Customer-base concentration, profitability and distress across the corporate life cycle

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Abstract

Using a recently expanded data set on supplier-customer links, we examine how customer concentration affects firm profitability. We find that the relation between customer concentration and firm profitability is more complex than recent literature suggests. We confirm that customer concentration promotes operating efficiencies for profitable firms. However, we find a different result for younger, less profitable firms where customer concentration impairs firm profitability and significantly increases distress risk. Thus, the relation between customer-base concentration and profitability is non-linear; it is significantly negative in the early years of a firm's public life, turning positive as the relationship matures. 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. These relatively high fixed costs mean that customer concentration is risky for young firms, but can significantly benefit the firm if the relationship survives.

JEL Classifications: L25; M41; G31; G33

Keywords: Customer concentration, customer-specific investment, selling, general and administrative expense, profitability, default risk.

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

[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.

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.

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 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] 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

[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.

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.

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:

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

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

[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.

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 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.

Sample composition

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).

[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).

3.1 Descriptive statistics

Figure 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 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 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 the 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 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

[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

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 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 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 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

in the same industry.

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.

4 Results

4.1 Customer concentration and firm performance

4.1.1 Correlation Analysis

Table 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 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. Panel A of Figure 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 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-

[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.

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.

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 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 is outlined in the graphs in Figure 3. Figure 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.

4.1.3 Regression Analyses

We verify the net effect of customer concentration on profitability and costs in Table 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 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 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 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 4.3.1.

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 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, $Rank(\Delta CC)$, 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 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 4 and 5.

[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.

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. $Rank(\Delta CC)$ adversely impacts future operating 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 $Rank(\Delta CC)$ 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 $Rank(\Delta CC)$ in Panel B, the effects seem to be concentrated in younger firms.

The results in Tables 4, 5, and 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.

4.2 Customer concentration and firm cost structure

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 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 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 7 we examine the effect of customer concentration on young firms' cash

[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.

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.

4.2.2 Elasticity of operating expenses, operating leverage, and demand uncertainty

In Section 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 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 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 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.

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 4.3.1 replicates the IPO failure model of Demers and Joos (2007) while Section 4.3.2 replicates the firm failure model of Campbell et al. (2008).

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 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 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. 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 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

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

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 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).

4.3.2 Broad failure

The analysis in Table 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 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.

In Column (2) of Table 10 we add the measure of customer concentration, $Rank(CC)$, to the regression. In Column (3) of Table 10 we include the interaction variable $AGE \times Rank(CC)$ 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 9 and 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

[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.

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.

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.

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Table 1: Variable definitions

Table 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 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 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 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 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: Descriptive statistics for the main variables

Table 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)

Figure 1: Time-series trend of customer-base concentration

Figure 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.

