Customer Concentration, Systematic Risk, and Equity Returns

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Abstract

A large number of firms transact with a relatively small number of "major" customers. But how do equity markets price exposure to customer concentration? To help resolve the conflicting conceptual arguments in the literature, we study the relationship between excess stock returns and various measures of firms' customer-base profile. We find that, on average, firms with major customers have significantly lower excess returns compared with firms without major customers. This finding is robust to controlling for various commonly recognized risk factors and firm characteristics. This effect is stronger for small firms, young firms, firms with lower analyst coverage, and during aggregate business cycle recessions. However, controlling for the presence of a major customer, excess stock returns do not vary with customer concentration. Our findings indicate that equity investors view firms with major customers as being less exposed to systematic risk because of the certification, insurance, and efficiency benefits provided by major customers.

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1 Introduction

Many U.S. firms rely on a small number of "major customers" that account for a significant portion of their total sales. A long-standing literature considers the implications of such major customers—and customer concentration—for firms' profits and financial policies. One strand of this literature argues that customer concentration comes with significant risks because of major customers' bargaining power to demand price concessions (e.g., Galbraith, 1952) and/or ex post contract renegotiation that exposes the seller to the hold-up problem (e.g., Klein et al., 1978; Williamson, 1979; Fee and Thomas, 2004; Bhattacharyya and Nain, 2011; Murfin and Njoroge, 2015). In addition, the firm could face significant revenue loss if a major customer experiences financial distress or switches suppliers (e.g., Hertzel et al., 2008; Kolay et al., 2016; Lian, 2017). However, another literature argues that a concentrated customer base can be associated with lower risks. Sales to reliable major customers during downturns can reduce the firm's exposure to systematic risk. Presence of major customers can also be a certification of the firm's quality because such customers closely monitor their suppliers (e.g., Johnson et al., 2010; Cen et al., 2016). In addition, a concentrated customer base can increase economies of scale and improve operational efficiency (e.g., Patatoukas, 2012; Irvine et al., 2016). An important question therefore arises: How do equity markets price the risk of exposure to major customers? This issue appears to have received surprisingly little attention. In this paper, we fill this gap in the literature.

Our main finding is that, on average, equity investors view firms with major customers (defined as customers that account for more than 10% of the firm's revenue) as less exposed to systematic risk compared with firms without major customers. However, among firms with major customers, equity risk does not vary with the degree of customer concentration. We establish these results by examining, first, the risk-adjusted returns (α), at monthly frequency, of the portfolio of firms without any major customers and the portfolio of firms with at least one major customer. We find that, on average, the portfolio of firms without major customers has a higher α than the portfolio of firms with major customers. This result is robust to the choice of the asset pricing model– CAPM, Fama and French (1993) three-factor model, Carhart (1997) four-factor model, and the Fama and French (2015) five-factor model– and is economically significant: the difference in α ranges between 0.22%-0.23% per month. However, among firms with major customers, there is no significant difference in α between the three portfolios corresponding to the three terciles of customer concentration, indicating that conditional on the presence of a major customer, customer concentration does not significantly lower the risk premium.

A concern with the portfolio analysis is that the differences in α across the portfolios may be driven by differences in firm/industry characteristics that happen to be correlated with firms' major customer profile (i.e., presence of a major customer and customer concentration). To address this concern, we examine the relation between equity returns and major customer profile using Fama-MacBeth regressions. We include industry fixed effects in these regressions and control for firm characteristics like size, book-to-market ratio, profitability, asset growth, cash flow volatility, cash holdings, lagged returns, and momentum. Consistent with the results from the portfolio analyses, we find a negative and significant relation between equity return and presence of a major customer. We also find a negative relation between equity return and various measures of customer concentration, but this is mainly driven by differences between firms in the highest tercile of customer concentration versus those with either no major customers (i.e., zero customer concentration) or very low values of customer concentration.

Conceptually, the potentially conflicting effects of major customers for the equity risk premium can be motivated from the fundamental asset-pricing result that equilibrium excess returns are proportional to the (negative of) the covariance between firm's equity payoffs (i.e., dividends and capital gains) and the stochastic discount factor. The bargaining power and hold-up problems by major customers to demand price concessions, especially in downturns (i.e., high discount factor states), can ceteris paribus raise the firm's risk premium by amplifying its covariance risk; and, similarly, exposure to default risk of major customers during downturns can increase the risk premium. In contrast, presence of major customers and the operational efficiencies they help generate can insure firms against lower revenues in downturns, mitigating covariance risk and lowering the risk premium. Meanwhile, imperfect information on firms' cash flow processes can ceteris paribus raise the equity risk premium (e.g., Kumar et al., 2008). Certification provided by presence of major customers, therefore, lowers the risk premium, other things being equal. Thus, received asset pricing theory provides a useful framework to consolidate the conflicting predictions in the literature on the relation of major customers and systematic risk.

Our finding of a significant negative relation between excess stock returns and the presence of a major customer indicates that the insurance, operational efficiency, and certification benefits of major customers for lowering firms' systematic risk exposure outweigh their potential disadvantages. Our analysis indicates that these benefits mainly accrue from the presence of a major customer. That is, conditional on having a major customer, additional major customers do not have significant incremental negative effects on firms' equity risk premium. We find this to be an intuitively appealing result.

The certification and monitoring benefits of major customers should be more valuable when outside investors have the less reliable information about firm fundamentals. We, therefore, expect that the negative effect of major customer presence on the risk premium will be stronger for smaller firms, younger firms, and firms with lower analyst coverage, which typically face greater information asymmetry and higher capital costs. To test whether the certification effect is more pronounced for these firms, we use firm size, firm age, and analyst coverage as proxies for information asymmetry and interact them with our customer concentration measure in the regression model. Consistent with the predictions of the certification hypothesis, our results show that the certification effect is indeed stronger among smaller, younger firms and those with lower analyst coverage.

Furthermore, we directly examine that effects of insurance, efficiency and certification benefits of customer concentration on firms' cyclical risk. The observed lower average negative relation of customer concentration and equity risk premium suggests that the benefits of having major customers are especially stronger in recessions, thereby reducing exposure to cyclical—and, hence, covariance—risk. We indeed find that the effect of customer concentration on equity return is weaker (and, in fact, insignificant) during business cycle expansions, indicating that the risk reduction benefits of major customers accrue only during non-expansionary periods.

As noted above, a significant risk with major customers is that they may leverage their bargaining power to hold-up their suppliers; e.g., by demanding price concessions (e.g., Fee and Thomas, 2004; Bhattacharyya and Nain, 2011) or trade credit (e.g., Wilner, 2000; Jorion and Zhang, 2009; Murfin and Njoroge, 2015) which increases suppliers' financial risk. If so, we expect the negative relation between equity return and presence of major customers to be weaker or even insignificant for firms in highly-competitive industries and for firms that provide extensive trade credit to their customers. We test these hypotheses using the accounts receivable as a proxy for suppliers' trade credit exposure; and the text-based network industry classification Herfindahl-Hirschman Index from Hoberg and Phillips (2016) as an inverse proxy for competition. However, we find that the negative relation between equity return and major customer presence does not vary with either suppliers' industry competition or trade credit provision.

Our baseline results show that customer concentration is negatively associated with stock returns. A potential concern is endogeneity: unobserved firm characteristics may jointly influence a supplier's customer concentration and its returns. To address this concern, we implement a two-stage least squares (2SLS) instrumental-variable approach following Dhaliwal et al. (2016), using lagged industry-average customer concentration as an instrument for firm-level customer concentration. The 2SLS estimates remain negative and statistically significant, consistent with our baseline findings, suggesting that our main results are unlikely to be driven by omitted-variable bias.

To our knowledge, our study is the first to examine the empirical effects of major customers on firms' equity risk premium, i.e., exposure to systematic risk. Our findings help resolve the conflicting conceptual relation of major customers and risk premiums. In particular, we analyze the empirical significance of certification, insurance and efficiency benefits of major customers in lowering firms' systematic risk exposure.

Our paper is linked to the larger literature on the effects of supply-chain relationships and product market competition on financial policies. Titman and Wessels (1988) and Allen and Phillips (2000) show that firms that rely on major customers invest more in relationship-specific assets. Given the high redeployment costs associated with relationship-specific assets, firms in bilateral relationships maintain lower leverage (e.g., Kale and Shahrur, 2007; Banerjee et al., 2008), hold more cash as a precaution (e.g., Itzkowitz, 2013), and pay lower dividends (e.g., Wang, 2012). None of these papers consider the role of customer concentration, per se. We contribute to this literature by showing that, due to the benefits provided by major customers (annunciated above), investors in the equity markets view firms with major customers as less exposed to systematic risk, on average, compared with firms without major customers.

Our paper also contributes to the existing literature on the effects of customer concentration on the cost of debt and accounting-based measures of cost of capital. Existing empirical studies that examine the pricing of customer concentration in other financial markets find mixed evidence. Examining a large sample of bank loans to US manufacturing firms, Campello and Gao (2017) find that firms with higher customer concentration face higher loan spreads, more restrictive covenants, and shorter maturities. Their results suggest that banks perceive firms with a concentrated customer base as riskier *despite* the higher profitability. On the other hand, using a large sample of corporate bond issues, Cai and Zhu (2020) show that firms with higher customer concentration have lower cost of debt. The sharply contrasting results from these two papers suggest that even for debt securities, pricing of customer concentration risk varies dramatically between private debt and public debt markets. We note that the analyses in both these papers is based on firms that *chose* to issue loans or bonds, respectively, and relates the issuance spread to customer concentration. Therefore, these conflicting results may arise because of differences in omitted characteristics that affect the timing of debt issuance, and the choice between bank loans and bonds. In contrast, our analysis is based on a clean characterization of risk premium based on covariance risk, and is not affected by the timing and manner of capital issuance, and is not restricted to firms that issue capital.

