Supply-Chain Spillover Effects and the Interdependence of Firm Financing Decisions

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ABSTRACT

We analyze spillover effects of supplier equity financing decisions to assess the importance of major trading relationships in creating interdependent valuation effects. We find supplier issuance decisions have important negative spillover effects for large customers, which are more pronounced as information asymmetry or economic dependence of suppliers and customers rises, relationship-specific investment increases, or more valuable product guarantees are offered. Furthermore, customer incentives to maintain supplier relationships are undercut by supplier equity financing decisions, leading to shorter post-issuance trading relationships and larger declines in relationship-specific investments. Our results provide strong evidence of financial and investment policy interdependence across major supply chain members.

Durable trading relationships between individual suppliers and customers are major fixtures in business practice. These relationships are known to create significant operating and financial interdependence across firms in neighboring stages of production (Titman (1984), Maksimovic and Titman (1991), Banerjee, Dasgupta and Kim (2008), Cremers, Nair and Peyer (2008)). This implies that durable, difficult to replace relationships between customers and suppliers can have important spillover effects down the supply chain by transmitting the effects of corporate policies from one firm to the other. Yet, despite the importance of these widespread major trading relationships, our understanding of corporate policy spillover effects across major supply chain members is very limited.

To illustrate the important economic interdependence of such major supply chain relationships, consider Apple which was for many years a major customer to Motorola/IBM. Apple terminated a 20-year relationship with Motorola/IBM to purchase computer chips and then formed a new relationship with Intel in 2005. Motorola/IBM experienced a significant drop in their profits, and they were left with substantial excess manufacturing capacity, which could not be easily utilized after the loss of the Apple account.[1] This example highlights how a firm's operating and investment policies can be influenced by the decisions of its major trading partners. Furthermore, the supply chain literature suggests that customers are concerned about the financial reliability of major suppliers and it is common practice for customers to rely on a variety of ancillary financial indicators including the supplier's stock price to infer potential supply chain disruptions (Babich, Burnetas and Ritchken (2007), Trkman and McCormack (2009)). This anecdotal evidence and findings in the supply chain literature imply that major supplier financial decisions, which significantly affect stock price, can lead to major changes in customer purchasing and investment policies.

In this study, we examine how supplier financing decisions trigger vertical spillover effects down the supplier-customer relationships and show that major supplier-customer relationships create financial and

[1] "Apple is poised to shift to Intel as chip supplier - Move could open door to more-powerful Macs; Cutting long ties to IBM," Wall Street Journal, June 6, 2005.

investment policy interdependence among major trading partners.[2] Specifically, we focus on the effect of seasoned equity offers (SEOs) on the valuation and subsequent investment and operating decisions of an issuer and its large customers. There are several reasons to study stock offers, among the many possible corporate financial decisions we might analyze in the context of major supplier-customer relationships. First, stock offers are important financial decisions which significantly impact a firm's capital structure and often its investment policy. Second, they are largely unanticipated and typically greeted in the market by a large negative stock price reaction, which reflects an adverse selection effect and important changes in a firm's leverage and often its investment and operating decisions. Thus, the economic consequences of equity offers in the context of major supplier-customer relationships, especially the magnitude of their information spillover effects, can be relatively easy to detect.

Our goals are several-fold. First, we empirically test and document the existence of spillover effects of equity offers on major supply chain customers. By estimating the magnitude and economic significance of vertical spillover effects on firm valuation, we show the importance that investors attach to economic interdependence when assessing the market value of suppliers and customers. Second, we examine the transmission mechanism through which the effects of an equity offer spread to other firms that are in the neighboring stages of production and the factors that play a significant role in this spillover process. Third, we examine how a firm's corporate policies are related to the investment and purchasing decisions of its major trading partners. We focus on the real effects of equity offers, which influences the value of assets specifically devoted to a firm's trading relationship with a major customer or supplier.

We propose two competing hypotheses of how SEOs affect firm valuation and behaviour, not only that of issuers, but also of large customers, namely, the supply-chain hypothesis and the capital structure hypothesis. These two hypotheses concern the impact of SEOs on the incentives of trading partners to

[2] We focus on vertical spillover effects for several important reasons. First, we are interested in examining the interaction between supplier-customer relationships and a firm's financial policies. Second, we are interested in investigating how factors related to product market characteristics including supplier-customer relationship duration, relationship switching costs and supplier asset specificity affect the value and investment consequences of SEOs. However, to the extent that other firms in the same industries are also likely to be affected by a firm's SEO, in examining vertical spillover effects, we also control for horizontal spillover effects in our analyses. Although we find some weak evidence of horizontal spillover effects in our data, our vertical spillover effects are robust to controlling for these horizontal spillover effects.

either continue or abandon their trading relationships. To develop testable implications of our main hypotheses, we need a theoretical framework that can describe and predict the general behavior of trading partners in choosing to strengthen, maintain the status quo or reduce the importance of their bilateral trading relationships and in the extreme to terminate the relationships and revert to arm's length spot transactions. The theoretical arguments developed from the transaction cost economics (TCE) literature are drawn upon for this purpose. The TCE literature suggests that factors which affect trading partner transaction costs also create incentives for them to choose the least costly form of economic exchange, between long term trading relationships and arm's length spot market transactions (Williamson (1985), Rao (2003)). Furthermore, certain firm and relationship-specific characteristics are predicted to affect these costs of exchange and thus, have a strong influence on the choice between long term bilateral trading relationships and arm's length spot transactions. We use these characteristics to develop important testable predictions, formally stated as our two main hypotheses.

Specifically, Shleifer and Summers (1988) suggest that supplier-customer relationships are governed mainly by implicit contracts since explicit contracts, which tightly bind trading partner actions, are too costly and inflexible. Thus, trading partners bound by implicit contracts may freely breach their partner's trust and indulge in opportunistic behavior when it is profitable. TCE literature suggests that firms are more likely to abide by their implicit contracts and maintain bilateral trading relationships when (1) relationship breakup costs are high, (2) firms are required to make large trading relationship-specific investments (Williamson (1985)), (3) prospects for existing trading relationships are less uncertain (Telser (1980), Raman and Shahrur (2008)), or (4) a supplier's post-sale product support is important (Titman (1984)). Focusing on these factors, we examine changes in major supplier and customer equity values and their behavior toward their major trading relationships around SEOs and use these changes to distinguish between our two posited hypotheses.

Our first hypothesis extends the Myers and Majluf (1984) model, which analyzes a firm′s financing decision in isolation, to a more general TCE setting where important economic interdependencies between firms exist. According to the supply-chain hypothesis, trading partners generally face an

information asymmetry problem with respect to the financial health of their major trading relationships, so that an equity offer announcement can signal negative news about the supplier's financial condition, which can have negative implications for its major trading relationships. Thus, any negative financial news release by a supplier that has a major customer relationship is predicted to decrease a supplier's expected reliability, which undercut both customer and supplier incentives going forward to invest in cooperative activities. Reductions in relationship specific investment can adversely affect both supplier and customer market values. The supply-chain hypothesis also predicts that a supplier releasing negative news has adverse effects on the values of its own firm and its customer, which become more severe when (1) relationship breakup costs are higher, (2) relationship-specific investments are larger, (3) information asymmetry is greater, (4) future prospects are more uncertain (Raman and Shahrur (2008)), and (5) post-sale supplier product support is critically important to customers (Titman (1984).[3] Further, negative information spillover effects that are observed down the supply chain lead to a subsequent deterioration of supplier-customer relationships, manifested in (1) declines in trading relationship-specific investment, (2) declines in the importance of customer sales, and (3) a reduction in the remaining life of its major trading relationships, which ultimately leads to (4) deterioration in both supplier and customer operating performance.

The second main hypothesis we test is labeled the capital structure hypothesis. This hypothesis posits that SEOs, which reduce an issuer's leverage, can benefit major customers because the likelihood of supplier financial difficulty is reduced, decreasing the probability of a disruption in the delivery of a key input. Moreover, customers who employ very specialized inputs suffer more significant relationship breakup costs in the event of a major supplier's financial distress or bankruptcy (Titman (1984), Titman and Wessels (1988)). Even if customers bear no direct costs from supplier financial difficulties, they are likely to experience significant indirect costs. This occurs because a financially weak supplier has poorer

[3] Note that a bilateral trading relationship is a key element of this vertical spillover effect. SEO suppliers with a diffuse customer base are minimally affected since each atomistic customer only places a small fraction of a supplier's sales at risk. And thus, an SEO issuer with a diffuse customer base is unlikely to suffer from deterioration of its distribution channel, revealing no SEO spillover effects down the supply chain. By the same logic, we can predict that the more valuable the current supplier-customer relationships are, the greater are predicted SEO vertical spillover effects.

incentives to maintain its strong reputation for product quality, prompt and reliable delivery, and fulfilling implicit contracts with its customers (Maksimovic and Titman (1991)). Thus, financially weak suppliers can impose added costs on customers, which are passed back to suppliers in the form of reduced demand, lower product prices, and less favorable terms of trade with major customers. These arguments suggest that major trading relationships create synergistic gains for the trading partners, causing a supplier with excess leverage and valuable investment opportunities to have strong incentives to issue seasoned equity so as to reduce its leverage, as high leverage impairs customer incentives to cooperate with an SEO issuer for the aforementioned reasons. Consequently, an SEO-induced reduction in supplier leverage lowers these expected costs and as a result, benefits both customers and suppliers (Titman (1984), Maksimovic and Titman (1991)). If a customer is aware of its supplier's financial difficulties, then a supplier SEO announcement would be good news for the major customers and should make supplier financing of customers more likely, which can benefit major customers.

According to the capital structure hypothesis, SEOs by firms with large sales to a single customer create value because they encourage more cooperative behavior among major trading partners and this leads to more favorable contract terms and higher prices realized by suppliers (Titman (1984)). Thus, the hypothesis predicts that issuers with large customers experience less negative announcement returns compared with SEO firms with a diffuse customer base. The hypothesis also predicts that major customers of issuers experience positive returns from SEO announcements. Further predictions of this hypothesis are that two factors emphasized in the TCE literature and our supply-chain hypothesis, namely relationship breakup costs and asset relationship specificity, are important determinants of SEO announcement returns for issuers and major customers. However, the predicted sign of the announcement effects and relationship effects of the capital structure hypothesis are exactly opposite to those of the supply-chain hypothesis

In addition to these two main hypotheses, we examine several alternative arguments that might explain our results. For example, under a reverse causality argument, a supplier preemptively issues equity when it anticipates a future deterioration of its major customer relationship. A firm could sell new

equity because its customer's financial condition has deteriorated and the firm is concerned that its existing loans to its major customer are less likely to be repaid in full. Yet another possibility is that some negative news affects both customers and suppliers simultaneously and this produces our main findings. We test these alternative explanations in the robustness section and find little evidence to support them.

We find that our issuer announcement effects are largely consistent with the supply-chain hypothesis and inconsistent with the capital structure hypothesis: stock issuers with large customers experience more negative, rather than less negative announcement returns. More specifically, issuers with a large public customer realize a mean CAR (-1, 1) of -4.15%, while issuers without a large public customer experience a mean CAR (-1, 1) of only -2.90%. In multivariate analysis, we find that consistent with the predictions of the supply-chain hypothesis, all of the aforementioned TCE related variables have a significant negative association with the stock price response to SEOs by issuers with large customers. We also find that the negative announcement effect is less pronounced when an issuer with a large customer plans to repay debt with the offer proceeds. Major customers also experience a less negative announcement day return when a supplier's SEO proceeds are used to repay debt. This finding is consistent with both the supply-chain hypothesis and the capital structure hypothesis. Alternatively, the result may suggest that an SEO signals that issuers value their customer relationships very highly and try to strengthen these relationships by reducing their leverage ratios, thereby increasing their attractiveness to customers.

Even though we find some evidence for the capital structure hypothesis, further analysis of major customer stock price reactions to supplier security offer announcements produces added support for the supply-chain hypothesis. Specifically, we find that customer stock prices exhibit a significant negative mean CAR (-1, 1) of -1.09% on a supplier's offer announcement.[4] Consistent with the negative customer stock price reaction reflecting expected deterioration of major customer relationships, we find customer announcement returns are negatively related to measures of issuer information asymmetry, namely supplier stock volatility and discretionary accruals. We also find this negative stock reaction is evident

[4] Likewise, a non-parametric sign-rank test shows that the median values are statistically different from zero at the 5% level.

only for customers having major trading relationships with an issuer, and not for other firms in a customer's industry, implying that the information spillovers borne by large customers are supply chain-specific, lending further support to the supply-chain hypothesis.

An analysis of the post-issue dynamics of major trading relationships provides further support for the supply-chain hypothesis, but little support for the capital structure hypothesis. We find significant weakening of issuers' major customer relationships in the post-offer period compared to non-issuers with large customers, manifested in larger declines in sales dependence on major customers, shortened durations of major customer relationships, and greater reductions in relationship-specific investments by suppliers. In terms of operating performance, issuers with large public customers experience significantly larger industry-adjusted declines in their returns on assets (ROA) measured from the year before to the year after the offer, compared to issuers without large public customers (-0.03 versus -0.01). Large public customers of issuers also exhibit significantly more negative changes in industry-adjusted ROA than large public customers of non-issuer matching firms over the same calendar period (-0.01 versus +0.01).

We perform a battery of robustness checks on these results, and test several alternative explanations for our empirical findings. First, to rule out a reverse causality argument that relationship deterioration leads to a firm's SEO, we perform a variety of tests using competitors of an issuer with the same major customer as the issuer as well as other large customers of issuers when the issuer has more than one customer purchasing at least 10% of issuer sales. We find that an SEO adversely impacts all large customers of SEO firms, implying that the large customer is not driving the adverse impact, but rather that the SEO is the causal factor. Second, we examine whether supplier moral hazard problems drive our results. Supplier CEOs can entrench themselves when the relationship with a large customers is closely tied to the expertise or social connections of the CEO (Shleifer and Summers (1986)), so that the CEO has greater latitude to extract private benefits of control. To the extent that managers of SEO firms impair the efficiency of firm operations and their market values, their customer's market value may be impaired as well. To rule out moral hazard explanations, we compare issuers with and without large customers by

growth rates of managerial compensation and frequency of diversifying acquisition activity around stock offers and in terms of the use of offer proceeds. If supplier moral hazard problems drive our main results, then CEOs with large customers should disproportionately increase their salaries or make diversifying acquisitions, something we do not find support for in the data. In addition, we find very similar uses of offer proceeds across the two samples. Finally, to rule out the argument that an exogenous shock that affects both SEO firms and their customers is the cause of our main findings, we examine the abnormal performance of firms in the same industries. We find competing firms have no abnormal stock returns around SEOs, undermining the exogenous shock argument. In summary, our robustness analysis yields further support for the supply-chain hypothesis, and uncover little support for these alternative explanations.

By examining how a major supplier customer relationship affects market reactions to SEOs, we contribute to the literature in several ways. First, to the best of our knowledge, this study is the first to examine announcement effects of stock offers from the perspective of an issuer's relationships with a large customer. Several studies investigate the influences of major supplier-customer relationships on various corporate policies including capital structure (Titman (1984), Maksimovic and Titman (1991), Kale and Shahrur (2007)), information disclosure (Raman and Shahrur (2008)), corporate governance (Cremers, Nair, and Peyer, 2008)), bankruptcy (Hertzel, Li, Officer, and Rodgers (2008)), and IPOs (Johnson, Kang, and Yi (2010)). However, no study to date has investigated how having large customers influences the announcement effects of SEOs and how corporate interactions among firms in neighboring stages of production can lead to spillover effects down the supply chain, which can in turn lead to significant customer market reactions to supplier SEOs.

Second, our research extends recent studies that examine how interdependencies among competitors affects corporate policies including capital structure and corporate governance (John and Kadyrzhanova (2007), Leary and Roberts (2009), Cheng (2009)). Although our study also investigates how major trading relations lead to interdependence in corporate policies that have important spillover effects, it differs from these studies in several important respects. Most importantly, our study focuses on policy

interactions that have important real effects, which significantly affect the subsequent life of major supplier-customer relationships.

Third, we extend the security offer literature by examining how supplier stock offers affect customers in downstream markets. Previous studies show that SEO announcements have a wealth effect on existing shareholders (Asquith and Mullins (1986), Masulis (1988), Smith (1986), Eckbo, Masulis, and Norli (2007)) and bondholders (Eberhart and Siddique (2002)), but no study examines valuation effects from the perspective of an issuer's relationships with major trading partners. In this way, we also extend the strand of literature that investigates interactions between product markets and financial markets (Brander and Lewis (1986), Chevalier (1995), Johnson, Kang, and Yi (2010)).

Fourth, we complement the previous SEO literature by documenting significant real effects of SEOs, which the existing literature has generally ignored. Rather than focusing on an SEO's real effects on an isolated firm, we examine the post-issuance changes in relationship specific investments of an issuer and its major trading partners and the trading partner's subsequent purchasing policy decision on whether to maintain these important bilateral trading relationships. SEOs also have significant economic consequences as major trading partners seek to reduce their exposures to their partners' opportunistic behavior, which weakens the role of reputation and trust in these economic relationships, causing deadweight losses for both trading partners. We show that the customer-borne cost of SEOs is economically large with a median loss in customer value of $57 million and a decline in future customer ROA of 1%. In addition, the percent of issuer sales made to the typical large customer drops by 9%, the customer investment in relationship specific assets drops by 7%, and the likelihood of relationship termination increases significantly over the 3 year post-SEO period.

Finally, our study is related to the literature that investigates the investment implications of SEOs, such as Lyandres, Sun, and Zhang (2008). We introduce a new perspective on this literature by showing how SEOs affect a specific type of investment, namely relationship-specific investments of

issuers. Our study complements the previous literature which treats firm issuance decisions as having purely internal implications

The study proceeds as follows. Section I discusses our main hypotheses and their testable implications. Section II describes the data and sample characteristics. In Section III we report abnormal returns for SEO firms and customers, and provide results from cross-sectional regressions. We examine the post-SEO changes in operating performance for SEO firms and their large public customers in Section IV. In Section V we study post-SEO relationship performance. In Section VI we present the results from our robustness tests. Finally, Section VII summarizes and concludes the paper.

I. Main hypotheses and testable implications

A. Supply-chain hypothesis

The supply-chain hypothesis suggests that SEO announcements by firms with large customers convey negative information about the value of existing and future major customer relationships, discouraging customers from maintaining these relationships. While the previous literature focuses on how a stock offer affects existing shareholders and debtholders, our hypothesis concerns how an SEO affects large customers that regularly purchase large amounts of intermediate products from an issuer and often make specialized investments to support these trading relationships.[5]

Examining the supply-chain hypothesis requires us to consider two questions. First, what type of information does an SEO announcement release? Myers and Majluf's (1984) adverse selection model suggests that offer announcements by firms with large customers convey negative information about the viability and market values of major customer relationships, similar to its implications for the market values of issuer assets-in-place. Thus, high information asymmetry faced by large customers exacerbates the equity offer's adverse selection effect documented in the existing literature. To the extent that a major

[5] In this context, our study is closely related to Almazan, Suarez, and Titman (2009) who study how firm transparency, measured by information disclosure concerning a firm's quality, is associated with the relationships between a firm and its stakeholders, especially for firms required to invest in non-contractible assets that enhance stakeholder relationships. Our study is also closely relate to Raman and Shahrur (2008), who examine how a specific form of information disclosure, namely earnings management, is determined within the context of supplier-customer relationships in which relationship-specific investments are important.

supplier-customer relationship is a valuable asset to both suppliers and customers, the information conveyed by an SEO can negatively affect them both.

