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Three Essays in Empirical Finance

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of the requirements for the degree
Doctor of Philosophy in Management

by

Chady Emile Gemayel

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ABSTRACT OF THE DISSERTATION

Three Essays in Empirical Finance

by

Chady Emile Gemayel

Doctor of Philosophy in Management

University of California, Los Angeles, 2019

Professor Mark J. Garmaise, Chair

In the first chapter of this dissertation, I show that firms strategically liquidate their growth options and reputational capital after loan covenant violations. Loan covenant violations increase creditors' relative bargaining power, shifting control rights towards debt holders. I use Amazon product metadata and product reviews in an event study framework to identify changes firms make to their product strategies after these violations. In the two quarters after new loan covenant violations, firms decrease both their product portfolio size and their product quality. I use product review text to show that firms actively reduce product quality by increasing the rate of product failure. These changes increase short-term cashflows, consistent with firms' decisions aligning with creditors' incentives. Violating firms apply these changes strategically within their product portfolios. After covenant violations, firms cull the set of products sold in product markets with more competitors and lower the quality of their less popular products. These strategic decisions reduce the long-term costs of changing product quality and product portfolio size.

In the second chapter of this dissertation (with Nimesh Patel), we find that domestic firms invest in their reputational capital in response to increases in international competition. Specifically, American firms increase the quality of their products after positive Chinese import competition shocks. We determine that this is an active decision by identifying product level changes, finding significant reductions in the rate of product failures for domestic firms.

Firms build reputational capital by increasing product quality, allowing them to differentiate their products from those of their competitors. We find that product portfolio size attenuates our results, consistent with less diversified firms having greater incentive to differentiate their products.

In the third chapter of this dissertation, I study the effects of initial public offerings on product quality. Public firms, unlike private firms, are required to regularly disclose financial and business information. The relative lack of information on private firms that results from this regulatory difference makes quantifying how firms change as a result of going public difficult. I use Amazon product data spanning both private and public firms in an event study framework to identify a decrease in product quality after firms complete their initial public offerings. I find that the decrease in product quality after firms go public is driven by an increase in both the rate of negative brand recognition and the rate of negative customer service experiences.

The dissertation of Chady Emile Gemayel is approved.

Simon Adrian Board

William Giles Mann

Ivo I. Welch

Mark J. Garmaise, Committee Chair

University of California, Los Angeles

2019

To my parents, my family, my friends, and Alice.

Thank you for your love, your support, and your patience.

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CHAPTER 1

Creditor Control Rights and Product Strategy

Differences between equity holders and debt holders are a fundamental source of friction for firms. The structure of loan contracts causes both the payoff structures and investment horizons of these stakeholders to diverge and influences what each party perceives to be optimal firm actions. While equity holders typically retain residual control rights, loan contracts often include covenants which, if violated, allow for the control rights of solvent firms to shift towards creditors. These shifts in control rights result in many firm level changes. What these changes mean for firms and their stakeholders is not always apparent. In this research, I identify strategic decisions made by firms after their control rights shift towards creditors and quantify how these decisions impact firm outcomes.

After solvent firms experience a shift in control rights towards creditors, I find that they are more willing to liquidate their reputational capital and growth options. I identify these channels using changes in firms' product strategies after loan covenant violations. Specifically, I use Amazon product data in an event study framework and find decreases in violating firms' average product quality and product portfolio size. I also show that firms apply these changes strategically, reducing the number of products in their more competitive product markets and lowering the quality of their less popular products. After loan covenant violations, firms' product strategy decisions better align with creditors' incentives, increasing short-term performance at the cost of future performance.

I quantify firms' product strategies using Amazon product metadata and Amazon product reviews. This data allows me to identify differences over time in both the quality of individual products and the set of products available. Many papers that consider the relationship between product reputation and firms assume a transparent and uniform link between the two (e.g. Titman (1984) and Maksimovic and Titman (1991)). My evidence, however, suggests that the relationship between firms and their products is more nuanced. Firms often have multiple brands with different levels of product quality. Brands can be further segmented by convoluted firm-subsidiary structures, which make identifying the parent company of particular products or brands challenging for consumers. Segmentation helps insulate the reputations of brands from both the reputations of their parent companies and the reputations of other brands that are held by the same firms. This segmentation of brands and products gives firms the option to reduce the quality of their products and the reputation of their brands strategically, which my data allow me to observe.

To study how loan covenant violations affect firms' product strategies, I link Amazon data to DealScan syndicated loan data. This data allow me to observe firms' financial covenants, which set thresholds on observable accounting or financial measures. Crossing any of these thresholds triggers technical default, which gives creditors the option to accelerate repayment of their loans. This threat increases creditors' bargaining power, effectively transferring control rights towards creditors (e.g. Chava and Roberts (2008)). I quantify the effect of loan covenant violations on firms' product strategies by using an event study specification on the two quarters before and the two quarters after new violations. I ensure that the first-order difference between violating firms and non-violating firms is the shift in control rights towards creditors by limiting my sample to firms that are near their violation thresholds. Product level data allow me to select firms that are direct competitors; I only include Amazon product categories common to both violating and non-violating firms.

I find that firms liquidate reputational capital after violating loan covenants by actively decreasing product quality. The average rating of firms' existing products decreases by 3% after a violation. Several channels may cause this decline in product quality. I distinguish among them by utilizing the written reviews of each product. I identify key phrases in reviews that correspond to different aspects of product quality and find an increase in the rate of product failure after loan covenant violations. The increase in product failure rate indicates an active decision by firms to decrease product quality, which reduces costs and allows for a short-term increase in cashflows. As highlighted by Maksimovic and Titman

(1991), customers will not be willing to pay the same premiums for products after identifying a decrease in product quality. Hence, by actively decreasing product quality, violating firms shift cashflows forward.

After loan covenant violations, I show that firms liquidate their growth options, reducing both the size of their product portfolios and the number of product introductions. New products require time and investment to develop, manufacture, and advertise. Throughout this process, firms have the option to discontinue their products. Existing products extend this problem, as firms evaluate future demand versus costs. In levered firms, the payoffs to each stakeholder are such that equity holders have incentives to exercise options that do not benefit debt holders. By not exercising these growth options to the same extent after covenant violations, firms increase short-term cashflows and reduce cashflow volatility.

I show that violating firms reduce product quality and product portfolio size strategically. Post-violation, firms concentrate the culling of both their product portfolios and their product introductions in their more competitive product markets. The decrease in average product quality after violations is also not uniform, as only firms' less popular products see significant declines in quality. These strategic choices liquidate firms' less valuable growth options and mitigate the loss of reputational capital.

After loan covenant violations, I find evidence of a decrease in sales volume for existing products. I first establish that review volume predicts sales rank, a proxy for sales volume. I then show that review volume declines after loan covenant violations. This result is consistent with Nini, Smith, and Sufi (2012), who show that firm level sales growth decreases in the year after new loan covenant violations. The observed decline in review volume is small, which suggests that customers do not immediately identify changes to product quality.

