Input Price Shocks and Investment: Evidence from OEMs ☆

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Abstract

In a competitive market, a producer who experiences an increase in input prices cannot pass-through one-hundred percent of that increase to consumers. In the presence of market frictions, what effect does the internalization of an increase in input price have on firm investment? Using a novel setting, this paper finds that firms facing a shock to internal capital because of an increase in input prices do not uniformly cut back on all types of investment, but allocate capital away from investments with uncertain returns. I use the setting of the 1999 Taiwan earthquake, which disrupted the global semiconductor supply chain and increased production costs for a *subset* of original equipment manufacturers (OEMs) in the US high-technology industry, causing a drain on internal capital. I find that firms negatively impacted by the shock did not cutback on capital expenditures, but reduced R&D investment.

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1. Introduction

In a competitive market, firms internalize the effect of input price shocks as they cannot pass through one-hundred percent of the price increase to consumers, particularly when the shock affects only a subset of firms in the industry (Ashenfelter et al., 1998; Gron and Swenson, 2000). What effect does this internalization of input price shocks have on firm investment? Although the pass-through literature has studied extensively the effect of changes in input costs on output prices, there is limited evidence on how these changes influence firms' investment decisions.[1]

It is difficult to identify the effect of a change in input prices on firm investment because these changes are endogenous to firms' investment opportunities and market demand. Changes in market demand could influence product-market competition (more firms entering or exiting the industry) and pass-through rates of input prices. Changes in market demand could also affect firms' cash flows and investment opportunities, and therefore firms' investment decisions. To deal with the empirical challenge, I use the setting of the Taiwan earthquake of 1999. The earthquake disrupted the global semiconductor supply chain and resulted in supply shortages and rising prices for semiconductor wafers and other electronic components, which are used as raw materials in the manufacture of high-technology devices such as computers and mobile phones. Taiwan, at the time, was responsible for 17% of the global semiconductor wafer supply, and two-thirds of the supply of other computer components (Leachman and Leachman, 1999; Papadakis, 2006). The shock increased input prices for a *subset* of US high-technology manufacturing firms: those that primarily sourced semiconductor wafers and other electronic components from Taiwan, or had "just-in-time" inventory-management systems which required holding lower levels of inventory, making these firms

[1]For a review of the literature, see "Cost pass-through: theory, measurement, and potential policy implications." Report prepared for the Office of Fair Trading, London. *RBB Economics*, 2014.

susceptible to short-term increases in input prices. The quake had less impact on US high-technology manufacturing firms that sourced from alternate locations such as Japan or South Korea, or held a higher stock of inventory. Because affected firms and their competitors were located in the United States, whereas the earthquake occurred in Taiwan, and because the increase in input prices was short-term, the shock did not impact the investment-opportunity set or market demand. However, affected firms faced an unexpected drain on internal capital resulting from an increase in the price of raw materials. Accordingly, this setting allows us to study the impact of an increase in input prices on firms' investment activity while holding constant market demand and the investment-opportunity set.

To understand the impact of the earthquake and the consequent rise in input prices on US high-technology manufacturing, it is necessary to provide some background on the evolution of the semiconductor industry, as well as the role of Taiwan in the manufacturing process. The semiconductor production chain broadly consists of chip design, manufacturing, assembly, testing, packaging, and distribution of the final product to OEMs, who buy semiconductors and integrate them into consumer end-products.[2] In the 1970s and 80s, the main aspects of production from chip design to packaging were handled by a single vertically integrated firm. By the late 1990s, the semiconductor industry had evolved from a fully integrated model to one with an increasing reliance on foundries that handled chip manufacturing (Warburg Dillon Read, 1998). At the beginning of 1999, 60% of foundries (by capacity) were located in Asia, 26% in the US, and 14% in Europe. Within Asia, four countries accounted for all the wafer production. These were Japan (46%), Taiwan (29%), South Korea (20%), and Singapore (6%). Therefore, globally, Taiwan accounted for a sizable 17% of the semiconductor manufacturing capacity (Leachman and Leachman, 1999).[3] Although it is difficult to get precise figures on quantities of chips that were exported from Taiwan to

[2]In this study, I focus on investment decisions of OEMs.

[3]As of 2015, only 13% of foundries were located in the US. 76% were located in Asia, including Japan, of which Taiwan's share was 24% (source: IC Insights, Global Wafer Capacity).

the US, data on trade flows provide a close approximate. Based on import data from the UN Comtrade database, presented in table 1, Taiwan accounted for 13.4% of US semiconductor imports in 1998, behind Malaysia (22.1%) and Japan (14.5%). In addition to chips manufactured abroad, the Comtrade data includes imports of units that were assembled, tested, and packaged in other countries, and explains why Malaysia accounts for the largest share of imports even though the country did not have any foundries.[4] Nevertheless, the data provide a lower bound for US reliance on semiconductor imports from Taiwan.

As table 1 further shows, in 1999, the year of the shock, Taiwan captured only 5% of new semiconductor imports and witnessed a 16% increase in the price per unit imported, from $1.30 in 1998 to $1.50 in 1999. This increase in the price per unit compared to an average decrease in price per unit of 5% across all countries. That the quake had significant effect on semiconductor prices is also supported by data on memory prices. Figure 1 shows that the price of one megabyte of memory increased by 180%, from $0.84 at the beginning of 1999 to $2.35 following the quake. Such a spike in the price of memory was unusual. Because of advances in integrated chip manufacturing, the prices of memory chips had been falling consistently for decades. The average price of a megabyte of memory was $6,480 in 1980, $78 in 1990, $1 in 2000, and $0.004 in 2016. In 1957, the price per megabyte of memory was $411 million.[5]

US producers of high-technology devices were less successful in passing on these increased costs of raw material to consumers, as evidenced by no corresponding increase in the price of a major end-product, personal computers. Figure 2 shows the producer price indices for semiconductor manufacturers and computer manufacturers around the time of the shock.

[4] Units that were manufactured in Taiwan's foundries, but assembled, tested, or packaged in Malaysia and then imported to the US, would show up as trade from Malaysia.

[5] A common explanation for the price decline is attributed to Moore's law (Moore, 1965). Moore's law is the observation that the number of transistors in a chip doubles every two years, reducing the manufacturing cost per transistor and the cost of chips overall. Moore's law is used by the semiconductor industry to plan investments, and set targets for research and development (Muley, 2015).

The indices are sourced from the Bureau of Labor Statistics, and track the average price received by producers of goods and services. Figure 2a shows that while semiconductor manufacturers witnessed an increase in prices, figure 2b shows that manufacturers of computers did not witness a corresponding increase in prices, suggesting that they were unable to pass-through the increase in input costs to consumers. Theory suggests that pass-through rates depend on the relative elasticity of demand and supply, and in a competitive market, firms will generally pass-through only a portion of the change in cost to consumers.[6] As I discuss in section 6.2, the US high-technology manufacturing industry is highly competitive. Furthermore, because input prices increased only for a subset of high-technology manufacturers, they would have lost market share to rivals had they passed on the price increase to consumers.[7]

The above discussion illustrates that in the aftermath of the earthquake input costs for US high-technology manufacturers increased, and not all of that increase could be passed on to customers. Input price shocks affect firms' investment decisions through their impact on internal capital. When faced with an increase in the price of raw materials, if firms do not have adequate internal capital, they raise external capital in the form of debt or equity. In the absence of market frictions, there is no difference in the cost of internal versus external finance, and investment would not decline due to a decrease in internal capital (Modigliani and Miller, 1958). However, external capital is more expensive because

[6] Under conditions of perfect competition, it can be shown that industry-wide pass-through (the share of input cost increase that is passed on to consumers through increases in output prices) is given by the following expression:

$$\text{Pass-through} = \frac{1}{1 + \frac{\text{elasticity of demand}}{\text{elasticity of supply}}}.$$

However, under conditions of perfect competition, firms cannot pass-through firm-specific changes in input costs.

[7] For instance, Dell was hit by the memory-chip shortage resulting from the earthquake, leading to higher procurement costs, and a decline in profit margins. Dell issued a pre-earnings announcement warning that its third quarter earnings would fall three cents short of consensus estimates. Also, to deal with the memory shortage, Dell attempted to push sales of devices that required less memory. (Source: "A DRAM Shame! A shortage of memory chips nips away at Dell's profits," *Barron's*, October 25, 1999.)

of information asymmetry and agency costs (Grossman and Hart, 1982; Myers, 1984; Myers and Majluf, 1984), due to which firms cut back on investment activities (Fazzari et al., 1988; Kaplan and Zingales, 1997; Lamont, 1997; Rauh, 2006). Therefore, firms that experience a rise in input prices would divert resources from other areas to purchase raw materials, resulting in a decline in investment activities. However, firms would not reduce all investment uniformly. It is easier for firms to raise external finance for capital expenditures as opposed to R&D because capital expenditures can be collateralized. Furthermore, future cash flows from R&D investment are more risky compared to cash flows from capital expenditures because R&D expenses are for projects that have not reached technological feasibility and cannot yet be marketed for profit (Kothari et al., 2002; Shi, 2003). Therefore, given limited capital, firms would divert resources away from projects with uncertain returns.

I study investment decisions of firms adversely affected by the shock by using a firm as its own control, as well as within a difference-in-differences design. The "treated" sample includes firms that were adversely affected by the supply-chain shock resulting from the earthquake, whereas the "control" sample includes firms in the same industry that were not adversely affected. I find firms that face an increase in input prices reduce R&D spending by 0.4% to 0.9% of total assets. In general, these firms spent 3.8% of total assets on R&D-related expenses in the period prior to the shock. Therefore, the decline in R&D translates to between 11% and 24% making it economically significant. Also, consistent with the above argument, I find affected firms did not make significant cutbacks to capital expenditures.

In additional analyses, I find that financially constrained firms were more likely to cutback on R&D. Measures of financing constraints in prior studies relate to firm characteristics such as size, age, credit rating, dividend payouts, or measures of excess cash (Kaplan and Zingales, 1997; Hadlock and Pierce, 2010). Based on measures developed in prior work, I find firms that were more financially constrained in the period prior to the shock, were more likely to reduce R&D spending in the ex post period. As further evidence of a shock to internal capital, I study firms' accounts payable, a variable that reacts to fluctuations in input prices. I find that accounts payable increased in the quarters following the earthquake for firms that were negatively impacted by the shock. The increase in accounts payable could have occurred both because of an increase in input prices (figure 1), or because, in response to the shock, suppliers extended the payback period (Burkart and Ellingsen, 2004; Petersen and Rajan, 1997). Both these reasons are consistent with a shock to internal capital. Accounts payable increased by up to 2.5% of assets in the first two periods after the shock. Prior to the shock, average accounts payable for these firms was 12% of assets, making the ex-post increase economically significant. Firms that were not adversely affected did not show such a large and significant increase in accounts payable. Furthermore, affected firms reduced selling, general, and administrative expenses (SG&A), providing further proof of a capital crunch. The decline in SG&A amounted to 1.4% of total assets. These firms, in general, spent 10.6% of assets on SG&A, which translates to an economically significant decline of 13%. Finally, I conduct several tests to rule out alternative hypotheses that the decrease in R&D was primarily a response to product-market competition or bankruptcy risk.

This paper makes several contributions to the literature. First, it links two major streams of work: the pass-through literature and the literature on financing constraints. Although the pass-through literature has studied the impact of changing costs, exchange rates, and taxes on prices (Berman et al., 2012; Gopinath et al., 2010; Hellerstein, 2008; Kenkel, 2005; Nakamura and Zerom, 2010), there is much less work on the impact of cost internalization on firms' investment decisions. The difficulty in assessing the effect of input price shocks on investment is that these factors are endogenous to the investment-opportunity set and market demand. By using a novel setting that allows me to hold constant the investment-opportunity set and market demand, I am able to assess the effect of an input price shock on firm investment.

Second, this paper contributes directly to the literature on financing constraints (Almeida and Campello, 2007; Chava and Roberts, 2008; Rauh, 2006; Lamont, 1997; Fazzari et al., 1988; Kaplan and Zingales, 1997) by studying the effect of financing constraints on R&D versus capital expenditures. The evidence is mixed on the effect of shocks to internal capital on R&D investment *per se*. Whereas Rauh (2006) finds no impact of financing constraints on R&D investment,[8] Li (2011) argues that financially constrained firms are more likely to reduce R&D activity as opposed to capital expenditures. I find that financially-constrained firms do not cut back on all types of investment equally, but are more likely to reduce R&D investment. The focus on an R&D-intensive industry makes it easier to identify the effect of financing constraints on R&D investment. Also, by focusing on a single industry, I mitigate concerns that industry-specific factors could be driving outcomes.