Second, unlike the Myers-Majluf (1984) model where a firm is considered in isolation, the supply-chain hypothesis considers how the information signaled by SEOs affect the behavior of trading partners. Klein, Crawford, and Alchian (1978), Williamson (1985), and Milgrom and Roberts (1992) suggest that customers who make relationship-specific investments, and who face poorly delineated rights to earn rents from these relationships, are exposed to post-investment opportunism by their trading partners. Anticipating this risk, trading partners in major relationships can be reluctant to make large relationship-specific investments (the hold-up problem). Telser (1980) suggests that one way to persuade transacting parties to maintain a relationship is to make implicit contracts self-enforcing so that transacting parties believe that payoffs from continuing these business relationships exceed the one-time gain from deviating from cooperative action.[6] When one transacting party takes actions that signal these future payoffs may be smaller than currently believed (SEOs), this signal will generate concerns about potential opportunistic behavior by a trading partner and create incentives for trading partners to reduce their relationship specific investments, causing deterioration of the relationship and increasing the probability of its termination. This is costly to both SEO issuers and their customers since they cannot fully realize the gains from the established trading relationships or from any prior supporting investments.

We consider the supply-chain to be important for several reasons. First, the importance of the information asymmetry effect of major trading relationships is strongly supported by the existing literature and recent survey results. For example, Shleifer and Summers (1988) suggest the terms of a bilateral trading relationship are hard to specify in an explicit contract for every contingency. Thus, implicit contracts between suppliers and customers predominate, causing the trading relationship to be a highly information sensitive asset. Furthermore, Goffin, Szwejczewski, and New (1997), Raman and

[6] Telser (1980) argues that for transacting parties to abide by implicit contracts, the sequence of transactions supported by implicit contracts should have no definite last transaction in which the probability of a subsequent transaction is zero, so that after every transaction there is a positive probability of further transactions. Thus, to avoid an unravelling of the incentives to abide by the implicit contract, an ending date of trading can not be formally set, so the termination date must remain uncertain. Furthermore, a supplier's desire to maintain a good reputation with potential trading partners can alleviate the problem Telser (1980) raises (Lorenz (1999)).

Shahrur (2008), and Trkman and McCormack (2009) document that supplier-customer information asymmetry severely affects customer policies.[7] Consistent with this perspective, a recent survey reports that firms recognize supplier failure as a critical source of business risk and consider their supplier's financial reliability to be a fundamental concern.[8] This evidence indicates that vertical information spillover effects captured by the supply-chain hypothesis are an important economic issue, warranting a serious investigation.

A.1 Announcement effects

The arguments above suggest that several factors can affect announcement returns to issuers and their major customers, namely, information asymmetry, relationship breakup costs, relationship uniqueness, the expected extent of post-SEO deterioration of the customer-supplier relationship, the importance of product guarantees, and commitments to use offer proceeds to reduce financial leverage. We discuss each of these issuer characteristics below.

Information asymmetry

According to the supply-chain hypothesis, high levels of information asymmetry concerning issuer valuation exacerbate the costs inherent in equity offers. Further, the expected negative announcement returns borne by both issuers and their customers are exacerbated as the information asymmetry faced by investors and customers rises. If customers face higher information asymmetry about a supplier′s financial condition, then these customers are likely to reduce their reliance on this supplier and these relationships will experience greater post-offer deterioration. We measure the level of information asymmetry using a supplier′s prior stock volatility, physical distance to its major customer, and prior abnormal accounting accruals (Lee and Masulis (2009)).

[7] Consistent with the findings in these studies and anecdotal evidence, we also find no evidence in our data of pre-SEO customer activities that are consistent with customers being informed players. For instance, we find no evidence that customers diversify across suppliers prior their SEOs

[8] "Uncertainty around supply chain stability puts added strain on US companies, Ernst and Young LLP finds," Reuters, February 17, 2009).

Major supplier-customer relationship breakup costs

A second factor that can affect stock market reactions to equity offers is the expected size of losses to trading partners if the relationship is terminated. Higher expected breakup costs cause more negative announcement effects for issuers and their major customers. The losses associated with a breakup of a major trading relationship should rise monotonically with an issuer's dependence on its customer. Two variables that we examine which affect expected relationship breakup cost are 1) supplier dependence on a customer, measured by the percent of a supplier's cost of goods sold to the customer and 2) the pre-offer existence of a strategic alliance between a supplier and its largest customer (Chan, Kensinger, Keown, and Martin (1997)). Strategic alliances frequently involve investments in product development and joint marketing and distribution agreements. These joint investments and legal commitments by joint venture partners reduce the likelihood of early dissolution of a major customer relationship, which lowers the relationship's expected breakup cost (Chan, Kensinger, Keown, and Martin (1997)).[9]

Relationship uniqueness

Major supplier-customer relationships sometimes involve high levels of asset specificity (i.e., the amount of specialized assets dedicated to a particular commercial relationship), which makes it costly for suppliers and customers to switch trading partners (Williamson (1985, 1991)). Thus, we predict more negative equity offer announcement effects for issuers and their large customers as the asset specificity in the relationships rises. We measure the degree of asset specificity by R&D intensity, defined as R&D expenses scaled by sales (Acs and Isberg (1991), Santarelli (1991)). We also measure relationship

[9] A possible counter argument is that breakup costs make the trading partners more reluctant to end their relationship even if an SEO occurs, and hence this would result in less severe negative reactions for the customer, which is exactly the opposite of our interpretation. However, this argument is inconsistent with a rational supplier comparing the benefits (one time gain from deviation) and costs of an SEO (including expected relationship breakup costs) and then deciding to issue stock only when benefits outweigh costs. So, in an equilibrium, where suppliers behave rationally, the relationship subsequently deteriorates irrespective of the size of relationship breakup costs.

uniqueness by industry trademark intensity, defined as the total number of trademarks filed with the US Patent and Trademark Office in the 1997-2005 period by firms in a supplier's industry (Gorecki (1975)).

Importance of product guarantees

Titman (1984), Cornell and Shapiro (1987) and Cremers, Nair, and Peyer (2008) argue that producers of goods and services where guarantees are especially important, particularly firms in durable goods and technology intensive industries, are vulnerable to supplier financial distress risk. Since financial weakness of suppliers raises serious questions about the integrity of a supplier's product guarantees and servicing commitments, customers of such products are likely to flee to financially stronger competitors, when such a supplier exhibits evidence of financial weakness. It also follows that large customers of such suppliers are likely to be more sensitive to these concerns, since the effects on their operations can be especially severe, given the relationship's economic importance to them. Thus, the negative effects of equity offer announcements for suppliers and their large customers are expected to be more severe when these suppliers produce highly specialized products, or are in durable goods or high-tech industries.

Supplier commitment to reduce financial leverage

If a supplier commits to use offer proceeds to lower its financial leverage by paying off debt, then it lowers its risk of financial distress. This commitment should reassure customers of the viability of their relationships with the supplier, thus strengthening customer commitments to the relationship (Titman (1984)). Thus, when issuers commit to use offer proceeds to repay existing debt, we expect the SEO's impact on the trading relationship to be more positive for both issuers and their customers. To measure the commitment to reduce a firm's financial leverage, we employ an indicator variable equal to one if the firm plans to repay debt with its offer proceeds and zero otherwise.[10]

[10] We find that the most commonly disclosed use of SEO proceeds (n=578) is for general corporate purposes. However, while reducing financial leverage has strong implications for the supply-chain hypothesis and the capital structure hypothesis, other uses of proceeds have unclear implications for major customers.

In summary, the supply-chain hypothesis yields the following set of predictions about equity offer announcements for both SEO firms and their large customers: (1) Issuers with large customers have a more negative stock price response to a stock offer announcement than issuers without large customers, (2) customers have a negative stock price response to a major supplier's stock offer announcement, (3) announcement returns for issuers and their large customers are significantly more negative with greater (i) issuer information asymmetry, (ii) relationship breakup costs, (iii) specialization of investments and products, and (iv) portion of a product's value that depends on future availability of supplier parts and servicing support, (v) and when an issuer does not commit to use its offer proceeds to reduce financial leverage.

A.2. Post-offer operating performance

The supply-chain hypothesis also predicts changes in post-offer operating performance. Since an SEO reveals adverse information about an issuer's financial health and the continued viability of its major customer relationships, this adverse information should also manifest itself by a deterioration in the post-SEO operating performance of both major trading partners. When issuers have important trading relationships with large customers, these issuers can have difficulty switching to alternate trading partners, at least in the short run. Furthermore, customers' weakened incentives to support the long-term relationship can impose costs on suppliers, lowering their ex post operating performance. For example, large customers may cut their purchases, provide less timely payments to their suppliers, renege on previously agreed upon terms of trade or look for new suppliers (Klein, Crawford, and Alchian (1978)). Therefore, the supply-chain hypothesis predicts that issuers with large customers will subsequently underperform relative to issuers with a more diverse customer base. It also predicts that the same factors discussed in the last section that exacerbate stock offer announcement effects also amplify the effects on subsequent issuer operating performance.

A.3. Post-offer trading relationships

The supply-chain hypothesis has implications for the long-term viability of the post-SEO customer relationship as well. Since major trading relationships are governed by non-enforceable implicit contracts, the incentives of issuers and their major customers to make relationship-specific investments and to coordinate their operations are dependent on the perceived viability of the relationship. In the immediate post-offer period, we expect issuers with large customers to experience (1) a larger decline in investments in relationship specific assets, (2) a weakening in large customer sales, and (3) a shorter subsequent life of its major customer relationships. These three effects are likely to be more pronounced when issuers (i) have greater information asymmetry, (ii) plan to use offer proceeds for investment purposes, rather than debt repayment, and (iii) have more negative offer announcement CARs, which measures the market's revision of an issuer's value. We test the validity of all of these predictions.

B. Capital structure hypothesis

According to the capital structure hypothesis, SEOs benefit both issuers and their customers since the infusion of new equity capital increases the supplier's perceived reliability. This increase in reliability strengthens trading partner commitment and cooperation, which enhances the value of the relationship. Thus, the capital structure hypothesis predicts that (1) SEO firms with major customers experience more positive announcement returns than those without major customers and (2) customers of SEO firms experience positive announcement returns around their suppliers' SEO announcements. This hypothesis also predicts higher post-offer operating performance and stronger post-offer trading relationships for SEO firms and their major customers.

Since the capital structure hypothesis suggests that SEOs increase the incentives of trading partners to behave in a cooperative way, the aforementioned TCE related variables should strengthen this effect. Thus, the hypothesis predicts that the TCE variables are important determinants of the announcement returns and post-offer operating performance for SEO firms and their customers. However, the predicted

directions of the effects of TCE related variables on supplier and customer announcement returns and post-offer operating performance are exactly opposite to those of the supply-chain hypothesis.

II. Data and summary statistics

We begin our sample selection with the universe of firms that issue seasoned common stock reported in Thompson's SDC new issues database during the 1986-2005 period. We delete offers in the banking (SIC 6000-6199) and utilities (SIC 4910-4940) industries where offers are often motivated by regulatory concerns (Eckbo and Masulis (1995)). In addition, we exclude offers by REITS, ADRs, simultaneous offers of equity and debt, unit offers, and pure secondary offers.[11] Since we examine both short-term and long-term issuer performance using various measures, we follow Healy and Palepu (1990) and eliminate offers by any firm that has sold equity within the past five years, to reduce concerns that a small number of frequent issuers drive our results. For each issue, we use the date a stock offer is first mentioned in Lexus Nexus as the initial announcement date. In addition, we search Lexus Nexus for major confounding corporate news within one trading day before and after the initial announcement and exclude such observations.[12] These sample criteria yield a final sample of 1,946 SEOs.

To examine the impact of an equity offer within the context of supplier-customer relationships, we focus on issuer's large customers for the following reasons. [13] First, the previous literature suggests that spillover effects should be more evident down the supply chain (from supplier to customer), rather than up the supply chain (from customer to supplier). Customers have strong incentives to react sensitively to important decisions of major suppliers that have implications for the supplier's financial health because major supplier trading partners often make large investments in relationship-specific assets and the values of these investments can be compromised by a supplier's weakening financial condition or changes in its

[11] We eliminate pure secondary offerings since we are interested in the adverse information disclosed by the SEO itself. A large block-holder selling shares does not imply that management knows shares are over-valued, but has other potential interpretations.
[12] Major confounding corporate news events we exclude are earnings announcements, annual report filings, quarterly report filings, CEO turnover, and analyst recommendation changes.
[13] Given that many U.S. firms have large customers, our findings concerning information spillover effects can have implications for other firm and industry specific information events. In our sample of 1,946 SEO firms, 372 (19% of the sample) have large public customers in the SEO year. We also find that there are 429 SEO firms (22% of the sample) whose customers are privately held in the SEO year.

operating policies and commitment to the trading relationship. These investments can also be essential for the continued profitability of the trading relationship (Williamson (1983, 1985)). Furthermore, large customers not only account for a substantial portion of a supplier's revenue, but often exercise significant influence over its important strategic decisions (Blois (1972)). Lastly, U.S. disclosure rules make a study of major customers much more reliable, since suppliers must disclose the identities and sales levels of major customers, but customers are not required to reveal such details about their major suppliers. Utilizing these disclosures allows us to construct a unique dataset of supplier-customer pairings and their relationship characteristics. [14]

For each observation, we use the COMPUSTAT Segment Customer database to identify whether the SEO firm discloses a large customer in its financial statements for the offer year.[15] To determine if the large customer is a privately held or publicly traded firm, we manually match the customer names to the universe of firms in COMPUSTAT. Detailed information regarding the data collection process for large customers of SEO firms is provided in Appendix A.[16] Of the 1,946 SEOs in our sample, we find that 372 have a large public customer and 429 have a large private customer.[17] It is important to note that while our main hypotheses yield the same predictions for SEO firms that maintain relationships with large public and private customers, our analysis of the effects of supplier equity offers on large customers is limited to large public customers due to data availability.[18]

[14] Measuring the degree of relationship durability and "difficulty to replace" relationships between customers and suppliers is essential to address the research question of how durable, difficult to replace relationships transmit the effects of corporate policies such as new equity offerings from one firm to the other. Our database allows us to construct several variables quantifying these relationship characteristics.

[15] Our large customer definition is slightly different from that of Fee, Hadlock, and Thomas (2006). Where Fee, Hadlock, and Thomas include all disclosed customers as "large customers," we include only customers that account for 10% or more of sales. We make this distinction because of the endogenous nature of the disclosure of customers smaller than 10% of sales. However, our qualitative results are invariant to including all disclosed large customers as in Fee, Hadlock, and Thomas (2006) or if we define large customers more strictly as those that account for more than 15% of sales.

[16] We are careful in classifying the firm relationships to check for name changes of large customers since in some tests, we need to know not only the presence of a relationship with a large customer, but also the ultimate length of this relationship over time.

[17] We find that 15% of our SEO firms have more than one large public customer. When an SEO firm has multiple large public customers reported in the COMPUSTAT segment level data, we use the customer with the largest sales level for the year. While the percent of the SEO firm′s sales to the second largest customer averages 15%, the largest customer accounts on average for 26% of the SEO firm′s sales.

[18] We also examine whether having a government body as a large customer affects the market reaction to an SEO. Only 95 issuers in our sample have the government as their largest customer. Our results are unaffected by including an indicator variable for these SEO firms.

Financial statement and stock price data for both issuers and their large customers are drawn from the COMPUSTAT and CRSP databases, respectively. In addition, segment-level financial reporting data is drawn from the COMPUSTAT Segment Customer database and supplemented by SEC filings (predominantly 10-Ks, along with 10-Qs and offer prospectuses).

Table I reports the distribution of the 1,946 sample observations by year and industry. The table shows a significant increase in the frequency of offers during the early 1990s and a decline during the early 2000s. The most frequent equity issuers come from business services (N=253), pharmaceutical products (N=172), electronic equipment (N=165), and retail industries (N=140), with the balance coming from 6 other industries, each having fewer than 140 observations.[19] Table I shows that with the exception of retail firms, the issuers with a large customer are reasonably well distributed across the business services (N=45), pharmaceutical products (N=45), and electronic equipment (N=59) industries.

To draw meaningful inferences about SEO firms with large public customers, we use two types of firms as control groups. First, to answer the question of whether major customer relationships play an important role in explaining offer announcement effects, we use common stock issuers without a large public customer as a reference group. Second, to better understand why firms with large public customers issue equity and whether the nature of customer relationships differs between equity issuers and non-issuers, we use non-issuers with large public customers as a matching sample, where we match on Fama and French (1997) 48 industries, the pre-offer duration of the large customer relationship, pre-offer issuer size (equity capitalization), and offer year. We match on the pre-offer duration of the customer relationship to insure that the expected strength of the customer relationships is similar for issuers and matching non-issuers.[20] Overall, these procedures insure that firm characteristics and relationship strength are relatively homogenous across the issuers and matching non-issuers.[21]

[19] For expositional purposes, industry data in Table I use Ken French's 10 industry sectors. In the rest of the study, we use Fama and French (1997) industry classifications (48 industries). Table I results are not substantially different using the Fama and French (1997) classification.

[20] In addition, we examine samples matched on the percent of sales to the large customer and find qualitatively similar results.

[21] We also experiment with matching firms using a propensity score technique. Our results are qualitatively similar when we use this approach. However, this technique does not insure that matching firms are from the same industry as SEO firms. Therefore, we use the more conservative matching technique based on industry, size, and relationship length.

To assess how similar the reference and matching sample firms are to the issuers with large customers, we compare their firm characteristics. Table II.A shows the comparison of issue and issuer characteristics for the sample of SEO firms with a large public customer (N=372), the matching sample of non-issuers with a large public customer (N=372), and the reference sample of SEO firms without a large public customer (N=1,574).[22] Comparing the offer characteristics of the two groups of issuers, we find that offer proceeds, the percent of secondary shares sold, and the fraction of firms using offer proceeds to repay debt are statistically indistinguishable. Specifically, for issuers with (without) a large public customer, the mean offer proceeds is $88 million ($85 million), the mean percent of secondary shares is 29% (31%), and the mean percent of firms using offer proceeds to repay debt is 24% (26%).

Firm size as measured by total assets is $600 million for issuers with a large public customer, $304 million for non-issuers with a large public customer, and $751 million for issuers without a large public customer. T-tests of the mean differences in firm assets show statistical insignificance between the firms in the three categories, although skewness in total assets is apparent in comparing medians. Although market capitalization and firm leverage are similar across issuers with and without large public customers, we find that non-issuer reference firms tend to be smaller and have lower leverage. Comparing other firm characteristics between issuers with and without a large public customer, we find that issuers with a large public customer have a higher Tobin′s Q, higher prior stock volatility, a lower likelihood of NYSE listing, higher R&D intensity, a higher pre-SEO stock price run-up, and a higher level of abnormal discretionary accruals. In addition, issuers with large public customers are more likely to be in industries where firms tend to have large public customers than is the case for issuers without large public customers. These results suggest that issuers with large public customers are more likely to have higher information asymmetry compared to issuers without large public customers, everything else the same.

Comparing issuers and non-issuers, where both have a large public customer, we find issuers have higher Tobin′s Qs, stock return volatility, R&D intensity, and pre-SEO stock price performance. These

[22] In untabualted tests, we repeat our analysis using SEO firms with large customers (either private or public) versus SEO firms without large customers. Our results are similar to those reported in Table II.

results suggest that among firms with a large customer, those more likely to issue equity are firms with greater growth opportunities, higher asset specificity levels, and possibly greater share mis-valuations.