Our study is also related to the accounting literature that examines the relationship between customer concentration and *implied cost of capital* (ICC), which is the cost of equity implied in current stock prices and analysts' earnings forecasts, and is derived from the residual valuation model of Ohlson (1995). accounting Dhaliwal et al. (2016) who examine the relationship between customer concentration and *implied cost of capital* (ICC), which is the cost of equity implied in current stock prices and analysts' earnings forecasts, and is derived from the residual valuation model of Ohlson (1995). In sharp contrast to our paper, they find a positive relationship between customer concentration and ICC, suggesting that equity investors view firms with high customer concentration as riskier. However, it is well-known that ICC measures are highly sensitive to the underlying valuation model (see Lee et al., 2021), assumptions of expected growth rates (see Lewellen, 2010), and the methods for generating earnings forecasts. In particular, the ICC measure is silent on the covariance risk determination of equilibrium risk premium emphasized by the finance literature.

Nevertheless, we complement our analysis based on equity returns, we examine how ICC varies with presence of a major customer and customer concentration. We use two alternative measures of ICC for this analysis which differ in the method for generating earnings forecasts: a "model-based ICC" which is estimated using the cross-sectional earnings prediction model of Hou et al. (2012); and an "analyst-based ICC" which relies on analyst forecasts from IBES and is the same measure employed in Dhaliwal et al. (2016). A *striking finding* is that the relation between ICC and customer concentration is highly sensitive to the measure of ICC employed. Consistent with our results with equity returns, we find that firms with major customers have a lower model-based ICC than firms without major customers; and that ICC does not vary with customer concentration among firms with major customers. In sharp contrast, the analyst-based ICC employed by Dhaliwal et al. (2016) is increasing in customer concentration. We note that our equilibrium asset-pricing based approach does not require any subjective assumptions regarding future earnings forecasts of firm-level expected growth rates and is based only on the firm's factor loadings, i.e., risk-exposures to priced factor risks. Indeed, unlike with the ICC approach but consistent with asset pricing theory, we show that our results are robust to the choice of the underlying asset pricing model.

The remainder of the paper proceeds as follows. Section 2 develops testable predictions on how major-customer relationships and customer concentration affect the equity risk premium. Section 3 describes the data, sample construction, and variable definitions. Section 4 outlines the empirical design and reports the main results, and Section 5 concludes.

2 Hypotheses Development

Our hypotheses follow directly from an equilibrium asset-pricing view in which expected excess returns compensate equity investors for exposure to systematic (covariance) risk, that is, the extent to which a firm's cash flows are especially weak in bad macro states when the stochastic discount factor is high. In this framework, a firm's customer base matters because major customers can shape both the level and cyclicality of suppliers' revenues and profits.

2.1 Customer Concentration and Equity Risk Premium

A concentrated customer base can reduce systematic risk through several channels. First, a stable, high-quality major customer can provide a form of demand insurance by sustaining purchases during downturns, thereby dampening the supplier's exposure to adverse aggregate shocks. Second, major customers can improve supplier performance through operational efficiencies (e.g., scale economies, lower overhead, higher asset turnover), which can make cash flows more resilient across the cycle (e.g., Patatoukas, 2012; Irvine et al., 2016).

Third, when supplier quality is not fully observable, relationships with prominent customers can serve as certification of supplier quality and can reduce information frictions between the supplier and capital markets (e.g., see Johnson et al., 2010; Cen et al., 2016). This is because large customers have strong incentives to monitor their suppliers to ensure the stability of their supply chains. Consistent with this view, prior research finds that customer oversight lowers suppliers' cost of debt (Cai and Zhu, 2020), improves stock liquidity (Do et al., 2023), and reduces misconduct and penalties among firms (Chen et al., 2025).

On the other hand, reliance on major customers also exposes firms to substantial risks. Suppliers risk significant revenue losses if major customers switch to alternative suppliers or internalize production. Dependence on a small set of large customers exposes the supplier to customer-specific financial distress (Lian, 2017), with negative shocks potentially spilling over from customers to suppliers (e.g., Hertzel et al., 2008; Kolay et al., 2016). In addition, major customers may exploit their bargaining power to negotiate lower prices or extend payment terms, thereby eroding the supplier firm's profit margins and limiting their capacity to invest (e.g., Fee and Thomas, 2004; Bhattacharyya and Nain, 2011; Murfin and Njoroge, 2015). Consistent with these risks, prior research finds that higher customer concentration is association with higher cost of bank loans (Campello and Gao, 2017), higher implied cost of capital (Dhaliwal et al., 2016), higher idiosyncratic volatility (Mihov and Naranjo, 2017), and higher crash risk (Ma et al., 2020).

Taken together, these arguments imply that customer concentration affects the risk premium through competing mechanisms. The insurance, certification, and efficiency benefits highlighted above should lead equity investors to demand a lower risk premium from firms with a concentrated customer base. In contrast, the concentrated credit risk and hold-up risk should lead equity investors to demand a higher risk premium from firms with a concentrated customer base. Our empirical setting focuses on whether, on net, equity investors view major-customer relationships primarily as risk-reducing or risk-increasing. We hypothesize that the insurance, certification, and efficiency benefits of concentrated customer base outweigh the effects of concentrated credit risk and hold-up risk. This leads to our main testable prediction regarding the relation between customer concentration and equity returns.

Prediction 1: Firms with major customers, and more generally, firms with greater customer concentration, earn lower expected risk-adjusted equity returns than otherwise similar firms.

2.2 Variation with Information Asymmetry

The certification and monitoring benefits of major customers should be more valuable when outside investors have the less reliable information about firm fundamentals. Smaller and younger firms, and firms followed by fewer analysts, typically face greater information asymmetry and higher costs of external finance. In these settings, a major customer relationship can provide a more meaningful signal of supplier quality and reduce uncertainty about future cash flows.

Of course, the problems of concentrated credit risk and hold-up risk associated with a concentrated customer base should also be more severe for smaller and younger firms that face higher costs of external finance and may rely heavily on customer relationships for external financing (e.g., Saboo et al., 2017; Do et al., 2023). However, given our primary hypothesis that the insurance, certification, and efficiency benefits of concentrated customer base outweigh the effects of concentrated credit risk and hold-up risk, we have the following prediction about how the relationship between customer concentration and equity returns varies with information asymmetry.

Prediction 2: The negative relation between major-customer presence (or customer concentration) and expected stock returns is stronger for firms with greater information asymmetry (e.g., smaller firms, younger firms, and firms with lower analyst coverage).

2.3 Variation over Aggregate Business Cycles

The potential insurance, efficiency, and certification benefits of major customers should be especially beneficial to firms during business cycle recessions (relative to expansions). The general demand-contraction effects of aggregate cyclical recessions lead to significantly lower firm revenues, profits, internal liquidity, and hence dividends, other things being equal. These financing constraints are aggravated by counter-cyclical external costs of financing, especially for small firms (e.g., Gertler and Gilchrist, 1994; Bernanke et al., 1999). Consequently, firms in general, and small firms in particular, are forced to cut capital investment (e.g., Chodorow-Reich, 2014; Duygan-Bump et al., 2015; Bottero et al., 2020), lowering expected cash flows and hence equity prices (e.g., Atkeson et al., 2025).

These real and financial negative effects of aggregate recessions amplify the covariance risk of firms due to the counter-cyclical stochastic discount factor (SDF) highlighted in the consumption-based asset pricing literature. Major customers can help alleviate this covariance risk by reducing the firm's exposure to demand contractions and scale inefficiencies during recessions. In addition, the certification benefits of major customers can ceteris paribus lower the firm's exposure to counter-cyclical costs of external financing by reducing information asymmetry and default risk.

Prediction 3: The negative relation between major-customer presence (or customer concentration) and expected stock returns is stronger during aggregate business cycle recessions compared with expansions.

2.4 Variation with Trade Credit

Trade credit is a natural channel through which firms may be exposed to concentrated credit risk and hold-up risk from their major customers (e.g., see Fee and Thomas, 2004; Bhattacharyya and Nain, 2011; Murfin and Njoroge, 2015). When suppliers extend substantial trade credit (i.e., high accounts receivable) to their major customers, they become more exposed to delayed payment or default, which can heighten liquidity risk and propagate financial distress from major customers to suppliers (e.g., see Jorion and Zhang, 2009).

In contrast, the certification benefit of major customers derives mainly from the existence of the customer relationship, rather than from specific contractual terms such as trade credit. That is, the amount and terms of trade credit extended to major customers are not expected to have a significant impact on the certification benefit in financial markets.

This tension suggests that trade credit can dampen, or potentially overturn, the risk-reducing effect of major customers by increasing the supplier's sensitivity to customer-specific financial shocks.

Prediction 4: The negative relation between major-customer presence (or customer concentration) and expected stock returns is weaker among firms that extend high trade credit to customers.

2.5 Variation with Product Market Competition

The net effect of customer concentration on equity risk may also vary with the level of product market competition. In more competitive product markets, customers tend to have greater bargaining power due to the presence of many alternative suppliers, which increases the likelihood of customer turnover (e.g., Hui et al., 2012) due to lower switching costs, and increases hold-up risk for the suppliers. The lower switching costs can also weaken the major customers' incentives to invest in monitoring any single supplier, potentially muting certification benefits.

Prediction 5: The negative relation between major-customer presence (or customer concentration) and expected stock returns is weaker for firms operating in more competitive industries.

In sum, our predictions center on whether the net effect of customer concentration on equity risk premium is negative, due to the insurance, certification, and efficiency benefits of major customers, or positive due to the concentrated exposure to customer shocks and bargaining frictions. We also highlight how these effects vary with information asymmetry, cyclical risk, trade credit provision and product market competition. In the next section, we describe the data sources and key variables needed to test these predictions.

3 Data and Variables

3.1 Sample Selection

This study covers the period from January 1985 to December 2022. Stock return data are obtained from CRSP, and accounting variables are from COMPUSTAT. We exclude firms in the financial (SIC 6000–6999) and utility (SIC 4900–4999) sectors. Factor data and NYSE breakpoints are from the Kenneth R. French Data Library.[1] Major customer information is sourced from the Compustat Segment Link data compiled by Cohen and Frazzini (2008) and Cen et al. (2017). Under Statement of Financial Accounting Standards (SFAS) No.131, firms are required to disclose major customers in their 10-K filings when a single customer accounts for more than 10% of total revenue. Some firms voluntarily disclose customers that account for less than 10% of sales. To mitigate potential selection concerns, we exclude these voluntarily disclosed customers from the construction of our customer concentration measures. Monthly implied cost of capital (ICC) estimates are from Lee et al. (2021). Each estimate reflects a firm's expected return over the subsequent month.[2]

Following Campello and Gao (2017), we focus on the effects of recurring major customers. Specifically, a firm must have at least one major customer that appears in its disclosures at least three times before the end of the sample period. Customers with fewer than three appearances are excluded.[3] After applying this criterion, we construct customer concentration measures using supplier-customer-year-level data and require that observations have non-missing values for control variables before merging them with monthly stock data. The final sample consists of 601,470 firm-month observations.