My research makes several contributions to the literature. I add to the literature relating product quality and financing frictions. Titman (1984) and Maksimovic and Titman (1991) build theoretical frameworks to understand the relation between firms in financial distress and their customers. Phillips and Sertsios (2013) show that airline on-time performance and mishandled baggage rate suffer in financial distress, but improve in bankruptcy. I show that when solvent firms make decisions better aligned with creditors' incentives, product quality decreases. Kini, Shenoy, and Subramaniam (2017) find that after a negative cashflow shock, higher leverage is correlated with federal product recalls. I observe a higher rate of product defects after covenant violations, however I do not have any evidence that these changes would lead to product recalls. My results add to the literature exploring the role of firm reputation and customers (e.g. Rogerson (1983), Wernerfelt (1988) and Choi (1998)), and build on the use of product reviews to understand firm level changes (e.g. Tirunillai and Tellis (2012), Sheen (2014), Huang (2018)). I also contribute to the literature on how firms respond to loan covenant violations (e.g. Chava and Roberts (2008), Roberts and Sufi (2009), Nini, Smith, and Sufi (2009), Nini, Smith, and Sufi (2012), Falato and Liang (2016), and D. Ferreira, M. A. Ferreira, and Mariano (2018)).

This chapter proceeds as follows. In Section 1.1, I describe my data. I define my empirical methodology in Section 1.2. Section 1.3 presents my results and Section 1.4 concludes.

1.1 Data

My sample data begins with Amazon product metadata and reviews. I use available metadata to identify the CRSP firm that owns each product. Quarterly firm level characteristics are from Compustat, and stock returns are from CRSP. I obtain syndicated loan data from DealScan.

1.1.1 Amazon

Amazon data was kindly provided by Julian McAuley. The dataset, as used in He and J. McAuley (2016) and J. J. McAuley et al. (2015), contains Amazon reviews and product metadata from 1996 to 2014 for 9.4 million products. Each Amazon product has a unique identifier, the ASIN (Amazon Standard Identification Number), and product metadata collected at the end of the sample. The product metadata includes the product's brand, the product category it is listed under, and its sales rank within that product category. Products are classified into one of 31 product categories, which span the set of products available on

Amazon.[1] Within each product category, products are given a sales rank. Amazon does not clearly define how sales ranks are determined, but states that lower rankings are a "good indicator" that products have higher sales (Amazon (2018a)). Along with product meta-data, I have every Amazon review of these products. Each review is time-stamped, has a written review, and a numerical product rating of 1, 2, 3, 4, or 5. Amazon does not provide guidelines to reviewers regarding what each numerical rating is meant to signify. For the written review, Amazon provides the prompt "What did you like or dislike? What did you use this product for?" (Amazon (2018b)).

Matching Amazon products to CRSP firms requires several intermediate steps. At each point in time, I link Amazon product brands to valid trademarks using data from the United States Patent and Trademark Office. I link trademarks owned by corporations to Corp-Watch's firm parent-subsidiary dataset and match the ultimate parent companies to CRSP. To ensure match quality, I only keep exact matches. I also only keep matches that uniquely link, at any point in time, one firm to each brand. This procedure allows me to observe if and when a brand moves from one firm to another. I discuss my matching methodology in more detail in Section 1.5.

For each firm-year-quarter, I define several product level and product category-brand level measures. I define each product's average rating as the average numerical rating in that quarter (every review is required to have a numerical rating). I also count the number of reviews left for each product that quarter. Each Amazon product is listed in a single product category and is sold under a single brand. I define product category-brand measures to identify variation both within and across brands and product categories. One limitation of this dataset is that I am not able to see when products are first listed on Amazon and if they are unavailable at any time before the end of my sample. Due to this limitation, I define the number of products as the number of products with at least one review in that

[1]Data includes products in the following product categories: Books, Software, Video Games, Cell Phones & Accessories, Grocery & Gourmet Food, Electronics, Toys & Games, Automotive, Health & Personal Care, Music, Magazines, Pet Supplies, Camera & Photo, Sports & Outdoors, Kitchen & Dining, Musical Instruments, Shoes, Home & Kitchen, Jewelry, Clothing, Beauty, Office Products, Industrial & Scientific, Computers & Accessories, Patio, Lawn & Garden, Arts, Crafts & Sewing, Home Improvement, Movies & TV, Watches, Gift Cards Store, Baby, Appliances, Prime Pantry.

quarter, and the number of new products as the number of products whose first review is posted in the same quarter.

1.1.2 DealScan

Syndicated loan data is from Thomson Reuters' DealScan dataset. I merge it with Compustat using Michael Roberts' linking table (Chava and Roberts (2008)). For each firm-year-quarter, I identify all loans that might be active.[2] I limit the sample to firm-year-quarters that have an active loan with at least one covenant on firms' debt-to-EBITDA ratio, leverage ratio, debt-service coverage, debt-to-tangible-net-worth, current ratio, or debt-to-equity ratio. Covenants based on debt-to-EBITDA ratios, leverage ratios, debt-to-tangible-net-worth, and debt-to-equity ratios define a maximum threshold that those measures can reach before violating the corresponding covenants. Covenants based on debt-service coverage and the current ratios define a minimum threshold that those measures can meet before violating the corresponding covenants. Firms can have multiple loan covenants active in any year-quarter as well as multiple loan covenants based on the same underlying measure.

I use Compustat quarterly data to define the relevant underlying measures. For financial covenants based on debt-to-EBITDA ratios, leverage ratios, debt-to-tangible-net-worth, or debt-to-equity ratios, if the underlying financial measures exceed covenant thresholds, I define the covenants as being in violation. For financial covenants based on debt-service coverage or the current ratios, I define the covenants as being in violation when the underlying financial measures are below their corresponding thresholds. Full definitions of the financial measures used are included in Table 1.13.

I define a firm's distance to violation $D_{i,t}$, at the quarterly level, as the minimum scaled distance between the covenant threshold and its corresponding financial ratio:

$$D_{it} = \min_{j} \tilde{D}_{itj}, \tag{1.1}$$

[2] I define a loan as active if its facility start date is before the Compustat quarter end date and its facility end date us after the Compustat quarter end date.

where

$$\tilde{D}_{itj} = \min_z \begin{cases} \frac{T_{itjz}-C_{itj}}{T_{itjz}}, & \text{if threshold a maximum} \\ \frac{C_{itj}-T_{itjz}}{T_{itjz}}, & \text{if threshold a minimum} \end{cases} \tag{1.2}$$

and i and t denote firm and year-quarter, respectively, j denotes covenant type, z denotes an active loan, C_{itj} is the value of the relevant covenant ratio, and T_{itjz} is the threshold ratio defined in the covenant. The firm is defined as being in violation of their loan covenants if the minimum distance $D_{i,t}$ is negative. This method of identifying covenant violations was first introduced by Chava and Roberts (2008) and has been subsequently used by others, including Falato and Liang (2016) and D. Ferreira, M. A. Ferreira, and Mariano (2018).

It is important to note a limitation of this approach. While I will refer to negative proximities to violation as covenant violations, I do not observe whether firms actually violated loan covenants. Firms are required to report if they violated a covenant in their 10-Q and 10-K filings. However, firms are not required to report which covenants were violated and are not required to report covenants that they have not violated. I use inferred violations in my specifications, as the ability to define a distance to violation at a quarterly level and identify firms near their violation thresholds is required for my empirical approach.