In Table II.B we compare the characteristics of large public customers of issuers and non-issuing matching firms. The firm size averages in the two samples are statistically indistinguishable from each other at $42 billion and $40 billion, respectively. However, their median Tobin's Qs are significantly different, with the former being 1.32 and the latter being 1.60. The mean (median) sales percentage to large customers of issuers is 26% (19%), and to large customers of non-issuers is 19% (16%). Tests of mean and median differences across the two groups reject the null hypothesis of equal dependence on large customers, suggesting that issuers' total revenue is more dependent on their large public customers than is the case for non-issuing matching firms.

Examining the percent cost of goods sold to large customers of issuers and non-issuers, we find that the mean (median) raw materials and intermediate products represents of 13% (0.35%) for issuers and 8% (0.05%) for non-issuers. Given that these ratios are highly skewed, we rely on a Mann-Whitney *z*-test, which shows a significant difference between the two groups. We find that there is no statistical difference in mean supplier-customer distances for large customers of issuers and non-issuers (1,430 miles versus 1,167 miles). Since SEO firms are matched to non-SEO firms based on the duration of the pre-offer relationship, the mean duration is identical for the two groups by construction (3.35 years versus 3.35 years). The mean duration of the post-offer relationship is also similar for the two groups (2.94 years versus 3.01 years).[23]

Lastly, we find the mean percentage of issuers and matching non-issuers that have strategic alliances with a large public customer is statistically indistinguishable (15% versus 12%), where suppliers and customers with joint venture agreements, marketing agreements, development agreements, and licensing agreements are all classified as having strategic alliances (Chan, Kensinger, Keown, and Martin (1997)).

[23] Note that because these relationship length variables are survival time variables and not normally distributed, *t*-tests and Mann-Whitney *z*-tests may not yield well specified tests. We address this issue later using a hazard function.

III. Empirical results

A. Announcement returns for SEO firms and large public customers

To examine the valuation effect of equity issuance announcements, we employ a standard event study methodology where we estimate a one-factor market model for daily returns on event days -301 to -46 using the CRSP equally weighted NYSE/Amex/Nasdaq index as the market portfolio.[24] Market model residuals (defined as daily abnormal returns) are compounded to obtain the cumulative abnormal return (CAR) from event day -*t* prior to the offer announcement date (defined as day 0) to event day +*t* following the announcement.

Table III.A reports abnormal announcement returns for issuers with and without a large public customer. The average CAR (-1, 1) for issuers with and without a large public customer is -4.15% and -2.90%, respectively, which are both statistically significant at the 1% level. The 1.25% difference in average CARs between these two groups of issuers is also economically large and statistically significant at the 1% level.[25] The median CARs show a similar pattern. Thus, equity issues by firms with a large public customer are greeted more negatively by investors, indicating that the adverse selection effects, documented in the prior equity offering literature, are more severe for firms with major customer relationships. This result supports the supply-chain hypothesis, but is inconsistent with the capital structure hypothesis. However, this evidence must be viewed tentatively, since the issue characteristics of the two samples may be quite different. We address this concern using multivariate regressions described below.

Table III.B shows the announcement effects experienced by large public customers of suppliers making SEOs. We find that the mean and median CARs (-1, 1) for large public customers are -1.09% and -0.96%, respectively, both which are significant at the 1% level.[26] These results suggest that equity offer

[24] Using a value-weighted index yields qualitatively similar results.

[25] When we group the sample as SEO firms with large customers versus SEO firms without large customers, we find that the CAR (-1, 1) for the two groups is -4.19% and -2.40%, respectively. These two figures are also statistically different at the 1% level. Our results do not support there being a difference between having a large non-public customer and having a large public customer.

[26] We also examine the customer CAR adjusting for the positive correlation between the customer and the SEO firm pre-issue returns, which averages 0.084. Since SEO firms and customer returns covary positively, we expect the customer to exhibit a

announcements by firms with large public customers convey information that affects not only an issuer's stock prices, but also the stock prices of firms further down the supply chain, particularly for an issuer's major customers.[27] The negative SEO announcement day return for the customers further supports the supply-chain hypothesis and is inconsistent with the capital structure hypothesis.

We also tabulate SEO customer CAR by the importance of the relationship with the customer as measured by the dollar sales to the customer divided by the customer cost of goods sold (COGs). The percent COGs is an important measure of how dependent the customer is on the SEO firm since any customer purchasing a high percent of their raw materials from a particular supplier is likely to be more dependent upon the supplier. We also separate the SEO firms into technology industry and non-technology industry firms since these firms are particularly likely to have important relationships with their large customers. In further tests, we find that customers with above median percent COGs in a technology industry have a CAR of -3.65%, while customers with below median percent COGs have a significantly different CAR of -1.40%. The difference between these two CARs is significant at the 5% level. In non-technology industries, the customer CAR with above (below) median COGs is -1.17% (-0.64%). The difference is not statistically significant. These results are tabulated in Appendix B1.

The major customers' mean CAR (-1, 1) is quite large considering that the mean (median) percent of a customer's total cost of goods sold produced by its supplier is 12.69% (0.53%). However, it is important to understand the economic implications of the signal being sent by an equity offering. The literature has shown that when a firm experiences a supplier induced supply chain disruption, the customer realizes an average loss in CAR (-1, 0) of -8.70% on the announcement and three year mean abnormal stock return underperformance of -40.66% (Hendricks and Singhal (2003, 2005a)). This supply chain disruption is

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negative abnormal return on the supplier SEO announcement. Adjusting for the covariance between the supplier and customer, we find the customer return is still a statistically significant -0.76% with a *t*-statistic of 3.75.

[27] We also examine the announcement effects for the suppliers of SEO firms by searching suppliers that disclose the SEO firms as large public customers in a manner similar to Fee, Hadlock, and Thomas (2006). We find that out of 1,946 SEO firms, 88 are disclosed as large customers. On an SEO announcement, the largest suppliers have a mean CAR (-1, 1) of -0.91 (*t*-statitic =0.91). Although the magnitude of this mean CAR (-1, 1) is quite comparable to that of the mean CAR (-1, 1) for large public customers of suppliers making SEOs (-1.09%), the small sample size makes it unlikely to be able to show statistical significance (Bill, you check the validity of this.).

also blamed for operating performance declines caused by increases in "costs associated with expediting, premium freight, obsolete inventory, additional marketing, and penalties paid to the customer" (Hendricks and Singhal (2005b)). Furthermore, the loss of reputation and credibility associated with supply chain disruptions may require suppliers to increase their public relation expenses to reestablish their credibility and reputation. It can also become more costly for firms "... to raise capital, because investors may ask for a higher premium to lend to firms whose credibility and reputation are questionable." (Hendricks and Singhal (2005b)). In addition, if the equity offer signals problems with a major customer relationship, then there will be costs associated with finding a new supplier, qualifying the supplier, and monitoring supplier reliability. In the context of a stock offer, this suggests a rise in the probability of a supply chain disruption due to an expected weakening of major customer relationships. As such, even a small rise in likelihood of a supply chain disruption can lead to a large negative abnormal return in the range of -1% for major customers of an equity issuer.

B. Multivariate analysis of SEO announcement returns

To further examine the validity the supply-chain hypothesis in explaining SEO announcement returns and examine the attributes associated with shareholder wealth losses for issuing firms with and without large customers, we estimate OLS regressions where the dependent variable is an issuer's 3-day CAR (-1, 1). Our key explanatory variable is an indicator that takes a value of one if an issuer has a large customer at the start of the offer year (*Large customer*) and is zero otherwise. Following previous research (Jung, Kim, and Stulz (1996), Kim and Purnanandam (2006)), we also use the following issue and issuer characteristics all measured at the pre-offer year-end as control variables: log of equity capitalization, offer proceeds scaled by equity capitalization, secondary shares scaled by total shares offered, an indicator variable that equals one if the stock is NYSE listed and is zero otherwise, long-term debt to total assets, Tobin's Q measured by book value of debt plus market value of equity divided by book value of total assets, stock return volatility in the 90 days prior to the offer announcement, stock price run-up for

the 90 trading days preceding the offer announcement, and an indicator variable that equals one if the offer is a Rule 415 shelf registration and is zero otherwise.[28, 29] We also include year and industry fixed effects to control for potential time trends and industry effects, respectively. Detailed definitions of these variables are presented in Appendix C.

Table IV reports regression estimates based on the full sample of 1,946 equity offers. In model (1), the coefficient estimate for the *large customer* is -1.53 and is significant at the 1% level. This estimate indicates that the average announcement effect for issuers with large customers is on average 1.53% more negative than for issuers without large customers. In model (2), we decompose the indicator variable for large customers into separate indicators for large private customers (*Large private customer*) and large public customers (*Large public customer*). We find that both coefficients are negative and statistically significant, and the difference between these two coefficient estimates is neither economically large, nor statistically significant.[30] This suggests that having either a large private or public customer exacerbates the negative SEO announcement effect.

In models (3) through (9), we examine characteristics that may help to explain the more negative CARs of issuers with large customers using the explanatory variables discussed in Section I, i.e., SEO firm information asymmetry (measured by stock return volatility and discretionary accounting accruals), the importance of product guarantees (durable goods industry and technology intensive industry indicators), industry uniqueness (R&D intensity and industries with above median trademark intensity) and an indicator for commitments to use offer proceeds to reduce debt.

In models (3) and (4), we use the variables that measure issuer information asymmetry. We find that compared to issuers without large customers, issuers with large customers that also exhibit either higher

[28] We also consider the possibility that firms filing their SEO and selling shares within 3 days may be significantly different from other SEO firms. When we add an indicator variable for so-called accelerated filers, we find no change in our results. We thank Jay Ritter for providing information about accelerated filing firms.

[29] In addition, we consider the impact of dual-class share structures and/or block shareholders on the SEOs in our sample. We find 66 issuers have dual class shares and 67 issuers have blockholders. We find no major differences in our results if we either include a dual class indicator variable or eliminate all dual class firms. Likewise, adding a block shareholder indicator has no major effect on our results. These two variables are taken from Andrew Metrick's website.

[30] Our results are qualitatively similar if we focus only on issuers with large public customers or with large private customers, suggesting that the distinction between large public and private customers is unimportant here.

stock return volatility or more discretionary accruals, experience significantly lower announcement returns. These results suggest that having more information asymmetry and large customers exacerbates the negative SEO announcement effect.[31, 32]

In models (5) and (6), we examine the importance of product guarantees on stock offer announcement returns. We find issuers with large customers that operate in durable goods or technology intensive industries have significantly more negative announcement returns. Since we are using industry specific variables in these regressions, we exclude industry fixed effects, although our results are robust to their inclusion. Based on our results, the adverse information disclosed by offer announcements is particularly severe when issuers have large customers and their product guarantees are highly valued by customers.

In models (7) and (8), we include measures of industry uniqueness as key explanatory variables. Consistent with the supply-chain hypothesis, we find that among issuers with higher R&D intensity and higher trademark intensity, issuers that also have large customers realize more negative announcement returns than issuers without large customers. These results suggest that high asset specificity, which makes it costly for suppliers to switch trading partners, increases the moral hazard problem inherent in major supplier-customer relationships.

Model (9) shows that announcement returns of issuers with a large customer are significantly less negative when these issuers use offer proceeds to repay debt. This interesting finding suggests that investors perceive a supplier's commitment to lower its financial risk as a value increasing action that benefits its major customer relationship, as in Titman (1984) and Cornell and Shapiro (1987), which is consistent with the supply-chain hypothesis as well as the capital structure hypothesis.

Another important implication of Titman's (1984) model is that, not only do firms in durable goods and technology intensive industries have offer announcements more negative, but they also have more

[31] Measuring discretionary accruals requires the availability of several years of historical data, which reduces our sample size in model (4) from 1,946 to 1,819.

[32] We also use analyst forecast dispersion as a measure of information asymmetry and find qualitatively similar results. For instance, the coefficient on the interaction between having a large customer and forecast dispersion is -1.70, which is significant at the 1% level. However, using analyst forecast dispersion reduces our sample size from 1,946 to 1,104, which makes using this measure impractical for the majority of our analyses.

negative post-offer long term performance. In untabulated tests, we find that issuers with large public customers in technology (durable goods) industries experience a significantly (insignificantly) larger decline in operating income over sales compared to issuers with large public customers in non-technology (non-durable goods) industries. When we use an estimate of a firm's bankruptcy probability, Altman's z-score, as our measure of firm performance, we find that issuers in technology (durable goods) industries experience an insignificantly (significantly) larger decline. Thus, there is some weak evidence that adverse information revealed by SEO announcements is particularly severe for issuers in durable goods and high technology industries. Taken together, these results are consistent with Titman's (1984) arguments that producers of goods and services in industries that depend on long-term product guarantees are especially vulnerable to financial distress risk, and they support the view that issuers offering valuable product guarantees are subject to greater SEO adverse selection problems.[33]

To ensure that our results are not driven by events clustering in calendar time, we repeat our analysis using a variety of alternate specifications. For instance, we repeat our tests after clustering standard errors by SEO issuance year and find that all models except for (6), (8), and (9) have statistically significant coefficients for the variables of interest. Likewise, clustering standard errors by month result in all models, except for (6) and (8) having statistically significant coefficients. Clustering by industry and year, all the coefficients of interest remain statistically significant, except for models (4), (6) and (9). These additional tests show that our results are not driven by time-specific factors.[34]

Another econometric concern with results reported in Table IV is the possibility of serious multicollinearity in the regressions with interaction terms. To allay this concern, we run a variance inflation factor (VIF) test on the interaction terms used in the regressions. We find that models (3), (4),

[33] Because there was a potential change in disclosure requirements regarding large customers in 1998, we repeat our analysis in Table IV deleting SEOs occurring after 1998. Although this weakens the power of our tests due to the loss of observations (from 1,946 to 1,354), we find in Table IV.A models (1) through (8) that variables associated with large customers and their interactions with information asymmetry, importance of durable product guarantees, and industry uniqueness remain significant at the 10% level or better. Only model (9) no longer has a significant interaction between a commitment to repay debt and having a large customer.

[34] We also estimate the regressions in Table IV after eliminating all technology firms. Given the high frequency of equity offerings by technology firms in our sample period, eliminating these firms is likely to alleviate the concern that our results are entirely driven by them. Our main results remain statistically significant after excluding technology firms from our sample.

and (5) have a VIF above 5, a figure that is considered problematic by Kutner, Nachtsheim, and Neter (2004). For these models, we repeat our prior analysis, separately examining firms with and without large customers and find that the variables of interest are statistically significant only for firms with large customers, and not for those without large customers.

In addition, in the case of issuers with large public customers where TCE-specific variables are available, we find that having a strategic alliance and being geographically closer to the large customer (as measured by log(1+distance in miles)) both reduce the negative issuer CARs (-1, 1). Since suppliers with strategic alliances are less likely to end their relationships with major customers given their economic importance, expected breakup costs should be smaller. These results highlight the importance of relationship breakup costs and information asymmetry in explaining SEO announcement effects.

In sum, the results in Table IV show that SEO announcements by firms with large customers convey negative information about the value of existing and future major customer relationships, and that the effect of such negative information on issuer value is particularly severe when information asymmetry is greater, industry uniqueness is higher, product guarantees are especially valuable, relationship breakup costs are larger, and the offer proceeds are not used to reduce debt.[35]

C. Multivariate analysis for customer returns

If the supply-chain hypothesis holds and if the negative information conveyed by SEO announcements passes along the supply chain, then we expect these announcements to affect customer stock prices in the same direction that they affect suppliers. To examine this issue, we regress customer CARs (-1, 1) on the same explanatory variables used in Table IV. Most of the control variables represent important issue and issuer characteristics, including equity capitalization, leverage, offer proceeds scaled by equity capitalization, secondary shares as a percent of offer proceeds, pre-offer stock price run-up.

[35] We also consider whether having a large customer changes the future sales prospects of SEO firms and whether this change affects issuer announcement returns. For instance, if a large customer makes future sales revenues more volatile because sales are not diversified across customers, then a change in future sales may have different effects on CARs of issuers with and without large customers. We use quarterly sales data for the two years after the SEO to calculate the post-SEO average sales change and sales volatility. Adding these two variables as controls does not qualitatively affect our earlier regression results.

Three other control variables represent important large customer characteristics, namely equity capitalization, leverage, and an indicator for customers in the issuer's industry. We expect this industry indicator to capture any spillover effects of SEO announcements on other firms in the same industry.[36]

The results are reported in Table V. In models (1) and (2), we find that customer CARs (-1, 1) are negatively related to issuer information asymmetry measures (i.e., stock return volatility and discretionary accruals). For instance, a one standard deviation increase in stock volatility results in a 0.62% more negative large customer CAR. Likewise, a one standard deviation increase in discretionary accruals results in a 0.14% more negative large customer CAR. Thus, measures of information asymmetry have significant economic and statistical effects on a customer's equity value. These results suggest that information asymmetry increases a large customer's stock price sensitivity to supplier equity offer announcements and exacerbates the adverse selection problem inherent in major customer relationships.

In models (3) and (4), we find a significant negative relation between customer announcement returns and variables that measure the importance of product guarantees. Specifically, large customers of issuers in durable goods (model (3)) and technology intensive industries (model (4)) have more negative CARs relative to large customers of issuers in other industries. In models (5) and (6), customer returns are also negatively related to industry uniqueness measures, i.e., indicators for high R&D intensive issuers and high trademark intensive industries, suggesting that asset specificity raises adverse selection concerns.

In model (7), we find that when offer proceeds are used to repay debt, major customer stock prices experience a significant *positive* effect. Thus, a supplier's decision to substantially reduce its financial risk, which signals a continued commitment to its major customer relationships, is greeted more favorably by both shareholders of the customer and supplier. This result is consistent with both the predictions of the supplier-chain information and capital structure hypotheses. In model (8), we examine the importance of the supplier to the customer, measured by the percent of customer cost of goods sold, and find that customer CARs are more negative as the supplier relationship becomes more substantial. In model (10),

[36] We exclude control variables that are not significantly related to customer CAR (SEO firm Tobin's Q, an indicator for SEO firm's being traded on the NYSE, and an indicator for SEO shelf registrations).

we observe that information asymmetry between an issuer and its large customer, measured by the trading partners' log (1+ distance), has a significant negative association with customer CARs.

In last two models, we examine the associations between customer CARs and ex-post weakening of major supplier-customer relationships. Models (11) and (12) respectively show that customer CARs are more positive when the post-SEO major customer relationship lasts longer, and when the post-SEO supplier R&D expenses decline less. While these are ex post variables, we view this as evidence that the market is making a forecast of how strong the major customer relationship will be going forward.

Overall, we find a substantial body of evidence that the TCE variables, which explain a substantial portion of the cross-sectional variation in issuer CARs, also play an important role in explaining cross-sectional variation in customer CARs, further supporting the supply-chain hypothesis.[37] We also find some weak evidence supporting the capital structure hypothesis, specifically the positive effect on SEO firm and customer CARs of using SEO proceeds to repay debt.

IV. Changes in operating performance of issuers and their customers

The prior event study evidence is consistent with the market's ex ante expectation of significant declines in major customer relationships following supplier stock offers. In this section, we present supporting evidence that SEO announcements by firms with major customer relationships are associated with material declines in the post-offer operating performance of both trading partners. There are a number of reasons why a decline in a major customer relationship could impose significant costs on both trading partners. For example, issuers and their major customers may find it a slow and costly process to establish new trading relationships to replace their lost relationships. If the two trading partners have invested in relationship-specific assets, then these investments can be substantially reduced in value as the trading partners are forced to employ these assets in their second best uses. These arguments suggest that

[37] In untabulated tests, we examine the possibility that customers may own substantial equity stakes in key suppliers that issue stock, linking customers to suppliers through these equity investments. In our sample, however, there are only 10 customers who own at least 3% of the stock of their suppliers and including an equity ownership indicator variable does not appreciably affect our results. We find no cases where SEO suppliers own at least 3% of the stock of their large public customers.

issuers and their large public customers experience poorer post-offer operating performance than issuers without large public customers. Changes in post-offer operating performance of issuers and their large customers are measured using industry-adjusted ROAs from one year before (year -1) to one year after the offer (year +1) or up to four years after the offer (year +4). To adjust for industry-wide effects, we subtract the median ROA of other firms in an issuer's Fama and French (1997) industry.

