interaction term is as strong as it is in Table 3.2, which suggests that stronger PEADs for more complex firms cannot be attributed to firms that recently have become conglomerates.

Second, we do find that PEAD is significantly stronger for new conglomerates than it is for single-segment firms as well as it is for existing conglomerates. The product of SUE and

[23] The estimates of PEAD would be roughly twice in magnitude for both single-segment firms and existing conglomerates if we instead use the difference between the 97.5th and the 2.5th percentiles of SUE.

NewConglo dummy is statistically significant and its coefficient implies that for new conglomerates PEAD is 4.7% per three months, almost double that of existing conglomerates and more than four times that of single-segment firms.

How are new conglomerates created? In roughly two-thirds of the cases, we are able to trace the increase in the number of segments to M&A activity using SDC data. In the other one-third of the cases it appears that the firm expands from within, starting a new line of business on its own.

In the next two columns of Panel A we try to estimate the PEADs of new conglomerates formed through acquisitions (we replace NewConglo with NewCongloM&A, which equals one only if the change in the conglomerate status can be attributed to a merger with a firm from a different two-digit SIC code on SDC) and the PEADs of new conglomerates created from within (replacing NewConglo with NewCongloNoM&A, which equals one only if the change in the conglomerate status cannot be traced back to a corresponding merger).

We do not have a strong prior regarding whether becoming a new conglomerate through M&A activity or via expansion from within leads to more confusion on the part of investors. On the one hand, the segment added through M&A activity is more likely to be completely new to the firm (whereas the new line of business could have been developing within the firm for several years before the firm starts reporting it as a separate segment) and firms may prefer to expand through M&A activity when venturing into more “distant” industries. These considerations would suggest that stronger PEADs for new conglomerates would be more attributable to new conglomerates formed through M&A activity. On the other hand, both the acquirer and the target receive a lot of scrutiny during a merger, and the target also has a history as a stand-alone firm before the merger. Such scrutiny and the availability of historical information about the target might suggest that higher PEADs for new conglomerates might be driven by new conglomerates that are formed via expansion from within rather than those that are formed through M&A activity.

Panel A strongly supports the latter view. In column two, which singles out new conglomerates that are created through mergers, we find that PEAD is higher only by 0.5% per three months for these new conglomerates than it is for existing conglomerates (the difference, measured by the slope on the product of SUE and NewCongloM&A, is statistically insignificant). In column three though, we focus on new conglomerates that are created from within (i.e., not through a merger), and we discover a huge difference in the PEADs of these new conglomerates and the PEADs of existing conglomerates. Substituting the difference in SUE between the 95th and the 5th percentiles into the regression in the third column, we estimate the average PEAD for single-segment firms at 1.1% (per three months after the announcement), the average PEAD of existing conglomerates at 2.3%, and the average PEAD of new conglomerates created from within at a whopping 8.8%. We conclude therefore that the stronger average PEAD for firms that have recently become conglomerates is attributable primarily to firms that have created a new line of business from within, without merging with another firm from a different industry.

In Panel B, we utilize a different measure of increase in complexity: the SegInc dummy that equals 1 for all firms that experience an increase in the number of segments in the past two years and zero otherwise (by definition, SegInc is zero for all single-segment firms). Firms with SegInc=1 include firms with NewConglo=1 as a subset, but some firms with SegInc=1 are not new conglomerates, they are old conglomerates that have expanded into yet another industry (for example, a firm that reports three segments in year t and four segments in years t+1 and t+2 will have SegInc=1 in years t+1 and t+2).

The obvious upside of using SegInc instead of NewConglo is that there are more firms that experience an increase in the number of segments than those that become new conglomerates. In fact, in a representative year, there are on average 180 firms that add a new segment, while the number of single segment firms that become new conglomerates never exceeds 100 (the number of firm-years with SegInc(NewConglo)=1 is twice the number of firms that experience an increase in segments (that become a new conglomerate), because we track new conglomerates and firms with an increase in the number of segments for two years). The downside of using SegInc is that adding an extra segment to a three-segment firm is clearly a less drastic change than turning a single-segment firm into a conglomerate.

In the first column of Panel B, we regress CAR on SUE, its product with the number of segments (NSeg), and its product with SegInc, as well as NSeg and SegInc by themselves. We use NSeg rather than the Conglo dummy (used in Panel A), because now we are comparing not the PEADs of new and old conglomerates, but rather the PEADs of conglomerates with the same number of segments that have and have not recently experienced an increase in the number of segments. This is what the slope on the product of SUE and SegInc measures: the difference in PEADs between, say, two three-segment firms, one of which has recently become a three-segment firm (out of a single-segment or a two-segment firm) and the other that has stayed as a three segment firm for at least two years.

The first column of Panel B finds that firms with a recent increase in the number of segments have significantly higher PEADs as compared to firms with the same number of segments that have not experienced a change in their number of segments. Substituting the differential between the 95th and the 5th SUE percentiles, we estimate the average PEAD for a single-segment firm at 1.15% (per three months after the announcement)[24], for a three-segment firm with no recent increase in the number of segments at 2.59%, and for a three-segment firm that recently added a new segment (or two) in the past two years at 4.88%. As the regression suggests, the difference in PEADs between the latter two types of firms is also statistically significant with a t-statistic of 2.26.

In the next two columns, we disaggregate segment increase (SegInc=1) events into two subsets: one group of events attributable to M&A activity (those cases of a firm adding a segment or several segments that can be traced to M&A activity on SDC) and a second group of events that are not attributable to such activity, and instead most likely attributable to adding a new line of business for which the firm deploys its internal resources. The estimates in the second column suggest that an increase in the number of segments through M&A has an economically sizeable, but statistically insignificant effect on PEAD: the difference in PEAD between two, say, three-segment firms, one of which added a segment or two through M&A in the past two years and the other one that did not is 1.31% (per three months after the earnings announcement), with a t-statistic of 0.93.

The third column of Panel B, consistent with the third column of Panel A, shows that adding segments from within impacts firm complexity more. Comparing two firms with the same number of segments shows that, the firm that adds a new line of business by growing from within has a PEAD that is 3.85% greater than the PEAD of the firm which adds a new line of business through M&A activity.

To sum up, Table 3.5 strongly suggests that the increase in complexity (defined either as an increase in the number of segments or as the change in the conglomerate status) is associated

[24] The regressions in Panel B assume that the slope on SUE equals $a + b \cdot Nseg + c \cdot SegInc$, where a is the slope of the SUE term, b is the slope of the interaction of SUE and NSeg, c is the slope of the interaction of SUE and SegInc. Hence, the PEAD of single-segment firms is a + b times the SUE differential.

with a large increase in PEAD, consistent with our hypothesis that it is firm complexity (and not any other characteristic common to conglomerates) that creates stronger PEAD. We also find that investors are most confused about firms that expand from within, i.e. about those firms that add segments without being involved in M&A activity.