The remainder of this paper is organized as follows. Section 2 discusses the background and empirical setting. Section 3 presents the theoretical framework. Section 4 presents the data and sample. Section 5 presents the empirical analyses and a discussion of the results. Section 6 presents additional analyses, and section 7 concludes.

2. Background and empirical setting

A 7.6 magnitude earthquake hit Chi-Chi, Taiwan, on September 21, 1999. The quake led to significant loss of life and property, with fatalities estimated to be close to 2,400. It also led to disruption of the global semiconductor supply chain as well as the supply of other electronic components manufactured in Taiwan, raw materials that are used in the production of high-technology devices such as computers, mobile phones, medical devices, and other consumer electronics. Most of the semiconductor fabrication facilities were located in the Hsinchu Science Based Industrial Park, 110 kilometers north of the epicenter. This included

[8] Rauh (2006) finds that financially constrained firms reduce capital expenditures, but not investment in R&D. In tests using subsamples of firms in the high-tech sector, the paper finds similar results.

two of the largest manufacturers of semiconductors, Taiwan Semiconductor Manufacturing Company (TSMC) and United Microelectronics Corporation (UMC). Figure 3 maps the location of manufacturing facilities relative to the epicenter of the earthquake, and shows that many facilities were in areas that experienced tremors from the earthquake.[9] Because semiconductor foundries work with delicate precision machinery, tremors from the earthquake damaged machinery and disrupted the production process. The earthquake not only affected chip makers' facilities, but also disrupted utilities for extended periods, leading to a supply shortage and an increase in the price of semiconductor wafers.[10] The semiconductor industry was relatively unprepared for disruptions caused by an earthquake, as evidenced by their decision to send a team of experts to assess damage to fabrication facilities in the aftermath. The stated purpose of the team was to prepare the industry for future disruptions caused by earthquakes (Sherin and Bartoletti, 1999).

The earthquake adversely affected several US high-technology manufacturing firms that sourced their raw materials, such as semiconductor wafers and other components, from Taiwan and had "just-in-time" inventory management systems which, in general, required holding low quantities of inventory. Taiwan, in 1999, was responsible for 17% of the world's supply of wafers and two-thirds of other computer components such as motherboards, monitors, liquid-crystal displays, batteries, and chargers (Leachman and Leachman, 1999; Papadakis, 2006). The disruption to manufacturing facilities in Taiwan led to an increase in the price of memory, resulting in higher production costs for US manufacturers who mainly relied on suppliers in Taiwan, or who had an inventory-management system that made them susceptible to short term price fluctuations.

The earthquake differentially affected US manufacturing firms based on their supply-chain-management systems. Supply-chain-management can follow a "push system" or a "pull

[9] Taiwan had 28 foundries at the time, and several facilities that manufactured electronic components. See "Picking up the pieces in Taiwan", *EE Times*, October 01, 1999.

[10] The spot price of memory chips went up five-fold and contract prices went up by 25% (Papadakis, 2006).

system" (also called just-in-time). In a push system, firms manufacture large quantities of the final output to deliver to wholesalers and retailers. Therefore, they maintain higher levels of inventory. On the other hand, in a pull system, production takes place only when customer orders are received, resulting in lower levels of inventory and working capital, thereby making these firms susceptible to increases in input prices (Curry and Kenney, 1999; Papadakis and Ziemba, 2001). As table 2 shows, in the period prior to the shock, firms that were adversely affected by the earthquake held significantly lower levels of inventory compared to other firms in the industry. Furthermore, because products in technology become obsolete quickly, many buyers do not maintain large stockpiles of inventory.

For the reasons elaborated above, many US high-technology manufacturing firms faced a sudden and unexpected supply shock, and a rise in component prices. Several news outlets reported that manufacturers that sourced semiconductors from Taiwan saw a decline in their share prices, whereas those that sourced from South Korea or elsewhere witnessed an increase in share prices.[11] The stock price reaction suggests that market participants were aware which firms would be adversely affected by the shock, either because they sourced from Taiwan, or had just-in-time inventory management systems that exposed them to short-term price increases. As such, I use market returns to identify firms that were adversely impacted by the shock. I describe the sample selection procedure in greater detail in section 4.

3. The sensitivity of R&D investment to internal capital

In this section, I present a theoretical framework to motivate how R&D investment can vary with shocks to a firms' internal capital. The framework is based on Kaplan and Zingales (1997) who present a one-period model of a profit maximizing firm that chooses an investment

[11]See, for example, "Quake rattles chip supply," *CNN Money*, September 21,1999; "Taiwan Quake to be Costly to World Technology Makers," *The New York Times*, September 23, 1999.

I to maximize the following function:

$$Max \;\; F(I) - C(E,k) - I, \;\; \text{such that } I = W + E \;,$$

where $F(I)$ is the return to investment. $C(.)$ is the cost of external capital and is a function of the amount of capital raised (E), as well as the wedge between internal and external capital (k). k is driven by information or agency problems. The model assumes $F'(I) > 0$, $F''(I) < 0$, and $C'(I) > 0$, $C''(I) > 0$. Based on the model, Kaplan and Zingales (1997) derive the following result for the dependence of investment on internal capital:

$$\frac{dI}{dW} = \frac{C_{11}}{C_{11} - F_{11}} \;, \tag{1}$$

where C_{11} and F_{11} represent the second differential of $C(.)$ and $F(.)$ with respect to the first argument.

I modify this model to arrive at the investment sensitivity of R&D and capital expenditures to internal capital, by introducing the following two assumptions.

1. Returns from R&D ($G(I)$) are more uncertain compared to returns from capital expenditures, that is, $G(I)$, is realized with some probability p, where $0 < p < 1$.
2. $E[G(I)] > E[F(I)]$, where $F(I)$ represents the returns to capital expenditures.

The firm's problem of choosing R&D investment, I, can now be written as follows:

$$Max \;\; p * G(I) - C(E,k) - I, \;\; \text{such that } I = W + E \;.$$

The first-order condition is:

$$p * G_1(I) = 1 + C_1(I - W, k) \;.$$

Implicit differentiation of the first-order condition gives the following result:

$$\frac{dI}{dW} = \frac{\frac{dp}{dW}G_1 + C_{11}}{C_{11} - pG_{11}} \ . \tag{2}$$

If $p = 1$, then the equations (1) and (2) are equivalent. If the sensitivity of R&D investment to internal capital is greater than the sensitivity of capital expenditures, then

$$\frac{\frac{dp}{dW}G_1 + C_{11}}{C_{11} - pG_{11}} > \frac{C_{11}}{C_{11} - F_{11}} \ .$$

The above relation will hold if (a) $\frac{dp}{dW} > 0$, that is, the probability of success of the project increases with an increase in internal capital; and (b) $pG_{11} > F_{11}$.

(a) implies that higher internal capital increases the probability of success of an R&D project. The condition holds because, typically, R&D projects are long-term and require multiple rounds of financing. Also, due to a lack of collateral and risky returns, it is more difficult to raise external capital for R&D projects. Prior work shows that R&D-intensive firms hold higher levels of cash balances, and allude to the importance of internal capital in the success of R&D projects (Bates et al., 2009; De Simone et al., 2018; Foley et al., 2007; Pinkowitz et al., 2015; Opler et al., 2010). (b) implies that returns from R&D investment have to be sufficiently higher than returns from capital expenditures, and is an assumption in the model.

4. Data and sample

I identify US high-technology manufacturing firms that were adversely affected by the supply-chain disruption caused by the earthquake, by using two different methods, the first based on a text search of financial statements (sample 1) and the second using one-day abnormal returns on the day of the earthquake (sample 2). Sample details are provided in Appendix

A. To construct sample 1, I search the text of financial statements, including 8-Ks (material corporate events) in the years 1999 to 2001, and identify firms that mention the words "Taiwan" and "earthquake" within 10 words of each other. The first disclosure in 1999 was made on September 30, or nine days after the quake, by Silicon Image Inc.[12] The company stated the following in their filings:

> We do not own or operate a semiconductor fabrication facility. We rely on Taiwan Semiconductor Manufacturing Company, an outside foundry, to produce all of our semiconductor products ...We do not have a long-term supply agreement with Taiwan Semiconductor Manufacturing Company, or TSMC, and instead obtain manufacturing services on a purchase order basis. This foundry has no obligation to supply products to us for any specific period, in any specific quantity or at any specific price, except as set forth in a particular purchase order... we do not yet know the extent to which we will be adversely affected, if at all, by difficulties experienced by TSMC, ASE or any of our significant Taiwanese customers due to the earthquake.

The text search resulted in a sample of 72 unique firms that could be matched with Compustat using CIK codes. To expand the sample, and include firms that were adversely affected but did not make references to the earthquake in their financial statements, I use one-day abnormal returns for the firm on the day of the earthquake.[13] The earthquake occurred at 1:47 am local time on September 21, 1999, which was 17:47 UTC on September 20, 1999. Therefore, when markets opened in the United States on September 21, 1999, news of the quake was already out and market participants had the opportunity to react to the news during the trading day. Accordingly, I use one-day abnormal returns for September 21, 1999, to construct sample 2. The expanded sample consists of firms in the high-technology

[12] Silicon Image provides video, audio, and data connectivity solutions for the mobile, consumer electronics, personal computer, and enterprise markets (Source: Bloomberg).

[13] Abnormal returns are calculated as firm returns including dividends, less a value-weighted market index.

manufacturing industry, where industry definitions are based on three-digit SIC codes and include the same sub-industries as in the sample constructed using the text search.[14] I sort firms into quintiles based on one-day abnormal returns, and designate firms in the bottom two quintiles as sample 2 firms, or those that were adversely affected by the shock. Analysts and market participants are generally well-informed about firms' sourcing locations and their inventory-management systems, making market reaction a reasonable method of identifying firms that were adversely affected by the shock. All firms in sample 2 had negative one-day abnormal returns, and a mean abnormal return of -3.8%. Columns (1) and (2) of table 2 present descriptive statistics for firms in samples 1 and 2. As can be seen from the table, firms in the two samples differ on log of assets ($SIZE$) and total inventory scaled by lagged assets ($INVENTORY$). Firms that made disclosures related to the earthquake (sample 1 firms) tended to be larger and held less inventory, consistent with the idea that large firms are more likely to have advanced just-in-time inventory management systems, and are likely to make more disclosures in their financial statements.

I also use one-day abnormal returns described above to identify firms that were not adversely affected by the shock (control firms). Several media sources reported that stock prices of US producers that relied on chip foundries in Taiwan fell, whereas the stock prices of competitors that sourced from other countries such as South Korea rose.[15] I classify firms that fall in the top two quintiles of one-day abnormal returns as those that were not adversely affected by the shock. All firms in this sample had positive one-day abnormal returns, and a mean abnormal return of +3.9%. In later analysis, this group of firms is used as the control sample in a traditional difference-in-differences model. Column (3) of Table 2 presents descriptive statistics for these firms. As can be seen from the table, firms that were not adversely affected by the shock (control firms) differ from sample 2 firms (treated firms) on several firm-level

[14] These firms are a subset of industry number 6 (computers, software, and electronic equipment) in the Fama-French 12-industry classification.

[15] See, for example, "Quake rattles chip supply," *CNN Money*, September 21,1999; "Taiwan Quake to be Costly to World Technology Makers," *The New York Times*, September 23, 1999.

characteristics. Notably, firms that were not adversely affected tended to have higher levels of inventory and were smaller in size, consistent with the idea that large firms that had just-in-time inventory-management systems were more likely to be adversely affected by the shock. Treated firms, probably because they were larger, held higher levels of cash and had higher levels of R&D spending, consistent with prior literature that finds R&D spending to be a critical determinant of cash holdings (Bates et al., 2009; De Simone et al., 2018; Foley et al., 2007; Opler et al., 2010; Pinkowitz et al., 2015). In line with higher investment in R&D, affected firms also spent more on capital expenditures.

Although treated and control firms vary across several firm-level characteristics, these differences do not necessarily disqualify firms with positive abnormal returns as a valid control. Unless these differences drive the behavior of treated firms in the post-treatment period for reasons unrelated to the earthquake, inferences from the analysis will be valid.[16]

Firm-level data to calculate the outcome and control variables are sourced from Compustat and CRSP. Market data to calculate abnormal returns are also sourced from CRSP. Appendix B presents definitions of variables.