[1] Kenneth R. French Data Library: https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

[2] Data available at: https://leesowang2021.github.io/data/

[3] Our results remain consistent without this restriction. Similar findings hold when including firms that have reported at least one major customer before the end of the sample period.

To mitigate the impact of outliers, all variables—except stock returns and firm age—are winsorized at the 1% and 99% levels each month.

3.2 Measures of Customer Concentration

We use two variables to quantify customer concentration. The first measure is *Major Customer*, a dummy variable equal to one if a supplier discloses at least one corporate customer that accounts for 10% or more of its annual revenues, and this customer is reported by that firm at least three times before the end of the sample period, and zero otherwise.

The second measure, *Major Sale*, represents the proportion of a firm's sales attributed to its major customers (i.e., customers that account for at least 10% of the firm's revenue and are reported by the firm at least three times before the end of the sample period). It is defined as:

$$\text{Major Sale}_i = \sum_{j=1}^{n_i} \frac{\text{Sales of firm } i \text{ to Major Customer } j}{\text{Total Sales of firm } i} \tag{1}$$

where n_i represents the number of major customers for firm i. A higher *Major Sale* value indicates that a significant share of a firm's sales is concentrated among its major customers.

3.3 Control Variables

We include several standard control variables commonly used in the asset pricing literature when conducting the Fama-MacBeth regression in Section 4.2.1. *Size* is measured as the natural logarithm of the firm's market capitalization. The Book-to-Market ratio (*BTM*) represents the ratio of the book value of equity and debt to the market value of equity and debt. *Gross Profit* serves as a measure of profitability, while *Asset Growth* captures the annual change in total assets. *One-Month Return* refers to the stock's return from the previous month. *Momentum* is defined as the cumulative return measured over a horizon from 11 months prior to the current month, ending two months before the current month. Given the potential relationship between cash flow uncertainty and customer concentration, as well as its impact on stock returns, *Cash Flow Uncertainty* is included as a control variable. Furthermore, firms with high customer concentration often hold more cash as a precautionary measure (e.g., Itzkowitz, 2013). To account for this, *Cash* is also incorporated as a control variable as well. Detailed calculations for all variables are provided in the Variable Definition section.

3.4 Descriptive Statistics

Table 1 presents summary statistics for customer concentration measures, control variables, and firm characteristics at the firm-year level. The mean of *Major Customer* is 0.479, indicating that approximately 48% of firm-year observations report having at least one major customer. The mean of *Major Sales* is 0.163, with a standard deviation of 0.233.[4]

The table also reports summary statistics for additional firm characteristics. On average, firm size (*Size*), measured as the log of market capitalization, is 5.300. The average Book-to-Market ratio (*BTM*) is 0.664, and the mean gross profitability (*GrossProfit*) is –0.049. Firms in the sample exhibit average asset growth (*AssetGrowth*) of 0.180, a cash ratio (*Cash*) of 0.220, and cash flow volatility of 1.210. The average firm age (*Age*), defined as the number of years with non-missing stock price data on CRSP, is 14.47 years. R&D intensity (*R&D*), computed as R&D expenses divided by total assets, averages 0.070. Accounts receivable (*Accounts Receivable*), measured as a fraction of total assets, averages 0.168. Finally, analyst coverage (*Analyst Coverage*), defined as the number of unique analysts issuing annual earnings forecasts in the year prior to fiscal year-end, averages 8.768.

[4] This distribution aligns closely with prior studies. For example, Do et al. (2023) report a mean of 0.166 and a standard deviation of 0.250 for *Customer Sales*, which is equivalent to *Major Sales* in our setting.

4 Empirical Results

4.1 Portfolio Analysis

We test Prediction 1 using a portfolio-sorting approach based on customer concentration measures, covering the period from January 1985 to December 2022. Following Patatoukas (2012), we assume that firms' customer disclosures become available by the end of the fourth month following the fiscal year-end. Accordingly, we match each firm's annual customer concentration data to the fifth month following its fiscal year-end and carry it forward for twelve months. Portfolios are formed monthly. Table 2 reports equal-weighted excess returns and alphas estimated using four asset pricing models: the CAPM, the Fama and French (1993) three-factor model, the three-factor model augmented with the Carhart (1997) momentum factor, and the Fama and French (2015) five-factor model. Standard errors (in parentheses) are adjusted for heteroskedasticity and autocorrelation using twelve-lag Newey–West adjustments (e.g., Newey and West, 1986).

We first examine whether the presence of a major customer reduces firms' perceived equity risk. Each month, firms are divided into two groups based on the *Major Customer* dummy: those without any major customers (Dummy = 0) and those with at least one major customer (Dummy = 1). Panel A of Table 2 reports the results. Columns (1) and (2) show excess returns and alphas for the two groups, and Column (3) presents a long-short portfolio ($Zero - One$) formed by taking a long position in firms without major customers and a short position in those with at least one.

Firms without major customers consistently exhibit higher excess returns and alphas than those with major customers across all models. Specifically, the annualized excess return for firms without major customers is approximately 14% (1.150 × 12), compared to 11% (0.923 × 12) for firms with major customers. The long-short portfolio generates an annualized excess return of 3% (0.227 × 12), significant at the 1% level. This return differential remains robust after adjusting for risk factors. For example, the monthly CAPM alpha for the long-short portfolio is 22 basis points, rising to 23 basis points with the inclusion of SMB and HML factors, and remains stable with the addition of the momentum factor. Even after including profitability and investment factors in the five-factor model, the alpha remains significant at around 23 basis points per month. These results indicate that the presence of major customers reduces firms' perceived risk in the equity market, providing support for certification theory.

We next examine whether perceived risk varies with the degree of customer concentration. Given the large number of observations with zero customer concentration, it is difficult to sort the firms into quartiles each month. To address this, we group firms with zero customer concentration separately and sort the remaining firms into terciles based on their level of customer concentration using NYSE breakpoints. This yields four distinct groups: zero customer concentration (*Zero*), and low (*Low*), medium (*Mid*), and high (*High*) levels of customer concentration. Panel B of Table 2 presents the results.

In Panel B, Columns (1) through (4) correspond to portfolios of firms categorized as *Zero*, *Low*, *Mid*, and *High* customer concentration, respectively. Column (5) presents the results for the long-short portfolio ($Zero - High$), which takes long positions in firms without major customers and short positions in firms with high customer concentration. Column (6) presents another long-short portfolio ($Low - High$), which takes long positions in firms with low customer concentration and short positions in firms with high concentration. Panel B shows that firms without major customers consistently have higher returns compared to those with the most concentrated customer bases. For example, the annualized excess return of the $Zero - High$ portfolio is approximately 3% (0.250×12), closely mirroring the results in Panel A. These differences remain statistically significant after controlling for standard asset pricing factors. However, the returns and alphas for the $Low - High$ portfolio are statistically insignificant across all pricing models.

Overall, these findings reinforce the certification view: the presence of major customers lowers perceived risk by enhancing transparency, mitigating information asymmetry, and signaling supplier quality. However, beyond the presence of major customers, further increases in concentration do not significantly alter stock returns.

4.2 Baseline Regression

4.2.1 Model Framework and Specification

Because differences in portfolio alphas may reflect firm or industry characteristics correlated with customer concentration rather than its direct effects, we conduct Fama and MacBeth (1973) regressions using the same sample as our portfolio tests to examine the cross-sectional relation between customer concentration and stock returns while controlling for firm-level characteristics. We include Fama–French 48 industry fixed effects to account for industry-specific return variation and adjust standard errors using a twelve-lag Newey–West correction (e.g., Newey and West, 1986). All regressions include a standard set of control variables commonly used in the asset pricing literature, including *Size* (log market capitalization), *Book-to-Market*, *Gross Profit*, *Asset Growth*, *Cash Flow Uncertainty*, *Cash*, *One-Month Return*, and *Momentum* (see Section 3.3 for definitions).

We estimate the following baseline specification:

$$\mathrm{R}_{i,t} = \beta_{0t} + \beta_{1t}\text{Customer Concentration}_{i,t} + \text{Controls}_{i,t} + \gamma_j + \epsilon_{i,t}, \tag{2}$$

where $\mathrm{R}_{i,t}$ denotes firm i's stock return in month t. Customer concentration is measured using either *Major Customer*, a binary indicator equal to one if the firm has at least one major customer, and *Major Sales*, defined as the fraction of sales attributed to major customers.

We next examine whether the number of major customers affects firms' perceived risk. We construct indicator variables for firms with exactly one major customer (*One Major Customer*) and with more than one major customer (*More than One Customer*), using firms with zero major customers as the omitted reference group. We estimate the following panel regression with industry-by-month fixed effects and standard errors clustered at both the firm and month levels:

$$\begin{aligned} \mathrm{R}_{i,t} = \beta_{0t} + \beta_{1t}\,\text{One Major Customer}_{i,t} + \beta_{2t}\,\text{More than One Customer}_{i,t} \\ + \text{Controls}_{i,t} + \delta_{j,t} + \epsilon_{i,t}. \end{aligned} \tag{3}$$

Finally, to examine whether incremental variation in customer concentration matters among firms with major customers, we follow the portfolio-sorting procedure in Section 4.1. Each month, firms are classified into four groups based on *Major Sales*: firms with no major customers and the low, medium, and high terciles among firms with at least one major customer. Using firms with zero major customers as the reference group, we estimate:

$$\begin{aligned} \mathrm{R}_{i,t} = \beta_{0t} + \beta_{1t}\,\text{Low Major Sales}_{i,t} + \beta_{2t}\,\text{Medium Major Sales}_{i,t} + \beta_{3t}\,\text{High Major Sales}_{i,t} \\ + \text{Controls}_{i,t-1} + \delta_{j,t} + \epsilon_{i,t}. \end{aligned} \tag{4}$$

4.3 Customer Concentration and Stock Returns

Baseline regression results are presented in Table 3. Columns (1) and (2) report the time-series averages of coefficient estimates from monthly cross-sectional regressions based on Equation 2. Both customer concentration measures are significantly negatively associated with stock returns. Specifically, the coefficient on *Major Customer* is -0.194, indicating that firms with at least one major customer earn monthly returns approximately 19.4 basis points lower than those without any major customers—consistent with prior findings suggesting that the equity market perceives firms with concentrated customer bases as less risky. The coefficient on *Major Sales* is -0.507 and highly significant, implying that a one-unit increase in *Major Sales* is associated with an approximate 51 basis point decline in stock returns.