Table VI.A reports changes in industry-adjusted operating performance for SEO firms around stock offers. Consistent with the Loughran and Ritter (1997) results, we find issuer ROA peaks in the offer year and substantially declines thereafter. Examining issuers with large public customers, we find a mean change in ROA from year -1 to year + 1 of -3%. We find similar patterns for issuers without large public customers, though their mean change in ROA from year -1 to year +1 is only one third as large (i.e. -0.01), which is significantly less negative than issuers with large public customers. However, the changes in ROA beyond year 1 are not significantly different. This evidence suggests that beyond year + 1, issuers are able to offset their impaired large customer relationships, possibly by developing new major relationships or otherwise diversifying their customer base.

Table VI.B reports post-offer changes in ROA for large public customers of issuers. We find between years -1 and +1 that the ROA of large public customers declines by 0.01, whereas for large public customers of non-issuers it increases by 0.01. The difference in mean ROA between these two groups is statistically significant at the 5% level. Note that in all the alternative estimation periods, the ROA changes for large public customers of issuers are negative, while for large public customers of non-issuers they are all positive. These results are consistent with equity offers leading to weaker customer relationships and poorer operating performance by large public customers.

In Table VII, we examine changes in ROA from year -1 to +1 using a multivariate regression to determine which issuer characteristics drive the changes in ROA. We examine the cross-sectional variation in operating performance changes along similar lines to Allen and Phillips (2000) where our control variables include all their explanatory variables, plus several added offer characteristics. The key regressors are indicator variables for issuers with (1) large public customers, (2) high information

asymmetry (stock return volatility), and (3) commitments to reduce financial leverage with offer proceeds. We also include an indicator for high positive issuer CARs and its interaction with the large customer indicator as additional key explanatory variables in the last two regressions. Although our OLS regressions appear well specified, we focus on median regressions (i.e., least absolute deviation regressions) given that our dependent variable, ROA is highly skewed.[38] This estimation method focuses on marginal effects around median, rather than mean operating performance levels.

Model (1) of Table VII shows that there are significant differences in ROA changes for issuers with and without large customers, even after controlling for firm and industry characteristics. Model (2) decomposes the large customer indicator variable into indicator variables for large public and private customers. Our hypotheses predict negative coefficients for both indicators, although we find the large private customer indicator coefficient is insignificant at conventional levels. We also interact the large customer indicator variable with firm stock volatility, a measure of information asymmetry. As shown in model (3), highly volatile issuers with large customers experience larger declines in future operating performance, which is consistent with higher asymmetric information issuers being more severely affected. In model (4), we see that when an issuer with a large customer commits to use offer proceeds to repay debt, this commitment largely offsets the incremental impact of an issuer having a large customer (i.e., the coefficient on *large customer* and the coefficient on the interaction term between *proceeds used to repay debt* and *large customer* have nearly the same magnitude, but opposite signs). We also examine the association between high SEO announcement returns and the changes in ROA, but as seen in model (5), we find no significant empirical relation.[39]

Overall, our results suggest that issuers with large customers have larger post-offer declines in operating performance and this decline is exacerbated by information asymmetry, but appears to be alleviated when an issuer pre-commits to use offer proceeds to repay debt, possibly because this

[38] Our results are qualitatively similar using OLS regressions, though they have weaker significance (where the regression coefficients are significant only in models (1), (2), and (4)).
[39] As in earlier tests, we repeat our analyses for post-offering operating performance using standard errors clustered by time and find quantitatively similar results.

commitment negates the negative signal that the SEO announcement releases. These results support the supply-chain hypothesis.

V. Post-SEO relationships with large customers

The supply-chain hypothesis predicts that if a stock offer announcement releases information that existing large customer relationships are overvalued, then issuers with a large public customer suffer disproportionately more from expected declines in their major customer relationships. In contrast, the capital structure hypothesis predicts that if the issuance of equity helps to increase the strength of the supplier-customer relationship through lower leverage, then equity issuance results in an increase in post-offer relationship strength. In this section we examine the validity of each of these hypotheses in explaining post-offer changes in relationship strength by examining (1) the post-offer duration of key customer relationships (2) changes in issuer R&D investment, and (3) changes in sales to large customers.

A. Post-SEO duration of the major customer relationship

We examine whether the post-SEO hazard rate (i.e., the probability of post-SEO termination of a major customer relationship) is significantly different for issuers and non-issuer matching firms, both having large public customers. We estimate the probability of relationship termination using a hazard model specification similar to Fee, Hadlock, and Thomas (2006). In Table VIII, our hazard model uses the same explanatory variables as used in Table VIII and in Fee, Hadlock, and Thomas. We also include year and industry fixed effects. Note that we report the underlying proportional hazard function, which means that coefficients above (below) one indicate that the variable of interest shifts the hazard function up (down). Therefore, a coefficient above one is analogous to a negative coefficient in an OLS regression.

In models (1) through (4), we use a non-parametric Cox model to estimate the hazard models. The dependent variable is the number of years the relationship lasts after an equity offer. Each issuer trading relationship has one observation and our sample consists of 372 issuers with large public customers plus 372 non-issuers with large public customers. Consistent with the results in Fee, Hadlock, and Thomas, we

find that sales dependence squared, and an indicator variable for negative free cash flows are positively related to the likelihood of relationship termination (i.e., the relationship becomes shorter), whereas sales dependence and issuer size are negatively related to the likelihood of relationship termination (i.e., the relationship becomes longer). More importantly, model (1) shows that comparing firms with large public customer with and without SEOs, we find issuers are more likely to experience relationship termination. In model (2), we find that information asymmetry, measured by stock return volatility, increases the likelihood of relationship termination for issuers with large public customers. Model (3) shows that termination of a major trading relationship is more likely when issuers with large customers do not use offer proceeds to repay debt. Finally, in model (4), we find that when an issuer has a large negative announcement return, the duration of the subsequent customer relationship tends to be shorter, suggesting some ability on the part of investors to forecast a weakening of the major customer relationship. In further tests reported in Table B2, Appendix B, we repeat the analysis in Table VIII using a hazard model with a Weibull distributional assumption and find qualitatively similar results. We also repeat our analysis in Table VIII using a logit model where the dependent variable is an indicator variable that equals one if the major customer relationship terminates in a particular year after the equity offer and is zero otherwise. Once again, we find qualitatively similar results using this specification for our model. These results support the supply-chain hypothesis.

B. Post-SEO changes in R&D investment and dependence upon large customers

We use changes in an issuer's ratio of R&D to total assets and the percent of sales made to its large public customer to capture post-offer changes in the health of the major customer relationships. Changes in R&D can be a good measure of a relationship's health since a weakened relationship is likely to reduce relationship-specific investments including R&D (Acs and Isberg (1991)). A reduction in R&D can also indicate a general weakening in a firm's financial health, which can have negative implications for a large customer as discussed earlier. If an SEO announcement signals a future decline in an issuer's key

customer relationship, then investment in relationship-specific assets such as R&D should decline after an equity offer.

Consistent with the above prediction, we find in Table IX that issuers with large public customers on average reduce R&D investment by 7% from years -1 to +1, whereas non-issuers with large public customers, on average reduce R&D investment intensity by only 1% during the same period. The difference in these mean changes across the two groups is statistically significant at the 1% level. The results for other time intervals, such as years -1 to +2, years -1 to +3, and years -1 to +4, show similar patterns. These results suggest SEO announcements by firms with large customers signal a subsequent weakening in their major customer relationships, supporting the supply-chain hypothesis.[40]

Table IX also shows a large decline in the percent of sales to large public customers after SEOs. For example, the average percent of sales to large public customers by issuers falls by 9% from years -1 to +1, whereas the average percent of sales to large public customers by non-issuers over the same period falls by only 6%. *T*-tests for the difference in mean percentage change in sales across the two groups rejects the null hypothesis of equality of means. The results are similar for other time intervals, going out as many as four years. These results are again consistent with the view that SEO announcements by firms with large public customers signal a decline in the strength of their major customer relationships.

Table X shows that variables used to explain issuer and customer SEO announcement returns can also explain the cross-sectional variation in the post-offer changes in R&D intensity and sales to major public customers. We use a pooled sample of 372 issuers with a large public customer and 372 non-issuer matching firms with a large public customer that are matched by industry, firm size, and pre-offer number of years the major customer relationship existed.

In the first four regressions of Table X, the dependent variable is the change in the ratio of R&D expenditures to total assets from years -1 to +1. Since the dependent variable is a measure of a subsequent

[40] In untabulated tests, we also examine the difference in changes in R&D intensity between SEO firms with a large public customer and SEO firms without a large public customer. Although we do not find any statistically significant difference between these two groups, the changes in R&D investment are lower for the former in all intervals except for the changes in R&D investment from year -1 to year 2.

reduction in relationship investment, we no longer include as explanatory variables other measures of relationship dilution and relationship breakup costs previously reported in Table IV. We follow the previous literature in our choice of other control variables (Sundaram, John, and John (1996), Bushee (1998)). Note that interaction terms with issue and issuer characteristics (use of proceeds to repay debt or issuer CARs) are infeasible since these variables are not observable for the control sample firms. Instead we use two sets of indicator variables for issuers that do and do not use offer proceeds to repay debt (have high and low SEO announcement CARs, respectively). As in earlier regressions, each model also includes year and industry fixed effects.

In Table X model (1), we find that the post-offer decline in R&D intensity is larger for issuers than for non-issuers with large public customers. The coefficient of -0.061 suggests that issuers with large public customers experience a 6.1% larger subsequent decline in R&D investment than non-issuer matching firms. In model (2), we see that the result in model (1) is largely driven by issuers with greater information asymmetry (interaction term of indicators of high return volatility firms and SEO issuers). Model (3) shows that the decline in R&D investment after an equity offer is more pronounced when offer proceeds are not used to repay debt. Finally, we find in model (4) that there is no significant difference in post-SEO reductions in R&D for issuers with high versus low announcement CARs.

In the last four models of Table X, the dependent variable is an issuer's change in percentage of sales made to its large public customer from years -1 to +1. Since the dependent variable requires post-SEO data on the percent of sales, our analysis is conducted over a smaller pooled sample of 222 issuers and 222 non-issuer matching firms. We find that the results are similar to those in the prior four regressions, showing post-offer declines in the percent of sales to large customers are concentrated in issuers with high information asymmetry and those firms not repaying debt with offer proceeds. Finally, in model (8) we

find that when a supplier has a large negative SEO announcement return, the decline in the percent of sales made to the large public customer is especially severe.[41]

Overall, the results in Tables VIII, IX, and X show that SEO announcements by firms with a large customer signal a subsequent decline in the strength of their major customer relationships. The decline in the major customer relationships is larger for issuers with greater information asymmetry, when offer proceeds are not used to repay debt, and when SEO announcement returns are more negative. This evidence, together with that reported in Tables IV and V, strongly support the supply-chain hypothesis.

VI. Robustness tests

To check the robustness of our key results, we conduct a battery of additional tests. Below, we briefly summarize the findings from these tests.

A. Alternative explanations

A.1. Customer bargaining power

By construction, the focus of our investigation is on issuers with large customers. Heavy dependence on large customers and the specialized, noncompetitive nature of many large customer relationships (Klein, Crawford, and Alchian (1978)) can provide these customers with strong bargaining power over their often smaller suppliers. This customer bargaining power may be used to impose disadvantageous trading terms on suppliers, and provides grounds for an alternative explanation for our results.

To test this conjecture, we investigate whether issuers and their large customers operating in concentrated industries, measured by a Herfindahl index, experience more or less negative SEO announcement returns. Since customers in highly concentrated industries are more likely exert stronger bargaining power over their suppliers, who have a smaller number of alternative customers, a large customer Herfindahl index level should be negatively related to a supplier's SEO announcement effect.

[41] We also repeat our analyses in Table X using as a dependent variable an indicator for above the median change in R&D (for models (1)-(4)) and above the median change in percent sales (for models (5)-(8)). Using a probit regression, we find that models (1), (3), (4), (5), and (8) yield similar results as those reported in Table X.

However, we find product market competition of large customers, measured by a Herfindahl index, is insignificantly related to the SEO announcement returns of both issuers and large customers, suggesting that our results are not driven by customer bargaining power.

SEO announcement effects borne by suppliers and customers provide further evidence on the customer bargaining power hypothesis. When a supplier makes an equity offer, its financial resources and borrowing capacity both increase. This can give an issuer the financial capability to build major new relationships with other customers and thereby decrease a supplier's dependence on their large customers, which in turn weakens a large customer's bargaining power. This suggests that we should observe a more negative announcement effect for relatively larger customers, and a smaller negative announcement effect for these issuer-suppliers. An alternative hypothesis is that large customers may utilize their bargaining power over suppliers to extract some of the suppliers' new equity capital. This latter scenario would suggest a positive announcement effect for relatively larger customers and a more negative announcement effect for these issuer-suppliers. Our findings are inconsistent with all these sets of predictions since we show that both SEO firms with relatively larger customers and these relatively larger customers of SEO issuers have significant negative announcement returns.

A.2. Negative industry shock

A potential alternative explanation for the negative customer returns observed in Table III is that they reflect negative industry shocks around the SEO announcements and thus the changes in customer stock prices observed in Table III simply reflect negative industry information shocks or spillover effects. To investigate this alternative explanation, we examine the abnormal returns for competitors of issuers and the large public customers of these competitors. In addition, we examine the three day industry-adjusted returns of SEO issuers.

The prior literature has shown some important differences among industry classification systems (and Bhojraj, Lee, and Oler (2003), and Chan, Lakonishok, and Swamanathan (2007)). To ensure that our

results are not driven by a specific industry classification scheme, we use a variety of different industry classifications of firms: 4-digit COMPUSTAT SIC codes;[42] 4-digit CRSP SIC codes; current COMPUSTAT GICS (Global Industrial Classification Standard) codes; and historical COMPUSTAT GICS codes.[43,44]

Using each of these four industry classifications methods, we create a portfolio of competitors from the same industry for each SEO firm. Then using a market model, we estimate the equally-weighted abnormal return for this portfolio around the SEO announcement date and examine the mean CAR (-1, 1) for each of these portfolios.[45] Our results show that the 4-digit COMPUSTAT SIC code portfolio has a statistically significant mean CAR(-1, 1) of -0.16%.[46] When we use the 4-digit CRSP SIC code portfolios, the mean CAR (-1, 1) of the portfolio of SEO issuers' competitors is a statistically insignificant 0.01%. However, Bhojraj, Lee, and Oler (2003) show that GICS codes may be a better classification system since they are better at explaining firm stock price comovement. Therefore, we repeat our results using current and historical GICS codes. We find that the mean portfolio return of competitors of issuers is an insignificant 0.04% using current GICS codes and an insignificant 0.02% using historical GICS codes. In addition, we examine the competitor list provided by Hoberg and Phillips (2010a, 2010b). Using their competitor classification, we find an insignificant CAR (-1, 1) for competitors of -0.08%. The generally insignificant results, both statistically and economically, across industry classification methods fail to support the horizontal industry information spillover effect associated with SEO announcements.

[42] This industry classification is used by Slovin, Sushka, and Polonchek (1992).
[43] We also examine industry competitors using the Fama and French (1997) industry definitions. Our results using this definition yield insignificant announcement returns for both the SEO issuer competitor portfolio and the customer competitor portfolio.
[44] The COMPUSTAT database contains current GICS codes for all firms listed in COMPUSTAT. However, if firms change their industry classification over time, then the GICS codes reported in COMPUSTAT only reflect a firm's the most recent industry classification and thus, may not accurately reflect the firm's industry at the time of the SEO. Therefore, we use historical GICS classifications to more accurately reflect a firm's industry in the SEO year.
[45] We find qualitatively similar results using value weighted portfolios.
[46] The significant competitor CAR is not consistent with the earlier work of Slovin, Sushka, and Polonchek (1992) who find no significant CAR for competing industrial firms when there is an SEO announcement. We propose three possible explanations for the difference between our findings and theirs. First, they only look at AMEX and NYSE firms, while we include NASDAQ firms in our sample. Second, our sample period is much longer (1986-2005 versus 1980-1985) and our sample consists of many more data points (N=1,946 versus N=211). Third, the adverse information released is likely to be more severe for firms issuing equity in the 1990s (mostly growth firms) relative to the firms issuing equity in the 1980s (more value-oriented firms).

We next examine the SEO announcement effects for the large public customers of issuer competitors using the above industry classifications. If our results are driven by an industry shock, then that industry shock should not only affect issuer competitors, but it should affect customers of issuers' competitors. We find that the portfolio of large public customers of an SEO firm's competitors defined by 4-digit COMPUSTAT SIC codes yields a statistically insignificant mean CAR (-1, 1) of 0.06%. When we repeat the analysis using 4-digit CRSP SIC codes, COMPUSTAT GICS codes, or historical GICS codes to define competitors, we continue to obtain insignificant CARs (-1, 1) for issuer competitors' customers. These results are inconsistent with the prediction of the negative horizontal industry shock hypothesis.

As an additional robustness check of our significant issuer and major customer abnormal returns, we subtract the mean stock return of firms in an issuer's Fama and French (1997) industry from the issuer announcement return for the same three calendar days.[47] We find a significantly negative CAR of -2.41% with a *t*-statistic of 7.71. Likewise, adjusting an issuer's large customer announcement return for the customer's industry return yields a significantly negative customer CAR (-1, 1) of -0.71%, with a *t*-statistic of 3.85. The industry adjusted customer CAR (-1, 1) of -0.71% is slightly less negative than the market model customer CAR (-1, 1) of -1.09%, although they are not significantly different. These results are consistent with there being a small industry information spillover effect whose size is insufficient to drive our earlier results, implying that downstream firms are significantly affected by equity issues of their major trading partners.

A.3. Moral hazard

If managers of issuers with large customers face less market discipline and have greater incentives to run their firms suboptimally compared to managers of issuers without large customers, then it is possible that our main results are driven by differences in manager-shareholder agency problems between these two samples and not by the conflicts of interest inherent in major trading relationships. For example,

[47] Industry portfolio data is taken from Ken French's website: http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

firms with large customers may be less likely to be corporate control targets due to their extensive investment in major customer relationships or due to the possibility that potential acquirers will lose valuable target customers following an acquisition, which could insulate issuer managers from disciplinary (takeover) actions of the market for corporate control.

To rule out the possibility that differences in moral hazard between issuer managers with and without large customers can explain our main findings, we first examine differences in senior manager abnormal compensation and pursuit of empire building acquisitions between these two groups of firms. To capture changes in managerial financial benefits, we use changes in managerial compensation after equity offers. In addition, we control for managerial compensation contracts including compensation delta as a control variable and repeat a number of our earlier tests to ensure that the weaker performance of issuers with large public customers is not a result of larger managerial compensation packages for this sample.

As the first test that SEO issuers with large customers have a more serious manager-shareholder agency problem, we examine the extent to which managerial compensation differs across the two sets of firms. First, we look at the change in managerial compensation after stock offers. If managers of issuers with large public customers exhibit greater moral hazard problems compared to issuers without large public customers, then following a large equity infusion, we expect a larger increase in post-offer managerial compensation for issuers with large public customers. There are 59 firms with large public customers and 237 firms without large public customers represented in the ExecuComp database with data concerning the top five executives available from years -1 to +1. Using a difference in difference test we find that changes in executive compensation for issuers with and without large public customers are not significantly different.[48] These results are inconsistent with the view that firms with large public customers have a greater manager-shareholder agency problem.