5. Empirical analysis

In this section, I study firms' investment decisions in the quarters following the shock. I begin by presenting univariate changes for the four quarters following the shock where, to account for seasonality, change is calculated over the same quarter of the previous year. I then use a firm as its own control and assess changes to firms' R&D investment (RD), capital expenditures ($CAPEX$), selling, general and administrative expenses (SGA), as well as net

[16] In a later section, I assess pre-trends for the treated and control sample and find parallel trends in the periods prior to the shock. Parallel pre-trends are required for valid inferences from a difference-in-differences analysis.

equity issued ($NETEQUITY$), in a multi-variate setting. Finally, I use firms that were not adversely affected as a control sample and study treated firms' changes to investment and financing decisions within a difference-in-differences framework.

5.1. Univariate changes

Table 3 presents univariate changes for firms that were adversely affected by the shock, for both samples 1 and 2. As described in section 4, sample 1 firms were identified using a text search of firms' financial filings, whereas sample 2, a larger sample, was identified using one-day abnormal returns. Sample 1 is a subset of sample 2, except in cases where data on market returns were not available. Periods 1 to 4 represent four quarters after the shock. Periods were defined so that fiscal quarters and calendar quarters could be aligned. For instance, all fiscal quarters ending September 1999 to November 1999 are defined as period 1, which is the first period after the shock. Similarly, all fiscal quarters ending December 1999 to February 2000 are period 2, the second period after the shock. The remaining periods are defined in a similar manner to align fiscal and calendar quarters.

As can be seen from table 3, accounts payable increased by 0.7% to 2.5% of assets in the first two periods after the shock. This increase is consistent with higher prices for raw materials such as semiconductor wafers and other electronic components in the aftermath of the earthquake, or with suppliers extending the payback period. Both these explanations are consistent with a shock to internal capital. As table 2 shows, average accounts payable for these firms was 12% of assets in the period prior to the shock, making the increase economically significant.

Firms that were adversely affected by the shock reduced spending on R&D to the tune of 0.9% to 1.4% of assets. This decline is economically significant considering that, on average, affected firms spent between 2.6% and 4.5% of assets on R&D in the period prior to the shock. Firms also reduced spending on selling, general, and administrative expenses by between 0.6% to 2.7% of assets. In the period before the shock, firms spent approximately 10% of assets on selling, general, and administrative expenses, making the decline economically significant. Furthermore, firms did not reduce capital expenditures, which in fact increased by 0.4% to 0.5% of assets. That firms cut back on R&D expenses, but not capital expenditures, is consistent with firms reducing investment in projects with uncertain returns (Kothari et al., 2002; Shi, 2003).

Affected firms raised equity of up to 12% of assets (over the same quarter of the previous year), but did not raise much debt. The amount of new debt raised was less than 1% of assets. That affected firms raised equity as opposed to debt is consistent with the finding in Carpenter and Petersen (2002) that firms in the high-technology industry, given greater information asymmetry between the firm and investors, and high risk of project failure, are more likely to rely on equity. Affected firms also showed a large increase in cash, possibly related to the large amounts of equity raised. The increase in cash is substantial, of up to 16% of assets. However, firms in the technology sector tend to maintain high levels of cash (Foley et al., 2007; Opler et al., 2010), with firms in the affected sample maintaining cash balances of between 32% to 41.5% of assets in the period before the shock.

A somewhat surprising finding is that firms that were adversely affected by the shock witnessed an increase in margins. Firms adversely affected by the shock are unlikely to have been successful in passing on increased costs to customers. If they did increase prices, competitor firms that were not adversely affected by the shock would have gained market share at their expense. One explanation for the increase in margins is that affected firms engaged in strategic financial reporting to appear more profitable than they truly were. Such strategic reporting could be in response to a competitive threat (hiding weakness from competitors) (Bernard, 2016), or driven by incentives to window-dress prior to raising equity (Teoh et al., 1998). I explore this explanation in section 6.3, where I construct a measure of aggressive revenue-recognition and document that affected firms became more aggressive in their revenue-recognition practices after the shock.[17]

I present univariate changes for the control sample (firms not adversely affected) in Table 4. As can be seen from the table, although some changes to these firms' financing and investment decisions took place, the changes were nowhere near as pervasive as for the firms adversely affected by the shock. Firms that were not adversely affected increased net equity by a smaller amount of between 1.3% and 4.2% of assets. Also, in contrast to firms adversely affected, control firms witnessed an increase in selling, general, and administrative expenses.[18]

5.2. Multivariate analysis

5.2.1. Research design

In this section, I first examine changes to affected firms' financing and investment decisions by using the firm as its own control. I then examine the effect within a generalized difference-in-differences framework. A crucial assumption to ensure validity of inferences drawn from the analyses is firms that sourced from Taiwan and were adversely affected by the shock were not systematically different in ways that would have resulted in the observed effect in the ex-post period, regardless of the earthquake. As discussed in section 4, a key characteristic of affected firms is that they tend to hold less inventory than firms that were not adversely affected. That is, they were more likely to employ just-in-time inventory-management techniques.

Several observations make it unlikely that firms would have taken the observed actions in the ex post period had they not experienced an increase in input prices. First, firms did not

[17]Firms are aggressive in revenue recognition if they record earnings before the culmination of the earnings process.

[18]In un-tabulated analysis, I use data from Kantar Media and find that control firms increased spending on advertising, suggesting an increase in competitive threat for the affected firms.

anticipate the earthquake or the disruption it caused, and did not have processes in place to deal with such disruptions (Sherin and Bartoletti, 1999). Also, as presented in Table 4, firms that were not adversely affected but were in the same industry and plausibly faced similar economic conditions did not take comparable actions. Finally, as discussed later in section 6.1, on using observable measures of financing constraints I find affected firms that faced greater financing constraints were more likely to reduce R&D expenses.

I begin by estimating the following equation for the sample of affected firms (sample 2 firms):

$$Y_{it} = \alpha + \beta_n \times PERIOD_n + X_{it} + \epsilon_{it} \ , \tag{3}$$

where Y_{it} is the dependent variable of interest, and represents R&D investment, capital expenditures, net equity raised, or selling, general, and administrative expenses. $PERIOD_n$ is equal to 1 in the nth quarter after the shock, and zero otherwise. n takes values from 1 to 4. X_{it} is a vector of control variables, and ϵ_{it} is the error term. The control variables represent firm characteristics and include firm size, the market-to-book ratio, return on assets, and cash balances. Following Frank and Goyal (2003), asset tangibility is included as a control in the model for net equity issued. In models where the dependent variable is capital expenditures, net equity raised, or selling, general, and administrative expenses, R&D expense is included as a control. All control variables are measured in the quarter prior to the shock. β_n is the coefficient of interest and is expected to be economically and statistically significant.

Macroeconomic or industry-level factors could have changed around the time of the shock, resulting in affected firms making changes to their financing and investment decisions regardless of the shock. I therefore introduce a control sample that consists of firms likely to have been exposed to the same economic conditions. A natural and close control sample are firms that were from the same industry but were not adversely affected by the earthquake. Descriptive statistics presented in table 2, and discussed in section 4, shows that affected firms and their rivals differed on several characteristics in the period prior to the shock. However, the differences do not disqualify these firms as a valid control. Unless these differences drove the behavior of affected firms in the post-treatment period for reasons unrelated to the earthquake, inferences from the analysis will be valid. I present analysis in support of the parallel-trends assumption, which is required to draw valid inferences from a difference-in-differences design.

The main empirical specification is as follows:

$$Y_{it} = \alpha + \beta_n \left(TREAT_i \times PERIOD_n \right) + \delta_i + \gamma_t + \epsilon_{it} \ , \tag{4}$$

where δ_i represents firm fixed effects and γ_t represents quarter fixed effects. As before, Y_{it} is the dependent variable of interest and represents R&D investment, capital expenditures, net equity raised, or selling, general, and administrative expenses. The independent variable of interest $TREAT_i \times PERIOD_n$ is an indicator variable that takes the value of 1 for treated firms in the quarters after the shock, and 0 otherwise. $PERIOD_n$ is equal to 1 in the nth quarter after the shock, and zero otherwise. n takes values from 1 to 4. As described in section 5.1, $PERIOD$ represents calendar quarters and has been defined so as to align fiscal quarters to calendar quarters.

To assess parallel trends, which is required to draw valid inferences from the difference-in-differences analyses, I estimate the following regression:

$$Y_{it} = \gamma_t + \gamma_t \times TREAT_i + \epsilon_{it} \ , \tag{5}$$

where Y_{it} is defined above. $TREAT$ is an indicator variable that takes the value of 1 for treated firms, and 0 otherwise. γ_t is an indicator for the period t, and ϵ_{it} represents the error term. Results from this estimation are presented in Figure 4, which demonstrates that the parallel-trends assumption holds. The F-statistic for the test that pre-treatment coefficients jointly equal zero fails to reject the null of parallel trends.[19]

Descriptive statistics presented in Table 4 indicate the shock also affected control firms, albeit in a limited manner. Control firms raised equity, although not as much as that raised by treated firms. Therefore, estimates from the difference-in-differences analysis gives a net estimate for the industry as a whole. These results, combined with results from the univariate and multivariate tests using only the sample of firms that were adversely affected, suggests that firms reduced R&D spending in response to an increase in input prices.

5.3. Discussion of results

Table 5 presents results of the multivariate analysis using a firm as its own control (results from estimation of equation 3). Column (1) of Table 5 shows the change in quarterly net equity raised four quarters after the shock, relative to the quarters prior to the shock. The results indicate that firms that faced a negative shock to internal capital raise new equity of up to 9.9% of assets in the quarters following the shock, relative to the period before the shock. This result is statistically significant. Affected firms, on average, raised net equity of 4.7% of assets in the period prior to the shock (Table 2), suggesting that an increase in net equity of 9.9% of assets is economically significant.

In columns (2) to (4), I examine the change in capital expenditures ($CAPEX$), research and development costs ($R\&D$), and selling, general, and administrative expenses ($SG\&A$) in the four quarters following the shock. Capital expenditures experienced no significant changes in the four quarters after the shock. This finding is consistent with affected firms' maintaining investment in projects that are reasonably expected to generate future cash flows. However, affected firms made significant cutbacks to $R\&D$ and $SG\&A$ expenses. The decline in $R\&D$

[19] F-statistic (p-value) for this test is 0.75 (0.5204), 0.19(0.9005), 0.25(0.8579), and 1.40(0.2400) for $R\&D$, $CAPEX$, $SG\&A$, and $NETEQUITY$.

varied between 0.4% to 0.6% of total assets. The average $R\&D$ spending by affected firms was 3.8% of assets, corresponding to an 11% to 15% (0.4/3.8 to 0.6/3.8) reduction from the mean, making this ex post decrease in $R\&D$ economically significant. Spending on $SG\&A$ also declined by 0.5% to 1.0% of assets. Average spending on $SG\&A$ was 10.6% of assets in the period before the shock, corresponding to a 5% to 9% (0.5/10.6 to 1/10.6) reduction from the mean. That firms would continue to maintain capital expenditures but reduce investment in $R\&D$ suggests that given the uncertain nature of returns from $R\&D$, firms would prefer to reduce $R\&D$ to cutting back on capital expenditures. Also, unlike capital expenditures, R&D expenses cannot be collateralized making it difficult to raise external capital to fund R&D projects.

In Table 6, I present results from the difference-in-differences analysis. "Treated" firms are those that were adversely affected by the shock (sample 2 firms). "Control" firms are from the same industry that did not source from Taiwan or did not have just-in-time inventory-management systems, and therefore were not adversely affected by the shock. As described above, control firms were also affected by the shock albeit in a limited way. Therefore, estimates from this analysis gives magnitudes of the net effect on the industry. Combined with analysis presented in tables 3 to 5, we can draw valid inferences about the financing and investment decisions of firms that faced a shock to internal capital. Results from the difference-in-differences analysis supports the results presented in the univariate and multi-variate analysis by using a firm as its own control. Although control firms are not perfect, in the sense that they were also affected by the earthquake in a limited way, using this sample of control firms is preferable to using controls from a different industry, which may have economic drivers that differ significantly from those in the high-technology manufacturing industry.

Column (1) of Table 6 shows the change in net equity relative to control firms, in the quarters following the shock. Treated firms showed an increase in net equity of 5.8% of total assets, which is both statistically and economically significant. However, given that control firms also raised equity in this period (Table 4), the 5.8% increase is a conservative estimate. Columns (2) to (4) present results for changes in $CAPEX$, $R\&D$, and $SG\&A$. The results are consistent with those presented above, in that treated firms showed a decline in $R\&D$ and $SG\&A$ expenses, and no significant declines in capital expenditures.