There are several sources of measurement error to understand when using inferred covenant violations to proxy for actual covenant violations. One limitation of using DealScan data is the inability to adjust for loan contract renegotiations. Denis and Wang (2014) find that creditors use contract renegotiations to exert control rights dynamically. In their sample, 50% of loans with renegotiated covenants would have been in violation with the original terms. Roberts (2015) shows that loan contract renegotiations are frequent, and while the most common change is to the covenant package, renegotiations also target other terms of the loan, including maturity. Creditors also have the option to waive covenant violations; Chen and Wei (1993) find that 44% of the covenant violations in their sample were waived. As D. Ferreira, M. A. Ferreira, and Mariano (2018) discuss, the definitions of the financial measures used in financial covenants may vary across loan agreements. Many of these differences should bias the effect of inferred covenant violations towards zero, as some of the inferred covenant violations were likely not realized. It is unlikely that any of these sources of measurement error would bias my results towards the findings in this chapter. Importantly, as noted by Roberts (2015), the renegotiation of loans before implied covenant violations likely cause shifts in control rights similar to actual covenant violations, though they are less easily observed to outside parties.

1.1.3 External Validity

To what extent my results can be generalized is important to consider. Amazon is the largest online retailer but has a relatively small share of the overall retail market (Thomas (2018)). The set of products that firms sell on Amazon does not necessarily reflect their full portfolios, as Amazon historically focused on consumer products. In addition, I only consider public companies with loan data in DealScan. The coverage of DealScan's dataset, while significant, is not complete. From 1996 to 2014, I find 29% of firm-years in Compustat have at least one credit facility in DealScan, and 17% have at least one financial covenant active.

1.2 Empirical Approach

The objective of my empirical design is to identify the effects of loan covenant violations on firms' product strategies. The empirical challenge when using covenant violations is that financial covenants are directly linked to various measures of firms' financial health. The ideal experiment would have identical firms randomly assigned loan covenant violations so that the only difference between them would be the shifts in control rights that occur after violations.

My empirical design aims to isolate the effects of the shift in control rights associated with loan covenant violations on firms' products and product portfolios. To do so, I take steps to address both firm heterogeneity and product portfolio heterogeneity, by selecting firms that are similar outside of their covenant violations. I only consider firms with active loan covenants that have at least one financial covenant with a threshold based on the firm's debt-to-EBITDA ratio, leverage ratio, debt-service coverage, debt-to-tangible-net-worth, current ratio, or debt-to-equity ratio. For each event year-quarter τ, I select firms that have not had covenant violations in the past two quarters ($D_{i,\tau-2} > 0$ and $D_{i,\tau-1} > 0$) and that have a minimum distance to violation at the event year-quarter $D_{i,\tau}$ whose absolute value (the window) is less than a certain value. These selection criteria are chosen so that the first-order difference between firms is whether or not they violated loan covenants during the event year-quarter. I only consider new covenant violations to avoid including firms with repeated covenant violations, which may be indicative of worsening financial health.

Each parametric specification is tested across a range of windows, from $|D_{i,\tau}| \leq 0.3$ to $|D_{i,\tau}| \leq 0.7$. The set of firms in the 0.3 window ($|D_{i,\tau}| \leq 0.3$) are a subset of the set of firms in the 0.4 window ($|D_{i,\tau}| \leq 0.4$). All specifications include firm level controls, including all underlying measures used to calculate inferred covenant violations and the distance to violation itself. A list of controls and their definitions is included in Table 1.13. I include firm fixed effects to account for time-invariant firm level characteristics. I only include products and their respective firms when their product categories exist in both violating firms and non-violating firms. To address seasonal and time-varying trends across different product categories, I include product category-year-quarter fixed effects.

I utilize an event study framework so that I can contrast the pre-event trend with the post-event trend. For each event year-quarter, I include the two quarters before the event year-quarter and the two quarters after the event year-quarter. I drop the event year-quarter as the timing of loan covenant violations is not well-defined. Covenant violations can occur any time from the end of the prior quarter to the end of the event year-quarter. My product (product portfolio) results use the product level (product category-brand level) event study specification

$$\begin{aligned} y_{i,j,k,t,\tau} = \beta \times \mathbb{1}\left(t > \tau\right) \times \mathbb{1}\left(D_{i,\tau} < 0\right) + \Omega \times \mathbb{1}\left(t > \tau\right) + \Psi \times \mathbb{1}\left(D_{i,\tau} < 0\right) + \lambda_{\tau} \\ + \kappa \times X_{i,t} + \alpha_k + \delta_{j,t} + \gamma_i + \varepsilon_{i,j,k,t,\tau}. \end{aligned} \tag{1.3}$$

The subscripts represent firm i at year-quarter t, for product (product category-brand) k in product category j. For each event year-quarter τ, I only include observations where $t - \tau \in \{-2, -1, 1, 2\}$. The unit of observation is at the firm-year-quarter-product (firm-year-quarter-product category-brand) level. The dependent variable $y_{i,j,k,t,\tau}$ is a product (product category-brand) level measure. The coefficient of interest is β. The first term is an interaction of a post-violation indicator variable $\mathbb{1}(t > \tau)$ and an indicator variable equal to one if the firm violated a covenant in the event year-quarter τ ($\mathbb{1}(D_{i,\tau} < 0)$, where $D_{i,t}$ is the distance to violation defined in Equation 1.1). To correctly interpret the effect of this interaction, I include a post-event indicator variable $\mathbb{1}(t > \tau)$, a violation indicator variable $\mathbb{1}(D_{i,\tau} < 0)$, and a cohort fixed effect λ_τ. I include contemporaneous firm level controls $X_{i,t}$ (detailed in Table 1.13), as well as a product (product category-brand) fixed effect α_k, a product category-year-quarter fixed effect $\delta_{j,t}$, and a firm fixed effect γ_i. While each product has a unique product category, each product may not be uniquely linked to one firm across time. Brands and their products can change parent firms; hence, firm fixed effects are not always redundant when including product (product category-brand) fixed effects. Standard errors are clustered at the firm level.

To study changes in firms' product portfolios, I run my product portfolio specifications at the product category-brand level. As illustrated in Figure 1.1, firms in my sample have a diverse offering of products on Amazon. Many firms have products spread across multiple brands and multiple product categories. I observe that some brands have products in multiple product categories and that firms sometimes have multiple brands within a product category. For firms that sell products in multiple product categories, aggregating their product portfolios to the firm level would make controlling for product category trends difficult. Being able to isolate different brands is also important, as firms may make strategic changes across their brands after covenant violations. To properly control for heterogeneity across product categories and brands, my unit of observation is at the product category-brand level. This allows me to test whether firms focus their changes more across product categories, across brands, or across a combination of the two. I also include product category-brand fixed effects to capture any time-invariant characteristics of each product category-brand. These specifications are meant to capture how firms change their product portfolios in response to loan covenant violations. I limit the set of product category-brands to those that have at least one review each pre-event year-quarter.

To identify changes in the product quality of firms that violate loan covenants, I run my product quality regressions at the product level. I choose a finer unit of observation than for my product portfolio specifications so that I can capture product quality changes not only across firms' product category-brands but within them. Using product level observations allows me to include product fixed effects, capturing time-invariant product characteristics.