We also examine whether the compensation contracts of senior managers in SEO issuers with large public customers can explain their more negative announcement returns. We address this question by

[48] In our difference-in-difference model, we control for the change in assets and find that the CEO compensation change is highly positively correlated with changes in asset size (t=10.55)

following Kim and Purnanandam (2006) and examine the average managerial compensation delta, which measures pay for performance sensitivity (the correlation between managerial compensation and stock price movement).[49] Specifically, we calculate the sensitivity of the top five managers' compensation to firm stock price movements using ExecuComp database as described in the Appendix of Kim and Purnanandam (2006). After adding the log of the managerial compensation delta to total managerial compensation of the top five managers in the regression models reported in Table IV.A, we assess whether our results change significantly after a stock offer. Although the explanatory power of our variables is significantly reduced by the much smaller sample sizes (from 1,946 to 329), our key results remain qualitatively unchanged in models (1) through (5) and (8). Also, in all the modified regressions in Table IV, the coefficient on the managerial incentive measure is positive and significant at the 10% level or better. These results again indicate that our main findings concerning issuer SEO announcement returns are not driven by the managerial moral hazard hypothesis.

As an alternative test of differential agency problems, we focus on potential empire building activities of our two samples of firms. The first measure of empire building is an ex-ante indicator of offer proceeds used primarily for investment purposes. The argument is that managers with unbridled empire building incentives are prone to obtain as much funding as possible for expansion. However, in examining the use of proceeds, we find that only 6.0% (6.5%) of SEO firms with (without) large public customers disclose their primary use of proceeds as investment purposes. The frequency of using SEO proceeds as investment purposes is not significantly different between these two small sets of firms. As a second test, we use the relative size of the offering. If the issuer management is interested in empire-building, its offering size is likely to be larger since an increased offering size provides more discretion to managers. We use the ratio of shares offered to shares outstanding as a measure of the offering size and find that the offering size of SEO firms with (without) large public customers is 0.210 (0.215). These values are not significantly different from each other, lending no support for the view that SEO firms with large public

[49] Our sample size (329) is slightly smaller than the sample size of Kim and Purnanandam (2006) (457) because we eliminate SEOs within five years of the prior SEO while they eliminate SEOs only within one year of the prior SEO.

customers are more likely to empire-build. As another measure of empire building, we use an indicator of offer proceeds used for diversifying acquisitions, a type of investment more prone to moral hazard problems. If issuers with large public customers have greater managerial moral hazard problems, then after the inflow of equity capital, we expect these firms to spend more resources on empire building and realize larger increases in managerial compensation and perquisites after SEOs compared to managers of issuers without large customers.

Another measure of empire building incentives is the extent to which managers pursue large acquisitions, even when funds available for acquisitions are very limited. To test this possibility, we examine whether the two samples of SEO-acquirers use equity financing at different frequencies. To measure acquisition activity, we examine whether issuers make acquisitions within three years of an equity offer, using information from the SDC Mergers and Acquisitions database. If firms with large public customers disproportionately use equity offer proceeds for empire building, then we should observe more frequent post-SEO acquisition activity in this sample relative to issuers without large public customers. We find of issuers with (without) large public customers, that 6.1% (7.6%) undertake acquisitions within three years of their equity offers. The difference in acquisition frequency between these two groups is not statistically significant, so we are again unable to find any evidence that manager incentives for empire building are greater for issuers with large public customers. In another test of managerial empire building, we examine whether major customer relationships are associated with a greater frequency of issuers choosing to expand through acquisitions in other industries based on the Fama and French (1997) 48 industry classification. We find no significant difference in the frequency of diversifying acquisitions between issuers with and without large public customers (2.9% versus 1.9%). Overall, these results are not supportive of the predictions of the moral hazard hypothesis.

As a more precise measure of empire building, we examine the ratio of the size acquisitions relative to the market capitalization of SEO acquirers in the year preceding an acquisition. This measure is potentially informative since managers pursuing rapid expansion are expected to make larger acquisitions relative to their own size. We find that the average ratio of acquisition size to firm market capitalization is

0.47 for firms without large public customers and 0.35 for firms with large public customers (the difference between these two values is not significant). These results suggest that SEO firms with large public customers are not more prone to empire-building than SEO firms without large public customers.

Since acquisitions which exhaust the liquid assets and debt capacity of a firm are more indicative of empire-building motivations, we repeat our analysis to determine the percent of firms that undertake stock-financed acquisitions in the three years after an SEO. We find that only 18 firms (4.8%) with large public customers and 80 firms (5.1%) without large public customers undertake a stock-financed acquisition. Once again, these differences are not statistically significant.[50] Finally, in examining offering size relative to the market capitalization of stock financed acquisitions, we find the ratios are not significantly different, namely SEO firms with a large public customer have a ratio of 0.41 and those without have a ratio of 0.49. From this array of tests, we conclude that there is no evidence of a significant difference between the acquisition activities of SEO firms with and without large public customers, undermining the suggestion that our main results are driven by differences in manager-shareholder agency problems across the two samples of firms.

We next undertake a detailed analysis of the post-SEO operating performance decay, which is presented in Table VI.A. While the results in Table VI.A are consistent with the supply-chain hypothesis, it is important to examine whether our results could be caused by differences in moral hazard between firms with and without large customers. If the decay in operating performance is caused by empire building, then we expect to see evidence around equity offers of rising overhead costs associated with acquisitions that don't offer significant synergies or other economic benefits for the acquirer.

Following Chhaochharia, Grinstein, Grullon, and Michaely (2009), we decompose the change in a firm's ROA into the change in selling, general, and administrative costs (SGA) / sales, the change in cost of goods sold (COGS) / sales, and the change in asset turnover (sales / assets) to further explore the causes for the decline in post-SEO operating performance. According to Chhaochharia et al., the ratio of SGA to sales captures the tendency of management to consume perks, the ratio of COGS to sales is an

[50] The likelihood of a cash acquisition over a fully or partially stock-financed acquisition is not different between the two groups.

inverse measure of a firm's operating efficiency in producing goods, and the ratio of sales to total assets indicates how effectively management uses firm assets to generate sales. Thus, if moral hazard explains our results, then we expect to find a significant increase in overhead expenses or a decrease in operating efficiency. In contrast, if adverse selection explains our results, then we would expect to see a significant decline in asset turnover after an SEO. Our additional tests show that the mean asset turnover ratio (sales / assets) instead of rising, actually significantly drops, while the mean overhead rate (SGA / sales) and direct costs (COGS / sales) are unchanged after an offer. These results indicate that moral hazard is not responsible for the decline in issuer operating performance, but are consistent with the supply-chain hypothesis. We report these results in Appendix B, Table B3.

B. Reverse causality: Do suppliers issue equity to build a new customer-supplier relationship?

Another alternative explanation for our results is that the offers are caused by customer performance declines. When a supplier learns privately that its large customer is in financial difficulty, it can be prudent for the supplier to undertake an equity offer to exploit its current overvaluation and add to its financial reserves to survive a potential loss of its major customer, and give it resources to develop relationships with new customers.

To rule out this reverse causality explanation, we perform several tests. First, we examine the CARs of all other suppliers who share the same large customer as our issuer (hereafter "peer suppliers"). The supply-chain hypothesis predicts that an SEO announcement by a supplier reveals information about overvaluation of its relationship-specific assets, so the market value of other peer suppliers should not be affected by an SEO announcement. The reverse causality explanation, on the other hand, predicts that peer suppliers should experience a negative CAR around an SEO announcement because this news reveals negative information concerning a major customer's financial condition, which should adversely affect both issuers and peer suppliers. We find that for the sample of 4,772 peer suppliers, the mean CAR (-1, 1) is -0.03%, which is not significantly different from zero (*t*-statistic=0.23). This result is

inconsistent with the importance of the reverse causality explanation, but supports the supply-chain hypothesis. To more closely examine the reverse causality explanation, we divide the sample of 4,772 peer suppliers into four quartiles based on their sales dependence on the same large customers to see if the insignificant CARs of peer suppliers are due to a weak average level of importance of their customer relationships. However, we find that even for the quartile of peer suppliers with the highest sales dependence, the mean CAR is a statistically insignificant -0.19% (*t*-statistic = 1.08).

Next, we compare the frequency of equity offers by one or more peer suppliers to the case with no peer supplier equity offers in the same year.[51] The reverse causality hypothesis predicts that these other suppliers, who should also anticipate their major customers' financial difficulties, are likely to issue equity so as to create a financial cushion and give them time to develop new customer relationships. This prediction follows since the incentive to establish new customer relationships also exists for peer suppliers who share the same customers as the SEO suppliers. So the reverse causality predicts that peer suppliers should engage in equity offers with a greater frequency, resulting in clustering of offer activity by suppliers that share the same customer.

We test this prediction of equity offer clustering by major suppliers by examining the frequency of equity issues by these suppliers during the 1986-2005 period, as reported in SDC. We find the unconditional equity offer frequency for firms over this time period is 6.46%. The frequency of equity offers conditional on an equity issuer sharing a customer with another issuer is 6.48%. The conditional and unconditional offer frequencies are not statistically different, suggesting that customer performance is not likely to drive stock offer activity. Likewise, in multivariate tests, we find similar results implying that there is no significant difference between the frequencies of equity offers by other suppliers to SEO issuers' major customers and firms in general.

As another test of reverse causality, we examine the supplier SEO announcement effects on the second largest public customers of issuers (N=87). The supply-chain hypothesis suggests that negative

[51] We consider SEO activities only within a year since a long time interval between SEOs by peer suppliers may not be caused by the same information about their customer financial health. The mean (median) interval until the next SEO is 155 (170) days.

information revealed by a supplier SEO adversely affects not only its largest customer, but also its other large customers. The reverse causality explanation, on the other hand, suggests that if a supplier issues equity to survive losing its largest customer, its other large customers should benefit from the SEO, since their major supplier's financial condition is now strengthened.

We first document that the second largest customer is much less important for an issuer than the largest customer, accounting for only 14.5% of SEO firm sales as opposed to 25.8% of sales for the largest customer. When we examine equity issuers' second largest customers, we find a statistically insignificant negative mean CAR (-1, 1) of 0.34%. The lack of a significant CAR is most likely due to the small sample size involved and the fact that the average percent of sales to these firms is much smaller than that to the largest customers. When we examine the changes in the percent of sales made to the second largest customer, we find a significant 2.51% decline in the percent of sales over years -1 to +1 (*t*-statistic = 1.79) and a 2.97% decline over years -1 to +4 (*t*-statistic 2.32). Thus, it is clear that the negative information released by an SEO adversely affects, not only an issuer's largest customer, but also its second largest customer to a lesser degree. These results further support the supply-chain hypothesis since negative information disclosed by an SEO adversely affects the issuer and both its two largest customers. We also examine the SEO customer performance leading up to the SEO announcement to assess whether deterioration in customer performance could be causing the supplier to issue equity. However, we find no evidence that prior to the SEOs, customer performance declines (using measures of Tobin's Q and ROA).

C. Endogeneity of major customer relationships

Thus far, we have treated an issuer's decision to have a major customer relationship as exogenous to the offer announcement return. However, we now consider the possibility that the relation between the existence of a major customer relationship and the announcement return is endogenously determined. Following Eisenberg, Sundgren, and Wells (1998), Loderer and Martin (1997), and Becker, Cronqvist, and Fahlenbrach (2008), who argue that an efficient method for handling this type of endogeneity

problem is two equation system estimated by maximum likelihood estimation (MLE). The results of this MLE are reported in Table XI. Our selection equation uses as its instrument the percent of firms in the same industry as large public customer of the issuer. Since our instrument is industry specific, we do not include industry fixed effects in our system of equations. Our issuer SEO announcement effect equation has the same model specification as the OLS regression in Table IV where the relationship between the existence of a large customer and an issuer's CAR(-1, 1) is examined.

Using an MLE approach, the predicted value of the selection equation is no longer correlated with the error term in the regression of interest, so the estimated coefficients are consistent. We find that the coefficient on the predicted indicator for an issuer with a large customer is negative and significant, suggesting that the major customer relationship adversely affects issuer SEO announcement returns. Our key finding that issuers with large customers suffer larger negative announcement effects relative to issuers without large customers is robust to this control for endogeneity.

VII. Summary and Conclusions

We investigate how having major customer trading relationships affects market reactions to supplier financing decisions. The prior literature typically views business relationships as a series of individual arm's length transactions between anonymous suppliers and customers. Yet, the wide spread prevalence of long term trading relationships and the importance firms place on supply chain management suggests that vertical spillovers caused by interrelatedness of supply chain firms and firm incentives to support major customer relationships are two fundamental factors that should be taken into accounts to obtain a more complete picture of a supplier's economic situation. We investigate this issue by studying the effects of SEOs on issuer and customer stock prices and subsequent operating performance and the durability of these major trading relationships. We examine these potential supply chain effects under two competing hypotheses and find strong support for the supply-chain hypothesis, which posits that SEOs release negative information about the durability of the issuer's major customer relationship, and limited support

for the capital structure hypothesis, which posits that SEOs strengthen issuer financial condition. However, we find no support for the variety of other explanations we examine, such as a negative industry information shock, manager empire building, major customer bargaining power, prior weakening in major customer relationships, and endogeneity of major customer relationships.

More specifically, we find several important results that support the supply-chain hypothesis. First, we show that equity offer announcements by issuers with large public customers are greeted more negatively by the market than similar announcements by issuers without large public customers. We find that large customers also experience significantly negative abnormal returns around their suppliers' SEO announcements. This result suggests that equity offers have a significant vertical spillover effect along the supply chain.

Second, in multivariate regressions, we find that suppliers experience more negative offer announcement effects when (1) information asymmetry is more severe, (2) firms are more dependent upon their major customers, (3) firms operate in an industry where implicit and explicit product guarantees are of considerable importance to customers (i.e., durable goods and technology intensive industries), and (4) major customer relationships are more likely to deteriorate after an offer. These results imply that characteristics of the supply chains, namely the change in the probability of a major trading relationship breakup and the expected breakup costs can be important determinants of SEO announcement returns, which represents a major component of its flotation costs.

Third, consistent with these announcement effects, we find that the post-offer operating performance of issuers with large public customers declines significantly more than other issuers. Likewise, large public customers of these SEO issuers also experience significant declines in operating performance following the offers.

Finally, we find that equity offers have significant real effects on the major customer relationships of SEO issuers. Specifically, we find that compared to non-issuer matching firms that also have large public customers, issuers with large public customers experience significantly greater post-offer deterioration in their major customer relationships (i.e., a significantly higher hazard rate for the relationship, less

investment in relationship-specific assets, and a decline in the percent of revenue earned from their largest customers). The economic costs of SEOs to customers are large with a median equity value decline of $57 million and a drop in future ROA of 1%. The value of any future relationship between the issuer and its large customer also declines as the percent of sales made to the large customer drops by 9%, the customer investment in relationship specific assets drops by 7%, and the likelihood of relationship termination increases significantly. SEOs also lead these major trading partners to reduce their exposures to the other party's opportunistic behavior and reduce the role of reputation and trust in these economic relationships.

Overall, our results suggest that the existence of a major customer relationship and uncertainty over its current strength are major determinants of the adverse market reaction to an equity offer. We conclude that SEO announcements release negative information about the vitality and continued economic importance of these major customer relationships, which leads to negative spillover effects down the supply chain. The negative news conveyed by equity offers also reduces the incentives of major trading partners to continue to cooperate and make relationship specific investments. Ultimately, an equity offer signals an expected deterioration in an issuer's major customer relationships.

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Table I
Frequency distribution of SEOs by year and industry

The sample consists of 1,946 SEOs, 372 of which have a large public corporate customer, reported in Thomson Financial's SDC New Issues database in the 1986–2005 period. We use the COMPUSTAT Segment Customer database field, *customer name*, to identify whether SEO issuers have large corporate customers. An issuer is defined as having a large customer when a customer represents 10% or more of an issuer's total sales. When an issuer has multiple large customers, the customer purchasing the largest amount is identified as the large customer. To determine whether a customer is publicly traded or privately held, we match the names in the COMPUSTAT Segment Customer database with those in the COMPUSTAT database. Industry classifications are based on the 10 industry classification on Kenneth French's website. The numbers in parentheses are those of SEO firms with a large public corporate customer.

Year	Business services	Pharmaceutical products	Electronic equipment	Retail	Other industries	Total
1986	9(3)	4(1)	8(4)	6(1)	55(8)	82(17)
1987	5(0)	4(2)	2(0)	3(0)	53(7)	67(9)
1988	3(1)	1(0)	2(0)	3(0)	21(3)	30(4)
1989	4(1)	2(1)	3(0)	5(0)	36(5)	50(7)
1990	5(1)	1(1)	2(1)	4(0)	27(4)	39(7)
1991	7(2)	13(4)	9(1)	8(0)	74(10)	111(17)
1992	9(0)	19(4)	4(2)	9(0)	75(22)	116(28)
1993	7(0)	12(3)	20(6)	21(0)	106(24)	166(33)
1994	10(1)	3(0)	12(3)	7(0)	88(15)	120(19)
1995	23(3)	11(0)	19(9)	12(1)	96(17)	161(30)
1996	23(7)	20(7)	8(3)	7(0)	103(19)	161(36)
1997	24(3)	12(4)	9(7)	15(0)	89(17)	149(31)
1998	23(3)	6(1)	5(2)	7(0)	62(8)	103(14)
1999	18(3)	7(1)	16(7)	8(0)	47(4)	96(15)
2000	37(4)	18(3)	25(9)	0(0)	34(11)	114(27)
2001	7(1)	7(1)	7(1)	5(0)	41(6)	67(9)
2002	5(0)	2(1)	3(1)	9(0)	51(10)	70(12)
2003	12(5)	10(2)	2(1)	4(0)	47(10)	75(18)
2004	10(3)	9(5)	7(2)	5(0)	59(11)	90(21)
2005	12(4)	11(4)	2(0)	2(0)	52(10)	79(18)
Total	253 (45)	172 (45)	165 (59)	140 (2)	1,216 (221)	1,946 (372)

Table II
Issue, SEO firm, and customer characteristics

The sample consists of 1,946 SEOs, 372 of which have a large public corporate customer, reported in Thomson Financial's SDC New Issues database in the 1986–2005 period. The sample also includes 372 non-SEO matching firms with a large public customer. In Panel B, the sample consists of 372 large public corporate customers of SEO firms and 372 large public customers of non-SEO matching firms. Each non-SEO firm with a large public corporate customer is matched to an SEO firm with a large public corporate customer by industry (Fama and French (1997) 48 industry classification), size (market value of equity), and number of years the suppliers have maintained a relationship with their large public customers prior to SEOs. We use the COMPUSTAT Segment Customer database field, *customer name*, to identify whether SEO issuers have large corporate customers. An issuer is defined as having a large customer when a customer represents 10% or more of an issuer's total sales. When an issuer has multiple large customers, the customer purchasing the largest amount is identified as the large customer. To determine whether a customer is publicly traded or privately held, we match the names in the COMPUSTAT Segment Customer database with those in the COMPUSTAT database. Each non-issuer with a large public corporate customer is matched to an SEO firm with a large public corporate customer by industry (Fama and French (1997) 48 industry classification), size (market value of equity), and number of years a supplier maintains a relationship with its large public customer prior to the SEO. The symbols ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. *P*-values are in parentheses.