Columns (3) and (4) present results from a similar specification to Equation 2, estimated using a panel regression framework with industry-by-month fixed effects and standard errors clustered at both the firm and month levels. The findings are consistent with those from the Fama and MacBeth (1973) approach, further supporting the view that firms with major customers are perceived as less risky by the equity market.

Column (5) reports results based on Equation 3. The coefficient on *One Customer* is -0.160 and statistically significant, indicating that firms with exactly one major customer earn monthly returns 16 basis points lower than those without any major customers. The coefficient on *More than One Customer* is also significantly negative at -0.267. To evaluate whether the perceived risk continues to decline with more than one major customer, we test the difference between the two coefficients. Although the estimated difference (reported in the row labeled "β_1–β_2") is positive—suggesting that firms with multiple major customers may be perceived as less risky than those with only one—the difference is not statistically significant. This finding aligns with our portfolio-based results, which show that among firms with at least one major customer, further increases in customer concentration do not significantly affect stock returns.

Results from Equation 3 are presented in Column (6). While the coefficient on *Low Major Sales* is negative but not statistically significant, those on *Medium Major Sales* and *High Major Sales* are significantly negative, suggesting that firms with greater customer concentration are perceived as less risky by equity investors. To further assess the robustness of our portfolio-based findings, we test the differences between the coefficients on *Low Major Sales* and *Medium Major Sales* (reported in the row labeled "β_1–β_2"), and between *Medium Major Sales* and *High Major Sales* ("β_2–β_3"). Although both differences are positive, neither is statistically significant, indicating that incremental increases in customer concentration do not significantly affect stock returns among firms that already have major customers. However, the difference between the coefficients on *Low Major Sales* and *High Major Sales* is statistically significant, with an estimated value of 0.226.

4.4 Variation with Information Asymmetry

Section 4.3 highlights the central role of the certification hypothesis, showing that major customers certify and monitor suppliers, thereby reducing perceived risk in equity markets. We test Prediction 2 by examining whether this effect is stronger among smaller, younger, and low-coverage firms, which typically face greater information asymmetry.

To address this question, we use firm size, firm age, and analyst coverage as proxies for information asymmetry. Each proxy is interacted with the *Major Customer* variable, and both the interaction terms and main effects are included in a panel regression following Equation 2. The results are reported in Table 4.

We begin with firm size. Given the skewed distribution of market capitalization, firms are sorted into monthly quartiles based on market value. The indicator variable *Large Firm* equals one for firms in the top quartile and zero otherwise. As shown in Column (1) of Table 4, the interaction term *Major Customer* $\times$ *Large Firm* is significantly positive, indicating that the certification effect is weaker for larger firms, which generally face lower information asymmetry and thus have less need for external certification.

We next examine firm age. A firm is classified as *Young* if its age is below the monthly sample median, where age is measured as the number of years since listing on CRSP with non-missing return data. The interaction term *Major Customer* $\times$ *Young Firm*, reported in Column (2), is significantly negative, implying that customer concentration reduces perceived risk more for younger firms. This result is consistent with the idea that external certification is particularly valuable for firms with shorter track records.

Finally, we use analyst coverage as a direct proxy for information asymmetry. *High Analyst Coverage* equals one if the number of analysts issuing earnings forecasts in the prior year exceeds the monthly median. The interaction term *Major Customer* $\times$ *High Analyst Coverage*, shown in Column (3), is significantly positive, suggesting that the certification effect of major customers is attenuated when external information about the firm is already abundant, reducing the marginal value of customer-based signals.

Overall, the results in Table 4 indicate that the certification effect is weaker for large, mature firms and those with extensive analyst coverage, likely due to their established reputations and lower information asymmetry. In contrast, smaller and younger firms, as well as those with limited analyst attention, benefit more from the credibility provided by major customer relationships.

4.5 Variation over the Business Cycle

Our previous analysis finds a negative and statistically significant association between customer concentration and stock returns, consistent with insurance, operational efficiency, and certification benefits of major customers. In this section, we examine whether this relationship varies across different phases of the business cycle.

As discussed in Section 2.3, major customers can lower firms' systematic risk exposure by alleviating downside risk of equity payoffs during aggregate recessions, when the SDF is high. In particular, during recessions major customers providing "insurance " against revenue shortfalls, improving operational efficiency, and certifying the reliability of firms' cash flows, thereby reducing information asymmetry and external costs of financing, other things being equal. In contrast, during aggregate cyclical expansions risks on revenue shortfalls and operational inefficiencies are less salient, balance sheets are stronger, and the advantages of customer concentration become relatively less important.

To test this prediction, we classify each month in our sample as an expansion if the recession probability calculated using the slope of the yield curve falls within the bottom decile of all sample months.[5] We then construct an indicator variable, *Expansion*, equal

[5]Recession probability data are obtained from https://www.newyorkfed.org/research/capital_

to one for expansion months and zero otherwise. This indicator is interacted with our customer concentration measures (*Major Customer* and *Major Sales*) in the panel regression specified in Equation 2.[6] The results, presented in Table 5, show that the interaction terms for both measures are positive and significant. This indicates that the risk advantages of having major customers, i.e., lower firm returns, are diluted during expansions relative to non-expansionary periods (which, of course, include recessions). Indeed, we find that the sum of the coefficients of customer concentration measures and the interaction terms are not statistically significant. That is, the effect of customer concentration on equity return, or risk premium is not significant during expansionary periods.

The results Table 5 thus imply that the significant average negative effect of customer concentration on equity return, or risk premium, observed in Table 3 arises from benefits of major customers during non-expansionary periods. This analysis is also consistent with the view that firms with major customers are less exposed to systematic (covariance) risk.

4.6 Variation with Customer Bargaining Power

In this section, we examine whether the negative relation between major-customer presence and stock returns varies with the bargaining power of major customers. As we discussed in Section 2.4, suppliers that provide larger amounts of trade credit are more exposed to concentrated credit risk and hold-up risk from their major customers. Moreover, as we outlined in Section 2.5, major customers have greater bargaining power in more competitive product markets. At the same time, the certification benefits of having major customers should not vary with trade credit exposure or product-market competition. These arguments lead to predictions that the negative relation between major-customer presence and expected stock returns is weaker for firms with high trade credit (Prediction

`markets/ycfaq`. Our results are robust to using the bottom tercile, quartile, or quintile as alternative cutoffs.

[6] Because our specification includes Industry × Month fixed effects, the main effect of *Expansion* is subsumed by these fixed effects and is therefore not included separately.

4) and for firms operating in more competitive industries (Prediction 5).

We test these predictions using panel regressions that interact our customer concentration measure with indicators for high trade credit exposure and high industry competition. Following Dhaliwal et al. (2016), we measure trade credit exposure as accounts receivable divided by total assets, and define the indicator variable, *High Accounts Receivable*, to identify firms whose accounts receivable is above the monthly sample median. We use the Text-Based Network Industry Classification Herfindahl-Hirschman Index (HHI) developed by Hoberg and Phillips (2016) as a proxy for product market concentration (i.e., an inverse proxy of product market competition). We define the indicator variable, *High HHI* to identify firms whose text-based HHI exceeds the monthly sample median.

The results of these regressions are presented in Table 6. In Column (1), we find that the coefficient on *Major Customer* $\times$ *High Accounts Receivable* is statistically insignificant, which indicates that the relation between major-customer presence and expected stock returns does not vary with the extent of trade credit provision. In Column (2), we find that the coefficient on *Major Customer* $\times$ *High HHI* is statistically insignificant, which indicates that the relation between major-customer presence and expected stock returns does not vary with the level of product market competition. These results are inconsistent with Predictions 4 and 5. However, the coefficient on *Major Customer* is negative and significant in both columns, which is consistent with the insurance, certification, and efficiency benefits of major customers.

4.7 Customer Concentration and the Implied Cost of Capital

So far, we have used stock returns to show that firms with a concentrated customer base are perceived as less risky in equity markets—a finding that contrasts with Dhaliwal et al. (2016). To further complement this result, this section examines the relationship between customer concentration and the implied cost of capital (ICC), using two alternative measures based on different sources of earnings expectations.

We obtain monthly ICC estimates from Lee et al. (2021), who construct four ICC measures using four valuation models: two based on residual income valuation (Claus and Thomas, 2001; Gebhardt et al., 2001) and two based on abnormal earnings growth (Easton, 2004; Ohlson and Juettner-Nauroth, 2005). Each model is implemented using two types of earnings forecasts: model-based forecasts generated using the cross-sectional prediction model of Hou et al. (2012), and analyst forecasts from IBES. Given the lack of consensus on which valuation model performs best and to mitigate measurement error from any single approach, we follow prior literature and compute ICC as the average of the four model-specific estimates within each forecast group (e.g., Li, 2010; Dhaliwal et al., 2016; Hartzmark and Shue, 2022). This procedure yields two composite ICC measures: one based on model-generated forecasts (Model-Based ICC) and the other on analyst forecasts (Analyst-Based ICC).

The first measure, referred to as *Model-Based ICC*, uses expected future earnings from the cross-sectional earnings prediction model developed by Hou et al. (2012), which has been shown to produce forecasts with lower bias, stronger earnings response coefficients, and broader firm coverage compared to analyst forecasts. Using this measure, we test whether our earlier findings based on stock returns are robust to an alternative proxy for perceived risk. The second measure, *Analyst-Based ICC*, relies on IBES earnings forecasts and is the same measure used by Dhaliwal et al. (2016). This allows us to directly compare our results with theirs when using the same measure. Table 7 presents the regression results. Columns (1)–(3) use *Model-Based ICC* as the dependent variable, while Columns (4)–(6) use *Analyst-Based ICC*.