3.5 WHY DO COMPLEX FIRMS HAVE STRONGER PEAD?

3.5.1 FIRM COMPLEXITY AND ANNOUNCEMENT EFFECTS

One possible explanation of why complex firms have stronger PEAD is that the information revealed by complex firms on the announcement day takes longer to diffuse. If this is the case, then we should expect to see a smaller response around the announcement date, followed by a stronger drift. Another explanation would suggest that, per unit of SUE, more information hits the market on the announcement day in the case of complex firms. If this indeed is the case, then for complex firms we should see a stronger response around the announcement event followed by a stronger drift. Empirically, the first scenario would suggest that regressing announcement returns (CAR(-1;+1)) on the interaction of SUE and firm complexity, would yield a negative coefficient, while the second scenario would imply the opposite result.

In Table 3.6, we perform Fama-MacBeth regressions of announcement returns (size and book-to-market adjusted as in DGTW, cumulated over the period from the day before to the day after the earnings announcement) on SUE, its interaction with the proxy for complexity (the conglomerate dummy in Panel A, the continuous complexity measure, 1-HHI, in Panel B, and the number of segments in Panel C), its interaction with several limits to arbitrage variables that are studied in detail in Table 3.1, as well as the complexity measure and the limits to arbitrage variable themselves. Following our approach in Table 3.2, we exclude microcaps (firms with market cap in the lowest NYSE/AMEX size quintile) from the sample.

We find that irrespective of the control variables used and the complexity measure utilized, complicated firms have significantly larger announcement returns. We also show that the impact of firm complexity on announcement returns is more modest when compared to the impact of firm complexity on PEAD.[25] For example, Panel A suggests that around the earnings announcement date, for single-segment firms the difference in announcement CARs between firms with SUE in the 95th and the 5th percentiles is roughly 1.4% , while for conglomerates the same difference in announcement CARs is only slightly greater at 1.8%. We also find that firms with higher trading costs have stronger announcement effects (either because they are small and witness extreme SUEs more frequently, or because more pre-announcement information is pent up in the price due to infrequent trading) and firms with higher volatility (higher turnover, lower institutional ownership, lower age) have weaker announcement effects (probably because for these firms information takes longer to be incorporated into prices).

In untabulated results, we find that including microcaps back into the sample results in an even stronger positive relation between the announcement effect and firm complexity, as well as a stronger interaction between the announcement effect and trading costs or limits to arbitrage.

The results in Table 3.6 are consistent with the second scenario of stronger PEADs for complex firms: for complex firms, a unit of SUE contains more news, probably because

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[25] The two exceptions when the product of SUE and complexity is insignificant are the columns that control for the product of SUE and the Amihud measure and the product of SUE and institutional ownership. This is due to sample composition rather than being attributable to the effect of the interaction between complexity and the Amihud measure (institutional ownership). The subsample of firms with non-missing institutional ownership as well as the subsample of firms with at least 200 non-missing returns in a year (needed to compute the Amihud measure) and stock price above $5 are very different from the full sample, and in these subsamples the interaction between firm complexity and the announcement effect is weak even prior to controlling for the interaction of SUE with the Amihud measure (institutional ownership).

conglomerates are more diversified and less likely to experience large SUEs (as Panel A2 of Table 3.1 suggests). More news takes longer to digest, which leads to greater PEADs for complex firms.

Does the evidence in Table 3.6 undermine our main story that investors find it more difficult to process the information about complex firms? Could it be that PEAD is stronger for complex firms only because investors have more information to process (per unit of SUE)? The answer relies on a careful examination of the magnitudes of the coefficients. Dividing the slope on the interaction term by the slope on the SUE in Panel A, we find that the announcement effects are about 25-30% stronger for conglomerates. If higher PEADs for conglomerates could only be attributed to these complicated firms having more information per unit of SUE, then PEADs for conglomerates would have also been 25-30% stronger. Yet, Table 3.2 clearly shows that PEAD is twice as large for conglomerates as they are for single-segment firms. Thus, although investors have more information to digest in the case of conglomerates, the rate at which they process the information is also much slower.

3.5.2 CONTROLLING FOR PSEUDO-CONGLOMERATE RETURNS

The return predictability documented by Cohen and Lou (2012), though clearly different from our result, can potentially overlap with it in the following way: if the industries the conglomerate operates in are doing well in month t-1, the conglomerate is more likely to report good earnings in month t. If the earnings are particularly good, they will be followed by the post-announcement drift. However, part of this drift, at least in the first month (month t), can be explained by good returns to the pseudo-conglomerate in month t-1. Thus, the predictability documented by Cohen and Lou (2012) can partially explain why PEAD is stronger for conglomerates.

Our prior is that the overlap between our result and the Cohen and Lou result is not strong. First, Cohen and Lou show that their predictability of conglomerate returns in month t using pseudo-conglomerate returns in month t-1 is attributable primarily to the first two weeks of month t. Since an average earnings announcement happens in the middle of the month, it would be fair to say that we will be missing those two weeks most of the time. Second, the predictability in Cohen and Lou lasts for only one month, whereas the stronger PEAD for conglomerates lasts for at least two months, as Table 3.4 shows.

In Table 3.7, we explicitly control for pseudo-conglomerate returns (PCRet) by adding it into our main regressions of CARs on SUE, complexity, and the product of SUE and complexity. Following Cohen and Lou, PCRet is computed by first taking an equal-weighted average return of all single-segment firms in each two-digit SIC industry, and then, for each conglomerate, value-weighting the industry returns by the fractions of the segments with the same two-digit SIC code that comprise the total sales of the conglomerate.

Since our sample has to include both single-segment firms and conglomerates in order to compare the PEADs for the two types of firms, we have to substitute an alternative variable for "PCRet" for single-segment firms. We define "PCRet" of single-segment firms as the return to single segment firms in the same industry, thus turning it into a measure of industry momentum. We also control for in our regressions both PCRet itself and the interaction of PCRet with the conglomerate dummy, to allow for different slopes on it for single-segment firms and conglomerates.

In the first column of Table 3.7, we regress CARs on SUE, PCRet, and PCRet times the conglomerate dummy. We observe two results. First, controlling for industry momentum in the form of "PCRet" for single-segment firms makes the slope on SUE somewhat smaller: it declines from 0.118 in the first column of Table 3.2 to 0.101 in the first column of Table 3.7. Second, we observe that PCRet itself is significant, while its product with the conglomerate dummy has a tiny, insignificant coefficient. This evidence implies that pseudo-conglomerate returns proposed by Cohen and Lou as well as measures of industry momentum are positively related to CARs.[26] Indeed, since PCRet picks up industry momentum in the single-segment firms subsample and the Cohen and Lou predictability in the conglomerate subsample, the tiny insignificant coefficient on the interaction of PCRet and the conglomerate dummy suggests that the slopes on PCRet are the same in both subsamples and the Cohen and Lou predictability for conglomerates is just as strong as industry momentum for single-segment firms.

The other three columns of Table 3.7 add to the regression in the first column a measure of complexity and its product with SUE. The slopes on the interaction of complexity with SUE estimate the additional PEAD experienced by conglomerates. The slopes estimated after controlling for the predictability documented in Cohen and Lou (2012) are similar in magnitude to the slopes estimated earlier in Table 3.2. We conclude that the stronger PEADs experienced by conglomerates is a separate phenomenon that has no overlap with the predictability of conglomerate returns using returns to pseudo-conglomerates as suggested by Cohen and Lou (2012).