Panel A. Issue and issuer characteristics

	SEO firms with large public customers (N=372): A		Non-SEO firms with large public customers (N=372): B		SEO firms without large public customers (N=1,574): C		Test of difference (B-A)		Test of difference (C-A)	
	Mean	Median	Mean	Median	Mean	Median	*t*-test	Wilcoxon z-test	*t*-test	Mann-Whitney *z*-test
Issue characteristics										
Proceeds ($ millions)	88.45	45.00	NA	NA	85.27	46.40	NA	NA	-0.33	0.65
									(0.74)	(0.51)
Percent of secondary shares sold	0.29	0.16	NA	NA	0.31	0.14	NA	NA	0.78	0.68
									(0.44)	(0.50)
Proceeds used to repay debt (indicator)	0.24	0.00	NA	NA	0.26	0.00	NA	NA	0.82	0.82
									(0.41)	(0.41)
SEO firm characteristics										
Total assets ($ millions)	599.87	135.21	304.21	43.19	751.40	149.42	1.30	4.97***	1.00	1.91*
							(0.19)	(0.00)	(0.32)	(0.06)
Market capitalization ($ millions)	713.89	158.90	545.13	76.43	968.85	169.14	2.01**	18.32***	0.51	0.49
							(0.04)	(0.00)	(0.61)	(0.62)
Leverage	0.17	0.10	0.18	0.06	0.18	0.13	0.24	2.05**	1.51	0.88
							(0.81)	(0.04)	(0.13)	(0.38)
Tobin's Q	2.92	2.07	2.61	1.69	2.83	2.00	1.61	5.01**	0.52	0.55
							(0.11)	(0.00)	(0.60)	(0.58)
Stock return volatility	0.04	0.04	0.05	0.04	0.04	0.03	3.33***	2.44**	3.36***	4.32***
							(0.00)	(0.01)	(0.00)	(0.00)
NYSE listed (indicator)	0.20	0.00	0.15	0.00	0.30	0.00	1.75*	1.75*	4.02***	4.02***
							(0.08)	(0.08)	(0.00)	(0.00)
R&D intensity	0.11	0.03	0.10	0.01	0.04	0.00	0.29	2.63***	0.96	2.43**

							(0.78)	(0.00)	(0.34)	(0.02)
Stock price run-up	0.55	0.42	0.24	0.29	0.44	0.29	6.93***	7.82***	2.81***	3.26***
							(0.00)	(0.00)	(0.01)	(0.00)
Firm age (years)	9.18	5.00	10.39	6.00	9.82	5.00	1.54	0.57	1.01	0.35
							(0.12)	(0.57)	(0.31)	(0.73)
Abnormal discretionary accruals	0.09	0.01	0.06	0.01	0.05	0.01	0.70	2.33**	2.66***	1.21
							(0.48)	(0.02)	(0.01)	(0.23)
Percent of firms in same industry with a large customer	0.26	0.26	0.26	0.26	0.21	0.20	0.00	0.00	11.97***	11.36***
							(0.50)	(1.00)	(0.00)	(0.00)

Panel B: Characteristics of major supplier-customer relationships

	Large public customers of SEO firms (N=372): A		Large public customers of non-SEO firms (N=372): B		Test of difference (B-A)	
	Mean	Median	Mean	Median	*t*-test	Wilcoxon *z*-test
Customer characteristics						
Customer total assets ($ billions)	41.70	19.99	39.56	13.59	0.57	1.59
					(0.57)	(0.11)
Customer market capitalization ($ billions)	36.34	15.76	34.29	14.40	0.55	0.29
					(0.58)	(0.77)
Customer Tobin's Q	2.03	1.32	2.10	1.60	0.28	5.11***
					(0.78)	(0.00)
Percent of sales to customer	25.78%	19.15%	19.32%	15.87%	4.57**	6.14***
					(0.02)	(0.00)
Percent of cost of goods sold	12.69%	0.35%	7.59%	0.05%	0.61	9.01***
					(0.55)	(0.00)
Distance (miles)	1,430	945	1,167	702	1.49	0.88
					(0.14)	(0.38)
Relationship length						
Pre-SEO relationship length (years)	3.35	3.00	3.35	3.00	0.00	0.00
					(0.50)	(0.50)
Post-SEO relationship length (years)	2.94	2.00	3.01	2.00	0.41	1.20
					(0.68)	(0.23)
Product market arrangements						
Strategic alliance (indicator)	0.15	0	0.12	0	1.19	1.19
					(0.24)	(0.24)

Table III
Cumulative abnormal returns (CARs) for SEO firms and their large public customers around the SEO announcement date

In Panel A, the sample consists of 1,946 SEOs, 372 of which have a large public corporate customer, reported in Thomson Financial's SDC New Issues database in the 1986–2005 period. In Panel B, the sample consists of 372 large public corporate customers of SEO firms. We use the COMPUSTAT Segment Customer database field, *customer name*, to identify whether SEO issuers have large corporate customers. An issuer is defined as having a large customer when a customer represents 10% or more of an issuer's total sales. When an issuer has multiple large customers, the customer purchasing the largest amount is identified as the large customer. To determine whether a customer is publicly traded or privately held, we match the names in the COMPUSTAT Segment Customer database with those in the COMPUSTAT database. The abnormal returns are calculated using the market model estimated with returns from days -301 to -46 relative to the SEO announcement date (AD). The equally weighted CRSP index return is used as the proxy for the market portfolio. The daily abnormal returns are accumulated to obtain the cumulative abnormal return (CAR) from day *-1* before the announcement date to day *+1* after the announcement date. The symbols ***, **, and * denote values are significantly different from zero at the 1%, 5%, and 10% levels, respectively. + and ‡ denote that the two values are significantly different from each other at the 5% and 1% levels, respectively. *P*-values are in parentheses.

Panel A: Abnormal returns for SEO firms with and without a large public customer

	SEO firms with large public customers (N=372): A				SEO firms without large public customers (N=1,574): B				Test of difference (B-A)	
	Mean	*t*-test	Median	Sign-rank statistics	Mean	*t*-test	Median	Sign-rank statistics	*t*-test	Mann-Whitney *z*-test
AD-1	-0.78%	4.17*** (0.00)	-0.72%	4.54*** (0.00)	-0.25%	2.76*** (0.01)	-0.36%	5.13*** (0.00)	2.62+ (0.01)	2.16+ (0.03)
AD	-1.98%	10.03*** (0.00)	-1.55%	9.50*** (0.00)	-1.50%	14.73*** (0.00)	-1.11%	14.66*** (0.00)	2.09+ (0.04)	2.44+ (0.01)
AD+1	-1.28%	3.16*** (0.00)	-0.90%	5.07*** (0.00)	-1.13%	10.13*** (0.00)	-0.90%	10.97*** (0.00)	0.52 (0.60)	0.34 (0.73)
CAR (-1, 1)	-4.15%	7.72*** (0.00)	-3.86%	10.48*** (0.00)	-2.90%	17.61*** (0.00)	-2.71%	17.99*** (0.00)	2.93‡ (0.00)	3.30‡ (0.00)

Panel B: Abnormal returns for large public customers of SEO firms

	Large public customers (N=372)			
	Mean	*t*-test	Median	Sign-rank statistics
AD-1	-0.280%	2.31** (0.03)	-0.30%	2.83*** (0.00)
AD	-0.38%	3.79*** (0.00)	-0.30%	3.82*** (0.00)
AD+1	-0.23%	2.07** (0.04)	-0.25%	2.14** (0.03)
CAR (-1, 1)	-1.09%	5.37*** (0.00)	-0.96%	5.99*** (0.00)

Table IV
OLS regressions of cumulative abnormal returns (CARs) for SEO firms around the SEO announcement date on explanatory variable

The sample consists of 1,946 SEOs, 372 of which have a large public corporate customer, reported in Thomson Financial's SDC New Issues database in the 1986–2005 period. We use the COMPUSTAT Segment Customer database field, *customer name*, to identify whether SEO issuers have large corporate customers. An issuer is defined as having a large customer when a customer represents 10% or more of an issuer's total sales. When an issuer has multiple large customers, the customer purchasing the largest amount is identified as the large customer. To determine whether a customer is publicly traded or privately held, we match the names in the COMPUSTAT Segment Customer database with those in the COMPUSTAT database. The dependent variable is the CAR (-1, 1) for SEO firms. The abnormal returns are calculated using the market model. The market model is estimated using returns from days -301 to -46 relative to the SEO announcement date. The equally weighted CRSP index return is used as the proxy for the market portfolio. The daily abnormal returns are accumulated to obtain the CAR from day *-1* before the announcement date to day *+1* after the announcement date All regressions include indicator variables for each Fama and French (1997) 48 industry and year except where noted. Standard errors clustered by industry are reported in parentheses. Appendix C summarizes the definitions of the variables used in table. The symbols ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

Regression of issuer CARs for a total sample of 1,946 SEO firms

	(1)		**(2)**		**(3)**		**(4)**		**(5)**		**(6)**		**(7)**		**(8)**		**(9)**	
Large customer (indicator)	-1.527	***			0.837		-1.475	***	-1.414	***	-1.285	***	-0.933	**	-1.162	***	-1.858	***
	(0.335)				(1.111)		(0.365)		(0.319)		(0.302)		(0.390)		(0.275)		(0.436)	
Large private customer (indicator)			-1.630	***														
			(0.417)															
Large public customer (indicator)			-1.407	***														
			(0.413)															
Information asymmetry																		
Stock return volatility x large customer					-61.172	*												
					(30.396)													
Abnormal discretionary accruals							0.162	**										
							(0.078)											
Abnormal discretionary accruals x large customer							-0.176	**										
							(0.078)											
Importance of product guarantees																		
Durable industry (indicator)									2.336	***								
									(0.402)									
Durable industry x large customer									-3.250	***								
									(0.765)									
Technology industry (indicator)											-0.089							

											(0.690)									
Technology industry x large customer											-2.291	*								
											(1.351)									
Industry uniqueness																				
High R&D intensity (indicator)													1.328	***						
													(0.464)							
High R&D intensity x large customer													-1.704	***						
													(0.611)							
High trademark industry (indicator)															0.045					
															(0.469)					
High trademark industry x large customer															-1.060	*				
															(0.590)					
Commitment to reduce debt																				
Proceeds used to repay debt (indicator)																	0.241			
																	(0.426)			
Proceeds used to repay debt x large customer																	1.285	*		
																	(0.749)			
Control variables																				
Log (Market capitalization)	-0.345		-0.349		-0.321		-0.338		-0.302		-0.269		-0.346		-0.297		-0.300			
	(0.235)		(0.232)		(0.225)		(0.254)		(0.218)		(0.199)		(0.227)		(0.224)		(0.223)			
Proceeds / Market capitalization	-0.021	***	-0.021	***	-0.021	***	-0.050	***	-0.019	***	-0.019	***	-0.022	***	-0.019	***	-0.019	***		
	(0.004)		(0.004)		(0.004)		(0.011)		(0.004)		(0.004)		(0.004)		(0.004)		(0.004)			
Percent of secondary shares sold	-0.703	*	-0.697		-0.703		-0.991	**	-0.701		-0.644		-0.631		-0.654		-0.530			
	(0.418)		(0.420)		(0.432)		(0.473)		(0.424)		(0.432)		(0.413)		(0.419)		(0.436)			
NYSE listed (indicator)	0.550		0.555	*	0.564	*	0.209		0.528	*	0.510	*	0.598	*	0.511		0.520	*		
	(0.330)		(0.329)		(0.334)		(0.297)		(0.291)		(0.300)		(0.336)		(0.309)		(0.298)			
Leverage	0.608		0.597		0.648		0.866		0.951		0.735		0.817		0.783		0.442			
	(0.763)		(0.755)		(0.740)		(0.848)		(0.724)		(0.798)		(0.776)		(0.677)		(0.676)			
Tobin’s Q	0.123		0.123		0.105		0.177		0.130		0.131		0.107		0.126		0.137			
	(0.113)		(0.113)		(0.123)		(0.142)		(0.111)		(0.111)		(0.110)		(0.112)		(0.115)			
Stock return volatility	-44.620	**	-44.649	**	-23.535		-46.949	**	-43.883	**	-41.982	**	-45.505	**	-41.773	**	-42.265	**		

	(21.477)		(21.406)		(25.998)		(21.182)		(20.337)		(19.820)		(21.855)		(20.571)		(20.339)			
Stock price runup	-0.663	**	-0.666	**	-0.624	**	-0.563		-0.676	**	-0.642	**	-0.657	**	-0.657	**	-0.664	**		
	(0.296)		(0.297)		(0.300)		(0.348)		(0.291)		(0.300)		(0.302)		(0.292)		(0.290)			
Rule 415 Shelf (indicator)	2.605	***	2.588	***	2.570	***	2.608	***	2.643	***	2.474	***	2.612	***	2.548	***	2.658	***		
	(0.612)		(0.605)		(0.609)		(0.634)		(0.571)		(0.562)		(0.623)		(0.581)		(0.559)			
Industry fixed effects	Yes		Yes		Yes		Yes		No		No		Yes		No		Yes			
Year fixed effects	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes			
N	1,946		1,946		1,946		1,819		1,946		1,946		1,946		1,946		1,946			
Adjusted R^2	0.07		0.07		0.07		0.07		0.06		0.06		0.07		0.06		0.06			

Table V

OLS regressions of cumulative abnormal returns (CARs) of large public corporate customers of SEO firms around the SEO announcement date on explanatory variable

The sample consists of 372 large public customers of SEO firms, reported in Thomson Financial's SDC New Issues database in the 1986–2005 period. We use the COMPUSTAT Segment Customer database field, *customer name*, to identify whether SEO issuers have large corporate customers. An issuer is defined as having a large customer when a customer represents 10% or more of an issuer's total sales. When an issuer has multiple large customers, the customer purchasing the largest amount is identified as the large customer. To determine whether a customer is publicly traded or privately held, we match the names in the COMPUSTAT Segment Customer database with those in the COMPUSTAT database. The dependent variable is the CARs (-1, 1) for large public customers. The abnormal returns are calculated using the market model. The market model is estimated using returns from days -301 to -46 relative to the SEO announcement date. The equally weighted CRSP index return is used as the proxy for the market portfolio. The daily abnormal returns are accumulated to obtain the cumulative abnormal return (CAR) from day *-1* before the announcement date to day *+1* after the announcement date. All regressions include indicator variables for each Fama and French (1997) 48 industry and year except where noted. Standard errors clustered by industry are reported in parentheses. Appendix C summarizes the definitions of the variables used in table. The symbols ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	(1)		(2)		(3)		(4)		(5)		(6)	
Information asymmetry												
Stock return volatility	-34.695	**										
	(15.975)											
Abnormal discretionary accruals			-0.011	**								
			(0.005)									
Importance of product guarantees												
Durable Industry (indicator)					-0.862	**						
					(0.346)							
Technology Industry (indicator)							-1.373	***				
							(0.297)					
Industry uniqueness												
High R&D intensity (indicator)									-0.983	*		
									(0.522)			
High trademark industry (indicator)											-1.032	**
											(0.462)	
Control variables												
Log (Market capitalization)	-0.369	*	-0.286		-0.242		-0.187		-0.254		-0.232	
	(0.207)		(0.176)		(0.149)		(0.141)		(0.175)		(0.147)	
Proceeds / Market capitalization	-0.078	**	-0.069	*	-0.065	*	-0.064	*	-0.072	**	-0.064	*
	(0.038)		(0.034)		(0.034)		(0.036)		(0.033)		(0.033)	
Percent of secondary shares sold	-1.285	**	-1.160	*	-1.121	**	-1.138	**	-1.429	**	-1.116	*
	(0.604)		(0.657)		(0.546)		(0.537)		(0.593)		(0.551)	
Leverage	-2.262		-2.134		-2.211		-2.589		-2.797		-2.886	
	(2.089)		(2.264)		(1.711)		(1.670)		(2.098)		(1.780)	
Stock price runup	0.334		0.023		0.059		0.117		0.127		0.114	
	(0.359)		(0.427)		(0.379)		(0.352)		(0.404)		(0.374)	
Log (Customer market capitalization)	0.170		0.150		0.171		0.143		0.170		0.142	
	(0.127)		(0.130)		(0.130)		(0.129)		(0.128)		(0.136)	
Customer leverage	3.623		3.955	*	3.024		2.743		3.707		2.644	
	(2.257)		(2.242)		(1.984)		(1.958)		(2.235)		(1.926)	
SEO firm and customer in same	0.893		0.899		0.682		0.508		0.901		0.452	
industry (indicator)	(0.541)		(0.557)		(0.521)		(0.437)		(0.555)		(0.468)	
Industry fixed effects	Yes		Yes		No		No		Yes		No	

Year fixed effects	Yes		Yes		Yes		Yes		Yes		Yes		Yes
N	372		356		372		372		372		372		372
Adjusted R^2	0.22		0.22		0.13		0.13		0.22		0.14		
	(7)		**(8)**		**(9)**		**(10)**		**(11)**		**(12)**		**(13)**
Commitment to reduce debt													
Proceeds used to repay debt (indicator)	1.126	**											
	(0.453)												
Relationship breakup cost													
Percent of cost of goods sold			-0.198	**									
			(0.092)										
Strategic alliance (indicator)					0.062								
					(2.700)								
Information asymmetry within relationship													
Log (1+distance)							-0.165	*					
							(0.098)						
Ex post relationship dilution													
Post-SEO relationship length									0.180	*			
									(0.104)				
High drop in R&D intensity (indicator)											-1.235	**	
											(0.529)		
High drop in percent sales to customer (indicator)													0.422
													(0.420)
Control variables													
Log (Market capitalization)	-0.292		-0.248		-0.288		-0.265		-0.276		-0.287		-0.289
	(0.180)		(0.170)		(0.198)		(0.177)		(0.176)		(0.183)		(0.178)
Proceeds / Market capitalization	-0.066	*	-0.066	*	-0.068	*	-0.064	*	-0.071	*	-0.077	**	-0.067 *
	(0.033)		(0.034)		(0.035)		(0.035)		(0.037)		(0.036)		(0.034)
Percent of secondary shares sold	-0.982		-1.306	*	-1.251	*	-1.251	*	-1.278	*	-1.405	**	-1.279 *
	(0.667)		(0.647)		(0.637)		(0.633)		(0.673)		(0.624)		(0.654)
Leverage	-3.144		-2.270		-2.258		-2.383		-2.165		-2.682		-2.238
	(2.365)		(2.167)		(2.137)		(2.142)		(2.148)		(2.199)		(2.209)
Stock price runup	0.062		0.023		0.038		0.037		0.056		0.043		0.037
	(0.388)		(0.412)		(0.430)		(0.416)		(0.417)		(0.387)		(0.418)
Log (Customer market capitalization)	0.171		0.146		0.181		0.189		0.173		0.186		0.185
	(0.133)		(0.132)		(0.135)		(0.135)		(0.133)		(0.132)		(0.132)
Customer leverage	3.986	*	3.738		3.822		4.238	*	3.648		3.488		3.777 *
	(2.168)		(2.241)		(2.280)		(2.226)		(2.252)		(2.333)		(2.223)
SEO firm and customer in same industry (indicator)	0.829		0.765		0.796		0.805		0.731		0.777		0.807
	(0.570)		(0.541)		(0.542)		(0.513)		(0.568)		(0.546)		(0.552)
Industry fixed effects	Yes		Yes		Yes		Yes		Yes		Yes		Yes
Year fixed effects	Yes		Yes		Yes		Yes		Yes		Yes		Yes
N	372		372		372		372		372		372		372
Adjusted R^2	0.21		0.21		0.21		0.21		0.21		0.22		0.21

Table VI
Changes in ROA for SEO firms and large public customers of SEO firms

The sample consists of 1,946 SEOs, 372 of which have a large public corporate customer, reported in Thomson Financial's SDC New Issues database in the 1986–2005 period. We use the COMPUSTAT Segment Customer database field, *customer name*, to identify whether SEO issuers have large corporate customers. A customer is defined as large when it represents 10% or more of an issuer's total sales. When an issuer has multiple large customers, the customer purchasing the largest amount is identified as the large customer. To determine whether a customer is publicly traded or privately held, we match the names in the COMPUSTAT Segment Customer database with those in the COMPUSTAT database. Each non-issuer with a large public corporate customer is matched to an SEO firm with a large public corporate customer by industry (Fama and French (1997) 48 industry classification), size (market value of equity), and number of years a supplier maintains a relationship with its large public customer prior to SEO. A change in ROA is measured as data13 / data 6 in year *t* minus data13 / data 6 in year -1 (the year before the SEO) less the industry median value. The symbols ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. *P*-values are in parentheses.