We begin by estimating Equation 2, where the main explanatory variables are *Major Customer* and *Major Sales*. All regressions use a panel specification with industry-by-month fixed effects, and standard errors are clustered at both the firm and month levels. Columns (1) and (4) report results using *Major Customer*, while Columns (2) and (5) use *Major Sales*.

Columns (1) and (2) show that *Major Customer* is significantly negatively associated with *Model-Based ICC*. Specifically, the presence of a major customer corresponds to a 3.4 basis point reduction in monthly ICC. Given that the sample mean of Model-Based ICC is 0.42%, this represents a decline of approximately 8% relative to the mean (= 0.034/0.42). This result supports our earlier evidence from stock returns, suggesting that major customer relationships reduce firms' perceived risk in equity markets. While the coefficient on *Major Sales* is also negative, it is not statistically significant.

In contrast, Columns (4) and (5), which use *Analyst-Based ICC* as the dependent variable, show that *Major Sales* is significantly positively associated with ICC. This result aligns with Dhaliwal et al. (2016), indicating that firms with more concentrated customer bases are perceived as riskier when analyst forecasts are used to estimate ICC.

We next investigate whether our earlier result—that increasing customer concentration does not significantly affect stock returns among firms with at least one major customer—also holds when ICC is used as the dependent variable. To test this, we estimate Equation 4, in which the key explanatory variables are the tercile dummies: *Low Major Sales*, *Medium Major Sales*, and *High Major Sales*. These regressions again include industry-by-month fixed effects, with standard errors clustered by firm and month. The results are reported in Columns (3) and (6).

In Column (3), where *Model-Based ICC* is the dependent variable, the coefficients on *Low Major Sales*, *Medium Major Sales*, and *High Major Sales* are generally negative and statistically significant. However, the difference between *Low Major Sales* and *Medium Major Sales* (as reported in the row labeled "β_1, β_2"), as well as the difference between *Medium Major Sales* and *High Major Sales* (reported in the row labeled "β_2, β_3"), are not statistically significant. The difference between *Low Major Sales* and *High Major Sales*, although not reported in the table, is also statistically insignificant. This pattern is consistent with the results in Table 2, reinforcing the idea that, among firms with major customers, higher customer concentration does not further reduce perceived risk.

By contrast, the results in Column (6) differ markedly from those based on *Model-Based ICC*. When *Analyst-Based ICC* is used as the dependent variable, the coefficient on *High Major Sales* is significantly positive. While the difference between *Low Major Sales* and *Medium Major Sales* (as reported in the row labeled "β_1, β_2") is not significant, the difference between *Medium Major Sales* and *High Major Sales* (row labeled "β_2, β_3") is positive and significant at the 5% level. The difference between *Low Major Sales* and *High Major Sales*, though not reported in the table, is also negative and statistically significant. These findings indicate that, among firms already engaged with major customers, greater customer concentration is associated with higher perceived risk—opposite to the pattern observed with stock returns and *Model-Based ICC*.

Overall, Table 7 shows that the choice of ICC measure—specifically, how earnings forecasts are constructed—can lead to opposite conclusions. Results based on *Model-Based ICC* indicate that firms with major customers are perceived as less risky, consistent with our earlier findings using stock returns. In contrast, *Analyst-Based ICC* results suggest that greater customer concentration is associated with higher perceived risk, consistent with Dhaliwal et al. (2016) but in sharp contrast to the evidence from stock returns and model-implied forecasts. These differences highlight the importance of how earnings expectations are constructed and suggest that conclusions about perceived risk may vary depending on the inputs used to estimate the cost of capital.

4.8 Endogeneity

Our results thus far show that customer concentration is negatively associated with stock returns. A concern is that this relation may be biased by endogeneity. For example, omitted firm characteristics may affect both a supplier's customer concentration and its stock returns. To mitigate this concern, we implement a two stage least squares (2SLS) instrumental variable strategy.

A valid instrument must satisfy two conditions. First, it must be relevant, meaning it is correlated with the supplier's customer concentration after controlling for covariates and fixed effects. Second, it must satisfy the exclusion restriction, meaning it affects the supplier's stock returns only through its effect on the supplier's customer concentration, conditional on the full set of controls. Following Dhaliwal et al. (2016), we use the two year lagged industry average of customer concentration as instruments. Specifically, for each supplier year, we construct the Fama French 48 industry by year average of customer concentration measures (for example, *Industry Major Customer*$_{j,t-2}$ and *Industry Major Sales*$_{j,t-2}$), excluding the focal supplier from the industry average. Because firms within the same industry face similar product market and contracting environments, these lagged industry averages are expected to be strongly correlated with a supplier's own customer concentration, satisfying the relevance condition. Moreover, because equity investors price the supplier's forward looking risk, it is less likely that past (two year lagged) industry average customer concentration is directly related to the supplier's current stock returns once we condition on firm fundamentals and fixed effects, supporting the exclusion restriction.

It is also important to note that while our baseline analyses use monthly stock returns, our customer concentration measures, firm level controls, and the instruments are measured at the annual frequency. Running the first stage regression repeatedly within the same fiscal year would be redundant because both the dependent variable Customer Concentration$_{i,t}$ and the instrument Industry Customer Concentration$_{i,j,t-2}$ are measured at the annual frequency. Most firm level controls are also annual. As a result, within a given fiscal year, the first stage would use the same left hand side and largely the same right hand side across months, offering little additional variation while mechanically inflating the number of observations. To align measurement frequency and avoid redundant estimation, we aggregate monthly stock returns to the annual level and estimate 2SLS at the annual frequency. The two stage system is:

$$
\begin{aligned}
\text{Customer Concentration}_{i,T} = \beta_0 + \beta_1 \,&\text{Industry Customer Concentration}_{i,j,T-2} \\
&+ \text{Controls}_{i,T} + \mu_j + \lambda_T + \epsilon_{i,T}, \qquad (5a) \\
\text{R}^A_{i,T+1} = \beta_2 + \beta_3 \,&\text{Customer } \widehat{\text{Concentration}}_{i,T} \\
&+ \text{Controls}_{i,T} + \mu_j + \lambda_T + \nu_{i,T}. \qquad (5b)
\end{aligned}
$$

where $\text{R}^A_{i,T}$ is the firm's annual stock return in year $T+1$. $\text{Customer Concentration}_{i,T}$ is measured by either *Major Customer* or *Major Sales*. $\text{Industry Customer Concentration}_{i,j,T-2}$ is the two year lagged Fama French 48 industry by year average of the corresponding customer concentration measure, computed excluding supplier i. $\text{Customer } \widehat{\text{Concentration}}_{i,T}$ is the fitted value from the first stage in Equation 5a and captures the component of firm level customer concentration explained by lagged industry customer concentration. $\text{Controls}_{i,T}$ denotes the full set of lagged firm level controls used in Equation 2, except for *Momentum* and *One-month ret*, which are defined at the monthly frequency. Because the 2SLS estimation is conducted at the annual frequency, we replace these monthly return based controls with the firm's lagged annual stock return. Finally, μ_j and λ_T are industry and year fixed effects, respectively.

Table 8 reports the results from the 2SLS regressions. Columns (1) and (3) present the first stage estimates from Equation 5a. The results show that the industry average measures, $\text{Major } \widehat{\text{Customer}}$ and $\text{Major } \widehat{\text{Sales}}$, are positively and significantly related to the corresponding firm level customer concentration measures, *Major Customer* and *Major Sales*, as expected. The first stage F-statistics and the Kleibergen-Paap LM statistics reported in the bottom rows of Columns (1) and (3) reject weak identification and underidentification concerns, respectively.

Columns (2) and (4) report the second stage estimates from Equation 5b, which regress stock returns on the instrumented customer concentration measures. Column (2) uses

$\widehat{\text{Major Customer}}$, and Column (4) uses $\widehat{\text{Major Sales}}$. The coefficients on the instrumented customer concentration measures remain negative and statistically significant, consistent with our OLS results. In economic terms, the estimate of -45.742 in Column (2) implies that firms with a major customer earn annual returns that are 45.7 percentage points lower than firms without a major customer, holding other covariates constant. Relative to the sample mean annual return of 16.278%, this difference is economically large. The absolute magnitude of the effect is about 2.8 times the sample mean annual return (45.742/16.278). While our baseline analysis uses monthly stock returns, we implement the 2SLS framework at the annual frequency because the instruments and customer concentration measures are constructed annually. Importantly, the results remain qualitatively unchanged after moving from monthly to annual returns, indicating that our conclusions are robust to this change in frequency. Overall, the 2SLS evidence supports our earlier conclusion that firms with more concentrated customer bases are associated with lower stock returns, suggesting that our main findings are unlikely to be driven by omitted variable bias.

5 Conclusion

The impact of customer concentration on firm risk and its pricing by financial markets remains contested. Some studies emphasize the certification role of major customers, while others stress the vulnerability created by dependence on a key buyer. We contribute to this debate by examining how customer concentration relates to equity risk and stock returns.

Using a comprehensive sample of supplier firms from 1985 to 2022, we find a robust negative association between customer concentration and stock returns after controlling for standard risk factors and firm characteristics. The presence of a major customer is associated with lower required returns, while additional increases in concentration beyond having a major customer do not further reduce required returns. Overall, the evidence supports the view that investors value the demand insurance, operational efficiency, monitoring and certification provided by major customers.

Cross-sectional and time-series results reinforce this interpretation. The negative association is strongest for firms with greater information asymmetry and more limited access to external finance, including smaller firms, younger firms, and firms with less analyst coverage. We do not find evidence that trade credit provision or product market competition significantly changes the pricing of customer concentration. We also show that the certification benefits of major customers are stronger outside economic expansions.

We further examine implied cost of capital measures. When ICC is based on analyst forecasts, the results align with prior work suggesting higher perceived risk for concentrated firms. In contrast, when ICC is computed using model-based forecasts following Hou et al. (2012), which rely less on analyst coverage, the results mirror the return evidence: firms with major customers exhibit a lower implied cost of equity.

Taken together, our findings provide consistent support for the certification hypothesis. Major customer relationships are associated with lower perceived risk, especially among firms with higher information frictions, and the results are robust across stock returns and model-based ICC measures.