[26] Strictly speaking, the correct way to estimate industry momentum would be to compute industry returns using all firms in the industry, including conglomerates. We tried that and found little change in the slope of "PCRet" for single-segment firms defined this way, which suggests that the average return to all single-segment firms in an industry is a good enough proxy for the true industry return.

3.5.3 FIRM COMPLEXITY AND ANALYST COVERAGE

If information about conglomerates is harder to process, analysts can be discouraged from following conglomerates, which, in turn, can lead to stronger PEADs for conglomerates. In Table 3.8, we analyze the link between firm complexity and analyst coverage by comparing single-segment firms and conglomerates across several dimensions. In addition to utilizing the traditional measure of analyst coverage, the number of analysts following the firm, we also measure the quality of the coverage by analyzing the number and fraction of specialists following the firm. An analyst following a firm is categorized as a specialist in that quarter, if the analyst covers five or more firms in the same industry in a given quarter (we use both two-digit and three-digit SIC codes to define an industry). For a conglomerate, specialists are defined using the industry affiliation of its main segment.

Size potentially has a large confounding effect on the link between firm complexity and analyst following. While conglomerates are harder to understand due to their complexity, the benefits of understanding conglomerates can be greater due to their larger size. Thus, in order to assess how complexity impacts analyst coverage, we have to control for size by comparing conglomerates to single-segment firms of similar size.

In Panel A of Table 3.8, we define firm size as its market cap and distribute conglomerates and single-segment firms into size deciles formed using CRSP breakpoints. While this method of controlling for size is imperfect, it turns out powerful enough to elicit that conglomerates have less analyst coverage and their coverage is of lower quality than that of single-segment firms. In all size deciles, conglomerates are followed by fewer analysts and fewer specialists. We also observe that a smaller percentage of analysts covering conglomerates are specialists. The biggest difference is in the number of specialists, as single-segment firms have 25% to 40% higher percentage of specialists. Both the relative and absolute differences in the analyst coverage peak in size deciles six to eight, suggesting that conglomerates which suffer from lower quality coverage are relatively large firms and are not obscure/micro-cap multi-segment firms.

Once we control for size we also find that conglomerates suffer from larger analyst forecast errors due to the lower quality and the quantity of analyst coverage they receive. As the second bottom row of Panel A suggests, conglomerates have larger analyst forecast errors in all size deciles but one (decile two), and the difference is material: on average, conglomerates have 15% larger forecast errors compared to single-segment firms controlling for size. Once again, the difference is mainly observed in the deciles with the largest conglomerate population: the differences in forecast errors are particularly large, in relative terms, in size deciles seven, nine and ten.

In Panel B1, we control for size in a different way: we match each conglomerate to a single-segment firm with the closest market cap. We observe again, consistent with Panel A, that conglomerates are followed by 1-2 analysts and specialists less than single-segment firms of comparable size, which constitutes a difference of 20-30% in the quality of analyst coverage. In terms of fraction of specialists, we find, for example, that on average 70% of analysts covering a single-segment firm specialize in its three-digit SIC industry, but only 57% of analysts covering a conglomerate specialize in the three-digit SIC industry of its main segment. All differences in analyst coverage are highly statistically significant and are observed in the vast majority of quarters.

As a consequence of lower quality analyst coverage, Panel B1 also reports that analyst forecast error is 19% higher for conglomerates than it is for single-segment firms of the same size, and the difference is significant with a t-statistic of 3.29.

Panel B2 illustrates the importance of controlling for size when comparing analyst coverage of conglomerates and single-segment firms by removing the size-matching. If we do not match by size, we find that conglomerates, due to their larger market cap, are followed by significantly more analysts. However, the difference in specialist coverage is not significant prior to controlling for size, and in relative terms, the fraction of specialists among analysts following conglomerates is still smaller than the same fraction for single-segment firms even without the size control.

We conclude that while a representative conglomerate is covered by somewhat larger number of analysts than a representative single-segment firm due to the conglomerate being much larger, this extra coverage is of poor quality, since it comes primarily from non-specialists and probably even dilutes the average analyst quality. Controlling for the confounding effect of size makes the negative relation between firm complexity and the quality of analyst coverage really stand out: when compared to single-segment firms of similar size, conglomerates are followed by a fewer number of analysts and specialists, and those analysts make larger forecast errors.

3.5.4 IS ANALYST COVERAGE RESPONSIBLE FOR STRONGER PEAD OF COMPLEX FIRMS?

Stronger PEADs experienced by conglomerates could be attributed to the lower quality and quantity of the analyst coverage they receive. Lower quality and quantity of analyst coverage would imply a less transparent information environment for conglomerates, which would make complicated firms harder to value and as a result would deter arbitrageurs from betting against any perceived mispricing of complicated firms. But, can the relatively lower quality and quantity of analyst coverage of conglomerates fully explain higher PEADs experienced by complicated firms? Or is there more to firm complexity per se that makes the firm harder to value?

In an attempt to disentangle the impact of firm complexity on PEAD from the impact of analyst coverage on PEAD, in Table 3.9, we perform a horse race between these two alternative sources of PEAD. In doing so, we regress post-announcement CAR on the interaction of SUE and complexity (the slope on which captures stronger PEAD for complex firms) and the interaction of SUE and the number of analysts/specialists covering the firm. If differences in analyst coverage between conglomerates and single-segment firms drive stronger PEADs for complex firms, then we would expect the slope on the product of SUE and complexity to diminish drastically once we control for the product of SUE and the number of analysts/specialists.

Since the analysis in Table 3.8 shows that controlling for size is critical when comparing analyst coverage of conglomerates and single-segment firms, in Table 3.9 we orthogonalize our alternative measures of analyst coverage with respect to firm size: Every quarter we regress analyst coverage on size in the full cross-section of firms and denote the residuals of this regression as our measure of relative / residual analyst coverage.

In column one, we re-estimate our baseline regression of CAR on SUE, firm complexity (defined as 1-HHI), and the product of SUE and complexity using only the firms for which we have analyst coverage data. Since the number of specialists covering the firm is computed using IBES detail files, our sample for Table 3.9, as well as for Table 3.8, starts in January 1984. We find that in this new sample the relation between PEAD and complexity is about a third stronger than it is in the full sample.

In columns two, four, and six of Table 3.9, we regress CAR on SUE, number of analysts/specialists and the interaction of SUE with the number of analysts/specialists. We observe that the product of SUE with all measures of analyst coverage is significantly negative, resulting in significantly stronger PEADs for firms with relatively low analyst coverage, as expected. The negative relationship between PEAD and analyst coverage documented in Table 3.9, to the best of our knowledge, is new to the literature.

Columns three, five, and seven present the main tests of Table 3.9. In these columns, we simultaneously control for both interactions: SUE times complexity and SUE times analyst coverage. We observe that, consistent with the hypothesis that relatively low analyst coverage of conglomerates leads to stronger PEADs for complex firms, the slope on the interaction of SUE and analyst coverage is positive, and economically as well as statistically highly significant even after we control for the interaction of SUE and complexity. On the other hand we find that the interaction of SUE and complexity becomes visibly smaller and is sometimes only marginally significant after we control for the interaction of SUE and analyst coverage.