Panel A. Change in industry adjusted ROA for SEO firms with and without large public customers

	SEO firms with large public customers (N=372): A		SEO firms without large public customers (N=1,574): B		Test of difference (B-A)	
Time from SEO	Mean	Median	Mean	Median	*t*-test	Mann-Whitney z-test
Year -1 to Year 0	0.0163	0.0046	0.0205	0.0002	0.41	0.34
					(0.68)	(0.74)
Year -1 to Year 1	-0.0292	-0.0223	-0.0061	-0.0061	1.89*	2.67***
					(0.06)	(0.01)
Year -1 to Year 2	-0.0467	-0.0228	-0.0325	-0.0156	0.60	1.53
					(0.55)	(0.13)
Year -1 to Year 3	-0.0351	-0.0235	-0.0331	-0.0183	0.12	0.63
					(0.90)	(0.53)
Year -1 to Year 4	-0.0380	-0.0302	-0.0356	-0.0236	0.10	0.81
					(0.92)	(0.42)

Panel B. Change in industry adjusted ROA for large customers of SEO firms and large customers of non-SEO firms

	Large public customers of SEO firms (N=372): A		Large public customers of non-SEO matching firms (N=372) : B		Test of difference (B-A)	
Time from SEO	Mean	Median	Mean	Median	*t*-test	Wilcoxon z-test
Year -1 to Year 0	0.0011	0.0029	0.0019	-0.0023	0.09	1.21
					(0.92)	(0.22)
Year -1 to Year 1	-0.0079	-0.0003	0.0061	-0.0004	2.18**	0.48
					(0.03)	(0.63)
Year -1 to Year 2	-0.0100	-0.0034	0.0006	-0.0025	1.40	0.91
					(0.16)	(0.36)
Year -1 to Year 3	-0.0117	-0.0044	0.0008	0.0004	1.65*	1.18
					(0.09)	(0.24)
Year -1 to Year 4	-0.0084	0.0027	0.0027	0.0066	1.06	0.84
					(0.29)	(0.40)

Table VII
Median regressions of changes in SEO firm operating performance (ROA)

The sample consists of 1,946 SEOs, 372 of which have a large public corporate customer, reported in Thomson Financial's SDC New Issues database in the 1986–2005 period. We use the COMPUSTAT Segment Customer database field, *customer name*, to identify whether SEO issuers have large corporate customers. An issuer is defined as having a large customer when a customer represents 10% or more of an issuer's total sales. When an issuer has multiple large customers, the customer purchasing the largest amount is identified as the large customer. To determine whether a customer is publicly traded or privately held, we match the names in the COMPUSTAT Segment Customer database with those in the COMPUSTAT database. The dependent variable is the change in the industry adjusted ROA, defined as Compustat data items data13 / data 6 in year +1 (the year after the SEO) minus the same ratio in year -1, (the year before the SEO), minus the industry median ROA, based on the issuer's industry (Fama and French (1997) 48 industry classification). Standard errors clustered by industry are reported in parentheses. Appendix C summarizes the definitions of the variables used in table. The symbols ***, **, and * denote statistical significance of a two tailed test at the 1%, 5%, and 10% levels, respectively.

	(1)		**(2)**		**(3)**		**(4)**		**(5)**	
Large customer (indicator)	-0.012	***			-0.003		-0.016	***	-0.012	**
	(0.003)				(0.009)		(0.004)		(0.005)	
Large private customer (indicator)			-0.004							
			(0.006)							
Large public customer (indicator)			-0.019	***						
			(0.006)							
Stock return volatility					0.736	***				
					(0.148)					
Stock return volatility x large customer					-0.366	*				
					(0.206)					
Proceeds used to repay debt (indicator)							-0.004			
							(0.005)			
Proceeds used to repay debt x large customer							0.017	**		
							(0.008)			
SEO firm with high CAR (indicator)									0.000	
									(0.005)	
SEO firm with high CAR x large customer									0.000	
									(0.007)	
Log (Market capitalization)	0.001		0.001		0.002		0.001		0.001	
	(0.001)		(0.002)		(0.002)		(0.002)		(0.001)	
Proceeds / Market capitalization	0.001	***	0.001	***	0.001	***	0.001	***	0.001	***
	(0.000)		(0.000)		(0.000)		(0.000)		(0.000)	
Investment credit rating (indicator)	0.003		0.003		0.004		0.002		0.003	
	(0.008)		(0.011)		(0.009)		(0.009)		(0.009)	
High R&D Intensity (indicator)	0.016	***	0.017	***	0.016	***	0.017	***	0.016	***
	(0.004)		(0.005)		(0.004)		(0.004)		(0.004)	
Industry fixed effects	Yes		Yes		Yes		Yes		Yes	
Year fixed effects	Yes		Yes		Yes		Yes		Yes	
N	1,946		1,946		1,946		1,946		1,946	
Pseudo R^2	0.03		0.04		0.03		0.03		0.03	

Table VIII
Post-SEO relationship duration for SEO firms with a large public customer and non-SEO matching firms with a large public customer

The sample consists of 372 SEO issuers with large public customers and 372 non-issuer firms reported in Thomson Financial's SDC New Issues database in the 1986–2005 period. We use the COMPUSTAT Segment Customer database field, *customer name*, to identify whether SEO issuers have large corporate customers. An issuer is defined as having a large customer when a customer represents 10% or more of an issuer's total sales. When an issuer has multiple large customers, the customer purchasing the largest amount is identified as the large customer. To determine whether a customer is publicly traded or privately held, we match the names in the COMPUSTAT Segment Customer database with those in the COMPUSTAT database. Each non-issuer with a large public corporate customer is matched to an SEO firm with a large public corporate customer by industry (Fama and French (1997) 48 industry classification), size (market value of equity), and number of years a supplier maintains a relationship with its large public customer prior to SEO. The dependent variable is the number of years the relationship lasts after the SEO. Each firm relationship has one observation. The control variables are measured at the beginning of each year. All regressions include indicator variables for each Fama and French (1997) 48 industry and year. Standard errors clustered by industry are reported in parentheses. Appendix C summarizes the definitions of the variables used in table. The symbols ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	(1) Cox		(2) Cox		(3) Cox		(4) Cox	
SEO firm (indicator)	1.142	**	0.918					
	(0.076)		(0.116)					
Stock return volatility			18.615	**				
			(27.594)					
Stock return volatility * SEO firm indicator			174.536	*				
			(477.703)					
SEO firm using proceeds to repay debt (indicator)					1.113			
					(0.178)			
SEO firm not using proceeds to repay debt (indicator)					1.151	**		
					(0.061)			
SEO firm with high CAR (indicator)							1.023	
							(0.065)	
SEO firm with low CAR (indicator)							1.268	***
							(0.127)	
R&D intensity	1.358		1.302		1.355		1.399	*
	(0.285)		(0.269)		(0.284)		(0.290)	
Percent of sales to customer	0.172	***	0.170	***	0.173	***	0.176	***
	(0.071)		(0.073)		(0.071)		(0.072)	
(Percent of sales to customer)^2	3.337	**	3.418	**	3.321	**	3.218	**
	(1.744)		(1.885)		(1.744)		(1.640)	
Strategic alliance (indicator)	1.007		1.002		1.007		0.985	
	(0.093)		(0.089)		(0.093)		(0.094)	
Log (1+ firm age)	0.938		0.947		0.938		0.940	
	(0.041)		(0.045)		(0.041)		(0.041)	
Log (total assets)	0.929	***	0.941	***	0.929	***	0.927	***
	(0.021)		(0.022)		(0.021)		(0.022)	
Negative free cash flows (indicator)	1.220	**	1.181		1.218	**	1.207	*
	(0.123)		(0.124)		(0.123)		(0.119)	
Industry fixed effects	Yes		Yes		Yes		Yes	
Year fixed effects	Yes		Yes		Yes		Yes	
N	744		744		744		744	
Log likelihood	-3599.660		-3597.269		-3599.634		-3598.210	

Table IX

Changes in R&D investment and sales dependence on the large public customer around the SEO events for SEO firms with a large public customer and non-SEO matching firms with a large public customer

The sample consists of 372 SEO issuers with large public customers and 372 non-issuers reported in Thomson Financial's SDC New Issues database in the 1986–2005 period. We use the COMPUSTAT Segment Customer database field, *customer name*, to identify whether SEO issuers have large corporate customers. An issuer is defined as having a large customer when a customer represents 10% or more of an issuer's total sales. When an issuer has multiple large customers, the customer purchasing the largest amount is identified as the large customer. To determine whether a customer is publicly traded or privately held, we match the names in the COMPUSTAT Segment Customer database with those in the COMPUSTAT database. Each non-issuer with a large public corporate customer is matched to an SEO firm with a large public corporate customer by industry (Fama and French (1997) 48 industry classification), size (market value of equity), and number of years a supplier maintains a relationship with its large public customer prior to SEO. Change in R&D intensity is measured as data46 / data 6 in year *t* minus data46 / data 6 in year -1 (the year before the SEO). Change in sales dependence is measured as the percent of sales made to the large public customer in year *t* minus the percent of sales made to the large public customer in year -1. The symbols ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. *P*-values are in parentheses.

	SEO firms with a large public customer (N=372): A		Non-SEO matching firms with a large public customer (N=372): B		Test of difference (B-A)	
	Mean	Median	Mean	Median	*t*-test	Wilcoxon z-test
Change in R&D intensity:						
Year -1 to Year 0	-0.0356	0.0000	-0.0043	0.0000	2.39**	2.77**
					(0.02)	(0.01)
Year -1 to Year 1	-0.0658	0.0000	-0.0100	0.0000	3.82***	5.66***
					(0.00)	(0.00)
Year -1 to Year 2	-0.0545	0.0000	-0.0089	0.0000	3.11***	4.70***
					(0.00)	(0.00)
Year -1 to Year 3	-0.0305	0.0000	0.0038	0.0000	2.44**	3.12***
					(0.01)	(0.00)
Year -1 to Year 4	-0.0250	0.0000	0.0115	0.0000	2.77**	2.18**
					(0.01)	(0.02)
Change in sales dependence:						
Year -1 to Year 0	-0.0211	0.0000	-0.0034	0.0000	1.77*	2.32**
					(0.08)	(0.02)
Year -1 to Year 1	-0.0906	-0.0700	-0.0631	-0.0298	2.01**	2.57**
					(0.04)	(0.01)
Year -1 to Year 2	-0.1405	-0.1211	-0.1140	-0.0905	1.69*	2.83***
					(0.09)	(0.01)
Year -1 to Year 3	-0.1847	-0.1600	-0.1403	-0.1100	2.77***	4.06***
					(0.01)	(0.00)
Year -1 to Year 4	-0.2068	-0.1703	-0.1609	-0.1232	2.89**	4.30***
					(0.00)	(0.00)

Table X

OLS regressions of changes in R&D investment and sales dependence on the large public customer around the SEO events for SEO firms with a large public customer and non-SEO matching firms with a large public customer on explanatory variables

The sample consists of 372 SEO issuers with large public customers and 372 non-issuer firms reported in Thomson Financial's SDC New Issues database in the 1986–2005 period. We use the COMPUSTAT Segment Customer database field, *customer name*, to identify whether SEO issuers have large corporate customers. An issuer is defined as having a large customer when a customer represents 10% or more of an issuer's total sales. When an issuer has multiple large customers, the customer purchasing the largest amount is identified as the large customer. To determine whether a customer is publicly traded or privately held, we match the names in the COMPUSTAT Segment Customer database with those in the COMPUSTAT database. Each non-issuer with a large public corporate customer is matched to an SEO firm with a large public corporate customer by industry (Fama and French (1997) 48 industry classification), size (market value of equity), and number of years a supplier maintains a relationship with its large public customer prior to SEO. In models (1) through (4), the dependent variable is the change in R&D / total assets from the year before the SEO to the year after the SEO. In models (5) through (8), the dependent variable is the change in percent of sales to the large public customer from the year before the SEO to the year after the SEO. All regressions include indicator variables for each Fama and French (1997) 48 industry and year. Standard errors clustered by industry are reported in parentheses. Appendix C summarizes the definitions of the variables used in table. The symbols ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Change in R&D/assets from year -1 to year +1								**Change in percent sales from year -1 to year +1**							
	(1)		**(2)**		**(3)**		**(4)**		**(5)**		**(6)**		**(7)**		**(8)**	
SEO firm (indicator)	-0.061	***	0.022						-0.055	*	0.039					
	(0.017)		(0.036)						(0.029)		(0.052)					
Stock return volatility			0.804								0.849					
			(0.610)								(0.860)					
SEO firm * stock return volatility			-2.037	*							-2.370	**				
			(1.150)								(1.142)					
SEO firm using proceeds to repay debt (indicator)					-0.029	**							0.041			
					(0.012)								(0.051)			
SEO firm not using proceeds to repay debt (indicator)					-0.072	***							-0.094	**		
					(0.020)								(0.037)			
SEO firm with high CAR (indicator)							-0.061	**							-0.030	
							(0.023)								(0.044)	
SEO firm with low CAR (indicator)							-0.060	***							-0.085	**
							(0.015)								(0.039)	
Log (Market capitalization)	-0.010	**	-0.009	**	-0.009	**	-0.015		0.002		0.002		0.005		-0.056	
	(0.004)		(0.004)		(0.005)		(0.026)		(0.014)		(0.014)		(0.013)		(0.051)	
Leverage	-0.042	**	-0.039	**	-0.044	**	0.009		-0.020		-0.012		-0.032		-0.094	*
	(0.020)		(0.018)		(0.020)		(0.010)		(0.038)		(0.038)		(0.044)		(0.055)	

Cash / total assets	-0.015		-0.003		-0.004		-0.010	**	-0.058		-0.039		-0.025	0.002
	(0.025)		(0.023)		(0.026)		(0.004)		(0.048)		(0.047)		(0.054)	(0.014)
Investment credit rating	0.008		-0.002		0.007		-0.042	**	-0.084		-0.094		-0.089	-0.020
(indicator)	(0.011)		(0.012)		(0.011)		(0.019)		(0.058)		(0.057)		(0.063)	(0.038)
Negative free cash flows	0.036	**	0.038	**	0.036	**	0.036	**	0.003		0.003		0.005	0.009
(indicator)	(0.017)		(0.016)		(0.017)		(0.017)		(0.042)		(0.044)		(0.043)	(0.046)
Industry fixed effects	Yes		Yes		Yes		Yes		Yes		Yes		Yes	Yes
Year fixed effects	Yes		Yes		Yes		Yes		Yes		Yes		Yes	Yes
N	744		744		744		744		444		444		444	444
Adjusted R2	0.15		0.17		0.16		0.17		0.10		0.11		0.12	0.11

Table XI
MLE regression of cumulative abnormal returns (CARs) for SEO firms around the SEO announcement date on explanatory variables: Controlling for endogeneity

The sample consists of 1,946 SEOs, 372 of which have a large public corporate customer, reported in Thomson Financial's SDC New Issues database in the 1986–2005 period. We use the COMPUSTAT Segment Customer database field, *customer name*, to identify whether SEO issuers have large corporate customers. An issuer is defined as having a large customer when a customer represents 10% or more of an issuer's total sales. When an issuer has multiple large customers, the customer purchasing the largest amount is identified as the large customer. To determine whether a customer is publicly traded or privately held, we match the names in the COMPUSTAT Segment Customer database with those in the COMPUSTAT database. Each non-issuer with a large public corporate customer is matched to an SEO firm with a large public corporate customer by industry (Fama and French (1997) 48 industry classification), size (market value of equity), and number of years a supplier maintains a relationship with its large public customer prior to SEO. We use a maximum likelihood instrumental variables approach to control for the endogeneity of the presence of a large customer. We use the percent of firms with a large public customer that operate in the same industry as SEO firms with a large public customer as an instrument for having a large public customer. We use this instrument in the MLE system to predict the affect of the presence of a large customer on the SEO firm CARs (-1, 1). The abnormal return is calculated using the market model, which is estimated using returns from days -301 to -46 relative to the SEO announcement date. The equally weighted CRSP index return is used as the proxy for the market portfolio. The daily abnormal returns are accumulated to obtain the cumulative abnormal return (CAR) from day *-1* before the announcement date to day *+1* after the announcement date. All regressions include indicator variables for each industry and year. Standard errors are clustered by industry are reported in parentheses. Appendix C summarizes the definitions of the variables used in table. The symbols ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	Dependent variable = an indicator variable for having a large public customer	Dependent variable = SEO firm CAR (-1, 1)
Instrument		
Percent of firms in same industry with a large customer	5.518*** (0.865)	
Presence of a large customer		
Instrumented large customer (indicator)		-1.538** (0.663)
Control variables		
Log (Market capitalization)	-0.068** (0.029)	-0.334 (0.225)
Proceeds / Market capitalization	-0.003*** (0.001)	-0.021*** (0.004)
Percent of secondary shares sold	0.318*** (0.083)	-0.669 (0.426)
NYSE listed (indicator)	-0.151* (0.090)	0.598* (0.345)
Leverage	0.036 (0.153)	0.757 (0.619)
Tobin's Q	-0.017** (0.008)	0.126 (0.109)
Stock return volatility	2.268 (3.061)	-44.648** (20.330)
Stock price run-up	0.080 (0.054)	-0.655** (0.291)
Rule 415 Shelf (indicator)	-0.005 (0.130)	2.583*** (0.575)
Industry fixed effects	No	
Year fixed effects	Yes	
N	1,946	
Log Pseudo likelihood	-7780.4725	

Appendix A: Large customer sample selection

This appendix provides details of the process of determining the large customers of SEO issuers. Our primary data source is the COMPUSTAT Segment Level Customer database, which includes the field *customer name* and *customer sales*. When multiple large customers are disclosed, we label as the "largest customer" the customer which accounts for the largest dollar amount of sales. For each customer reported in the COMPUSTAT database, we go to the SEO firm prospectus filing and the most recent SEO firm 10-K for confirmation that the customer remains a firm's largest. For a small subsample, we also examine other filings such as 10-Qs and 8-Ks, but are unable to find reliable information about customers in these filings. Oftentimes, if the large customer's name is ambiguous in the COMPUSTAT database, the SEC filings can give additional information that is helpful in accurately determining a customer's true identity. Information concerning large customers is typically disclosed in the Management Discussion and Analysis section of the 10-K and SEO prospectus although there is often related information in the business description and the risk sections of the prospectus.

The COMPUSTAT database sometimes reports that a customer exists, but does not give the customer's name or dollar amount of sales. If sales information is not available in SEC filings in the SEO year, we search annual reports up to three years after the SEO to find information on large customer sales. Annual reports often give historical information for many years earlier, reporting sales to key customers back three or more years. We also use annual reports in the years before and after the SEO to confirm the ultimate length of the relationship between the SEO firm and its large customer. For situations where the COMPUSTAT database omits a customer's name, it is often because the issuer actually obfuscates the large customer's identity in its SEC filings (for instance, by using a label such as "Firm A"). In this case, we examine prior and subsequent filings to

determine the large customer's identity. Using this approach, we are able to accurately identify an issuer's large customers from previous or subsequent SEC filings.