References

Allen, J. W. and G. M. Phillips (2000). Corporate equity ownership, strategic alliances, and product market relationships. *Journal of Finance 55*, 2791–2815.

Atkeson, A., J. Heathcote, and F. Perri (2025). Reconciling macroeconomics and finance for the us corporate sector: 1929 to present. Technical report, National Bureau of Economic Research.

Banerjee, S., S. Dasgupta, and Y. Kim (2008). Buyer–supplier relationships and the stakeholder theory of capital structure. *Journal of Finance 63*, 2507–2552.

Bernanke, B. S., M. Gertler, and S. Gilchrist (1999). The financial accelerator in a quantitative business cycle framework. *Handbook of macroeconomics 1*, 1341–1393.

Bhattacharyya, S. and A. Nain (2011). Horizontal acquisitions and buying power: A product market analysis. *Journal of Financial Economics 99*, 97–115.

Bottero, M., S. Lenzu, and F. Mezzanotti (2020). Sovereign debt exposure and the bank lending channel: impact on credit supply and the real economy. *Journal of International Economics 126*, 103328.

Cai, K. and H. Zhu (2020). Customer-supplier relationships and the cost of debt. *Journal of Banking & Finance 110*, 105686.

Campello, M. and J. Gao (2017). Customer concentration and loan contract terms. *Journal of Financial Economics 123*, 108–136.

Carhart, M. M. (1997). On persistence in mutual fund performance. *Journal of finance 52*, 57–82.

Cen, L., S. Dasgupta, R. Elkamhi, and R. S. Pungaliya (2016). Reputation and loan contract terms: The role of principal customers. *Review of Finance 20*, 501–533.

Cen, L., E. L. Maydew, L. Zhang, and L. Zuo (2017). Customer–supplier relationships and corporate tax avoidance. *Journal of Financial Economics 123*(2), 377–394.

Chen, J., X. Su, X. Tian, B. Xu, and L. Zuo (2025). Do major corporate customers deter supplier misconduct? *Journal of Accounting and Economics*, 101801.

Chodorow-Reich, G. (2014). The employment effects of credit market disruptions: Firm-level evidence from the 2008–9 financial crisis. *The Quarterly Journal of Economics 129*(1), 1–59.

Claus, J. and J. Thomas (2001). Equity premia as low as three percent? evidence from analysts' earnings forecasts for domestic and international stock markets. *The journal of finance 56*(5), 1629–1666.

Cohen, L. and A. Frazzini (2008). Economic links and predictable returns. *The Journal of Finance 63*(4), 1977–2011.

Dhaliwal, D., J. S. Judd, M. Serfling, and S. Shaikh (2016). Customer concentration risk and the cost of equity capital. *Journal of Accounting and Economics 61*, 23–48.

Do, T. K., H. H. Huang, and A.-T. Le (2023). Customer concentration and stock liquidity. *Journal of Banking & Finance 154*, 106935.

Duygan-Bump, B., A. Levkov, and J. Montoriol-Garriga (2015). Financing constraints and unemployment: Evidence from the great recession. *Journal of Monetary Economics 75*, 89–105.

Easton, P. D. (2004). Pe ratios, peg ratios, and estimating the implied expected rate of return on equity capital. *The accounting review 79*(1), 73–95.

Fama, E. F. and K. R. French (1993). Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics 33*, 3–56.

Fama, E. F. and K. R. French (2015). A five-factor asset pricing model. *Journal of Financial Economics 116*, 1–22.

Fama, E. F. and J. D. MacBeth (1973). Risk, return, and equilibrium: Empirical tests. *Journal of Political Economy 81*, 607–636.

Fee, C. E. and S. Thomas (2004). Sources of gains in horizontal mergers: Evidence from customer, supplier, and rival firms. *Journal of Financial Economics 74*, 423–460.

Galbraith, J. K. (1952). *American capitalism*. Houghton Mifflin Co., Boston.

Gebhardt, W. R., C. M. Lee, and B. Swaminathan (2001). Toward an implied cost of capital. *Journal of accounting research 39*(1), 135–176.

Gertler, M. and S. Gilchrist (1994). Monetary policy, business cycles, and the behavior of small manufacturing firms. *The Quarterly Journal of Economics 109*(2), 309–340.

Hartzmark, S. M. and K. Shue (2022). Counterproductive sustainable investing: The impact elasticity of brown and green firms. *Available at SSRN 4359282*.

Hertzel, M. G., Z. Li, M. S. Officer, and K. J. Rodgers (2008). Inter-firm linkages and the wealth effects of financial distress along the supply chain. *Journal of Financial Economics 87*, 374–387.

Hoberg, G. and G. Phillips (2016). Text-based network industries and endogenous product differentiation. *Journal of Political Economy 124*, 1423–1465.

Hou, K., M. A. Van Dijk, and Y. Zhang (2012). The implied cost of capital: A new approach. *Journal of Accounting and Economics 53*(3), 504–526.

Hui, K. W., S. Klasa, and P. E. Yeung (2012). Corporate suppliers and customers and accounting conservatism. *Journal of Accounting and Economics 53*, 115–135.

Irvine, P. J., S. S. Park, and Ç. Yıldızhan (2016). Customer-base concentration, profitability, and the relationship life cycle. *Accounting Review 91*, 883–906.

Itzkowitz, J. (2013). Customers and cash: How relationships affect suppliers' cash holdings. *Journal of Corporate Finance 19*, 159–180.

Johnson, W. C., J.-K. Kang, and S. Yi (2010). The certification role of large customers in the new issues market. *Financial Management 39*, 1425–1474.

Jorion, P. and G. Zhang (2009). Credit contagion from counterparty risk. *Journal of Finance 64*, 2053–2087.

Kale, J. R. and H. Shahrur (2007). Corporate capital structure and the characteristics of suppliers and customers. *Journal of Financial Economics 83*, 321–365.

Klein, B., R. G. Crawford, and A. A. Alchian (1978). Vertical integration, appropriable rents, and the competitive contracting process. *Journal of Law and Economics 21*, 297–326.

Kolay, M., M. Lemmon, and E. Tashjian (2016). Spreading the misery? Sources of bankruptcy spillover in the supply chain. *Journal of Financial and Quantitative Analysis 51*, 1955–1990.

Kumar, P., S. M. Sorescu, R. D. Boehme, and B. R. Danielsen (2008). Estimation risk, information, and the conditional CAPM: Theory and evidence. *Review of Financial Studies 21*, 1037–1075.

Lee, C. M., E. C. So, and C. C. Wang (2021). Evaluating firm-level expected-return proxies: implications for estimating treatment effects. *The Review of Financial Studies 34*(4), 1907–1951.

Lewellen, J. (2010). Accounting anomalies and fundamental analysis: An alternative view. *Journal of Accounting and Economics 50*, 455–466.

Li, S. (2010). Does mandatory adoption of international financial reporting standards in the european union reduce the cost of equity capital? *The accounting review 85*(2), 607–636.

Lian, Y. (2017). Financial distress and customer-supplier relationships. *Journal of Corporate Finance 43*, 397–406.

Ma, X., W. Wang, J. Wu, and W. Zhang (2020). Corporate customer concentration and stock price crash risk. *Journal of Banking & Finance 119*, 105903.

Mihov, A. and A. Naranjo (2017). Customer-base concentration and the transmission of idiosyncratic volatility along the vertical chain. *Journal of Empirical Finance 40*, 73–100.

Murfin, J. and K. Njoroge (2015). The implicit costs of trade credit borrowing by large firms. *Review of Financial Studies 28*, 112–145.

Newey, W. K. and K. D. West (1986). A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. NBER working paper.

Ohlson, J. A. (1995). Earnings, book values, and dividends in equity valuation. *Contemporary Accounting Research 11*, 661–687.

Ohlson, J. A. and B. E. Juettner-Nauroth (2005). Expected eps and eps growth as determinantsof value. *Review of accounting studies 10*, 349–365.

Patatoukas, P. N. (2012). Customer-base concentration: Implications for firm performance and capital markets. *Accounting Review 87*, 363–392.

Saboo, A. R., V. Kumar, and A. Anand (2017). Assessing the impact of customer concentration on initial public offering and balance sheet–based outcomes. *Journal of Marketing 81*, 42–61.

Sheikh, S. (2022). CEO power and the likelihood of paying dividends: Effect of profitability and cash flow volatility. *Journal of Corporate Finance 73*, 102186.

Titman, S. and R. Wessels (1988). The determinants of capital structure choice. *Journal of finance 43*, 1–19.

Wang, J. (2012). Do firms' relationships with principal customers/suppliers affect shareholders' income? *Journal of Corporate Finance 18*, 860–878.

Williamson, O. E. (1979). Transaction-cost economics: The governance of contractual relations. *Journal of Law and Economics 22*, 233–261.

Wilner, B. S. (2000). The exploitation of relationships in financial distress: The case of trade credit. *Journal of Finance 55*, 153–178.

Table 1: Summary Statistics

This table presents summary statistics for the variables used in the portfolio analysis and regressions on the relationship between customer concentration and stock returns. The sample covers 1985–2019. Variable definitions and calculation details are provided in the Variable Definition section. All variables are reported at an annual level.