To understand how average product quality changes after loan covenant violations, I add several restrictions to the set of products included in my product level regressions. I only include products that are reviewed both before and after event quarters. This allows me to measure product quality before the violation and identify how it changes after the covenant violation. I also require products to have ten or more reviews in each of the pre-event year-quarters. I relax these restrictions in Section 1.6.

Table 1.1 presents summary statistics the quarter before the event year-quarter for firms within the 0.4 window ($|D_{i,\tau}| \leq 0.4$), split by whether or not firms violated any of their covenants during the event year-quarter. I include average values of variables at the product level, the product category-brand level, and the firm level. I also show the difference between the violation sample and non-violation sample and the p-value of the corresponding difference-in-means test. At the product level, products of violating firms have significantly higher average ratings (4.20 versus 4.13) in the quarter before the covenant violation. This difference is driven by a higher proportion of five-star ratings relative to the proportion of three-star and four-star ratings. At the product category-brand level, violating firms have significantly fewer products and product introductions. At the firm level, violating firms have products in fewer product categories. Violating firms are similar across most accounting measures; they have lower return on assets, higher current ratios, and lower debt-to-EBITDA ratios than non-violating firms.

1.3 Results

1.3.1 Decreasing Product Quality

I first establish that firms change their products after violating loan covenants. My parametric tests use the product level event study regression specification defined in Equation 1.3

and are run across all distance to violation windows (0.3, 0.4, 0.5, 0.6, and 0.7).

I identify a decrease in average product quality in the two quarters after loan covenant violations in Table 1.2. The dependent variable is the average rating of all reviews a product received during that quarter. I find that the average product rating decreases significantly post-violation across all windows. The coefficient increases in magnitude monotonically as I tighten the window, from -0.119 to -0.170. The coefficient should be interpreted as the change in violating firms' average product rating, measured in stars. Alternatively, by dividing the coefficient by the average product rating of violating firms pre-event, I find that the average product rating decreases between 2.9% and 4.2% post-violation. The coefficient represents between 24% and 34% of one standard deviation of average product ratings pre-event.

It is important to distinguish between changes in product quality directly caused by firms' decisions and changes in product quality due to firms' circumstances. Customers' evaluations of product quality can decrease without firms changing the products themselves. Titman (1984) highlights that when customers value future interactions with firms, such as for the purchase of spare parts or software updates, an increased likelihood of bankruptcy negatively affects those customers' product quality evaluations. Firms may also decide to reduce product quality. Maksimovic and Titman (1991) show that decreasing an established product's quality increases short-term cashflows, at the expense of brand reputation and future cashflows. Firms may reduce product quality by changing the physical product itself, using cheaper raw materials, simplifying production, or relaxing acceptable tolerances. Product quality may also decline through changes to the ownership experience if firms cut customer service staff or enact more stringent warranty policies.

I identify which of these channels drives the decrease in product quality by analyzing the text of all the reviews a product receives before and after covenant violations. As mentioned in Subsection 1.1.1, the prompt given by Amazon when leaving a written product review is broad, allowing reviewers the freedom to write about the aspects of product quality that are most salient to them. I take advantage of this by searching for key phrases that correspond to different aspects of product quality in each written review and measure if the frequency of these phrases changes after loan covenant violations.

I first try to find whether there are changes to the physical products themselves. Specifically, I identify the percent of reviews that mention product failures. I look for key phrases in reviews that would indicate products are in some way defective, such as "stopped working", "fell apart", and "broke".[3]

I find an increase in the rate of product failure after loan covenant violations in Table 1.3. The dependent variable is the percent of reviews a product received that quarter that include at least one key phrase associated with product failures. I find that the average rate of product failure increases significantly after covenant violations across all windows, with coefficient values between 3.1% to 4.1%. I interpret this coefficient as an upper bound for the increase in the rate of product failure. I expect the probability of purchasers posting reviews to be higher when they had strongly negative experiences with the products they bought. If this assumption is true, then the actual rate of failure and any change in that rate are smaller than the observed change in the rate of reviews that mention product failure.

I reinforce the product failure channel using a stricter measure of product failure in Table 1.15. I define the dependent variable as the percent of Amazon reviews a product received that quarter that mention a key phrase indicating product failure in a negative sentiment sentence. A review still needs to have one of the key phrases indicating product failure. In addition, at least one key phrase must be in a negative sentiment sentence. I define sentence level sentiment using Stanford's CoreNLP software (e.g. Manning et al. (2014)). Calculating sentiment at the sentence level, as opposed to word by word, allows for the ordering of words, as well as capitalization and punctuation of the sentence, to be factored into the overall sentence sentiment. I find that negative product failure increases significantly after loan covenant violations, though the corresponding coefficient is smaller in magnitude (2.3%-3.0% across tested windows) than that of the product failure specification.

I am unable to identify any changes in the ownership experience post-violation. I do not find a significant increase in the rate of negative customer service experiences. I look for key phrases identifying customer service, including "help line", "technical support", and

[3] A full list of phrases I use to find product failure mentions is included in Table 1.14.

"helpline", in negative sentiment sentences.[4] The use of sentence level sentiment in this specification is necessary, as mentions of customer service in themselves are not indicative of a change in the ownership experience. I do not find a statistically significant change in the percent of reviews that mention negative customer service post-violation. This is likely due to Amazon providing many of these services directly to customers, bypassing firms' own customer service systems. I also try to identify if there is any change in reputation associated with the firm by testing a dependent variable equal to the percent of a product's reviews in that quarter that mention the product's parent firm's name in a negative sentiment sentence. I find no evidence that customers are more aware of products' parent firms post-violation. Given the relative insulation of many Amazon products from their parent companies, it may be that customers are unaware of the financial health of the firms their products are from. Frieder and Subrahmanyam (2005) suggest that retail investors link strong brands to their parent firms; I might have found a significant change if I limited my sample to strong firm-brand pairings. The products listed on Amazon may also not require significant long-term support. Hortaçsu et al. (2013) find that an increase in automobile manufacturers' CDS spreads leads to lower auction prices for those firms' used cars, which require continued servicing and spare parts to function.

Actively decreasing product quality and increasing the rate of product failure after loan covenant violations effectively exchanges reputational capital for short-term cashflows. Customers do not expect product quality to change, so firms are able to sell lower quality products for the same price at first. This allows for lower product costs for the same revenues and therefore higher short-term cashflows. However, customers will incorporate the decreases in product quality over time. This will lead to declines in long-term brand reputations, as customers will no longer be willing to pay the same premium for those brands' products.

One way firms may be decreasing product quality is through relaxing quality control. The product changes are observable in the two quarters after loan covenant violations. While it

[4] A full list of phrases I use to find customer service mentions is included in Table 1.14

is possible that firms change inputs or aspects of their production lines in that timeframe, I believe that firms are simply selling products they would not have sold before. Most manufacturing adheres to some system of eliminating defects (such as Six Sigma). Allowing products that would previously have been scrapped to be sold is an effective way to quickly decrease costs.

1.3.2 Culling Product Portfolio

After violating loan covenants, firms cull their product portfolios. My parametric tests use the product category-brand level event study regression specification defined in Equation 1.3 and are run across all distance to violation windows (0.3, 0.4, 0.5, 0.6, and 0.7).