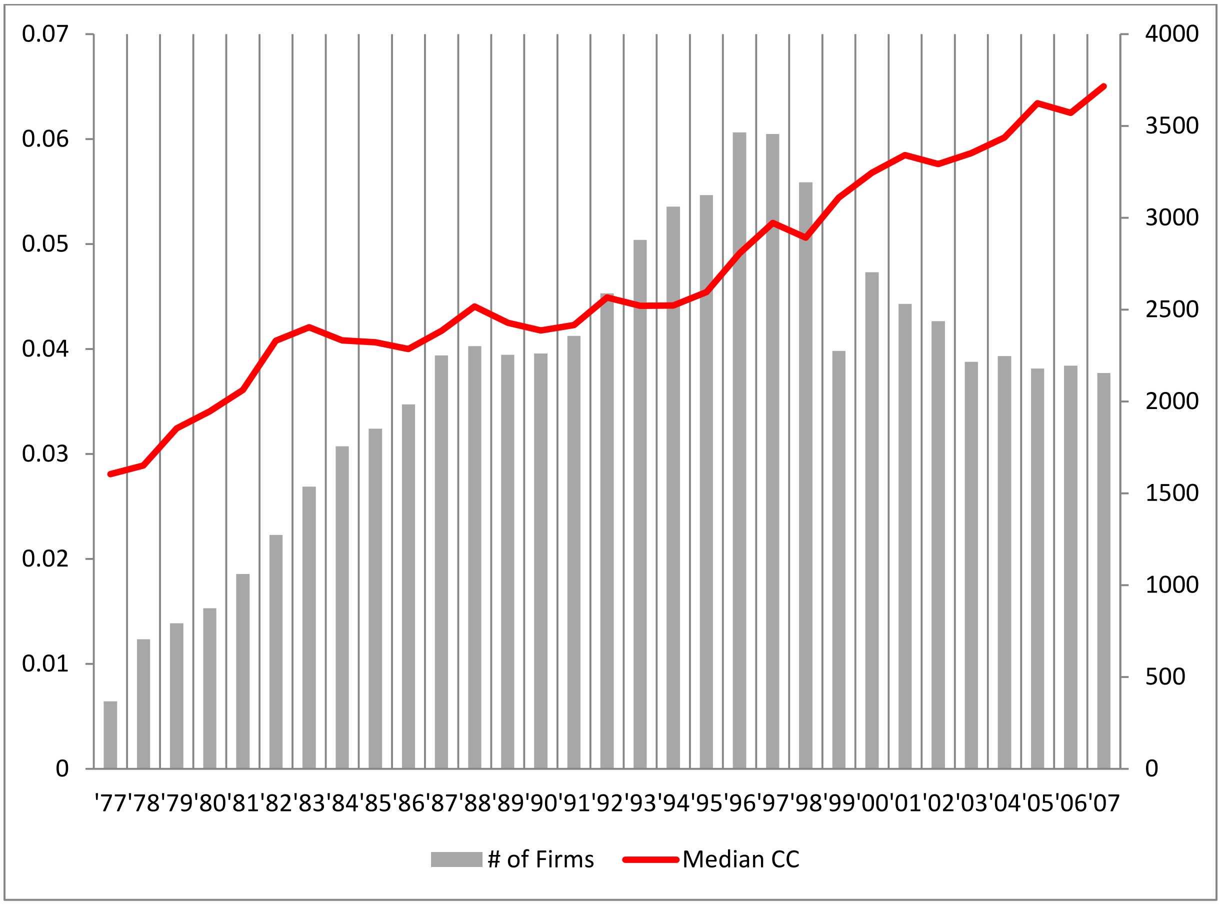


Table 3: Pearson (Spearman) correlations above (below) the main diagonal

Table 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	

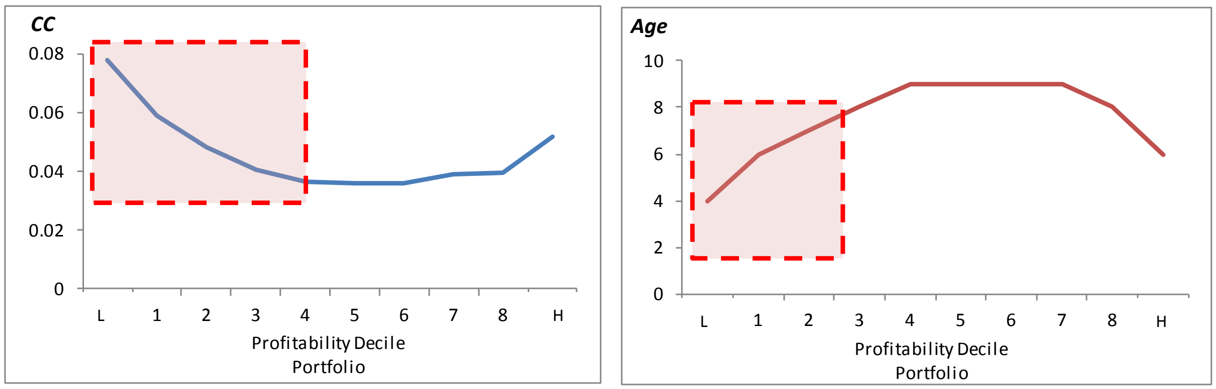
Panel C: Negative-OM sample

	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	

Figure 2: Median customer-base concentration and firm age in profitability deciles