6. Additional analyses

6.1. Observable measures of financing constraints

In this section, I use measures of financing constraints developed in prior work and provide evidence consistent with the main thesis of the paper: firms that face an increase in input prices cutback on R&D investment because of a shock to internal capital. I use two different measures of financing constraints: the natural log of assets ($SIZE$) as smaller firms are more likely to face financing constraints, and the Hadlock and Pierce (2010) re-estimation of the Kaplan-Zingales index (Kaplan and Zingales, 1997). The index combines cash flows, the stock of cash, dividends paid, Tobin's Q, and share of debt in total capital, to arrive at a measure of financing constraints. Both these measures are calculated as of 1998, or the year prior to the shock. I divide the sample into three groups based on terciles of these measures, and re-estimate Equation (3) within each sub-sample, where the dependent variable is investment in R&D.

The results of the estimation are presented in Table 7. Panel A of the table presents the coefficients of the period indicators by tercile of firm size. As can be seen from the panel, smaller firms were more likely to cutback on R&D investment. However, firm size could be correlated with multiple firm characteristics. Therefore, panel B presents the same analysis by tercile of the measure of financing constraints described above. Firms that scored high on the measure reduced R&D investment by between 0.5% to 0.7% of assets. By comparison, firms that scored low on the measure of financing constraints experienced a lower drop in R&D investment of between 0.3% and 0.4% of assets. Results from this analysis indicate that financially-constrained firms were more likely to reduce R&D in response to the shock.

6.2. Response to product-market competition or bankruptcy risk?

The high-technology manufacturing industry is highly competitive as evidenced by the Herfindahl index, sourced from the 1997 US Census Bureau's Concentration Ratios in Manufacturing, as well as data on industry price wars. The Herfindahl index for computer and electronic manufacturing was 136.6, compared to a mean of 166 and a maximum of 798 for all manufacturing industries. Furthermore, the top 50% of firms in computer and electronic manufacturing were responsible for 55% of industry sales, compared to a maximum of 90% for manufacturing industries.[20] I also analyze price wars from 1990 to 2005 and find they were more prevalent in the computers and consumer electronics industry than in other industries. Although the literature presents several causes for price wars, including demand, declining financial condition, or industry characteristics,[21] Heil and Helsen (2001), based on a review of price wars reported in the business press, suggest that price wars entail a strong focus on competitors rather than consumers. A search for the term "price war" on Factiva yielded 1,155 articles on the computers and consumer electronics industry for the period. These articles constitute 30% of all articles on the subject, across all industries. During this period, the computers and consumer electronics industry constituted 16% of the total number of firms and 8% of total sales.[22] Overrepresentation of the computers and consumer electronics industry in the press search suggests a high degree of competition in

[20] 1997 is the latest period before the shock for which these numbers are available. The Census Bureau's concentration measures include data from private firms and therefore provide a more complete picture of industry competition than do measures calculated using data from Compustat.

[21] See for example, Busse (2002) and Van Heerde et al. (2008).

[22] These figures are based on data from Compustat. I use industry number 6 from the Fama-French 12-industry classification (Business Equipment – Computers, Software, and Electronic Equipment) to calculate these percentages.

the industry.

R&D projects are more likely to fail under increased competition, because rival firms could win the race to innovate and therefore be the first to patent the new technology, resulting in minimal returns for losing firms (Dasgupta and Stiglitz, 1980; Doraszelski, 2003; Gu, 2016; Lee and Wilde, 1980; Loury, 1979; Reinganum, 1982). In my setting, it is conceivable that competition increased for affected firms because not all firms were negatively impacted by the shock. Therefore, rivals that were not adversely affected could have stepped up competitive pressure, suggesting that the decline in R&D could have been a response to increased competition.

To test this alternative hypothesis, I construct two measures of product-market competition: the herfindahl index, and a measure of the correlation of firm returns with industry returns based on Parrino (1997). While the Herfindahl index has been used extensively in prior literature as a measure of competition, the correlation measure captures the idea that firms that have correlated growth opportunities with other firms are more likely to face greater product-market competition (Chevalier, 1995; Haushalter et al., 2007). The Herfindahl index is calculated at the level of three-digit SIC code for the year 1998, the year prior to the shock. Following Parrino (1997), to calculate the correlation measure, I regress monthly firm returns on equally-weighted industry indices and the equally weighted market index, by firm, where industry is defined by three-digit SIC code. I require at least 24 months of data for each firm in the sample. I estimate the relation for the 10 years from 1989 to 1998. The years were chosen to have a sufficiently long time period, as well as to include the years just before the shock. The coefficient on industry indices gives a measure of correlation of returns.

As before, I divide the sample into three groups based on terciles of the measures of competition, and re-estimate Equation (3) within each sub-sample. Results of the estimation are presented in Table 8, and suggest that the cutback in R&D was not a response to product-market competition.

Finally, the risk of bankruptcy could have increased for firms that faced an increase in the price of raw materials. In response to an increase in bankruptcy risk, affected firms could have reduced investment in R&D projects. Using the Altman-Z score as a measure of bankruptcy risk (Altman, 1968), and a similar methodology as above, I do not find evidence to suggest that affected firms were reducing R&D spending because of an increase in bankruptcy risk.

6.3. Strategic financial reporting

The short-term increase in profit margins of affected firms, documented in section 5.1, is surprising because, given that only a subset of the industry was affected, these firms would not have been able to pass on the increased costs to customers. The increase in margins suggests that firms may have managed their accounting numbers to appear more profitable than they really were. An extensive literature in accounting studies managers' incentives to engage in earnings management and its impact on accounting quality.[23] Several papers document that firms manipulate their financial statements or make disclosure choices in response to equity offerings, financing constraints, and product-market competition (Balakrishnan et al., 2014; Bernard, 2016; Godsell et al., 2017; Teoh et al., 1998; Tomy, 2018). In this section, I study financial-reporting decisions of firms adversely affected by the shock, and find these firms became more aggressive in their revenue-recognition practices.[24]

I choose to study revenue-recognition practices of affected firms because of the pervasiveness of improper revenue recognition in fraud cases, and the prevalence of financial fraud in technology firms. For instance, a report commissioned by the Committee of Sponsoring Organizations of the Treadway Commission (COSO) found that 61% of all cases of financial-

[23] See Healy and Wahlen (1999) and Dechow and Skinner (2000) for a review of the literature.

[24] Firms are aggressive in revenue recognition if they record earnings before the culmination of the earnings process.

reporting fraud resulted from improper revenue recognition (Beasley et al., 2010). These cases were primarily related to recording fictitious revenue or recording revenues prematurely. Furthermore, the computer hardware and software industry accounted for the largest number of fraud cases.

US GAAP requires that revenue recognition be based on the culmination of the earnings process. That is, revenue has to be earned (goods delivered or services provided) and collectible (assurance of payment) before it can be recognized. Aggressive revenue recognition is the practice of recognizing revenues before the culmination of the earnings process. If the misstatement of revenue is material and detected by auditors, firms are required to restate their financial statements.[25] I build a predictive model of aggressive revenue recognition by using income-reducing restatements, related to inappropriate revenue recognition, as the outcome variable. These restatements are the result of more egregious revenue misstatements. However, some firms may have misstated their revenues below the materiality threshold, or auditors may not have detected and corrected their misstatements. The predictive model will help identify firms that, based on a set of explanatory variables, are most likely to have misstated their revenues. Furthermore, the model can also be applied to periods in which data on restatements are not available.

To build the model, I use data from the years 2004 to 2014. I choose these years because they are sufficiently far from the period in which I study the short-term impact of the shock, and also because restatement data are available for these years. The availability of restatement data precludes me from conducting the analyses using years before the shock. I source restatement data from the Audit Analytics Advanced Restatement database. I am able to identify 178 restatements that were due to revenue-recognition issues, and were

[25] For instance, International Rectifier, a California-based power management technology company, restated its financial statements for 2005 and 2006 because of premature revenue recognition of product sales. Omnicell Technologies, a manufacturer of medical equipment, restated 2002 revenue by $1.2 million because revenue was recognized prior to product installation.

income-decreasing. The restatement data were aligned with fiscal years by the restatement beginning period. The 178 restatements made up 1.24% of the overall sample. Also, the median length of a restatement was 1 year, and the mean was 1.3 years. Therefore, I only classify the year the restatement began as a restatement year.

A challenge in building the predictive model is the rareness of the restatement event and the associated class imbalance; that is, the outcome variable contains many more zeros than 1's. The rareness of the event makes using parametric methods difficult, because these models generally have low predictive power.[26] Therefore, I use non-parametric methods specifically developed for predicting rare events. I present and discuss results for both the parametric and non-parametric methods, using the same sample and variables to enable a comparison. The non-parametric model has superior out-of-sample predictive ability for the rare event.

I begin with the yearly sample of technology firms for the years 2004 to 2014, providing me with 14,496 firm-year observations, of which 1.24% are classified as aggressive revenue recognizers. I randomly divide the sample into training and test samples such that the proportion of aggressive revenue recognizers is the same in both samples. The predictive models are estimated using the training sample, and out-of-sample predictive power is gauged using the test sample. I use the algorithm *RUSBoost* developed by Seiffert et al. (2010). This algorithm was developed to deal with class imbalances and predict rare events. Traditional methods are not suited to predict rare events, because they are more likely to correctly classify the majority class. The algorithm randomly undersamples from the majority class and improves the performance of a predictor through *boosting*, which is explained below.

I use a supervised-learning method, namely, decision-trees, to build the predictive model. This method involves dividing the predictor space into a number of distinct non-overlapping

[26] I estimate a logistic regression model with firth corrections for rare events (King and Zeng, 2001), but find the model has low explanatory power with pseudo R^2 of 5.8%. The associated area under the ROC curve is only 0.6805, indicating a poor fit.

regions. The same value of the outcome is assigned for each observation that falls within a given region. For a classification tree, the predicted value of the outcome is the most commonly occurring class within a region.[27] To improve predictive power, I use a technique known as boosting. This technique combines several trees to produce a more powerful predictive model. Trees are grown sequentially, whereby each tree uses information from the previously fitted trees. Fitting a single large tree to the data could result in over-fitting. In this method, smaller trees are grown sequentially, where, given a model, a decision tree is fitted to the residuals from the model. The residuals are updated in each iteration. I set each tree to have five splits, and train a large number of trees. Figure 5 plots the out-of-sample test classification error as the number of trees increases to 20,000. Classification error measures the predictive inaccuracy of the model (fraction of observations that are not correctly classified), with a lower error indicating a better model. As the figure shows, classification error is lowest at around 2,500 trees, and increases subsequently. As more and more trees are fit after 2,500, over-fitting occurs, resulting in a higher classification error rate. I use 2,500 trees to build the predictive model.

Explanatory variables are drawn from prior literature and include variables that have been shown to be associated with financial fraud and restatements (Dechow et al., 1995; Floyd et al., 2017). Figure 6 presents a summary of the importance of each predictor. The importance measure is computed by summing changes in the mean squared error due to splits on every predictor and dividing the sum by the number of branch nodes.

Because the procedure randomly undersamples from the majority class, I repeat the procedure 1,000 times to assess the stability of the test classification error rate. Figure 7 presents the plots for the 1,000 iterations. The classification error rate is stable with a mean of 0.3547 and standard deviation of 0.0038. To assess the predictive ability of decision trees in relation to parametric methods, I estimate the model using a logistic regression and the same training

[27] Please see James et al. (2013) for an overview.

sample and variables. Results of the estimation are presented in Table 9. The model has low explanatory power with pseudo R^2 of 5.8%. Furthermore, the area under the ROC curve is 0.6805, indicating a poor fit. Table 10 presents a confusion matrix for out-of-sample prediction using both methods. Although both the logistic model and decision-tree-based model have a similar error rate (the percentage of total observations that are incorrectly classified), the decision-tree based model is better able to predict the rare event. The decision-tree-based model has a sensitivity of 51%, which is the percentage of true restaters that are classified as such by the model. This figure compares to a sensitivity of only 44% for the logistic model. The decision-tree-based model also scores slightly better on specificity (65% compared to 64% for the logistic model), which is the percentage of non-restaters (the majority class) that are correctly identified. Results presented in the confusion matrix suggest that the decision-tree-based method has superior predictive ability for rare events.

I finally apply the decision-tree-based predictive model to the study sample from the period 1990 to 2002. Figures 8 plots the percentage of time a firm is tagged as an aggressive revenue recognizer in a given year, for the treated and control groups. As the figure shows, treated firms became more aggressive in their revenue-recognition practices after the shock.