Table 1.4 shows that firms reduce the size of their product portfolios after loan covenant violations. The dependent variable is the number of products with at least one review in that product category-brand during that quarter. I find that the average number of products in a product category-brand decreases significantly post-violation across all windows, ranging from a decrease of -1.24 products to -2.58 products. The coefficient should be interpreted as the number of products that would have been listed under a product category-brand if it was not owned by firms that violated loan covenants.

I find in Table 1.5 that the decline in product portfolio size is driven, in part, by a decrease in product introductions. The dependent variable is the number of new products sold under that product category-brand during that quarter. A new product is defined as a product whose first review was written that quarter. The average number of new products in a product category-brand decreases significantly across all windows after loan covenant violations. The coefficient corresponding to this decrease ranges from -0.31 to -0.52. The decline in product introductions represents between 19.3% and 26.2% of the decline in the number of products sold.

The reduction in both product portfolio size and product introductions are evidence of firms liquidating growth options in response to loan covenant violations. Product decisions represent real option problems for firms. Introducing new products is costly; firms need to commit resources to design them, create production lines for them, and bring them to market. Firms can choose to discontinue new products at any point during their development. New products should only be pursued if the expected profit from sales is enough to offset the costs associated with bringing the products to market, a decision which firms can reevaluate over time. Firms face similar decisions for their existing products. There are fixed costs associated with maintaining a production line. Firms may choose to continue selling products that are currently unprofitable if they anticipate a shift in future demand for these products. Firms may also decide to discontinue products, having the option to reintroduce them in the future, a decision with its own costs and response time penalties. The payoff of real options in levered firms is such that the expected payoff for equity holders might be positive when the expected payoff for debt holders is not. Liquidating growth options is consistent with a shift in control rights towards creditors. There are costs associated with maintaining products. By dropping products, firms both increases their short-term cashflows and reduce the volatility of cashflows.

1.3.3 Strategic Choices Within Violating Firms

Firms do not reduce the size of their product portfolios and product quality uniformly after loan covenant violations. I find consistent within-firm differences post-violation, indicating that firms make strategic choices. After covenant violations, firms concentrate the reduction in product portfolio size and product introductions in more competitive product markets. Firms also lower product quality more for their less popular products post-violation.

To identify how firms target changes across their product category-brands, I add an additional independent variable to the product category-brand specification in Equation 1.3, the interaction indicator variable After $\times$ violation $\times$ more competitive ($\mathbb{1}\,(t > 0) \times \mathbb{1}\,(D_{i,0} < 0) \times \mathbb{1}\,(\text{More competitive})$). The corresponding coefficient measures the additional effect, beyond being a product category-brand owned by a violating firm after the loan covenant violation occurs, of the product category-brand being above the median competitiveness of product category-brands made by that firm in the two quarters before the event year-quarter. Competitiveness is defined as as the number of other brands in a product category. To measure within-firm differences, I exclude firms that only have products listed in one product category.

Adding the second interaction variable allows me to identify the differential effect loan covenant violations have on firms' more competitive and less competitive product market-brands. The first coefficient can be interpreted as the effect of loan covenant violations on firms' less competitive product markets. The effect of loan covenant violations on firms' more competitive product markets is the sum of the first and second coefficients. The second coefficient indicates if loan covenant violations cause a significantly different change for firms' more competitive product category-brands relative to their less competitive product category-brands. If firms base their product portfolio decisions on product market competitiveness, the second coefficient will be non-zero and significant.

Table 1.6 shows that the reduction in the number of products after loan covenant violations is concentrated in firms' more competitive product categories. The dependent variable is the number of products in that product category-brand during that quarter. The first coefficient indicates that the number of products listed for product category-brands that are in violating firms' less competitive product categories does not change significantly after loan covenant violations. Instead, the measured firm level decrease comes from reductions in firms' more competitive product markets. Adding the first and second coefficients, I find that the number of products of product category-brands that are in firms' more competitive product markets decreases significantly across all windows post-violation, from 2.59 to 5.58 products.

I find that the scaling back of product portfolios in more competitive product markets extends to product introductions in Table 1.7. The dependent variable is the number of product introductions for each product category-brand that quarter. Again I find no significant change for product category-brands in firms' less competitive product markets. The change is concentrated in firms' more competitive product markets, where I find that post-violation there is a significant decrease in the number of new products introduced across all windows, ranging between 0.66 and 1.00 new products.

I did not find any strategic differentiation within violating firms across any other measures. Importantly, I did not find any significant differences across different brands. Given the ability of brands to segment products, it is interesting to see that this channel is not leveraged by firms after loan covenant violations. I also tried to segment product category-brands by several measures, including average product quality and product market share, but did not find significant differences across them. This may be due to a power issue, as I may not have a sufficient number of violating firms with either multiple brands in a product category or brands in multiple product categories.

Reducing exposure to product markets with more competitors after loan covenant violations may be eliminating firms' less valuable growth options. Introducing a product or continuing to sell a product is an active choice made by firms. As discussed in Subsection 1.3.2, firms may exercise growth options that are not in creditors' best interests. This form of risk shifting may be more prevalent in product markets with more competitors. With more competitors, the ability to profit off of a demand shock may be smaller for any individual firm. The effects of product market competition may extend to the margins of individual products. While I do not observe data regarding the profitability of products, more competitors in a particular market are generally indicative of lower profit margins.

I use a similar specification to test for differential changes in product quality within violating firms. I add an additional independent variable to the product specification in Equation 1.3, the interaction indicator variable After $\times$ violation $\times$ less popular ($\mathbb{1}\,(t > 0) \times \mathbb{1}\,(D_{i,0} < 0) \times \mathbb{1}\,(\text{Less popular})$). The corresponding coefficient measures the additional effect, beyond being a product owned by a violating firm after the loan covenant violation occurs, of the product being below the median popularity of products made by that firm in the two quarters before the event year-quarter. I define popularity as the number of reviews a product receives divided by the total number of reviews in that product category. To measure within-firm differences, I exclude firms with only one product that satisfy the product level specification restrictions defined in Section 1.2. The interpretation of the first and second coefficients follows the same logic as described for the product category-brand specifications.

Within violating firms, I show in Table 1.8 that the reduction in product quality is larger for firms' less popular products. I find that the product quality of more popular products does decrease post-violation, though the decrease is not significant across all windows. However, there is a significant decrease in product quality across all windows for violating firms' less popular products relative to their more popular products. Adding the first coefficient and the second coefficient together, the average product quality of firms' less popular products decreases significantly across all windows, with the change ranging from -0.177 to -0.238.

I show that product failure rates are significantly higher for firms' less popular products in Table 1.9, consistent with the differential decrease in product quality. I find that the rate of product failure for firms' more popular products does not change significantly after loan covenant violations. I do find that there is a significant increase in product failures for firms' less popular products relative to their more popular products. Adding the two coefficients together, I find that rates of product failure increase significantly for less popular products across all windows, with changes between 5.2% and 6.1%.