Figure 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

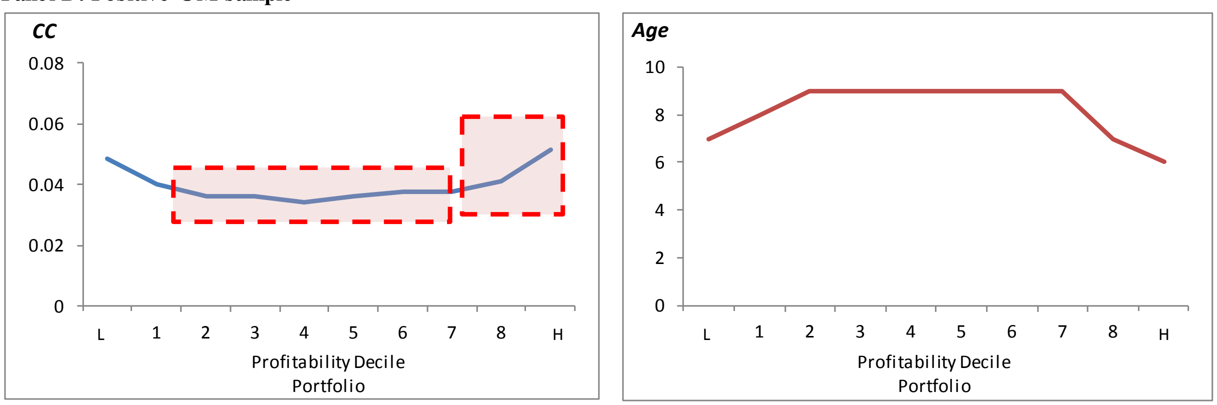


Table 4: Customer-base concentration sorts in different age and profitability groups

Table 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

		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%***
		(3.42%)	(2.58%)	(2.10%)	(1.67%)	(0.61%)	(-2.81%)***
	ROE	-0.53%	-6.41%	-8.83%	-10.16%	-14.36%	-13.83%***
		(7.49%)	(5.26%)	(4.04%)	(3.59%)	(1.31%)	(-6.17%)***
	SGA	37.93%	42.41%	44.73%	48.11%	69.36%	31.43%***
		(26.42%)	(27.97%)	(28.64%)	(27.15%)	(29.04%)	(2.62%)***
Mature Firms (AGE > 7)	*ROA*	3.40%	2.71%	1.62%	1.18%	-0.53%	-3.93%***
		(4.75%)	(4.59%)	(4.08%)	(3.82%)	(3.31%)	(-1.44%)***
	ROE	6.93%	5.13%	3.11%	1.79%	-1.52%	-8.45%***
		(10.75%)	(9.58%)	(8.50%)	(7.96%)	(6.53%)	(-4.22%)***
	SGA	26.07%	27.33%	28.49%	28.27%	37.11%	11.04%***
		(20.96%)	(21.62%)	(21.35%)	(19.92%)	(19.70%)	(-1.27%)*