Comparing the slopes on SUE times complexity before and after controlling for the interaction of SUE and analyst coverage, we estimate that only 20% to 30% of the additional PEAD experienced by complex firms can be accounted for by the lower quality and quantity of the analyst coverage received by complex firms. This finding is independent of the measure of analyst coverage utilized, though using three-digit SIC specialists (the largest and perhaps the most important difference in the coverage of single-segment firms and conglomerates) elicits the biggest overlap between SUE times complexity and SUE times coverage.

In untabulated results, we check whether the overlap between SUE times complexity and SUE times analyst coverage changes if we use the other two measures of complexity (the conglomerate dummy and the number of segments) and find that the overlap is roughly the same no matter which measure of complexity we use.

To sum up, Tables 3.8 and 3.9 suggest that the complexity of conglomerates makes them relatively unattractive targets for analysts to follow. This is especially true for specialist analysts, who cover firms from the same industry and rely on industry expertise. Thus, the analyst coverage of complex firms is both relatively thin and of relatively low quality once we control for size effects. The lower quality of the analyst coverage received by complex firms is one of the reasons why complex firms have stronger PEADs. Nevertheless, reduced coverage amount (quality) can account for at most 30% of the additional PEAD experienced by complex firms. We conclude therefore that there is more to firm complexity than the difference in the quality (quantity) of analyst coverage: even when a complex firm has the same amount and quality of analyst coverage as a single-segment firm of the same size, the complex firm will still have materially stronger PEAD than its size-and-coverage matched single-segment peer.

3.6 CONCLUSION

We propose using firm complexity, measured alternatively as the conglomerate status, the number of business segments and the concentration of segment sales, as a new limits to arbitrage variable. We hypothesize that information about complex firms is harder to process, and predict therefore that PEAD is stronger for complex firms per unit of SUE.

Firm complexity is an unusual limits to arbitrage variable, because, as we confirm, complex firms are significantly larger and their other characteristics, such as trading costs, volatility, analyst coverage, and institutional ownership, suggest that complex firms should have lower, not higher limits to arbitrage. Hence, if we find higher limits to arbitrage for more complicated firms, we can be sure that this effect is attributable to firm complexity, and not some other variable.

We do find, using cross-sectional regressions, that PEAD per unit of SUE is twice as large for complex firms as it is for single segment firms. The effect of complexity on PEAD is even stronger when we control for trading costs. The impact of complexity on PEAD lasts for at least two months, which leads us to conclude that investors of complex firms have even more trouble interpreting earnings-related information than they do interpreting industry-wide shocks (Cohen and Lou (2012) find that the returns to conglomerates are predictable using the returns to single-segment firms from the same industry, but this effect lasts for only one month).

We also find that the degree of complexity matters: PEAD is not only stronger for conglomerates than for single-segment firms, but it is also stronger for more complex conglomerates than for less complex conglomerates. This conclusion holds true irrespective of the measure of complexity used.

To address the concern that complexity is related to a certain unknown variable that also affects the strength of PEAD, we reexamine the effect of complexity on PEAD focusing on periods during which firm complexity increases. The analysis provides compelling evidence that supports our slower-information-processing hypothesis: PEAD is stronger for new conglomerates than it is for existing conglomerates, and it is also stronger for complicated firms that have recently experienced an increase in the number of segments. We also find that investors are most confused about complicated firms that expand from within rather than firms that diversify into new business segments via mergers and acquisitions.

We investigate whether the difference in the PEADs of complex and simple firms could be purely attributed to the difference in the amount of information revealed by these firms during earnings announcements. Our analysis suggests that for complex firms, one unit of SUE generates a stronger return reaction at the earnings announcement. Since extreme values of SUEs are less characteristic of conglomerates, we conclude that a unit of SUE contains more information for complex firms than it does for single-segment firms. Further analysis reveals that the return reaction around the announcement date for complex firms is larger by 25-30%, when compared to single-segment firms. Although the difference in announcement returns of complex and single-segment firms suggests that complex firms release more information per unit of SUE when compared to simple firms, the magnitude of this difference in the information content is not large enough to justify almost twice as large PEAD per unit of SUE experienced by complex firms. Taken together these results suggest that not only the earnings announcements of conglomerates contain more news than the earnings announcements of single-segment firms, but also that the rate of information processing is much slower for conglomerate firms.

We also investigate whether this phenomenon is related to the return predictability documented in Cohen and Lou (2012). We control for pseudo-conglomerate returns in our regressions and find that the interaction between SUE and complexity is unaffected, which means that there is virtually no overlap between the Cohen and Lou result and the stronger PEADs for conglomerates.

Finally, we entertain the possibility that stronger PEAD for complex firms is due to the fact that analysts tend to provide less and lower quality coverage for complex firms. We do find that conglomerates are followed by a fewer number of analysts compared to single-segment firms of similar size. The analysts covering conglomerates are also less likely to have industry expertise and more likely to make larger forecast errors than the analysts covering single-segment firms. We also document that lower analyst coverage is associated with stronger PEAD and that controlling for the relation between PEAD and analyst coverage reduces the impact of complexity on PEAD by about 20-30%.

In summary, our study of the reasons why complex firms have stronger PEAD reaches three main conclusions. First, the stronger PEAD for complex firms is independent from the return predictability documented by Cohen and Lou (2012) and thus represents a separate case of the impact of firm complexity on stock prices. Second, roughly a quarter of the relation between PEAD and complexity can be attributed to the fact that a unit of SUE has more information for complex firms than for simple firms and another quarter of the relation can be attributed to the relatively low analyst coverage of complex firms after one controls for size. Third, even after controlling for these alternative explanations, complexity per se plays an important role as a limits to arbitrage variable.

Table 3.1: Descriptive Statistics

The table presents mean (Panel A) and median (Panel B and C) values of numerous firm characteristics for single-segment firms ("Single"), conglomerates ("Conglo"), and all Compustat firms ("All"), as well as the difference between single-segment firms and conglomerates (S-C) and the difference between all Compustat firms and conglomerates. Conglomerates are defined as firms with business segments in more than one industry (industries are based on two-digit SIC codes), single-segment firms are all other firms with information in Compustat segment files. The definitions of the firm characteristics are in the Data Appendix. The t-statistics use Newey-West (1987) correction for heteroscedasticity and autocorrelation. The sample period is from January 1977 to December 2010.