Reducing product quality of less popular products may allow firms to minimize the long-term decrease in reputation while still increasing short-term cashflows. The primary indicator of a product's quality on Amazon is the product's average rating, reducing the relevance of that product's corresponding brand reputation. When there is no direct measure of an individual product's quality, brand reputation is the primary proxy for quality. Targeting decreases in product quality and increases in product failure on less popular products will allow firms to maintain the reputation of their more successful products. Targeting less popular products may also prevent changes that are easily observed by consumers. Amazon does not disclose how it selects the order in which products are displayed, but it is likely that more popular products will be shown before less popular ones. If so, consumers would not observe the change in an overall brand reputation if they do not look past its more popular products. While the same system does not apply to physical retailers, the relative popularity of brands' products and corresponding proportions of customers that update negatively on brands' reputations are likely similar.

1.3.4 Decrease in Product Sales

It is important to try to understand what impact, if any, the changes that occur to products post-violation have on their short-term sales volume. In the discretized setting of Maksimovic and Titman (1991), reducing product quality does not change firm revenue that period. Amazon product sales and consumer feedback do not update so cleanly. Nini, Smith, and Sufi (2012) find that firms experience lower sales growth in the year following loan covenant violations. While I do not have access to product sales data, I establish that review volume is a strong proxy of sales ranking and that review volume decreases after loan covenant violations.

Table 1.10 establishes a strong correlation between product category level sale ranking and the number of reviews that product received in the prior three months. While I do not have sales volume data, the product metadata I have access to includes each product's sales ranking within its product category at the end of the sample. Amazon does not clearly define sales ranking. They do not provide a time horizon over which it is determined, or if it is a raw measure of sales volume or features any adjustments. However, Amazon does establish a relative ranking within a product category. I only have product metadata at the end of my sample. I use reviews in the three months up to the end of my sample to establish a link between sales rank and the number of reviews. My regressions are at the product level, for all products with a product category sales rank. I first test the correlation between products' review count in the last three months and their corresponding product category sales rank. I find a strong negative relationship between the two. The coefficient is similar in magnitude and significance when I add product category fixed effects. To try and make the interpretation of the coefficient simpler, I also test the correlation between the within-product category percentile of the number of reviews for each product and the within-product category sales rank of that product. I again find a strong negative relationship between the two, with a coefficient of -0.599 with and without product category fixed effects. The significant and negative relationship between review count and sales rank suggests that review count is a reasonable proxy for sales volume, especially when accounting for differences across product categories.

I show that the log number of reviews decreases significantly after loan covenant violations in Table 1.11. I use the product level specification defined by Equation 1.3 and define the dependent variable as the natural logarithm of the number of reviews left that quarter. I find that the number of reviews decreases after a violation across all windows, though not significantly for my two widest windows. The coefficient ranges in value from -0.117 to -0.306 across the windows, corresponding to between a 2.6% and 3.2% decrease in review volume relative to review volume pre-event.

The observed decrease in the review volume of existing products will not necessarily align with changes in violating firms' cashflows. The decrease in product costs likely offsets the decrease in revenue from product sales, which would lead to an increase in violating firms' operating performances. The effect that I observe in Table 1.11 also ignore the product portfolio changes I find, which would also increase measures of operational performance. Hence, in this context, decreases in product sales may coincide with increases in cashflows.

1.3.5 Robustness

Table 1.12 highlights the difference in pre-treatment and post-treatment trends between treated firms and control firms. My empirical specification relies on the assumption that before the event quarter, all firms were equally likely to violate their loan covenants. The specifications used are quarter-level variations of the specification defined in Equation 1.3. I run the specifications on firms in the 0.4 window. Instead of an interaction variable of treated and post, the four presented coefficients correspond to indicator variables equal to one if the product is from a firm that violated a covenant in the event quarter τ and is an observation in quarter $\tau - 2$, $\tau - 1$, $\tau + 1$, or $\tau + 2$. These coefficients allow me to observe differences between groups within the pre-event and post-event period. I run this specification on both my product level and product portfolio-brand level specifications. Across all specifications, my two pre-event coefficients indicate no significant difference between firms that receive covenant violations in the event quarter and firms that do not receive covenant violations.

More importantly, the pre-event trend is flat, indicating that there were no differences in anticipatory effects between the groups of firms.

I run several alternative specifications to test the robustness of my results. Presented tables follow the format used in Table 1.12, where each dependent variable is tested on firms in the 0.4 window. I first show that my results are robust to two-way clustering of standard errors at the firm and year-quarter levels in Table 1.16. I find that all product and product portfolio results go through, though the product introduction specification is only significant at the 5% level.

Table 1.17 shows that my results are robust to winsorization. I winsorize all continuous variables at the 1% level and 99% level. The discussed coefficients are slightly smaller in magnitude in the winsorized specifications. Product specifications and the product portfolio size specification have the same level of statistical significance and the product introduction specification is significant at the 5% level.

As noted in Subsection 1.1.1, I do not observe the firm subsidiary structure of firms before 2003. In my main specification, I assume a firm's subsidiary structure before 2003 was the same as that firm's subsidiary structure in 2003. To verify my results are robust to errors that may have resulted from this assumption, I retest all specifications while dropping observations before 2003 in Table 1.18. I find that dropping observations before 2003 does not change any of the empirical results significantly.

One concern with my identification strategy is the potential for firms to manipulate their accounting measures to just avoid violating loan covenants. If firms are able to manipulate their distance to violation, it may result in a mass of firms just above their violation thresholds. I exclude these firms in an alternative specification by dropping observations in the immediate vicinity of their violations thresholds, which I define as firms whose minimum distance to violation is less than or equal to 0.1. Table 1.19 shows that the results hold when using this "donut" specification. Product specifications have the same level of statistical significance and the product portfolio specifications are significant at the 5% level.

I test my regressions using an alternative measure of distance to violation in Table 1.20.

The measure, defined fully in Section 1.7, is similar to the measure of covenant tightness defined by D. Ferreira, M. A. Ferreira, and Mariano (2018). To calculate the alternative distance to violation, instead of dividing the difference by the threshold ratio T_{itjz}, the difference is divided by the standard deviation of the threshold's corresponding financial ratio over the previous five years. Using the alternative measure of distance to violation accounts for firms whose accounting measures are known to be more or less volatile. In these specifications, I test using firms in the 1.0 window. All results are similar in statistical significance to those of the baseline specification. The magnitude of the product results are smaller than those of the baseline specification while the magnitude of the product portfolio results are larger.

I verify my product quality results with a review level specification. As described in Section 1.2, my product level specification sets constraints on which products I include in my sample. I relax these assumptions in the review level specification described in Section 1.6. The change in the unit of observation leads me to answer different but similar questions. How does the average rating change after loan covenant violations and what drives this change? I find that the average rating decreases significantly after a covenant violation and identify a significant increase in the likelihood of product failure. Coefficients are smaller in magnitude in the review level specifications than the corresponding product level specifications, likely due to a change in weighting.

One concern is the use of fake reviews on Amazon and other online retailers. While it is not clear when fake reviews started appearing on Amazon, fake reviews were publicly acknowledged by Amazon as early as 2004 (Harmon (2004)). One concern is that the change in average product ratings is a result of firms reducing expenses related to purchasing positive reviews. If this was true, I would expect that the distribution of ratings below five stars would not change significantly. I run the product level specification on the percent of product reviews that rated the product each of the five possible ratings in Table 1.21. Consistent with the increase in the rate of product failures I show in Table 1.3, I find an increase in the percent of one star ratings that is significant at the 1% level. I also find a significant decrease in the percent of five star ratings, though it is only significant at the 10% level.