7. Conclusion

The pass-through literature has studied the impact of an increase in input costs on output prices. Furthermore, the literature on financing constraints has studied the effect of market frictions on firms' investment decisions. However, there is limited work on how an input price increase can influence firms' investment decisions. This paper provides a link between the two streams of literature by studying the effect of an increase in input costs on firms' investment decisions in a well-identified empirical setting. The paper also contributes to the financing constraints literature by documenting that firms that experience a shock to internal capital do not reduce all forms of investment uniformly, but are more likely to make cutbacks in R&D. Compared to capital expenditures that are for projects with relatively assured returns, R&D expenses fund risky ventures with uncertain returns. Also, it is generally easier to raise external finance for capital expenditures because, unlike R&D, these can be collateralized.

Although this study uses a sample of manufacturers in the high-technology sector, the arguments presented in the paper are not unique to the high-tech industry, but are general and may apply to other industries. The focus on an R&D-intensive industry improves the internal validity of the study. As opposed to a cross-industry study, it reduces concerns that variation in industry-level factors could be driving the results. Also, the setting allows for the identification of input price shocks on firm investment by holding constant market demand and the investment-opportunity set.

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Appendix A. Sample selection

This appendix describes the sampling procedure to identify firms that were adversely affected by the shock. I create two samples of firms that faced supply-chain disruptions. The first (sample 1) is based on a text search of financial statements of firms in the high-technology manufacturing industry for the years 1999 to 2001, with the words "Taiwan" and "Earthquake" within 10 words of each other. The second (sample 2) contains firms in the bottom two quintiles of one-day abnormal returns on the day of the earthquake. All firms in sample 2 have negative abnormal returns. Sample 1 is a subset of sample 2, except in cases where data on market returns were not available. A description of the three-digit SIC codes of firms included in the sample is given below. These industries are a subset of industry number 6 (computers, software, and electronic equipment) in the Fama-French 12 industry classification.

SIC Code	**Description**	**Sample 1**	**Sample 2**
357	Computer and Office Equipment	12	59
366	Communications Equipment	8	57
367	Electronic Components and Accessories	50	87
381	Search, Detection, Navigation, Guidance, Aeronautical, and Nautical Systems, Instruments, and Equipment	1	2
382	Laboratory Apparatus And Analytical, Optical, Measuring, and Controlling Instruments	1	30
	Total Number of Firms	**72**	**235**

Appendix B. Variable Definitions

Variable	Definition
$ACC\_PAYABLE$	Trade obligations due within one year scaled by beginning assets
$ACQUISITION$	Acquisition related cash outflows (funds used for and costs related to acquisitions) scaled by beginning assets
AQI	Change in intangibles, divided by average total assets over the fiscal year. Current assets set to 0 if missing.
$CAPEX$	Cash flow related to capital expenditures scaled by beginning assets
$CASH$	Cash and short-term marketable securities, scaled by beginning assets
$CVEMP$	Coefficient of variation of the number of employees, 5-year rolling average; missing values set to industry average
EMP	Number of employees
ΔEMP	Percentage change in the number of employees less percentage change in assets
$INTC$	Categorical variable based on interest coverage ($INTC$). level $= INTC1$ if $INTC >= 2$; $INTC2$ if $0 < INTC < 2$; $INTC3$ if $INTC <= 0$
$INVENTORY$	Total inventory (raw materials, work-in-progress, and finished goods) scaled by beginning assets
LEV	Debt in current liabilities plus total long-term debt scaled by beginning assets
$MARGIN$	Net income scaled by revenue
MTB	Market value of equity divided by book value of equity
$NETDEBT$	Debt issuance less debt retirement scaled by beginning assets
$NETEQUITY$	Equity sales less equity purchases scaled by beginning assets

Variable	Definition
RD	Research and development expense scaled by beginning assets
RET	12-month buy-and-hold return for the fiscal year
ROA	Net Income scaled by beginning assets
$\Delta SALE$	Percentage growth in sales
SGA	Selling, general, and administrative expense scaled by beginning assets
$SIZE$	Natural log of total beginning assets
$STDRET$	Standard deviation of monthly returns for the fiscal year
$TANGI$	Asset tangibility, net property, plant and equipment scaled by lagged assets

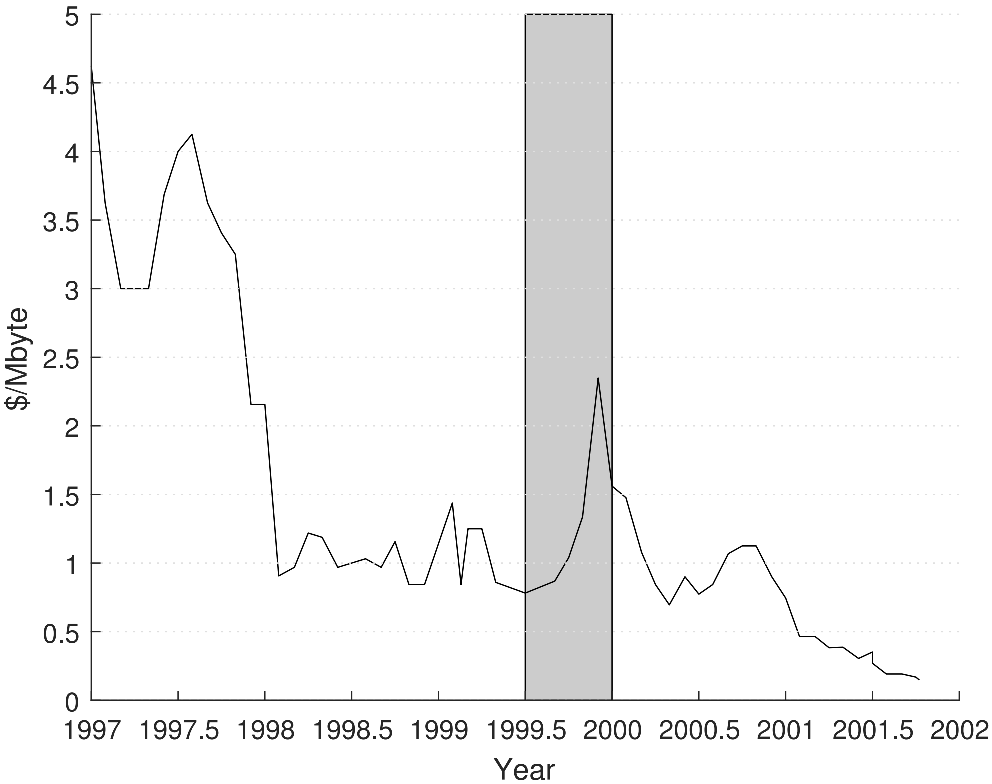
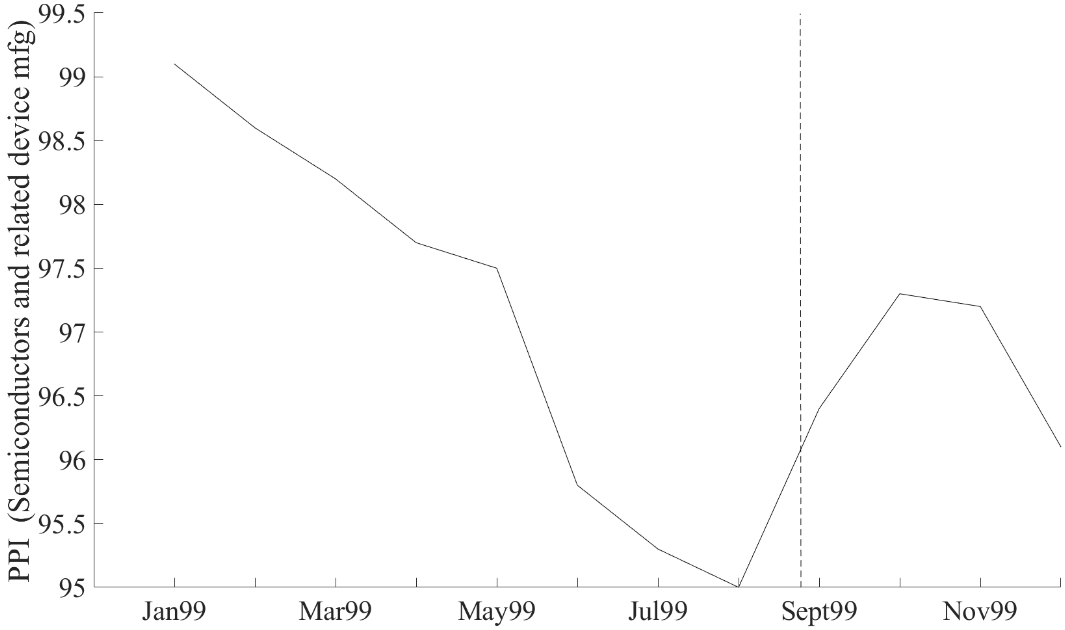
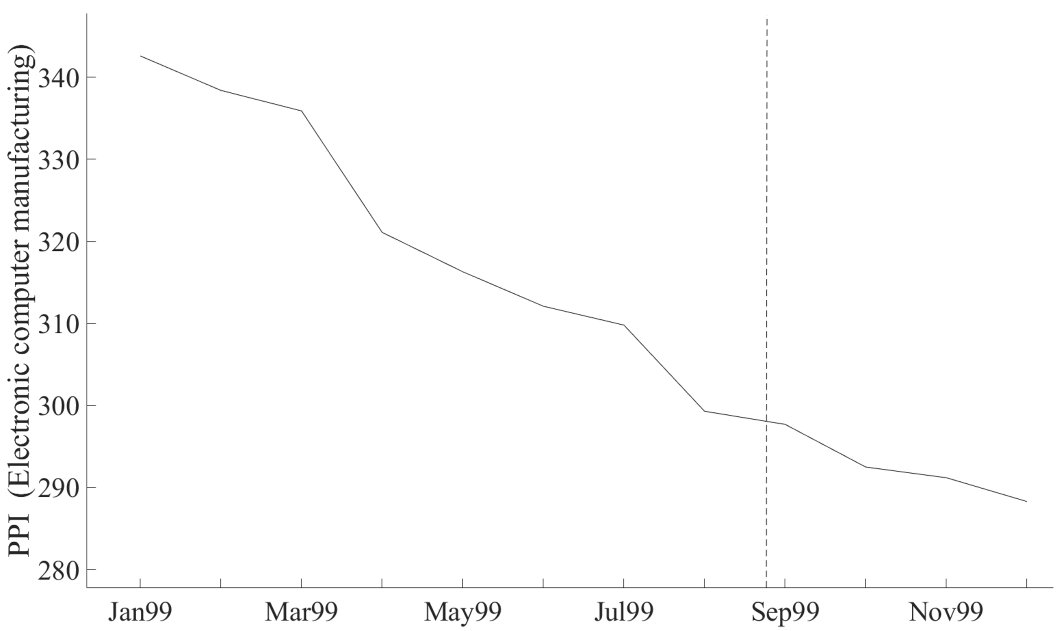


Figure 1: Memory prices (1997 to 2001)

This figure presents the evolution of the price (in US dollars) of a megabyte of memory from the years 1997 to 2001. The shaded region highlights the price rise after the 1999 earthquake in Taiwan. Prices are sourced from http://www.jcmit.net/memoryprice.htm.



(a) PPI for semiconductors and related device manufacturing



(b) PPI for computer manufacturing

Figure 2: These figures show the producer price index (PPI) for semiconductor and computer manufacturers. The indices are sourced from the Bureau of Labor Statistics.