Panel A1. SUE and Complexity Distribution - All Firms

	Mean	1%	2.5%	5%	10%	25%	50%	75%	90%	95%	97.5%	99%
SUE	0.010	-0.317	-0.145	-0.075	-0.034	-0.007	0.002	0.008	0.029	0.064	0.129	0.302
NSeg	1.547	1	1	1	1	1	1	2	2.7	3.4	4	4.7
Comp	0.117	0	0	0	0	0	0.023	0.143	0.449	0.546	0.608	0.678

Panel A2. SUE and Complexity Distribution - Conglomerates Only

	Mean	1%	2.5%	5%	10%	25%	50%	75%	90%	95%	97.5%	99%
SUE	-0.001	-0.271	-0.129	-0.067	-0.031	-0.007	0.002	0.008	0.026	0.053	0.101	0.220
NSeg	2.646	2	2	2	2	2	2.2	3.1	3.8	4.3	4.9	5.7
Comp	0.351	0.011	0.021	0.041	0.079	0.191	0.368	0.497	0.596	0.655	0.694	0.736

Panel B. Earnings Announcements

Panel B1. Raw Values

	Single	Conglo	All	S-C	A-C
SUE	0.156%	0.155%	0.160%	0.001%	0.005%
t-stat	6.86	4.03	5.44	0.06	0.32
EA	0.137%	0.161%	0.125%	-0.024%	-0.036%
t-stat	2.80	3.17	3.11	-0.59	-1.15

Panel B2. Absolute Values

	Single	Conglo	All	S-C	A-C
SUE	0.626%	0.660%	0.635%	-0.034%	-0.025%
t-stat	17.4	17.2	17.8	-1.52	-2.40
EA	3.575%	2.866%	3.160%	0.709%	0.294%
t-stat	12.5	14.4	14.2	5.67	4.46

Panel C. Liquidity

	Single	Conglo	All	S-C	A-C
Gibbs	0.540	0.389	0.489	0.151	0.100
t-stat	13.3	21.9	15.2	4.61	4.42
Spread	0.871	0.599	0.755	0.272	0.156
t-stat	12.4	13.0	14.4	5.20	4.92
Roll	1.525	1.200	1.417	0.325	0.217
t-stat	17.8	20.9	19.8	4.95	4.6
Amihud	3.686	2.201	2.463	1.484	0.262
t-stat	3.73	2.94	3.78	4.76	0.91
Zero	14.09	11.81	13.69	2.28	1.88
t-stat	*5.64*	*5.87*	*5.78*	*3.85*	*4.48*

Panel D. Information Environment

	Single	Conglo	All	S-C	A-C
Size	0.304	0.600	0.361	-0.296	-0.239
t-stat	5.25	5.64	5.16	-5.54	-5.55
IO	0.404	0.452	0.394	-0.048	-0.058
t-stat	6.76	8.17	7.14	-6.97	-9.40
# An	4.748	5.414	4.513	-0.667	-0.901
t-stat	11.7	16.1	13.2	-5.28	-9.68
IVol	2.033	1.598	1.854	0.435	0.255
t-stat	14.6	21.2	17.5	4.73	4.20
Turn	7.633	6.941	7.019	0.692	0.078
t-stat	4.91	5.07	5.04	2.38	0.75

Table 3.2: Conglomerates, Firm Complexity, and the Post-Earnings-Announcement Drift

The table presents quarterly Fama-MacBeth regressions of size and book-to-market adjusted cumulative returns in the 60 days following earnings announcements (CAR(2;60)) on earnings surprise (SUE) and its interaction with measures of firm complexity and trading costs. Amihud measures the price impact. Complexity is 1-HHI, where HHI is the Herfindahl index computed using segment sales within a conglomerate: for each segment, we compute the amount of sales generated by that segment as a fraction of the total sales of the firm and add up the squared fractions to compute HHI. Conglo is the conglomerate dummy, equal to 1 if the firm is a conglomerate and 0 otherwise. Conglomerates are defined as firms with more than one business segment. NSeg is the number of segments the firm has. Segments are counted as distinct business units if they can be assigned to different two-digit SIC industries. Definitions of firm characteristics are in the Data Appendix. The t-statistics use Newey-West (1987) correction for heteroscedasticity and autocorrelation. The sample period is from January 1977 to December 2010. The sample excludes firms with market caps in the lowest NYSE/AMEX quintile.

	1	**2**	**3**	**4**	**5**	**6**	**7**	**8**
SUE	0.118	0.143	0.095	0.115	0.099	0.123	0.051	0.079
t-stat	*4.98*	*4.62*	*4.17*	*3.48*	*4.36*	*4.00*	*1.63*	*1.70*
Amihud		-0.007		-0.007		-0.007		-0.007
t-stat		*-1.81*		*-1.90*		*-1.91*		*-1.88*
SUE×Ami		0.320		0.323		0.335		0.326
t-stat		*3.56*		*3.37*		*3.54*		*3.45*
Conglo			-0.001	-0.001				
t-stat			*-0.55*	*-0.27*				
SUE×Cong			0.084	0.107				
t-stat			*2.61*	*2.51*				
Complexity					-0.003	-0.002		
t-stat					*-0.64*	*-0.38*		
SUE×Comp					0.184	0.218		
t-stat					*2.73*	*2.70*		
NSeg							0.000	0.000
t-stat							*-0.30*	*-0.09*
SUE×N							0.048	0.052
t-stat							*2.56*	*2.17*

Table 3.3: Does the Degree of Complexity Matter?

The table studies PEAD in the subsamples of low and high complexity conglomerates. The columns labeled "All" use all firms in the sample, including those with market caps in the lowest NYSE/AMEX quintile. The column marked "0<Comp<Med" ("Comp>Med") uses only conglomerates with complexity measure, 1-HHI, below (above) the median. The column marked "NSeg>1" uses all conglomerates, but excludes single-segment firms. CompLow (CompHigh) is a dummy variable that equals 1 for conglomerates with complexity, 1-HHI, below (above) the median and 0 otherwise. CompLow and CompHigh are 0 for all single-segment firms. SegLow (SegHigh) is a dummy variable that equals 1 if a firm has 2 (more than 2) segments and 0 otherwise. SUE ×Low and SUE ×High are the products of SUE with CompLow and CompHigh, respectively (first column) and the products of of SUE with SegLow and SegHigh, respectively (fifth column). Definitions for all other firm characteristics are in the Data Appendix. The t-statistics use Newey-West (1987) correction for heteroscedasticity and autocorrelation. The sample period is from January 1977 to December 2010.

	All	0<Comp<Med	Comp>Med	All		All	NSeg>1	All
SUE	0.099	0.131	-0.074	0.093	**SUE**	0.059	0.096	0.094
t-stat	*5.26*	*3.04*	*-0.55*	*4.04*	**t-stat**	*2.43*	*1.46*	*4.24*
Complexity	-0.011	-0.012	0.002		**NSeg**	-0.002	0.000	
t-stat	*-2.39*	*-1.44*	*0.22*		**t-stat**	*-1.99*	*-0.32*	
SUE×Comp	0.127	0.448	0.458		**SUE×N**	0.038	0.026	
t-stat	*2.32*	*2.03*	*1.71*		**t-stat**	*2.81*	*1.05*	
CompLow				0.000	**SegLow**			-0.002
t-stat				*-0.04*	**t-stat**			*-0.86*
CompHigh				-0.002	**SegHigh**			-0.001
t-stat				*-0.95*	**t-stat**			*-0.46*
SUE×Low				0.110	**SUE×Low**			0.073
t-stat				*2.35*	**t-stat**			*2.30*
SUE×High				0.100	**SUE×High**			0.161
t-stat				*2.81*	**t-stat**			*3.17*

Table 3.4: For How Long Does Complexity Impact PEAD?

The table presents results of regressions of CAR on SUE, alternative measures of complexity, and the interactions of SUE with various complexity measures. CAR(N;M) is size and book-to-market adjusted cumulative daily return between the Nth and Mth days after the earnings announcement. Complexity variables are described in the header of Table 3.2 and Data Appendix. The t-statistics use Newey-West (1987) correction for heteroscedasticity and autocorrelation. The sample period is from January 1977 to December 2010. The sample excludes firms with market caps in the lowest NYSE/AMEX quintile.