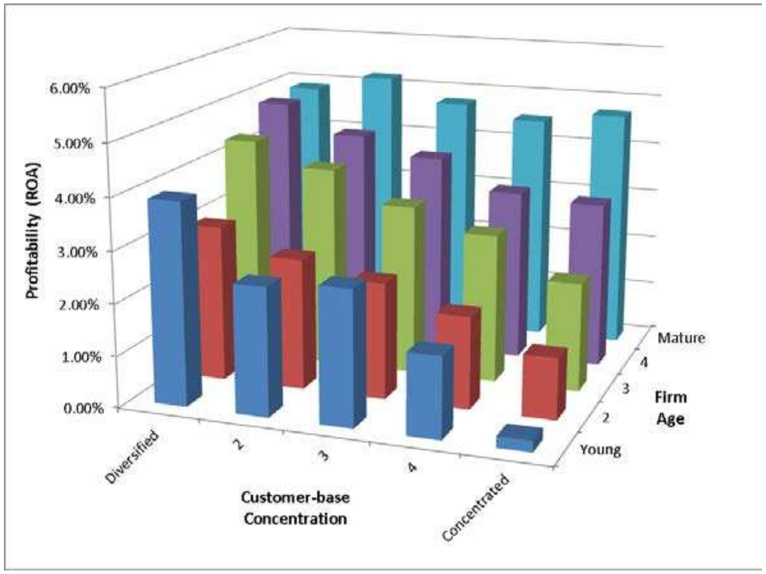
Panel B: Positive-OM sample

		Lowest CC	*2*	*3*	*4*	*Highest CC*	H-L
Young Firms (AGE ≤ 7)	*ROA*	6.00%	6.14%	5.81%	5.85%	6.94%	0.94%***
		(5.31%)	(5.40%)	(5.42%)	(5.48%)	(6.14%)	(0.82%)***
	ROE	11.26%	11.30%	10.06%	9.54%	12.58%	1.32%*
		(11.39%)	(11.19%)	(10.68%)	(10.62%)	(12.11%)	(0.72%)
	SGA	26.08%	26.32%	25.76%	23.93%	22.72%	-3.36%***
		(22.52%)	(23.43%)	(22.37%)	(21.23%)	(19.12%)	(-3.40%)***
Mature Firms (AGE > 7)	*ROA*	5.75%	6.17%	5.74%	5.66%	6.19%	0.44%**
		(5.50%)	(5.57%)	(5.26%)	(5.25%)	(5.47%)	(-0.03%)
	ROE	11.62%	12.22%	10.97%	10.93%	10.26%	-1.36%**
		(12.15%)	(11.49%)	(10.81%)	(10.87%)	(10.46%)	(-1.70%)***
	SGA	22.81%	22.33%	22.03%	20.91%	20.19%	-2.63%***
		(19.91%)	(19.91%)	(19.60%)	(18.28%)	(16.46%)	(-3.45%)***

Figure 3: Median of return on assets in customer-base concentration and age groups

Figure 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.

Panel A: Full sample



Panel B: Positive-OM sample

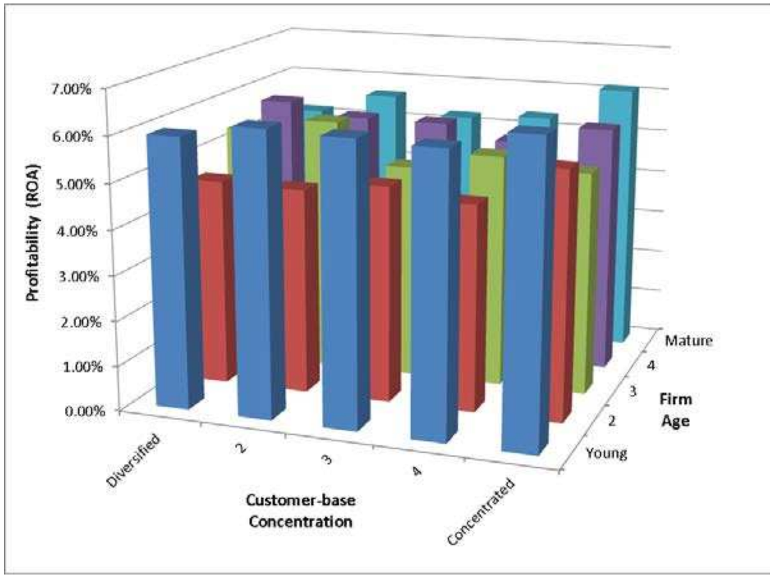


Table 5: Customer-base concentration and supplier firm performance

Table 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 6: Changes in customer-base concentration and changes in supplier firm performance

Table 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 7: Operating performance drivers for young firms

In Table 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 8: Elasticity of operating expenses with respect to sales and demand uncertainty in customer base concentration quintiles

Panel A of Table 8 reports panel data means of operating expenses as a percentage of sales. Panel B of Table 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 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 , $\Delta \ln COGS_{i,t}$ ($\Delta \ln SG\&A_{i,t}$), divided by the change in log-sales for firm i from year t-1 to year t ($\Delta \ln Sales_{i,t}$). 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 9: Determinants of firm failure within five (seven) years of initial public offering

Table 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 ≤ 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 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 1 through 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 10: Dynamic failure prediction

Table 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) Failure	(2) Failure	(3) Failure	(4) 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