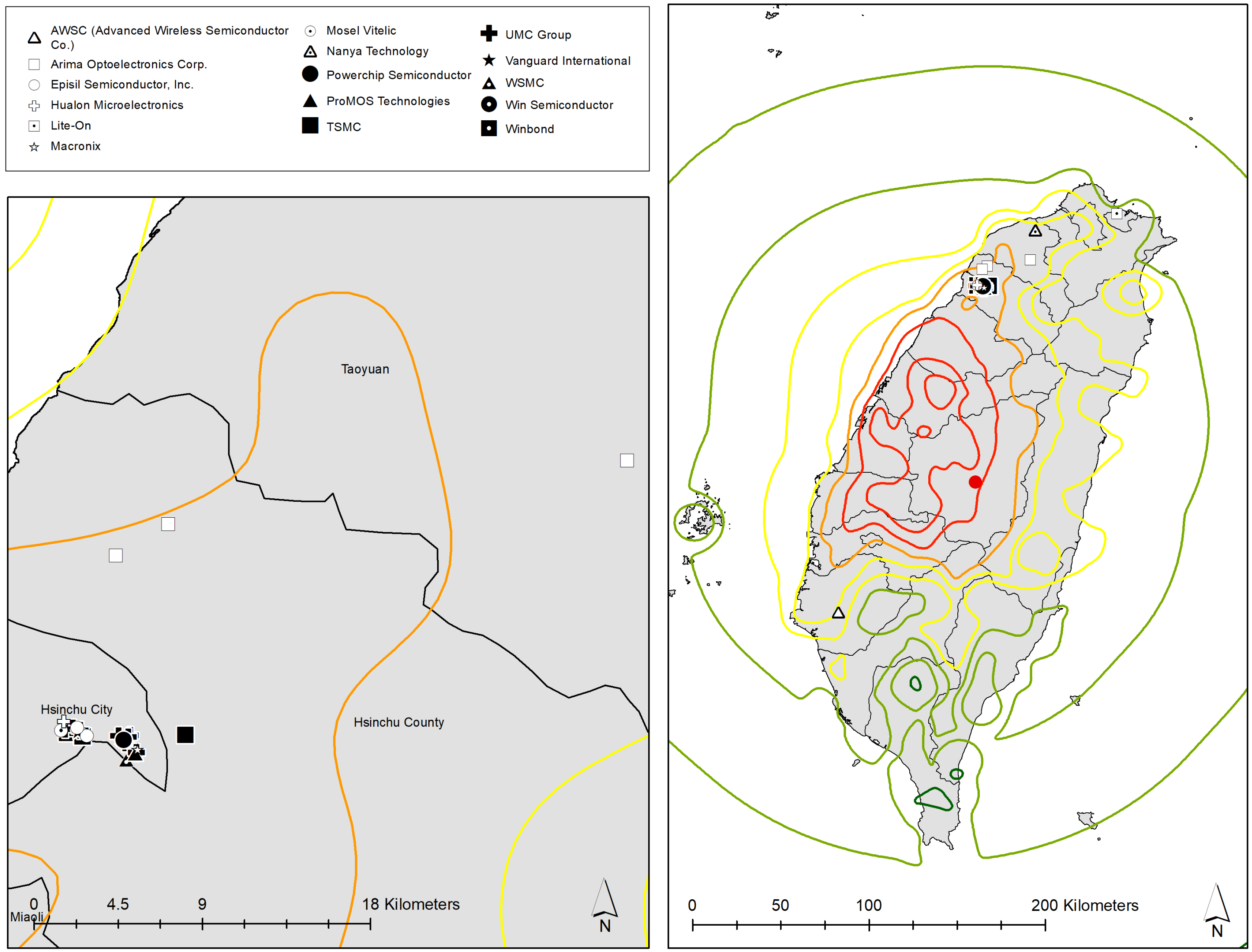
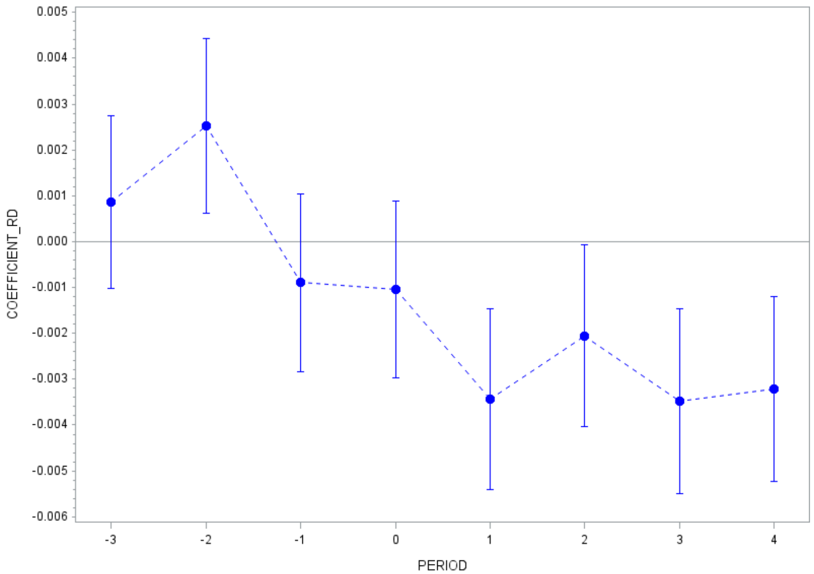
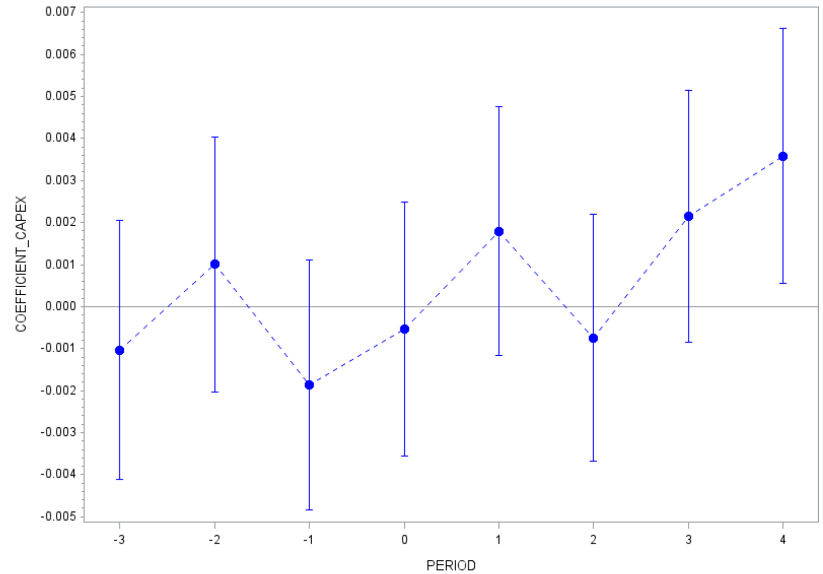


Figure 3: Map showing earthquake intensity and location of manufacturing plants

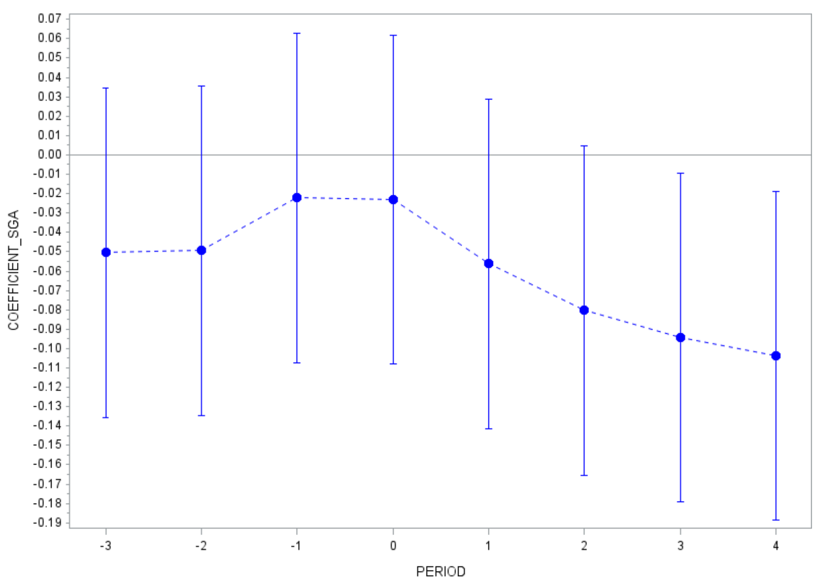
This figure shows location of semiconductor fabs and component manufacturers, as of 1998-99, relative to earthquake intensity, based on the Modified Mercalli Intensity Scale (https://earthquake.usgs.gov/learn/topics/mercalli.php). Location data were compiled from company annual reports, Dataquest, SEMI, and company websites.



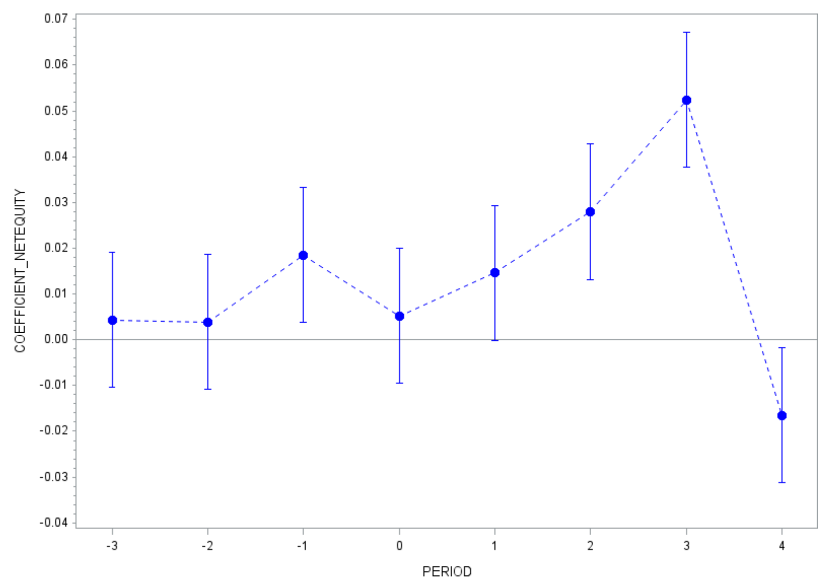
(a) Pre-trends analysis for *R&D*



(b) Pre-trends analysis for *CAPEX*



(c) Pre-trends analysis for *SG&A*



(d) Pre-trends analysis for *NETEQUITY*

Figure 4: Figures showing pretrends analysis for dependent variables

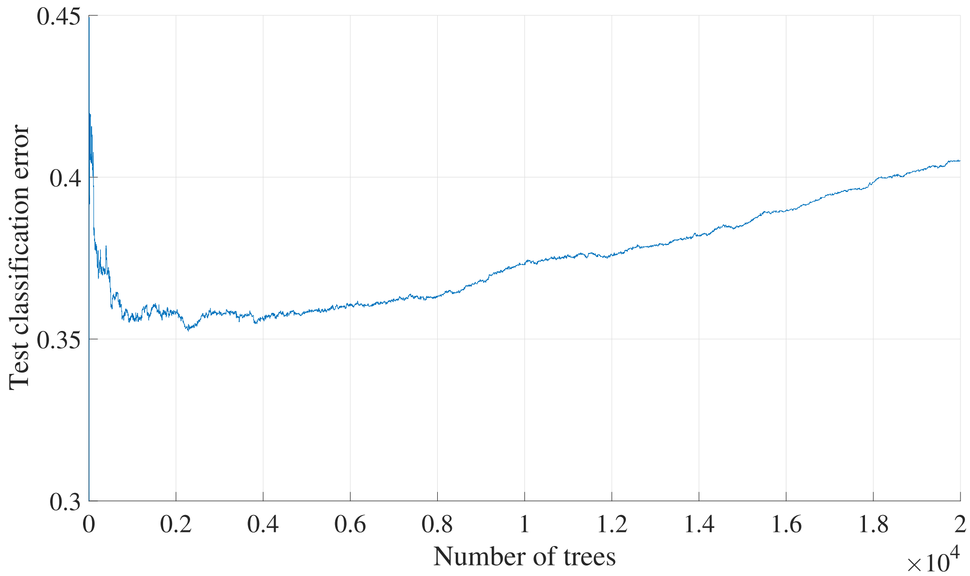


Figure 5: Classification error as a function of number of trees

This figure plots test classification error as a function of successive trees grown using boosting, where each successive tree predicts residuals from the preceding tree. Classification error represents the fraction of observations that are not correctly classified by the model.