Panel A. Conglomerate Dummy

	CAR(2;60)	CAR(2;20)	CAR(21;40)	CAR(41;60)
SUE	0.094	0.030	0.046	0.020
t-stat	*4.24*	*2.60*	*4.31*	*1.56*
Conglo	-0.002	-0.001	0.000	-0.001
t-stat	*-0.74*	*-1.04*	*0.22*	*-1.13*
SUE×Cong	0.093	0.030	0.039	0.025
t-stat	*3.02*	*1.79*	*2.24*	*1.10*

Panel B. Complexity

	CAR(2;60)	CAR(2;20)	CAR(21;40)	CAR(41;60)
SUE	0.098	0.030	0.046	0.023
t-stat	*4.29*	*2.65*	*4.59*	*1.78*
Complexity	-0.004	-0.002	0.000	-0.002
t-stat	*-0.92*	*-1.14*	*-0.18*	*-0.85*
SUE×Comp	0.199	0.066	0.097	0.033
t-stat	*3.09*	*1.53*	*2.69*	*0.69*

Panel C. Number of Segments

	CAR(2;60)	CAR(2;20)	CAR(21;40)	CAR(41;60)
SUE	0.051	0.002	0.038	0.014
t-stat	*1.78*	*0.15*	*2.53*	*0.67*
NSeg	-0.001	0.000	0.000	0.000
t-stat	*-0.50*	*-1.01*	*0.20*	*-0.53*
SUE×N	0.048	0.024	0.013	0.010
t-stat	*2.74*	*2.92*	*1.62*	*0.89*

Table 3.5: Post-Earnings-Announcement Drift and Changes in Complexity

The table presents quarterly Fama-MacBeth regressions of size and book-to-market adjusted cumulative returns in the 60 days following earnings announcement (CAR(2;60)) on earnings surprise (SUE), interaction of SUE with alternative measures of firm complexity (Conglo and NSeg), as well as the interaction of SUE with a dummy variable for newly created conglomerates (NewConglo, Panel A) or a dummy variable for increase in the number of segments (SegInc). NewConglo (SegInc) is one for two years after a one-segment firm (any firm) reports an increase in the number of segments and zero otherwise. Both NewConglo and SegInc are set to zero for all single-segment firms. SUE$times$M\&A (SUE$times$NoM\&A) is the interaction of SUE with NewConglo / SegInc for segment increases that can be attributed to diversifying M&A activity (that cannot be attributed to diversifying M&A activity). Definitions for all other firm characteristics are in the Data Appendix. The t-statistics use Newey-West (1987) correction for heteroscedasticity and autocorrelation. The sample period is from January 1977 to December 2010.

Panel A. PEAD and New Conglomerates				Panel B. PEAD and New Segments			
	1	**2**	**3**		**1**	**2**	**3**
SUE	0.080	0.080	0.080	**SUE**	0.031	0.031	0.036
t-stat	*4.25*	*4.25*	*4.25*	**t-stat**	*1.08*	*1.08*	*1.30*
Conglo	-0.002	-0.002	-0.002	**NSeg**	-0.001	-0.001	-0.001
t-stat	*-0.96*	*-0.96*	*-0.96*	**t-stat**	*-0.62*	*-0.64*	*-0.63*
NewConglo	-0.005	-0.004	-0.006	**SegInc**	-0.006	-0.004	-0.006
t-stat	*-2.04*	*-1.35*	*-1.60*	**t-stat**	*-2.59*	*-1.65*	*-2.07*
SUE×Cong	0.100	0.100	0.100	**SUE×NSeg**	0.052	0.054	0.048
t-stat	*2.91*	*2.91*	*2.91*	**t-stat**	*2.49*	*2.64*	*2.42*
SUE×New	0.158			**SUE×SegInc**	0.164		
t-stat	*2.13*			**t-stat**	*2.26*		
SUE×M&A		0.046		**SUE×M&A**		0.095	
t-stat		*0.39*		**t-stat**		*0.93*	
SUE×NoM&A			0.452	**SUE×NoM&A**			0.277
t-stat			*2.08*	**t-stat**			*1.63*

Table 3.6: Conglomerates, Firm Complexity, and the Earnings Announcement Reaction

The table presents quarterly Fama-MacBeth regressions of size and book-to-market adjusted cumulative returns in the three days around earnings announcements (CAR(-1;+1)) on earnings surprise (SUE) and on the interaction of SUE with measures of firm complexity and other firm characteristics. Complexity is 1-HHI, where HHI is the Herfindahl index computed using segment sales within a conglomerate: for each segment, we compute the amount of sales generated by that segment as a fraction of the total sales of the firm and add up the squared fractions to compute HHI. Conglo is the conglomerate dummy, equal to 1 if the firm is a conglomerate and 0 otherwise. Conglomerates are defined as firms with more than one business segment. NSeg is the number of segments the firm has. Segments are counted as distinct business units if they can be assigned to different two-digit SIC industries. Definitions of firm characteristics are in the Data Appendix. The t-statistics use Newey-West (1987) correction for heteroscedasticity and autocorrelation. The sample period is from January 1977 to December 2010. The sample excludes firms with market caps in the lowest NYSE/AMEX quintile.

Panel A. Conglomerate Dummy and Announcement Effects

	1	**2**	**3**	**4**	**5**	**6**
SUE	0.083	0.084	0.090	0.126	0.103	0.101
t-stat	*7.80*	*9.23*	*7.91*	*7.81*	*7.31*	*9.83*
Conglo	0.000	0.000	0.000	0.000	0.000	0.000
t-stat	*-0.22*	*-0.76*	*0.46*	*-1.17*	*0.12*	*-0.97*
SUE×Cong	0.025	0.010	0.026	0.032	0.028	0.027
t-stat	*2.38*	*0.81*	*2.43*	*3.06*	*2.53*	*2.22*
	Gibbs	**Amihud**	**Zero**	**IVol**	**Turn**	**IO**
Var	-0.147	-0.004	-0.023	-0.124	-0.016	0.006
t-stat	*-1.94*	*-2.31*	*-1.89*	*-4.54*	*-3.14*	*5.57*
SUE×Var	0.928	0.310	-0.046	-1.467	-0.375	0.040
t-stat	*0.71*	*3.40*	*-0.41*	*-3.94*	*-2.14*	*1.22*

Panel B. Complexity and Announcement Effects

	1	2	3	4	5	6
SUE	0.080	0.079	0.087	0.127	0.102	0.100
t-stat	*7.87*	*8.73*	*8.25*	*7.69*	*7.21*	*10.21*
Complexity	-0.001	-0.001	0.000	-0.001	-0.001	-0.001
t-stat	*-0.83*	*-1.63*	*-0.51*	*-1.82*	*-0.82*	*-1.53*
SUE×Comp	0.073	0.070	0.089	0.086	0.082	0.060
t-stat	*2.97*	*2.18*	*3.40*	*3.33*	*3.06*	*2.01*
	Gibbs	**Amihud**	**Zero**	**IVol**	**Turn**	**IO**
Var	-0.155	-0.004	-0.023	-0.127	-0.016	0.006
t-stat	*-2.01*	*-2.30*	*-1.91*	*-4.59*	*-3.15*	*5.59*
SUE×Var	0.896	0.316	-0.028	-1.503	-0.363	0.044
t-stat	*0.62*	*3.53*	*-0.27*	*-3.99*	*-2.07*	*1.35*