While these results suggest that purchased reviews are not driving my results, they do not mean that purchased reviews were not a part of firms' product strategies.

1.4 Conclusion

Firms' product quality and product portfolio decisions are affected by violations of their credit agreements. In the two quarters after new loan covenant violations, firms reduce the the quality of their products and the size of their product portfolios. Within violating firms, product portfolio reductions are concentrated in product markets with more competitors and product quality decreases are greater in less popular products. These changes indicate that after shifts in control rights towards creditors, firms liquidate both reputational capital and growth options.

One important but unanswered question is if firms adjust their products' prices after loan covenant violations. I find evidence that the sales of fimrs' existing products decrease post-violation. In Maksimovic and Titman (1991), the amount customers are willing to pay for products is based on the perceived quality of those products. I observe a decline in perceived quality. It would be interesting to identify if and how firms adjust prices and at what speed those adjustments occur. If firms are intentionally expending brand reputation, they would not immediately lower prices to reflect the decrease in product quality. The observed decrease in sales volume may be driven by consumers updating their beliefs about product quality more rapidly than firms adjust the prices of their products. If possible, quantifying these effects is an interesting avenue for future research.

Credit agreements with loan covenants are common and violations of loan covenants are frequent (Roberts and Sufi (2009)). The product and product portfolio changes documented in my research build on our knowledge of how significant the effects of these loan covenant violations can be on firms. One party that seems unaware of these events, but is subject to their effects, are retail consumers. Brand ownership structure is complex, and my evidence suggests that customers are not aware of the firms behind their purchases, let alone their financial states. The financial health of a product's manufacturer plays an important signaling role in Maksimovic and Titman (1991), and the absence of this signal may be detrimental to all firm stakeholders.

1.5 Appendix 1: Amazon to CRSP Match Methodology

I first attempt to match each Amazon product's brand name to that brand's trademark.[5] Trademark data is downloaded from USPTO's 2017 Trademark Case Files dataset, which contains information on 8.6 million trademark applications filed from January 1870 forward. My trademark selection methodology is guided by the discussion of J.H. et al. (2013), who document and discuss the Trademark Case Files dataset in detail.

Each trademark has an entry, which is updated throughout the trademark's life. As my goal is to link Amazon products to public firms, I only include registered text trademarks owned by corporations. For dead trademarks, I use the provided expiration date. For trademarks that were last updated as living, I define the expiration date as twenty years after the registration date if the trademark was filed before November 16, 1989. If the trademark was filed on or after November 16, 1989, I define the patent expiration date as ten years after the registration date. This difference in expiration date is due to the Trademark Law Revision Act of 1988, which eliminated the requirement of commercial use of a trademark prior to registration (Snyder (1990)). I require an exact match between the Amazon brand and the trademark's text, and that product reviews occur within the trademark's life.

I then try to link each matched trademark's owner to a subsidiary corporation, using data collected by CorpWatch. CorpWatch's dataset extracts firm subsidiary information listed in Exhibit 21 of firms' 10-K filings. Using this, I build a parent-subsidiary hierarchy and identify an ultimate parent company for each subsidiary firm. Firm subsidiary data is only available from 2003 onward, so I assume the 2003 subsidiary structure for all years prior. I attempt to standardize common firm name endings (for example, I replace the words "international", "intrntnl", and "internl" with "intl") before doing an exact match between the trademark owner name and firm subsidiary name. I require all exact matches to be overlapping in time.

[5] A trademark, as defined by the US Patent and Trademark Office, is "... any word, name, symbol, device, or any combination, used or intended to be used to identify and distinguish the goods/services of one seller or provider from those of others, and to indicate the source of the goods/services" (Patent and Office (2018)).

Finally, I match the firm subsidiary to its CRSP ultimate parent firm. Like in the previous step, I first standardize common firm name endings. I then do an exact match between the subsidiary's ultimate parent firm's name, defined with the CorpWatch dataset, to the CRSP firm name at that time using the CRSP Names dataset.

1.6 Appendix 2: Review Level Specifications

I confirm that my primary results hold in a more generalized specification, using a review level event study regression. When testing product level changes, using product level aggregate statistics has some limitations. The first are the product level requirements I set to include a product in my sample. These include requiring the product to have reviews in my entire event window, and having a sufficient number of reviews pre-event. Beyond that, when only considering an average rating, I lose all information on the distribution of those ratings. As highlighted by Holderness (2016), using an aggregated summary statistic to study an underlying distribution can lead to incorrect weightings and standard errors. To account for these possible sources of bias, I test an alternative specification, testing for changes in individual reviews, as opposed to the individual product. This allows me to answer similar, but distinct, questions from my product level specifications. Namely, how does the average rating change after loan covenant violations, and what drives that change? I use the following review level specification

$$\begin{aligned} y_{i,j,k,l,t,\tau} = {} & \beta \times \mathbb{1}\left(t > \tau\right) \times \mathbb{1}\left(D_{i,\tau} < 0\right) + \Omega \times \mathbb{1}\left(t > \tau\right) + \Psi \times \mathbb{1}\left(D_{i,\tau} < 0\right) + \lambda_\tau \\ & + \kappa \times X_{i,t} + \alpha_k + \delta_{j,t} + \gamma_i + \varepsilon_{i,j,k,l,t,\tau}. \end{aligned} \tag{1.4}$$

The subscripts represent firm i at year-quarter t, for the review l of product k in product category j. For each event year-quarter τ, I only include observations where $t-\tau \in \{-2,-1,1,2\}$. The unit of observation is at the firm-year-quarter-product-review level. The dependent variable $y_{i,j,k,l,t}$ is a review level measure. The coefficient of interest is β. The first term is an interaction of a post-violation indicator variable $\mathbb{1}\left(t > \tau\right)$ and an indicator variable equal to one if the firm violated a covenant in the event year-quarter τ ($\mathbb{1}\left(D_{i,\tau} < 0\right)$, where $D_{i,t}$ is the distance to violation defined in Equation 1.1). To correctly interpret the effect of this interaction, I include a post-event indicator variable $\mathbb{1}\left(t > \tau\right)$, a violation indicator variable $\mathbb{1}\left(D_{i,\tau} < 0\right)$, and a cohort fixed effect λ_τ. I include contemporaneous firm level controls $X_{i,t}$ (detailed in Table 1.13), as well as product fixed effects α_k, product category-year-quarter fixed effects $\delta_{j,t}$, and firm fixed effects γ_i. Standard errors in all of the event study specifications are clustered at the firm level.

Table 1.22 finds that Amazon products ratings decrease after loan covenant violations. The dependent variable is the product rating given by that review. The coefficient β indicates the change in rating for a review left for products produced by firms who violated loan covenants in the event year-quarter, after the event year-quarter. I find that the average rating decreases significantly post-violation across all windows, from -0.053 to -0.60. The coefficient is less than half the magnitude of the coefficient found in Table 1.2, the corresponding product level specification. This difference is likely due to the change in weighting. While before a product with ten reviews in a quarter received the same weight as a product with one hundred, here each review receives equal weight.