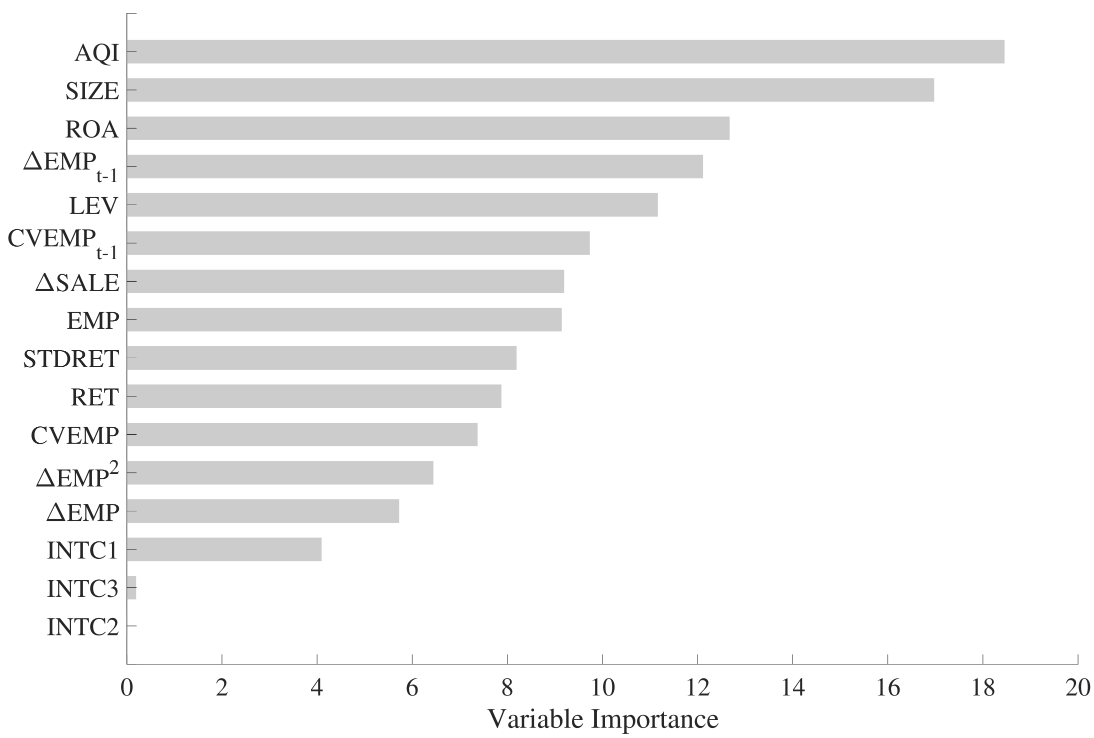


Figure 6: Plot showing importance of variables

This figure presents estimates of predictor importance, where 0 represents the smallest possible value of importance. The measure is computed by summing changes in the mean squared error due to splits on every predictor and dividing the sum by the number of branch nodes.

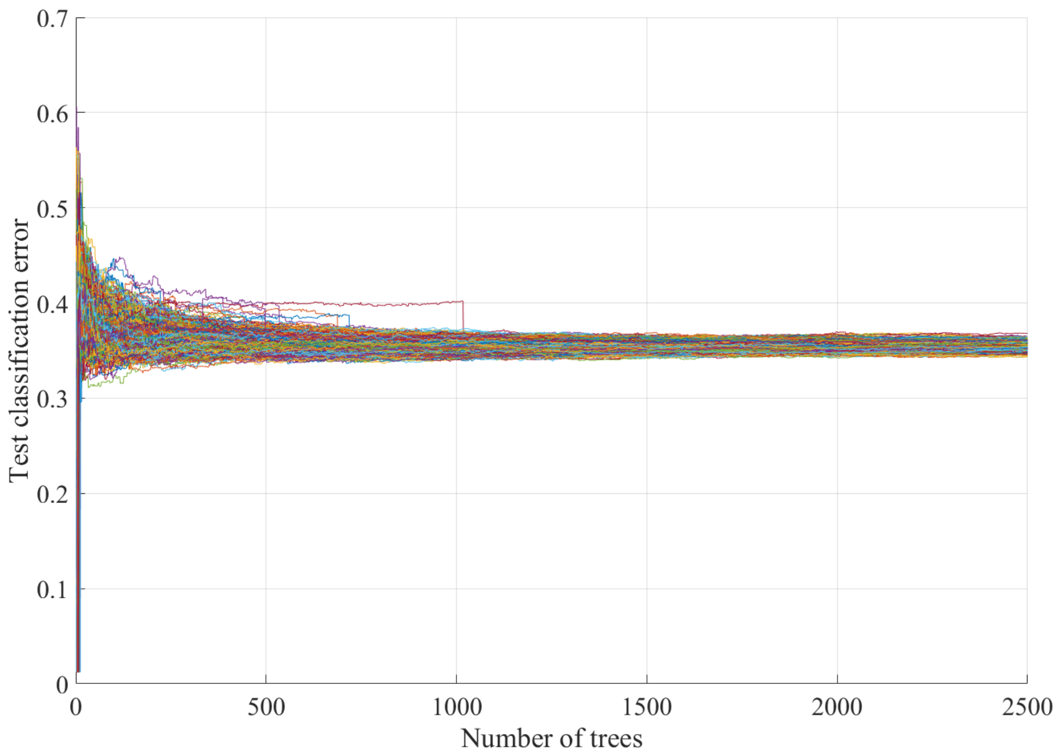


Figure 7: Classification error as a function of number of trees for 1,000 iterations

This figure plots test classification error as a function of 2,500 successive trees grown using boosting, for 1,000 iterations. Each iteration involves randomly undersampling from the majority class and fitting a predictive model. Classification error represents the fraction of observations that are not correctly classified by the model.

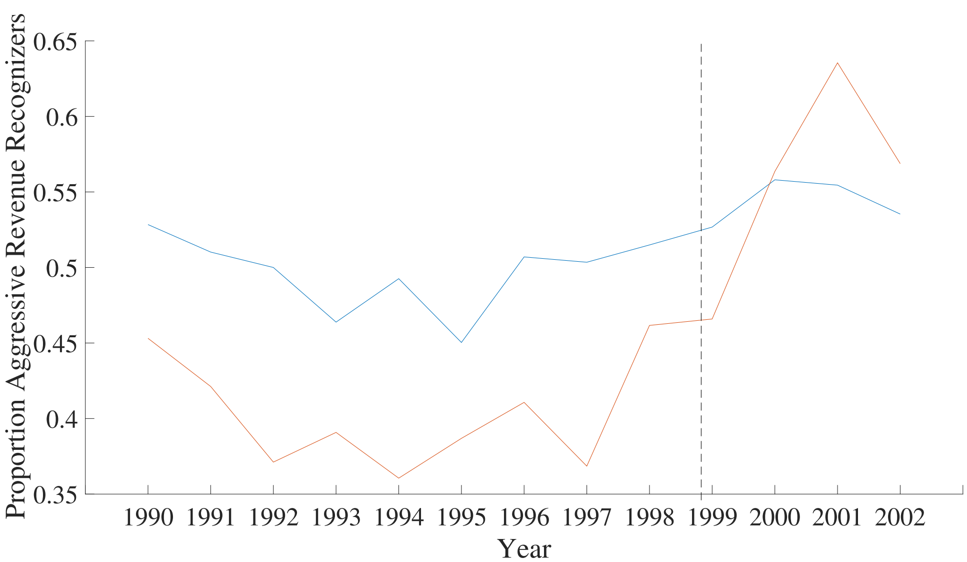


Figure 8: Proportion of aggressive revenue recognizers by treated and control groups

This figure plots the fraction of aggressive revenue recognizers flagged by a decision-tree-based predictive model, by year. The red and blue lines represent the treated and control groups.

Table 1: Semiconductor imports by the United States, by source location

This table shows semiconductor imports, in number of units, by the United States in the years 1998 and 1999. The data are sourced from the UN Comtrade database, and are for the commodity code 8542 (Electronic integrated circuits and microassemblies).

Panel A: Semiconductor imports by the US

	Number of units (In millions)		**Share of total**		**Share of change**
	1998	**1999**	**1998**	**1999**	**1998-99**
Malaysia	3,620	4,788	22.1%	24.7%	38%
Japan	2,366	2,945	14.5%	15.2%	19%
Taiwan	2,193	2,343	13.4%	12.1%	5%
Philippines	2,175	2,616	13.3%	13.5%	15%
South Korea	1,476	1,690	9.0%	8.7%	7%
Rest of the world	4,524	5,016	27.7%	25.9%	16%
Total Semiconductor Imports	**16,353**	**19,398**			

Panel B: Price per unit of semiconductor imports

	Price per unit (In USD)		**Percent change**
	1998	**1999**	**1998-99**
Malaysia	1.03	0.92	-11%
Japan	2.06	1.84	-11%
Taiwan	1.30	1.50	16%
Philippines	1.68	1.62	-4%
South Korea	3.51	3.88	11%
Rest of the world	2.13	1.91	-10%
Total Semiconductor Imports	**1.83**	**1.74**	**-5%**

Table 2: Descriptive statistics for firms in samples 1 and 2 in period before shock

This table reports descriptive statistics for the quarter before the shock. Columns (1) and (2) present descriptive data for sample 1 and sample 2, which include firms that were adversely affected by the shock. Sample 1 firms were identified using a text search of financial statements, whereas sample 2 firms were identified based on one-day abnormal returns. Column (3) presents descriptive data for firms that were not adversely affected by the shock. T-statistics are displayed in parentheses below the means. ***, **, and * represent significance at 1%, 5%, and 10%. See Appendix B for variable definitions.

	Firms adversely affected				**Firms not adversely affected**		**Difference in means**	
	Sample 1 (1)		**Sample 2 (2)**		**(3)**		**(2) - (1)**	**(3) - (2)**
Variables	**Mean**	**Std**	**Mean**	**Std**	**Mean**	**Std**		
ACQUISITION	0.016	0.10	0.006	0.03	0.005	0.02	-0.010 (-0.66)	-0.001 (-0.41)
ACC_PAYABLE	0.120	0.09	0.115	0.09	0.093	0.06	-0.005 (-0.33)	-0.023*** (-2.99)
CAPEX	0.015	0.01	0.017	0.02	0.013	0.01	0.002 (0.69)	-0.004*** (-2.94)
CASH	0.415	0.42	0.320	0.35	0.241	0.29	-0.095 (-1.33)	-0.079** (-2.48)
INVENTORY	0.123	0.10	0.163	0.11	0.201	0.11	0.039** (2.23)	0.038*** (3.49)
MARGIN	-0.079	0.37	-0.224	1.49	-0.077	0.44	-0.146 (-1.21)	0.147 (1.35)
NETDEBT	0.002	0.11	-0.001	0.04	-0.004	0.04	-0.003 (-0.15)	-0.003 (-0.89)
NETEQUITY	0.071	0.34	0.047	0.25	0.031	0.20	-0.024 (-0.43)	-0.017 (-0.74)
RD	0.045	0.04	0.038	0.04	0.026	0.02	-0.007 (-0.97)	-0.012*** (-3.55)
SIZE	5.357	1.75	4.669	1.69	4.241	1.53	-0.689** (-2.29)	-0.428*** (-2.66)
SGA	0.102	0.06	0.106	0.06	0.105	0.06	0.004 (0.32)	0.000 (-0.03)

Table 3: Univariate changes for firms adversely affected by the shock

This table reports means of changes in firm characteristics for treated firms four periods after the shock. Changes are calculated over the same quarter of the previous year. Sample 1 firms were identified using a text search of financial statements, whereas sample 2 firms were identified based on one-day abnormal returns. Data include years 1999 and 2000. T-statistics that test for a significant difference from zero are displayed in parentheses below the means. ***, **, and * represent significance at 1%, 5%, and 10%. See Appendix B for variable definitions.