Panel C. Number of Segments and Announcement Effects

	1	2	3	4	5	6
SUE	0.059	0.071	0.068	0.105	0.082	0.084
t-stat	*4.97*	*4.89*	*4.95*	*6.44*	*5.16*	*5.92*
NSeg	0.000	0.000	0.000	0.000	0.000	0.000
t-stat	*-0.49*	*-0.93*	*0.02*	*-2.19*	*-0.23*	*-1.13*
SUE×N	0.017	0.010	0.017	0.020	0.019	0.016
t-stat	*3.12*	*1.35*	*2.81*	*3.44*	*2.98*	*2.29*
	Gibbs	**Amihud**	**Zero**	**IVol**	**Turn**	**IO**
Var	-0.155	-0.004	-0.023	-0.126	-0.016	0.006
t-stat	*-2.03*	*-2.29*	*-1.90*	*-4.54*	*-3.11*	*5.55*
SUE×Var	1.054	0.304	-0.044	-1.497	-0.395	0.042
t-stat	*0.78*	*3.49*	*-0.39*	*-4.07*	*-2.12*	*1.33*

Table 3.7: Controlling for Pseudo-Conglomerate Returns

The table presents quarterly Fama-MacBeth regressions of size and book-to-market adjusted cumulative returns in the 60 days following earnings announcements (CAR(2;60)) on earnings surprise (SUE) and on the interaction of SUE with alternative measures of firm complexity controlling for pseudo-conglomerate returns (PCRet). PCRet is calculated one month before the earnings announcement. To compute PCRet, we first compute equal-weighted returns to all single-segment firms in an industry (industries are defined based on the two-digit SIC codes). For a single-segment firm, PCRet is calculated as the return to other single-segment firms in its two-digit SIC industry. For conglomerates, industry returns for affiliated segments are weighed by the respective sales shares of the business segments and the weighted average is referred to as PCRet. Complexity variables are described in the header of Table 2 and in the Data Appendix. The t-statistics use Newey-West (1987) correction for heteroscedasticity and autocorrelation. The sample period is from January 1977 to December 2010. The sample excludes firms with market caps in the lowest NYSE/AMEX quintile.

	1	**2**	**3**	**4**
SUE	0.101	0.080	0.083	0.035
t-stat	5.10	4.13	4.14	1.22
PCRet	0.057	0.056	0.054	0.054
t-stat	1.88	1.87	1.83	1.81
PCRet×Cong	0.006	-0.006	0.001	-0.001
t-stat	0.26	-0.26	0.07	-0.03
Conglo		-0.002		
t-stat		-0.75		
SUE×Cong		0.097		
t-stat		2.87		
Complexity			-0.005	
t-stat			-1.05	
SUE×Comp			0.209	
t-stat			3.12	
NSeg				0.000
t-stat				-0.37
SUE×N				0.051
t-stat				2.50

Table 3.8: Firm Complexity and Analyst Following: Descriptive Statistics

The table compares analyst coverage of single-segment firms and conglomerates. Specialists are analysts that cover five or more firms in the same industry (defined using either the two- or the three-digit SIC code, as indicated). For conglomerates, specialists are defined based on the industry affiliation of the firm's main segment. Forecast error is the difference between consensus earnings forecast and actual earnings, scaled by actual earnings. The t-statistics use Newey-West (1987) correction for heteroscedasticity and autocorrelation. The sample period is from January 1984 to December 2010.

Panel A. Analyst Following of Single-Segment Firms and Conglomerates across Size Deciles

Panel A1. Single-Segment Firms

Size	Small	2	3	4	5	6	7	8	9	Big
# Analysts	1.2	1.5	1.9	2.4	3.0	3.6	4.5	5.7	7.2	11.4
# Specialists (SIC2)	0.8	1.0	1.4	1.8	2.3	2.9	3.7	4.8	6.3	10.4
# Specialists (SIC3)	0.6	0.9	1.2	1.5	2.0	2.5	3.3	4.3	5.7	9.7
% of Specialists (SIC2)	0.604	0.657	0.682	0.702	0.725	0.754	0.771	0.805	0.837	0.896
% of Specialists (SIC3)	0.472	0.533	0.564	0.576	0.606	0.633	0.662	0.696	0.736	0.820
Forecast Error	1.169	1.154	0.909	0.824	0.762	0.662	0.540	0.474	0.384	0.293
# obs	16 344	16 079	15 768	15 180	14 615	14 132	13 351	12 268	11 048	9 579

Panel A2. Conglomerates

Size	Small	2	3	4	5	6	7	8	9	Big
# Analysts	1.1	1.4	1.7	2.0	2.4	2.8	3.4	4.3	6.0	10.1
# Specialists (SIC2)	0.6	0.7	1.0	1.2	1.6	1.9	2.4	3.2	4.7	8.6
# Specialists (SIC3)	0.4	0.5	0.7	1.0	1.2	1.5	1.9	2.7	4.0	7.6
% of Specialists (SIC2)	0.508	0.482	0.542	0.561	0.580	0.628	0.637	0.696	0.740	0.819
% of Specialists (SIC3)	0.367	0.377	0.402	0.420	0.415	0.463	0.498	0.570	0.608	0.711
Forecast Error	1.257	1.087	1.152	0.958	0.848	0.717	0.704	0.534	0.471	0.341
# obs	2 792	3 115	3 437	4 009	4 570	5 083	5 849	6 926	8 157	9 573

Panel B. Analyst Following of Single-Segment Firms and Conglomerates: The Role of Size Matching

Panel B1. Size Matching

	Conglo	Simple	diff	t-stat
# Analysts	5.4	6.6	-1.2	-7.53
# Specialists (SIC2)	4.3	5.8	-1.5	-10.01
# Specialists (SIC3)	3.6	5.2	-1.6	-11.06
% of Specialists (SIC2)	0.70	0.81	-0.12	-12.42
% of Specialists (SIC3)	0.57	0.71	-0.15	-14.46
Forecast Error	0.59	0.50	0.09	3.29

Panel B2. No Matching

	Conglo	Simple	diff	t-stat
# Analysts	5.4	4.7	0.7	5.28
# Specialists (SIC2)	4.3	4.0	0.3	2.41
# Specialists (SIC3)	3.6	3.6	0.1	0.74
% of Specialists (SIC2)	0.70	0.77	-0.07	-12.63
% of Specialists (SIC3)	0.57	0.66	-0.09	-14.45
Forecast Error	0.59	0.63	-0.04	-1.88

Table 3.9: Firm Complexity and Analyst Following

The table presents quarterly Fama-MacBeth regressions of size and book-to-market adjusted cumulative returns in the 60 days following earnings announcements (CAR(2;60)) on earnings surprise (SUE), interaction of SUE with firm complexity, (1-HHI), and different measures of analyst coverage: number of analysts following the firm (# An) and number of analysts who are specialists in the industry of the firm (# Spec2 if the industry is defined using two-digit SIC code and # Spec3 if the industry is defined using three-digit SIC code). All measures of analyst coverage are orthogonalized with respect to size by running quarter-by-quarter cross-sectional regressions of respective coverage measure on size and taking the residuals. The t-statistics use Newey-West (1987) correction for heteroscedasticity and autocorrelation. The sample period is from January 1984 to December 2010.