	Mean	25th	Median	75th	Std Dev	N
Major Customer	0.479	0.000	0.000	1.000	0.500	53018
Major Sales	0.163	0.000	0.000	0.250	0.233	53018
Size	5.300	3.645	5.197	6.853	2.256	53018
BTM	0.664	0.354	0.600	0.891	0.416	53018
GrossProfit	-0.049	-0.067	0.027	0.072	0.247	53018
AssetGrowth	0.180	-0.052	0.057	0.215	0.594	53018
Cash	0.215	0.032	0.120	0.323	0.236	53018
Cash Flow Volatility	1.205	0.177	0.374	0.871	3.179	53018
Age	14.472	5	12	22	11.289	53018
Analyst Coverage	8.871	3.000	6.000	12.000	8.388	39203
Accounts Receivable	0.168	0.079	0.148	0.232	0.118	52814
Text-Based HHI	0.320	0.098	0.201	0.458	0.291	42948

Table 2: Customer Concentration and α

This table reports average excess returns and alphas for portfolios sorted monthly by customer concentration. Panel A classifies firms into two groups based on the dummy variable *Major Customer*: Column (1) reports results for firms without major customers (*Dummy = 0*), and Column (2) for firms with at least one major customer (*Dummy = 1*). Column (3) presents results for the long-short portfolio *Zero−One*, which takes a long position in firms without major customers and a short position in firms with at least one major customer. Panel B classifies firms with zero customer concentration into a separate group (*Zero*), while the remaining firms are sorted into terciles based on *Major Sales*, using NYSE breakpoints. This yields four portfolios: *Zero* (Column (1)), *Low* (Column (2)), *Mid* (Column (3)), and *High* (Column (4)). Column (5) reports results for the *Zero−High* long–short portfolio, which takes a long position in zero-concentration firms and a short position in high-concentration firms. Column (6) reports results for the *Low−High* long–short portfolio, which takes a long position in firms in the lowest tercile and a short position in those in the highest tercile of customer concentration. Details on the calculation of *Major Sales* are provided in Section 3.2. For each portfolio, the table reports equal-weighted average excess returns (in excess of the risk-free rate) and alphas estimated using the CAPM, the Fama and French (1993) three-factor model, the three-factor model augmented with the Carhart (1997) momentum factor, and the Fama and French (2015) five-factor model. The sample spans January 1985 to December 2022. Standard errors, reported in parentheses, are adjusted for heteroskedasticity and autocorrelation using a twelve-lag Newey–West adjustment (e.g., Newey and West, 1986).

Panel A: Presence of a Major Customer

	Major Customer (Dummy = 0)	Major Customer (Dummy = 1)	Zero−One
r^e	1.150***	0.923***	0.227***
	(0.319)	(0.324)	(0.053)
α_{CAPM}	0.274	0.051	0.223***
	(0.197)	(0.202)	(0.052)
α_{FF3}	0.305***	0.080	0.226***
	(0.115)	(0.120)	(0.054)
$\alpha_{FF3+UMD}$	0.478***	0.261**	0.217***
	(0.127)	(0.123)	(0.054)
α_{FF5}	0.455***	0.222*	0.232***
	(0.125)	(0.127)	(0.056)

Panel B: Major Sales

	Zero	Low	Mid	High	Zero−High	Low−High
r^e	1.150***	0.993***	0.882***	0.900**	0.250***	0.092
	(0.319)	(0.299)	(0.313)	(0.354)	(0.083)	(0.120)
α_{CAPM}	0.274	0.144	0.010	0.012	0.262***	0.132
	(0.197)	(0.194)	(0.195)	(0.231)	(0.083)	(0.114)
α_{FF3}	0.305***	0.140	0.034	0.064	0.241***	0.076
	(0.115)	(0.127)	(0.115)	(0.149)	(0.078)	(0.108)
$\alpha_{FF3+UMD}$	0.478***	0.323**	0.214*	0.240	0.237***	0.082
	(0.127)	(0.127)	(0.117)	(0.153)	(0.078)	(0.105)
α_{FF5}	0.455***	0.211	0.161	0.268*	0.187**	-0.057
	(0.125)	(0.138)	(0.117)	(0.158)	(0.079)	(0.114)

Table 3: Customer Concentration and Stock Returns

This table reports results examining the effect of customer concentration—measured by either the number of major customers or the proportion of sales to major customers—on stock returns. Columns (1) and (2) estimate Equation 2 using *Major Customer* and *Major Sales* as alternative concentration measures. Columns (3) and (4) report results from a panel regression using the same specification, with industry-by-month fixed effects and standard errors clustered at both the firm and month levels. Column (5) estimates Equation 3 using dummy variables for the number of major customers: *One Customer* equals one if the firm has exactly one major customer; *More than One Customer* equals one if the firm has more than one. Column (6) estimates Equation 4 based on terciles of customer concentration. For example, *Medium Major Sales* equals one if the firm's *Major Sales* falls into the middle tercile, and *High Major Sales* equals one if it falls into the highest tercile.Control variables are defined in the Variable Definition section. The sample spans January 1985 to December 2022. Columns (1) and (2) include industry fixed effects and apply a twelve-lag Newey–West adjustment (e.g., Newey and West, 1986), while Columns (3) to (6) include industry-by-month fixed effects with standard errors clustered at both the firm and month levels. All regressions include controls for Fama–French 48 industry classifications.

	Fama-MacBeth		Fixed Effects			
	(1)	(2)	(3)	(4)	(5)	(6)
Major Customer	-0.194***		-0.189***			
	(0.058)		(0.047)			
Major Sales		-0.507***		-0.482***		
		(0.125)		(0.130)		
One Customer: β_1					-0.160***	
					(0.051)	
More than One Customer: β_2					-0.267***	
					(0.073)	
Low Major Sales: β_1						-0.046
						(0.071)
Medium Major Sales: β_2						-0.192***
						(0.070)
High Major Sales: β_3						-0.272***
						(0.068)
Size	-0.088**	-0.090**	-0.084*	-0.088**	-0.084*	-0.088**
	(0.040)	(0.040)	(0.044)	(0.044)	(0.044)	(0.044)
BTM	0.591***	0.586***	0.865***	0.859***	0.867***	0.861***
	(0.141)	(0.141)	(0.137)	(0.137)	(0.136)	(0.137)
Gross Profit	0.364	0.365	-0.206	-0.206	-0.200	-0.203
	(0.355)	(0.356)	(0.447)	(0.447)	(0.447)	(0.447)
Asset Growth	-0.699***	-0.705***	-0.648***	-0.646***	-0.648***	-0.647***
	(0.080)	(0.080)	(0.123)	(0.123)	(0.123)	(0.123)
Cash Flow Volatility	-0.014	-0.014	-0.012	-0.012	-0.012	-0.012
	(0.010)	(0.010)	(0.009)	(0.009)	(0.009)	(0.009)
Cash	0.755**	0.798**	0.697**	0.736**	0.691**	0.713**
	(0.334)	(0.336)	(0.291)	(0.292)	(0.291)	(0.292)
Momentum	-0.001	-0.001	0.000	0.000	0.000	0.000
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
One-month ret	-0.048***	-0.048***	-0.053***	-0.053***	-0.053***	-0.053***
	(0.006)	(0.006)	(0.008)	(0.008)	(0.008)	(0.008)
Constant	1.440***	1.645***	1.326***	1.329***	1.325***	1.344***
	(0.487)	(0.522)	(0.289)	(0.287)	(0.289)	(0.288)
$\beta_1 - \beta_2$					0.107	0.146
					(0.073)	(0.092)
$\beta_2 - \beta_3$						0.080
						(0.088)
Industry FE	Yes	Yes	No	No	No	No
Industry $\times$ Month FE	No	No	Yes	Yes	Yes	Yes
R-squared	0.062	0.063	0.150	0.150	0.150	0.150
Obs.	594479	594479	593987	593987	593987	593987
Number of months	456	456				

Table 4: Effect of Information Asymmetry

This table presents the results of panel regressions examining how information asymmetry influences the relationship between customer concentration and stock returns. We use firm size, firm age, and analyst coverage as proxies for information asymmetry. The dummy variable *Large Firm* equals one if the firm's market capitalization in the previous month is in the top quartile, and zero otherwise. *Young Firm* equals one if the firm's age is below the monthly sample median, and zero otherwise; firm age is measured as the number of years the firm has been listed on CRSP with non-missing stock return data. *High Analyst Coverage* equals one if the number of analysts issuing earnings forecasts over the prior fiscal year is above the monthly sample median, and zero otherwise. Control variables include *Size* (log of market capitalization), *BTM* (Book-to-Market ratio), *Gross Profit* (gross profitability), *Asset Growth* (percentage change in total assets over the last two years), *Cash Flow Volatility* (cash flow volatility), *Cash* (cash divided by total assets), *Momentum*, and *One-month ret* (last month's return). Full variable definitions are provided in the Variable Definition section. All specifications include industry-by-month fixed effects, where industries are defined using the Fama–French 48 classification. The sample period spans January 1985 to December 2022. Standard errors are clustered at both the firm and month levels.

	Returns		
	(1)	(2)	(3)
Major Customer	-0.239***	-0.063	-0.274***
	(0.062)	(0.060)	(0.075)
Major Customer × Large Firm	0.237**		
	(0.114)		
Large Firm	-0.091		
	(0.161)		
Major Customer × Young		-0.272***	
		(0.087)	
Young		0.263***	
		(0.082)	
Major Customer × High Analyst Coverage			0.197**
			(0.097)
High Analyst Coverage			-0.016
			(0.109)
Controls	Yes	Yes	Yes
Industry × Month FE	Yes	Yes	Yes
R-squared	0.150	0.150	0.191
Obs.	593987	593987	443993

Table 5: Variation over the Business Cycle

This table reports panel regression results examining how the business cycle shapes the relationship between customer concentration and stock returns. The dummy variable *Expansion* equals one if the month is classified as an expansion period. A month is classified as expansion if its recession probability, calculated using the slope of the yield curve, falls in the bottom decile of all sample months. Control variables include *Size* (log of market capitalization), *BTM* (Book-to-Market ratio), *Gross Profit* (gross profitability), *Asset Growth* (percentage change in total assets over the last two years), *Cash Flow Volatility*, *Cash* (cash divided by total assets), *Momentum*, and *One-month ret* (last month's return). Full variable definitions are provided in the Variable Definition section. All specifications include industry-by-month fixed effects, where industries are defined using the Fama–French 48 classification. The sample period is January 1985 to December 2022. Standard errors are clustered at both the firm and month levels.