	Sample 1 firms				**Sample 2 firms**			
Variables	**Period 1**	**Period 2**	**Period 3**	**Period 4**	**Period 1**	**Period 2**	**Period 3**	**Period 4**
$\Delta ACQUISITION$	-0.006	0.000	0.001	0.001	-0.004	0.002	0.000	0.000
	(-0.82)	(0.45)	(0.87)	(1.37)	(-1.06)	(0.73)	(0.09)	(0.14)
$\Delta ACC\_PAYABLE$	0.025***	0.009	-0.002	-0.024***	0.014***	0.007**	0.003	-0.014***
	(2.59)	(1.04)	(-0.23)	(-2.83)	(3.32)	(1.96)	(0.66)	(-2.82)
$\Delta CAPEX$	0.005**	0.003	-0.001	0.002	0.001	0.004***	0.000	0.000
	(2.07)	(0.70)	(-0.53)	(0.96)	(0.54)	(2.68)	(0.26)	(0.19)
$\Delta CASH$	-0.007	0.079*	0.162**	0.029	0.047***	0.059***	0.105***	0.053***
	(-0.28)	(1.79)	(2.02)	(0.72)	(3.32)	(3.92)	(4.06)	(3.37)
$\Delta INVENTORY$	0.005	0.010	0.021	0.003	0.000	-0.005	-0.004	-0.007
	(0.56)	(1.66)	(1.53)	(0.26)	(-0.07)	(-1.10)	(-0.84)	(-1.29)
$\Delta MARGIN$	0.203**	0.266**	0.328**	0.149**	0.123***	0.139***	-0.052	-0.068
	(2.24)	(2.24)	(2.29)	(2.47)	(2.87)	(3.84)	(-0.47)	(-0.77)
$\Delta NETDEBT$	-0.001	-0.003	0.007	0.010	-0.004	0.003	0.004	0.008**
	(-0.24)	(-1.60)	(0.94)	(1.63)	(-1.22)	(1.05)	(1.19)	(2.41)
$\Delta NETEQUITY$	0.007***	0.059	0.121*	-0.003	0.045***	0.039***	0.061***	0.002***
	(3.65)	(1.28)	(1.84)	(-0.52)	(3.18)	(2.85)	(2.51)	(0.37)
ΔRD	0.001	0.003	-0.004	-0.014**	0.001	-0.001	-0.001	-0.009***
	(0.31)	(1.29)	(-0.83)	(-2.19)	(0.36)	(-0.87)	(-0.86)	(-3.50)
ΔSGA	0.005	0.005	-0.015	-0.027***	0.001	-0.004	-0.006*	-0.014***
	(1.12)	(1.00)	(-1.61)	(-3.51)	(0.24)	(-1.42)	(-1.90)	(-4.38)

Table 4: Univariate changes for firms that were not adversely affected by the shock

This table reports means of changes in firm characteristics for control firms four periods after the shock. Changes are calculated over the same quarter of the previous year. Data include years 1999 and 2000. T-statistics that test for a significant difference from zero are displayed in parentheses below the means. ***, **, and * represent significance at 1%, 5%, and 10%. See Appendix B for variable definitions.

Variables	**Period 1**	**Period 2**	**Period 3**	**Period 4**
$\Delta ACQUISITION$	-0.001	-0.003	0.001	-0.003
	(-0.21)	(-1.01)	(0.53)	(-1.33)
$\Delta ACC\_PAYABLE$	0.008**	0.005	0.006	0.003
	(2.00)	(1.25)	(1.33)	(0.67)
$\Delta CAPEX$	0.000	0.001	0.000	-0.001
	(-0.03)	(1.40)	(0.46)	(-0.60)
$\Delta CASH$	0.000	-0.002	0.043***	0.013
	(0.01)	(-0.21)	(2.69)	(0.73)
$\Delta INVENTORY$	-0.002	0.000	0.005	0.007
	(-0.54)	(-0.03)	(0.94)	(1.43)
$\Delta MARGIN$	0.086**	0.133**	0.010	0.000
	(2.37)	(2.22)	(0.42)	(0.00)
$\Delta NETDEBT$	0.001	-0.003	-0.004	-0.002
	(0.31)	(-1.06)	(-1.13)	(-0.60)
$\Delta NETEQUITY$	0.013*	0.020**	0.042***	0.016
	(1.88)	(1.95)	(3.29)	(1.19)
ΔRD	0.000	-0.001	0.001	0.000
	(-0.06)	(-0.47)	(0.62)	(0.00)
ΔSGA	0.007**	0.005*	0.000	-0.002
	(2.25)	(1.90)	(0.08)	(-0.80)

Table 5: Results of multi-variate analysis by using a firm as its own control

This table reports coefficients from a regression of net equity issued ($NETEQUITY$), capital expenditures ($CAPEX$), research and development expense (RD), and selling, general, and administrative expense (SGA) on period indicators and control variables, for firms adversely affected by the shock (sample 2 firms). $PERIOD_{t+n}$ represents n periods (quarters) after the shock. Data include years 1998 to 2001. Control variables include natural log of assets ($SIZE$), market-to-book ratio (MTB), return on assets (ROA), cash holdings ($CASH$), asset tangibility ($TANGI$), and R&D expenses (RD). Standard errors are clustered by firm. T-statistics are displayed in parentheses below the coefficients. ***, **, and * represent significance at 1%, 5%, and 10%. See Appendix B for variable definitions.

	NETEQUITY (1)	**CAPEX** (2)	**RD** (3)	**SGA** (4)
Intercept	0.026	0.005**	0.024***	0.140***
	(1.48)	(1.95)	(4.78)	(10.53)
$PERIOD_{t+1}$	0.008	-0.001	-0.005***	-0.005*
	(0.45)	(-0.45)	(-2.48)	(-1.75)
$PERIOD_{t+2}$	0.011	0.002	-0.006***	-0.006**
	(0.63)	(1.20)	(-3.04)	(-2.05)
$PERIOD_{t+3}$	0.099***	0.000	-0.004**	-0.008***
	(3.53)	(-0.12)	(-2.21)	(-2.77)
$PERIOD_{t+4}$	-0.009	0.001	-0.003	-0.010***
	(-0.65)	(0.94)	(-1.04)	(-2.57)
$SIZE$	-0.009***	0.002***	0.000	-0.011***
	(-3.59)	(3.72)	(-0.47)	(-4.90)
MTB	0.005***	0.001***	0.001***	0.001
	(5.20)	(3.11)	(2.78)	(0.99)
ROA	-0.380**	-0.001	-0.125***	-0.067
	(-2.01)	(-0.08)	(-5.86)	(-0.52)
$CASH$	0.092***	0.002	0.024***	0.003
	(3.27)	(0.56)	(3.39)	(0.20)
$TANGI$	0.024			
	(0.72)			
RD	-0.103			
	(-0.45)			
R^2	10.7%	6.0%	22.8%	8.9%
N	1861	1861	1861	1861

Table 6: Results for difference-in-differences analysis

This table reports coefficient estimates from a generalized difference-in-differences analysis. Dependent variables include net equity issued ($NETEQUITY$), capital expenditures ($CAPEX$), research and development expense (RD), and selling, general, and administrative expense (SGA). $TREAT$ is an indicator variable that takes a value of 1 for treated firms, and 0 for control firms. Treated firms were adversely affected by the shock (sample 2 firms). Control firms are those that were not adversely affected by the shock. Standard errors are clustered by firm. T-statistics are displayed in parentheses below the means. ***, **, and * represent significance at 1%, 5%, and 10%. See Appendix B for variable definitions.

	NETEQUITY (1)	**CAPEX (2)**	**RD (3)**	**SGA (4)**
$TREAT \times PERIOD_{t+1}$	0.005	0.000	-0.003	-0.004
	(0.19)	(-0.34)	(-1.26)	(-1.14)
$TREAT \times PERIOD_{t+2}$	0.012	0.003*	-0.004*	-0.008**
	(0.50)	(1.92)	(-1.88)	(-2.12)
$TREAT \times PERIOD_{t+3}$	0.058*	0.001	-0.002	-0.005
	(1.66)	(0.74)	(-0.89)	(-1.20)
$TREAT \times PERIOD_{t+4}$	-0.032	0.002	0.000	-0.005
	(-1.37)	(1.33)	(-0.04)	(-1.05)
Firm FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
R^2	23.7%	55.8%	66.4%	79.3%
N	3830	3830	3830	3830

Table 7: Tests for response of $R\&D$ to observable measures of financing constraints

This table reports coefficient estimates from a regression of R&D scaled by lagged assets, on period indicators and control variables, by sub-sample of terciles of the natural log of firm assets ($SIZE$), and a measure of financing constraints based on Hadlock and Pierce (2010). Standard errors are clustered by firm. T-statistics are displayed in parentheses below the means. ***, **, and * represent significance at 1%, 5%, and 10%.

Panel A: Sorting by *SIZE*

	N	R^2	Period 1	Period 2	Period 3	Period 4
Large firms	620	18.6%	-0.003	-0.005	-0.003	-0.004*
			(-1.26)	(-1.72)	(-1.10)	(-1.88)
Mid firms	615	6.6%	-0.002	-0.003	-0.004	0.001
			(-0.90)	(-1.08)	(-1.44)	(0.15)
Small firms	626	33.9%	-0.008*	-0.009**	-0.006	-0.003
			(-1.84)	(-2.18)	(-1.22)	(-0.62)

Panel B: Sorting by measure of financing constraints

	N	R^2	Period 1	Period 2	Period 3	Period 4
High constraints	561	40.4%	-0.005*	-0.007*	-0.006*	-0.002
			(-1.70)	(-1.78)	(-1.63)	(-0.39)
Mid constraints	569	15.3%	-0.004	-0.002	-0.003	-0.002
			(-0.95)	(-0.59)	(-0.64)	(-0.43)
Low Constraints	575	13.8%	-0.002	-0.003*	-0.001	-0.004**
			(-1.32)	(-1.68)	(-0.53)	(-2.12)

Table 8: Tests for response of $R\&D$ to product-market competition and bankruptcy risk

This table reports coefficient estimates from a regression of R&D scaled by lagged assets, on period indicators and control variables, by sub-sample of terciles of measures of competition and bankruptcy risk. Standard errors are clustered by firm. T-statistics are displayed in parentheses below the means. ***, **, and * represent significance at 1%, 5%, and 10%.

Panel A: Sorting by Herfindahl Index

	N	R^2	Period 1	Period 2	Period 3	Period 4
High index value	467	8.4%	-0.005*	-0.004	-0.001	-0.003
			(-1.86)	(-1.49)	(-0.26)	(-0.58)
Mid index value	685	32.6%	-0.004	-0.006*	-0.006	-0.005
			(-1.05)	(-1.79)	(-1.45)	(-1.55)
Low index value	709	27.3%	-0.005	-0.006*	-0.005*	0.001
			(-1.55)	(-1.92)	(-1.71)	(0.22)

Panel B: Sorting by correlation of firm with industry returns

	N	R^2	Period 1	Period 2	Period 3	Period 4
High correlation	499	39.4%	-0.001	-0.002	-0.004	-0.006*
			(-0.55)	(-0.55)	(-1.42)	(-1.79)
Mid correlation	513	19.6%	-0.003	-0.002	0.000	0.007
			(-1.14)	(-0.73)	(-0.13)	(1.28)
Low correlation	505	13.3%	-0.010**	-0.010**	-0.009**	-0.009**
			(-2.42)	(-2.39)	(-2.18)	(-2.42)

Panel C: Sorting by measure of bankruptcy risk (Altman-Z score)

	N	R^2	Period 1	Period 2	Period 3	Period 4
High bankruptcy risk	1184	17.7%	-0.006	-0.006	−0.009*	-0.003
			(-0.76)	(-0.97)	(-1.92)	(-0.52)
Mid bankruptcy risk	1185	28.4%	0.006	0.004*	-0.003	0.004
			(1.10)	(1.92)	(-0.91)	(1.42)
Low bankruptcy risk	1185	20.2%	-0.002	-0.012**	-0.005	-0.008**
			(-0.43)	(-2.36)	(-1.07)	(-2.18)

Table 9: Estimates from logistic regression

This table presents parameter estimates from a logistic regression of income-decreasing restatements on explanatory variables. All explanatory variables are measured in period $t-1$ to predict restatements in t. See Appendix B for variable definitions.

Variables	**Estimate**	**Chi-sq**	**pvalue**
Intercept	-5.629***	82.29	<.0001
LEV	-1.357	1.88	0.171
AQI	-0.187	0.05	0.831
$SIZE$	0.203**	5.24	0.022
$\Delta SALE$	0.008	2.05	0.152
ROA	-0.439***	6.40	0.011
$INTC1$	0.632*	3.28	0.070
$INTC2$	0.090	0.01	0.920
$INTC3$	-0.170	0.10	0.753
RET	-0.307**	3.73	0.054
$STDRET$	3.889***	14.58	0.000
ΔEMP	0.003	0.22	0.637
ΔEMP_{t-1}	0.002**	4.98	0.026
$CVEMP$	-1.329	0.68	0.410
$CVEMP_{t-1}$	-1.163	0.73	0.394
EMP	-0.008	1.13	0.287
ΔEMP^2	0.000	0.04	0.845
Pseudo R^2	5.80%		
Likelihood Ratio	29.54		0.021
Percent Concordant	68		
Percent Discordant	32		
Percent Tied	0		
N	7248		

Table 10: Confusion matrix

This table presents the confusion matrix for out-of-sample predictions from a logistic regression model, and a decision tree based model. Sensitivity refers to the percentage of true restaters that are classified as such by the models. Specificity is the percentage of non-restaters that are correctly identified. Error rate refers to the total number of observations that are incorrectly classified.

		Logistic Model		**Decision Trees**	
		True class		**True class**	
		0	**1**	**0**	**1**
Predicted class	**0**	4573	50	4619	44
	1	2586	39	2540	45
Sensitivity			44%		51%
Specificity			64%		65%
Error rate			36%		36%