	1	2	3	4	5	6	7
SUE	0.066	0.091	0.083	0.091	0.084	0.092	0.086
t-stat	*3.03*	*4.36*	*3.86*	*4.39*	*3.94*	*4.45*	*4.02*
Complexity	0.000		0.002		0.003		0.003
t-stat	*0.03*		*0.30*		*0.53*		*0.59*
SUE×Comp	0.259		0.207		0.186		0.179
t-stat	*2.93*		*2.19*		*1.88*		*1.82*
Res # An		0.001	0.001				
t-stat		*1.21*	*1.10*				
SUE×# An		-0.022	-0.021				
t-stat		*-4.71*	*-4.10*				
Res # Spec2				0.001	0.001		
t-stat				*1.50*	*1.40*		
SUE×# Spec2				-0.020	-0.020		
t-stat				*-3.69*	*-3.39*		
Res # Spec3						0.001	0.001
t-stat						*1.39*	*1.33*
SUE×# Spec3						-0.017	-0.018
t-stat						*-3.03*	*-2.84*

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APPENDIX A

DATA APPENDIX FOR CHAPTER 3

The variables are arranged in alphabetical order according to the abbreviated variable name used in the tables in Chapter 3.

 # An (number of analysts; analyst coverage) - the number of analysts covering the firm (from IBES detail file).

Amihud (Amihud illiquidity measure) - the average ratio of absolute return to dollar volume, both from CRSP. The ratio is computed daily and averaged within each firm-year (firms with less than 200 valid return observations in a year and firms with stock price less than $5 at the end of the previous year are excluded)

CAR(-1;+1) (announcement return) - size and book-to-market adjusted cumulative daily returns between the day prior to the earnings announcement and the day after the earnings announcement. Earnings announcement dates are from COMPUSTAT, daily returns are from CRSP daily files, size and book-to-market adjustment is performed following Daniel et al. (1997)

CAR(2;60) - size and book-to-market adjusted cumulative daily returns between the second day after the earnings announcement and the 60th day after the earnings announcement.

CAR(2;20) (CAR(21;40), CAR(41;60)) - size and book-to-market adjusted cumulative daily returns between the second (21st, 41st) day after the earnings announcement and the 20th (40th, 60th) day after the earnings announcement.

Complexity (firm complexity) - 1-HHI, where HHI is the Herfindahl index computed using segment sales, $HHI = \sum_{i=1}^{N} s_i^2$. N is the number of segments (from Compustat segment files, segments with the same two-digits SIC code are counted as one segment), s_i is the fraction of total sales generated by segment i.

Conglo (conglomerate dummy) - 1 if the firm is a conglomerate, 0 otherwise. The firm is a conglomerate if it has business segments in more than one two-digit SIC industry.

Gibbs (Gibbs measure) - the slope from the regression $\Delta P_t = a + c\Delta Q_t$, where P_t is the stock price and Q_t is the trade direction indicator. The values of the Gibbs measure are taken from the website of Joel Hasbrouck and are available from January 1964 to December 2009. For more details, please refer to Hasbrouck (2009).

IO (institutional ownership) - the sum of institutional holdings from Thompson Financial 13F database, divided by the shares outstanding from CRSP. All stocks below the 20th NYSE/AMEX size percentile are dropped. If the stock is not dropped, appears on CRSP, but not on Thompson Financial 13Fs, it is assumed to have zero institutional ownership.

IVol (idiosyncratic volatility) - the standard deviation of residuals from the Fama-French model, fitted to the daily data for each firm-month (at least 15 valid observations are required).

NewConglo (new conglomerate dummy) - 1 if the firm became a conglomerate in the past two years (the year of the change in the conglomerate status excluded), zero otherwise. Single-segment firms always have NewConglo=0.

NSeg (number of segments) - the number of business segments the firm has (from Compustat segment files). Segments with the same two-digit SIC code are counted as one segment.

PCRet (pseudo-conglomerate return) - For each conglomerate firm, a pseudo-conglomerate consists of a portfolio of the conglomerate firm's segments made up using only stand-alone firms from the respective industries. For each portfolio that corresponds to a specific segment of the conglomerate firm an equal-weighted return is calculated. Returns corresponding to each segment are then value weighted according to that segment's contribution to the conglomerate firm's total revenues in order calculate a corresponding pseudo conglomerate return.

Res # An, Res # Spec (residual number of analyst/specialists) - the number of analysts/specialists following the firm orthogonalized to size. The orthogonalization is performed by running a cross-sectional regression of the number of analysts/specialists on size in each quarter and taking the residuals.

Roll (Roll measure) - the estimate of effective bid-ask spread, computed as $Roll_t = 200 \cdot \sqrt{abs(Cov(R_t, R_{t-1}))}$

SegInc (segment increase dummy) - 1 if the firm experienced an increase in the number of segments in the past two years (the year of the change excluded), zero otherwise. Single-segment firms always have SegInc=0.

 # Spec (number of specialists) - the number of analysts covering the firm who are specialists in the firm's industry. An analyst is considered a specialist in the firm's industry if he/she covers at least five other firms with the same two-digit (# Spec2) or three-digit (# Spec3) SIC code in the same quarter. For a conglomerate, an analyst is classified as a specialist based on the industry affiliation of the largest segment.

% Spec (percentage of specialists) - the number of specialists following the firm (# Spec) divided by the number of analysts following the firm (# An).

SUE (earnings surprise) - standardized unexpected earnings, computed as

$$SUE_t = \frac{E_t - E_{t-4}}{P_t}$$

where E_t is the announced earnings per share for the current quarter, E_{t-4} is the earnings per share from the same quarter of the previous year, and P_t is the share price for the current quarter.

Size (market cap) - shares outstanding times price, both from the CRSP monthly returns file. Size is measured in billion dollars.

Spread - the spread implied by the daily high and low prices. Spread is calculated by the formula from Corwin and Schultz (2012):

$$Spread = \frac{2 \cdot (exp^{\alpha} - 1)}{1 + exp^{\alpha}}, \quad \text{where}$$

$$\alpha = \frac{\sqrt{\beta} \cdot (\sqrt{2} - 1)}{3 - 2\sqrt{2}} - \sqrt{\frac{\gamma}{3 - 2\sqrt{2}}}, \quad \text{where}$$

$$\beta = log^2\left(\frac{HI_t}{LO_t}\right) + log^2\left(\frac{HI_{t+1}}{LO_{t+1}}\right) \ and \ \gamma = log^2\left(\frac{\max(HI_t, HI_{t+1})}{\min(LO_t, LO_{t+1})}\right)$$

where HI_t (LO_t) is the highest (lowest) price of the stock on day *t*.

Turn (turnover) - monthly dollar trading volume over market capitalization at the end of the month (both from CRSP), averaged in each firm-year.

Zero (zero frequency) - the fraction of zero-return days within each firm-year.