	Returns	
	(1)	(2)
Major Customer: β_1	-0.227***	
	(0.051)	
Major Customer $\times$ Expansion: β_2	0.362**	
	(0.142)	
Major Sales: β_1		-0.590***
		(0.138)
Major Sales $\times$ Expansion: β_2		1.030***
		(0.393)
$\beta_1 + \beta_2$	0.134	0.441
	(0.131)	(0.367)
Controls	Yes	Yes
Industry $\times$ Month FE	Yes	Yes
R-squared	0.150	0.150
Obs.	593987	593987

Table 6: Variation with Customer Bargaining Power

This table presents the results of panel regressions examining how hold-up problems influence the relationship between customer concentration and stock returns. We use a firm's accounts receivable and the degree of product-market competition it faces as proxies for hold-up problems. The dummy variable *High Accounts Receivable* equals one if a firm's accounts receivable, measured as accounts receivable divided by total assets, is above the monthly sample median, and zero otherwise. *High HHI* equals one if the firm's Text-Based Network Industry Classification HHI index, developed by Hoberg and Phillips (2016), exceeds the monthly sample median, and zero otherwise. Control variables include *Size* (log of market capitalization), *BTM* (Book-to-Market ratio), *Gross Profit* (gross profitability), *Asset Growth* (percentage change in total assets over the last two years), *Cash Flow Volatility*, *Cash* (cash divided by total assets), *Momentum*, and *One-month ret* (last month's return). Full variable definitions are provided in the Variable Definition section. All specifications include industry-by-month fixed effects, where industries are defined using the Fama–French 48 classification. The sample period is January 1985 to December 2022. Standard errors are clustered at both the firm and month levels.

	Returns	
	(1)	(2)
Major Customer	-0.211***	-0.228***
	(0.071)	(0.080)
Major Customer × High Accounts Receivable	0.041	
	(0.097)	
High Accounts Receivable	0.200**	
	(0.085)	
Major Customer × High HHI		0.158
		(0.112)
High HHI		-0.322**
		(0.125)
Controls	Yes	Yes
Industry × Month FE	Yes	Yes
R-squared	0.150	0.153
Obs.	591732	492997

Table 7: Customer Concentration and Implied Cost of Capital

This table presents results from panel regressions examining the effect of customer concentration on the implied cost of capital (ICC). Columns (1) to (3) use ICC estimates based on earnings forecasts from the cross-sectional model of Hou et al. (2012) as the dependent variable, while Columns (4) to (6) use ICC estimates based on analyst forecasts from IBES. Columns (1)–(2) and (4)–(5) present estimates from Equation 2 (with stock returns replaced by ICC), using two measures of customer concentration: *Major Customer* and *Major Sales*. Columns (3) and (6) report results from Equation 4, which focuses on different levels of customer concentration. Categorical dummy variables are constructed following the portfolio-sorting procedures described in Sections 4.1 and 4.2.1, and as implemented in Table 3. Control variables include *Size* (log of market capitalization), *BTM* (Book-to-Market ratio), *Gross Profit* (gross profitability), *Asset Growth* (percentage change in total assets over the last two years), *Cash Flow Volatility* (cash flow volatility), *Cash* (cash divided by total assets), *Momentum*, and *One-month ret* (last month's return). Full variable definitions are provided in the Variable Definition section. All specifications include industry-by-month fixed effects, where industries are defined using the Fama–French 48 classification. The sample period spans January 1985 to December 2022. Standard errors are clustered at both the firm and month levels.

	Model-Based ICC			Analyst-Based ICC		
	(1)	(2)	(3)	(5)	(6)	(7)
Major Customer	-0.034***			0.002		
	(0.009)			(0.005)		
Major Sales		-0.030			0.042***	
		(0.025)			(0.015)	
Low Major Sales: β_1			-0.039***			-0.004
			(0.011)			(0.006)
Medium Major Sales: β_2			-0.038***			-0.005
			(0.011)			(0.006)
High Major Sales: β_3			-0.028**			0.013*
			(0.013)			(0.008)
$\beta_1 - \beta_2$			-0.001			0.001
			(0.012)			(0.007)
$\beta_2 - \beta_3$			-0.010			-0.018**
			(0.013)			(0.008)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Industry $\times$ Month FE	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.498	0.498	0.498	0.378	0.378	0.378
Obs.	424824	424824	424824	232445	232445	232445

Table 8: Instrumental Variables Regressions

This table reports results from two stage least squares (2SLS) instrumental variable regressions. Columns (1) and (3) present the first stage estimates from Equation 5a, in which the endogenous customer concentration measures, *Major Customer* and *Major Sales*, are instrumented with the corresponding two year lagged Fama French 48 industry by year averages, *Industry Major Customer*$_{t-2}$ and *Industry Major Sales*$_{t-2}$. Columns (2) and (4) report the second stage estimates from Equation 5b, which regress annual stock returns on the instrumented customer concentration measures, $\widehat{\text{Major Customer}}$ and $\widehat{\text{Major Sales}}$. Control variables include *Size* (log market capitalization), *BTM* (book to market ratio), *Gross Profit* (gross profitability), *Asset Growth* (percentage change in total assets over the last two years), *Cash Flow Volatility* (cash flow volatility), *Cash* (cash divided by total assets), and *Last Year ret* (last year's stock return). Full variable definitions are provided in the Variable Definition section. All specifications include industry fixed effects based on the Fama French 48 classification and year fixed effects. The sample period spans 1985 to 2022. Standard errors are clustered at both the firm and year levels.

	First Stage	**Second Stage**	**First Stage**	**Second Stage**
	(1)	(2)	(3)	(4)
	Major Customer	Returns	Major Sales	Returns
Industry Major Customer$_{t-2}$	0.309***			
	(0.062)			
$\widehat{\text{Major Customer}}$		-45.742**		
		(23.068)		
Industry Major Sales$_{t-2}$			0.333***	
			(0.073)	
$\widehat{\text{Major Sales}}$				-171.667***
				(65.001)
Controls	Yes	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Adjusted R-squared	0.034	0.046	0.077	-0.070
First-stage F-test	24.70		20.93	
p-value	0.000		0.000	
Kleibergen-Paap LM Stat	12.88		9.36	
p-value	0.000		0.002	
Observations	43043	43043	43043	43043

Variable Definition

- **Major Customer**: A dummy variable equal to 1 if the firm has at least one major customer, and 0 otherwise.

- **Major Sale**: A one-year measure of customer concentration, representing the proportion of a supplier's total annual sales generated by customers who each contribute at least 10% of the supplier's total revenue.

- **One Customer**: Equals one if the firm has exactly one major customer, and zero otherwise.

- **More than One Customer**: Equals one if the firm has more than one major customer, and zero otherwise.

- **Low Major Sales**: Equals one if the firm falls into the lowest tercile of *Major Sales*, and zero otherwise. See Sections 4.1 and 4.2.1 for details on the grouping procedure.

- **Medium Major Sales**: Equals one if the firm falls into the second tercile of *Major Sales*, and zero otherwise. See Sections 4.1 and 4.2.1 for details on the grouping procedure.

- **High Major Sales**: Equals one if the firm falls into the highest tercile of *Major Sales*, and zero otherwise. See Sections 4.1 and 4.2.1 for details on the grouping procedure.

- **Large Firm**: Equals one if the firm's market capitalization in the previous month is in the top quartile, and zero otherwise.

- **Young Firm**: Equals one if the firm's age is below the monthly sample median, and zero otherwise. Firm age is measured as the number of years the firm has been listed on CRSP with non-missing stock return data.

- **High Analyst Coverage**: Equals one if the number of analysts issuing earnings forecasts over the prior fiscal year is above the monthly sample median, and zero otherwise.

- **High Accounts Receivable**: Equals one if total accounts receivable (*rect*) divided by total assets (*at*) is above the monthly sample median, and zero otherwise.

- **High HHI**: Equals one if a firm's industry Herfindahl-Hirschman Index (HHI), based on the Text-Based Network Industry Classification from Hoberg and Phillips (2016), is above the monthly sample median, and zero otherwise.

- **Size**: The natural log of market capitalization, which is the price (*prcc_f*) multiplied by shares outstanding (*csho*).

- **Book-To-Market**: Ratio of the sum of book values of equity and debt (*seq* + *dltt* + *dlc*) to the sum of the market value of equity (*prcc_f* × *csho*) and book value of debt (*dltt* + *dlc*).

- **Gross Profit**: Income before extraordinary items (*ib*) scaled by total assets (*at*).
- **Asset Growth**: The percentage change in total assets (*at*) over the last two fiscal years.
- **Cash Flow Volatility**: Measured as the coefficient of variation (CV) of cash flows. Cash flow is defined as the ratio of EBITDA (*ebitda*) to assets (*at*). For each fiscal year, I calculate the standard deviation of cash flows over the prior 4-year period and divide it by the absolute value of the mean cash flow for the same period to obtain the CV (e.g., Sheikh, 2022).
- **Cash**: Cash and Short-Term Investments (*che*) divided by total assets (*at*).
- **R&D**: R&D expense (*xrd*) divided by total assets (*at*).
- **Momentum**: The cumulative raw return measured over a horizon from 11 months before the current month, ending two months before the current month.
- **One-month ret**: Last month's stock return.
- **Expansion**: A dummy variable equal to 1 if the month is classified as an expansion period, and 0 otherwise. A month is classified as an expansion if its recession probability, calculated using the slope of the yield curve, falls in the bottom decile of all sample months.
- **Model-Based ICC:** The equal-weighted average of implied cost of capital estimates from four valuation models: two based on residual income valuation (Claus and Thomas, 2001; Gebhardt et al., 2001) and two based on abnormal earnings growth (Easton, 2004; Ohlson and Juettner-Nauroth, 2005). Earnings forecasts are generated using the cross-sectional earnings prediction model of Hou et al. (2012). Data are sourced from Lee et al. (2021).
- **Analyst-Based ICC:** The equal-weighted average of implied cost of capital estimates from the same four valuation models. Earnings forecasts are based on analyst estimates obtained from IBES. Data are sourced from Lee et al. (2021).
- **Industry Major Customer$_{t-2}$**: The two-year lagged Fama-French 48 industry-by-year average of *Major Customer*, computed excluding the focal firm from the industry average.
- **$\widehat{\textbf{Major Customer}}$**: The fitted value of *Major Customer* from the first-stage regression in Equation 5a, capturing the component of firm-level major customer status explained by the two-year lagged industry average of *Major Customer*.
- **Industry Major Sales$_{t-2}$**: The two-year lagged Fama-French 48 industry-by-year average of *Major Sales*, computed excluding the focal firm from the industry average.

- $\widehat{\textbf{Major Sales}}$: The fitted value of *Major Sales* from the first-stage regression in Equation 5a, capturing the component of firm-level customer sales concentration explained by the two-year lagged industry average of *Major Sales*.