Financial Accounting Standard Board No. 131 states that if any customer accounts for greater than 10% of sales, this sale information shall be disclosed in the accounting statements of the firm. However, the actual identity of the customer need not be disclosed. A recent paper by Ellis, Fee, and Thomas (2009) finds that in fact, many firms are in violation of this regulation, either not disclosing the names or dollar amount of sales of large customers representing sales of 10% or more. Fortunately, using our hand collection technique, we are able to obtain customer names and the dollar amount of sales for all the SEO firms with large customers in our sample.

To obtain the gvkey of issuer's large customers, we follow a process similar to Fee, Hadlock, and Thomas (2006) to match firm names as disclosed in SEC filings to the universe of firms in COMPUSTAT. Ultimately, this yields our sample of 372 SEO firms with large public customers, 429 SEO firms that disclose large customers that are not in COMPUSTAT (which we categorize as large private customers), and 1,145 SEO firms that have no large customers.

Appendix B: Additional Robustness Checks

This appendix contains additional robustness analysis of the future duration of a firm's relationship with its large customers and its post-offer operating performance. In Table X we show that under a Cox specification, the hazard rate of the SEO firm-customer relationships is greater for issuers with higher information asymmetry, issuers who do not use the SEO proceeds to repay debt, and issuers with customers having a more negative announcement CAR. To be sure our results are not driven by the model specification, we re-estimate our hazard models assuming a Weibull distribution and find qualitatively similar results. We also repeat our analysis using a logit model to predict the probability of relationship breakup in any particular year. For this particular specification, we include one observation for every year a relationship continues after an SEO. The dependent variable in the logit model takes a value of one in the year the relationship terminates and is zero in prior years. Estimates from the logit regressions are reported in Table B.1 below. We find that the likelihood of relationship termination is higher for SEO firms, particularly when issuer return volatility is higher, offer proceeds are not used to repay debt, and customers have larger negative announcement period returns.

In Table VI we show that the operating performance decline is substantially greater for issuers with large public customers than for issuers without them. To ensure that our results are not driven by differences in CEO perquisite consumption between firms with and without large public customers, we follow Chhaochharia, Grinstein, Grullon, and Michaely (2009) by decomposing the change in the return on assets (ROA) into a change in overhead measured by selling, general, and administrative costs (SGA) / sales, a change in operating efficiency, measured by cost of goods sold (COGS) / sales, and a change in the asset turnover ratio (sales / assets) to determine if an SEO is associated with a rise in perquisite consumption, manifesting itself in higher overhead costs or in managerial shirking which could manifest itself in lower operating efficiency. If moral hazard

explains our results, then we expect to find a significant increase in overhead expenses or a decrease in operating efficiency. In contrast, if adverse selection explains our results, then we would expect to see a significant decline in asset turnover after an SEO. Table B.2 Panels A, B, and C report post-offer changes in SGA / sales, COGS / sales, and asset turnover for SEO firms with and without large public customers. Our results show a significant decline in asset turnover, but no significant change in SGA/sales, suggesting our results are not driven by managerial perquisite consumption. Likewise, we find no decline in COGS / sales, suggesting our results are not driven by managerial shirking.

Table B.1
Abnormal returns for large public customers of SEO firms

The sample consists of 372 large public corporate customers of SEO firms. We use the COMPUSTAT Segment Customer database field, *customer name*, to identify whether SEO issuers have large corporate customers. An issuer is defined as having a large customer when a customer represents 10% or more of an issuer's total sales. When an issuer has multiple large customers, the customer purchasing the largest amount is identified as the large customer. To determine whether a customer is publicly traded or privately held, we match the names in the COMPUSTAT Segment Customer database with those in the COMPUSTAT database. The abnormal returns are calculated using the market model estimated with returns from days -301 to -46 relative to the SEO announcement date (AD). The equally weighted CRSP index return is used as the proxy for the market portfolio. The daily abnormal returns are accumulated to obtain the cumulative abnormal return (CAR) from day *-1* before the announcement date to day *+1* after the announcement date. The symbols ***, **, and * denote values are significantly different from zero at the 1%, 5%, and 10% levels, respectively. + and ‡ denote that the two values are significantly different from each other at the 5% and 1% levels, respectively. *P*-values are in parentheses.

Abnormal returns for large public customers of SEO firms by high percent cost of goods sold and technology industry

	Mean customer CAR Technology firms	Mean customer CAR Technology firms	Difference t-statistic (p-value)
Below median cost of goods sold for customer	-0.64% (N=168)	-1.40% (N=18)	1.01 (0.31)
Above median cost of goods sold for customer	-1.17% (N=164)	-3.65% (N=22)	2.39** (0.02)
Difference t-statistic (p-value)	1.24 (0.22)	2.12** (0.04)	

Table B.2
Post-SEO relationship duration for SEO firms with a large public customer and non-SEO matching firms with a large public customer

The sample consists of 372 SEO issuers with large public customers and 372 non-issuer firms reported in Thomson Financial's SDC New Issues database in the 1986–2005 period. We use the COMPUSTAT Segment Customer database field, *customer name*, to identify whether SEO issuers have large corporate customers. An issuer is defined as having a large customer when a customer represents 10% or more of an issuer's total sales. When an issuer has multiple large customers, the customer purchasing the largest amount is identified as the large customer. To determine whether a customer is publicly traded or privately held, we match the names in the COMPUSTAT Segment Customer database with those in the COMPUSTAT database. Each non-issuer with a large public corporate customer is matched to an SEO firm with a large public corporate customer by industry (Fama and French (1997) 48 industry classification), size (market value of equity), and number of years a supplier maintains a relationship with its large public customer prior to SEO. The dependent variable is the number of years the relationship lasts after the SEO. Each firm relationship has one observation. We estimate the hazard model under a Weibull distributional assumption for models (1)-(4). For models (5)-(8) we include one observation for each year the relationship continues post-offer and estimate a logit model for various specifications. The control variables are measured at the beginning of each year. All regressions include indicator variables for each Fama and French (1997) 48 industry and year. Standard errors clustered by industry are reported in parentheses. Appendix C summarizes the definitions of the variables used in table. The symbols ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

	(1)		(2)		(3)		(4)		(5)		(6)		(7)		(8)
	Weibull		Weibull		Weibull		Weibull		Logit		Logit		Logit		Logit
SEO firm (indicator)	1.228	**	0.905						0.173	*	0.027				
	(0.127)		(0.177)						0.105)		(0.207)				
Stock return volatility			94.362	**							8.508	**			
			(192.114)								(3.085)				
Stock return volatility * SEO firm indicator			1370.535	**							3.559				
			5060.605)								(4.982)				
SEO firm using proceeds to repay debt (indicator)					1.126								0.141		
					(0.290)								0.234)		
SEO firm not using proceeds to repay debt (indicator)					1.262	**							0.183	**	
					(0.104)								0.084)		
SEO firm with high CAR (indicator)							1.032								0.026
							(0.115)								(0.098)

SEO firm with low CAR (indicator)							1.463	**							0.320	**		
							(0.214)								(0.151)			
R&D intensity	1.554		1.463		1.541		1.638		-0.258		-0.258		-0.262		-0.218			
	(0.465)		(0.436)		(0.462)		(0.483)		0.285)		(0.296)		0.286)		(0.289)			
Percent of sales to customer	0.100	**	0.098	**	0.101	**	0.103	**	-2.450	**	-2.437	**	-2.447	**	-2.401	**		
	(0.060)		(0.063)		(0.061)		(0.060)		0.618)		(0.649)		0.618)		(0.608)			
(Percent of sales to customer)^2	5.050	**	5.212	**	4.930	**	4.758		1.703	**	1.715	**	1.696	**	1.641	**		
	(3.706)		(4.091)		(3.627)		(3.329)		0.783)		(0.827)		0.783)		(0.757)			
Strategic alliance (indicator)	1.009		1.002		1.009		0.965		0.085		0.071		0.084		0.048			
	(0.133)		(0.126)		(0.132)		(0.129)		0.131)		(0.123)		0.130)		(0.139)			
Log (1+ firm age)	0.912		0.926		0.912		0.914		-0.071		-0.059		-0.070		-0.066			
	(0.052)		(0.058)		(0.052)		(0.051)		0.077)		(0.083)		0.076)		(0.077)			
Log (total assets)	0.895	**	0.913	**	0.894	**	0.890	**	-0.117	**	-0.074	*	-0.116	**	-0.116	**		
	(0.028)		(0.029)		(0.028)		(0.029)		0.038)		(0.040)		0.038)		(0.038)			
Negative free cash flows (indicator)	1.336	**	1.277		1.328	**	1.314	**	0.166		0.126		0.166		0.157			
	(0.198)		(0.196)		(0.197)		(0.186)		0.127)		(0.136)		0.127)		(0.130)			
Relationship tenure									0.097	**	0.097	**	0.097	**	0.100	**		
									0.038)		(0.038)		0.038)		(0.039)			
Industry fixed effects	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes			
Year fixed effects	Yes		Yes		Yes		Yes		Yes		Yes		Yes		Yes			
N	744		744		744		744		2,143		2,143		2,143		2,143			
Log likelihood / Pseudo R^2	-713.077		-708.231		-712.800		-709.432		0.08		0.08		0.08		0.08			

Table B.3
Decomposition of Changes in ROA for SEO firms with and without large public customers

The sample consists of 1,946 SEOs, 372 of which have a large public corporate customer, reported in Thomson Financial's SDC New Issues database in the 1986–2005 period. We use the COMPUSTAT Segment Customer database field, *customer name*, to identify whether SEO issuers have large corporate customers. An issuer is defined as having a large customer when a customer represents 10% or more of an issuer's total sales. When an issuer has multiple large customers, the customer purchasing the largest amount is identified as the large customer. To determine whether a customer is publicly traded or privately held, we match the names in the COMPUSTAT Segment Customer database with those in the COMPUSTAT database. Each non-issuer with a large public corporate customer is matched to an SEO firm with a large public corporate customer by industry (Fama and French (1997) 48 industry classification), size (market value of equity), and number of years a supplier maintains a relationship with its large public customer prior to SEO. A change in ROA is measured as data13 / data 6 in year *t* minus data13 / data 6 in year -1 (the year before the SEO) less the industry median value. The symbols ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively. *P*-values are in parentheses.

Panel A. Change in industry adjusted SGA / sales for SEO firms with and without large public customers

	SEO firms with large public customers (N=372): A		SEO firms without large public customers (N=1,574): B		Test of difference (B-A)	
Time from SEO	Mean	Median	Mean	Median	t-test	Mann-Whitney z-test
Year -1 to Year 0	-0.0195	-0.0100	0.3144	-0.0083	0.53	0.62
					(0.59)	(0.53)
Year -1 to Year 1	0.0225	-0.0051	-0.1263	-0.0063	1.15	0.56
					(0.25)	(0.57)
Year -1 to Year 2	-0.0032	-0.0024	-0.1264	-0.0046	0.98	0.28
					(0.33)	(0.78)
Year -1 to Year 3	-0.0168	-0.0000	-0.1014	-0.0043	0.83	0.56
					(0.41)	(0.57)
Year -1 to Year 4	-0.0370	-0.0016	-0.1370	-0.0074	0.82	0.86
					(0.41)	(0.39)

Panel B. Change in industry adjusted COGS / sales for SEO firms with and without large public customers

	SEO firms with large public customers (N=372): A		SEO firms without large public customers (N=1,574): B		Test of difference (B-A)	
Time from SEO	Mean	Median	Mean	Median	t-test	Mann-Whitney z-test

Year -1 to Year 0	-0.1271	-0.0095	0.9484	-0.0033	0.41	1.73*
					(0.68)	(0.08)
Year -1 to Year 1	0.0050	-0.0006	0.6000	0.0010	0.37	0.62
					(0.71)	(0.54)
Year -1 to Year 2	0.4754	0.0017	0.1339	0.0053	0.23	0.22
					(0.82)	(0.82)
Year -1 to Year 3	0.5497	0.0082	2.6462	0.0070	0.26	0.24
					(0.79)	(0.81)
Year -1 to Year 4	0.8932	0.0096	-0.1528	0.0050	0.74	0.48
					(0.46)	(0.63)

Panel C. Change in industry adjusted Sales / assets for SEO firms with and without large public customers

	SEO firms with large public customers (N=372): A		SEO firms without large public customers (N=1,574): B		Test of difference (B-A)	
Time from SEO	Mean	Median	Mean	Median	t-test	Mann-Whitney z-test
Year -1 to Year 0	-0.2062	-0.2126	-0.0520	-0.0645	1.70*	2.14**
					(0.09)	(0.03)
Year -1 to Year 1	-0.2233	-0.1055	-0.1337	-0.0534	2.72**	3.80***
					(0.01)	(0.00)
Year -1 to Year 2	-0.1798	-0.1159	-0.1134	-0.0486	1.63*	2.32**
					(0.10)	(0.02)
Year -1 to Year 3	-0.1285	-0.0667	-0.1146	-0.0396	0.30	1.02
					(0.76)	(0.31)
Year -1 to Year 4	-0.1083	-0.0628	-0.1206	-0.0525	0.24	0.31
					(0.81)	(0.76)

Appendix C: Variable definitions

This appendix provides a detailed description of the construction of all the variables used in the tables.

Variable name	Definition
Abnormal discretionary accruals	To estimate abnormal discretionary accruals, we first calculate the total accruals from the COMPUSTAT data where total accruals (TA) = the change in item 4 – the change in item 5 + change in item 34 – item 14. We then run the following regression: TA = a + b1 (1/item 6) + b2 (change in item 12) + b3 (item 7) + e. Discretionary accruals is measured as the residual from the SEO firm regression (e) minus the residual from a firm matched to the SEO firm based on industry and ROA. This technique is utilized in Lee and Masulis (2009).
Asset turnover	COMPUSTAT data item 12 / data item 6.
Cash / total assets	COMPUSTAT data item 1 / item 6 in the previous year.
COGS / Sales	COMPUSTAT data item 41 / data item 12.
Distance (miles)	The distance from the geographic center of the supplier zip code to the customer zip code. Distances are measured using a great circle formula as described in Tian (2008).
Durable industry (indicator)	An indicator variable taking a value of one for SEO firms in durable industries as defined by the US Department of Census. The Census Bureau classification of durable industry firms is contained at: http://www.census.gov/indicator/www/m3/appendixb.pdf.
Firm age	The number of years since the SEO firm first reported data item 6 (book value of assets) in the COMPUSTAT database.
High drop in percent sales to customer	An indicator variable taking a value of one if the SEO firm has above the median decline in the percent of sales to the large customer from the year before the SEO to after the SEO.
High drop in R&D intensity	An indicator variable taking a value of one if the SEO firm has above the median decline in R&D / total assets from the year before the SEO to after the SEO.
High R&D intensity	An indicator variable taking a value of one if the SEO firm has above the median R&D / total assets and zero otherwise.
High trademark industry	An indicator variable taking a value of one if the SEO firm is in an industry with above the median number of trademarks and zero otherwise. The number of trademarks in each industry is obtained from the U. S. Patent and Trademark Office at www.uspto.gov/.
Investment credit rating (indicator)	An indicator variable taking a value of one if COMPUSTAT data item 280 is less than 11.
Large customer (indicator)	An indicator variable taking a value of one if the firm discloses a customer that accounts for greater than 10% of its sales and zero otherwise.
Large private customer (indicator)	An indicator variable taking a value of one if the firm discloses a customer that accounts for greater than 10% of its sales and that customer cannot be found in the COMPUSTAT database.
Large public customer (indicator)	An indicator variable taking a value of one if the firm discloses a customer that accounts for greater than 10% of its sales and that customer can be found in the COMPUSTAT database.
Leverage	COMPUSTAT data item 9 / data item 6 in the year before the offer, winsorized at the 95th percentile.
Market capitalization	COMPUSTAT data item 25* data item 199 in the year before the SEO. For firms missing COMPUSTAT observations, CRSP data using the shares outstanding and closing price for the month before the SEO announcement is utilized.
Negative free cash flows (indicator)	An indicator variable taking a value of one if COMPUSTAT data item 18 + data item 14 – data item 128 in the year before the SEO if less than zero and zero otherwise.
NYSE listed (indicator)	An indicator variable taking a value of one if the SEO firms trades on the New York Stock Exchange as reported in COMPUSTAT and zero otherwise.
Percent of cost of goods sold	The dollar amount of sales to the customer divided by the customer COMPUSTAT data item 41.

Percent of firms in same industry with a large customer	Number of firms in the same industry (Fama and French (1997) 48 industry) as the firm of interest that also have large customers based on the COMPUSTAT segment level data divided by the total number of firms in that same industry.
Percent of sales to customer	The sales made to the large public customer by SEO firm divided by COMPUSTAT data item 12.
Percent of secondary shares sold	Number of shares sold by firm insiders based on the offering prospectus divided by the total shares sold in the offer.
Post-SEO relationship length	The number of years from the SEO year until the relationship is terminated.
Pre-SEO relationship length	The number of years from the first time the customer shows up in filings as a large public customer until the SEO year.
Proceeds	Number of shares issued in the offer times the offer price as reported in the SDC Platinum New Issues database.
Proceeds used to repay debt (indicator)	An indicator variable taking on a value of one if the SEO firm reports that it will use at least half the proceeds to repay debt and zero otherwise.
R&D intensity	COMPUSTAT data item 46 / data item 6 in the year before the SEO.
Relationship tenure	The number of years the relationship has lasted.
ROA	ROA (return on assets) is measures as data item 13 / data item 6.
Rule 415 Shelf (indicator)	An indicator variable taking a value of one if the SEO offer is a shelf offer according to SEC Rule 415.
SEO firm (indicator)	An indicator variable taking a value of one if the firm goes through an SEO and one otherwise.
SEO firm and customer in same industry (indicator)	An indicator variable taking a value of one if the SEO firm and its large public customer are at least in the same 2 digit industry and zero otherwise.
SEO firm (not) using proceeds to repay debt	An indicator variable taking a value of one for SEO firms using (not using) proceeds to repay debt and zero otherwise.
SEO firm with high (low) CAR (indicator)	An indicator variable taking a value of one for SEO firms with above (below) the median SEO announcement date CAR (-1, 1).
SGA / sales	COMPUSTAT data item 189 / data item 6.
Stock price run-up	The buy-and-hold return for the SEO firm from day -90 to day -11 before the SEO announcement date. In 83 cases, there were insufficient returns available so we utilized the returns that were available.
Stock return volatility	Daily stock return standard deviation for the SEO issuer from day -90 to day -11 before the SEO announcement. See note above for past stock price run-up.
Strategic alliance (indicator)	An indicator variable taking a value of one if the SEO firm and the large public customer have a strategic alliance as described in the SEO firm prospectus of annual report. Alliances can be licensing agreements, development agreements, or marketing agreements.
Technology Industry (indicator)	Following Loughran and Ritter (2004) we define a technology firm as having one of the following 4-digit SIC codes: 3571, 3572, 3575, 3577, 3578, 3661, 3663, 3669, 3671, 3672, 3674, 3675, 3677-3679, 3812, 3823, 3825-3827. 3829, 3841, 3845, 4812, 4813, 4899, 7371-7375, 7378, and 7379.
Tobin's Q	COMPUSTAT data (item 5 + item 9 + item 25 * item 199) / item 6 in the year before the SEO. When item 25 or item 199 is missing, we utilized the market capitalization data from CRSP from the month before the SEO. For 50 customer firms, the accounting data is not available in the year before the SEO to perform the calculations. In these cases, we utilized data from the nearest year to the year before the SEO year.
Total assets	COMPUSTAT data item 6 in the year before the SEO.