Table 1.23 shows that the frequency of product failure increases after loan covenant violations. The dependent variable is an indicator variable equal to one if the review includes a phrase indicating product failure. A list of these phrases is included in Table 1.14. The beta coefficients across the different windows range from 0.004 to 0.005, but the coefficient is not significant at the ten percent level for the sample of firms in the 0.3 window. Unlike the product level specification, the β coefficient cannot be interpreted as a percent change. A value of β equal to 0.01 would indicate that the likelihood of a product failure mention post-violation increases by 1%. This still is a much smaller effect than the corresponding product level specification (Table 1.3), again likely due to the difference in weighting.

1.7 Appendix 3: Alternate Definition of Distance to Violation

I define an alternative measure of distance to violation that accounts for the volatility of the measure underlying each covenant. This alternate measure, based on the one used by D. Ferreira, M. A. Ferreira, and Mariano (2018), is defined as

$$D_{it} = \min_{j} \tilde{D}_{itj}, \tag{1.5}$$

where

$$\tilde{D}_{itj} = \min_{z} \begin{cases} \frac{T_{itjz} - C_{itj}}{\sigma(C_{itj})}, & \text{if threshold a maximum} \\ \frac{C_{itj} - T_{itjz}}{\sigma(C_{itj})}, & \text{if threshold a minimum} \end{cases} \tag{1.6}$$

and i and t denote firm and year-quarter, respectively, j denotes covenant type, z denotes an active loan, C_{itj} is the value of the relevant covenant ratio, T_{itjz} is the threshold ratio defined in the covenant, and $\sigma\left(C_{itj}\right)$ is the standard deviation of C_{itj} for the five years before t. I require at least ten quarters of valid observations in that time when defining the standard deviation. The firm is defined as in violation of a covenant if the minimum distance $D_{i,t}$ is negative.

Using this measure of distance to violation helps account for differences across firms. Consider two firms with the same current ratio, that both have identical covenants on their current ratios. If one firm's current ratio is more volatile than the other firm's current ratio, it is more likely that the firm with higher current ratio volatility violates its covenant. This measure of distance to violation tries to capture how meaningful the violation, scaling the extent of the violation by the measure's volatility.

Figure 1.1:
Product Portfolio Structure

This figure illustrates part of the product portfolio structure of one of the firms in my sample. I select three brands from the product portfolio of Central Garden & Pet Company. Product markets indicate the product categories that have products listed for each corresponding brand in my sample.

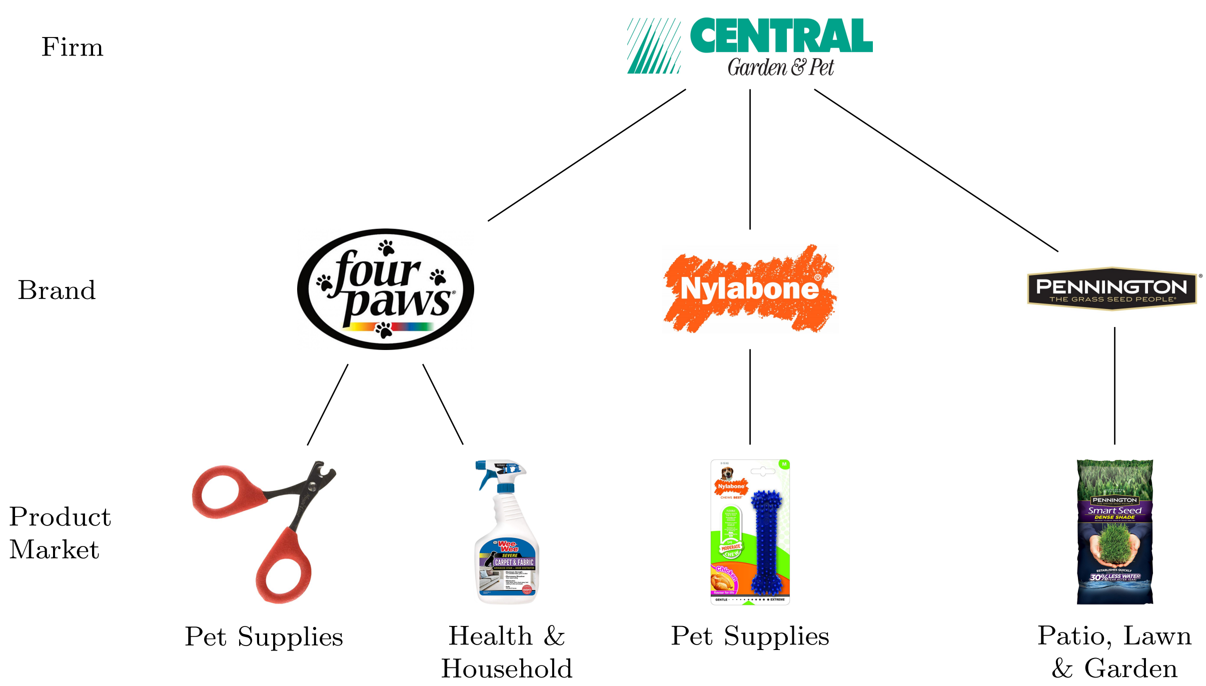

Table 1.1:
Loan Covenant Violation Summary Statistics

This table presents product level, product category-brand level, and firm level summary statistics for firms in my sample. Mean values are taken for firms at the quarter before the event year-quarter. If the firm violated a covenant at the event year-quarter, it is included in the violation column; otherwise, the firm is included in the non-violation column. Firms are only included if the absolute value of the minimum distance to violation is less than 0.4. The difference p-value is calculated using a two-sample t-test for equal means.

Panel A: Product level

	Violation	Non-violation	Difference
Average rating	4.20	4.13	0.06***
% of ratings equal to one	8.62	8.81	-0.20
% of ratings equal to two	5.19	5.25	-0.06
% of ratings equal to three	6.70	8.49	-1.79***
% of ratings equal to four	17.0	18.6	-1.6***
% of ratings equal to five	62.5	58.8	3.6***
# reviews	3.95	3.91	0.04
# observations	2,698	74,160	

Panel B: Product category-brand level

	Violation	Non-violation	Difference
# products	6.20	11.75	-5.54***
# new products	1.78	2.99	-1.21***
Average rating	4.17	4.08	0.09**
# reviews	24.5	46.0	-21.4***
# observations	435	6,314	

Panel C: Firm level

	Violation	Non-violation	Difference
# brand-product categories	3.66	5.03	-1.37***
# brands	2.81	3.38	-0.57
# product categories	2.45	3.06	-0.62***
Leverage	0.311	0.330	-0.019
Market cap	7.30	7.75	-0.45***
B/M ratio	0.664	0.769	-0.106
RoA	0.0270	0.0317	-0.0047***
Investments	0.0159	0.0180	-0.0021
Excess return	0.00821	0.00403	0.00417
FCF	0.00907	0.01081	-0.00174
Firm age	24.7	26.9	-2.2*

Table 1.1 Continued

Current ratio	2.19	1.90	0.29***
Debt to tangible net worth	1.58	2.00	-0.42
Debt service coverage	0.444	0.398	0.046
Debt to EBITDA	1.38	4.42	-3.04*
Debt to equity	0.234	0.234	-0.000
# observations	119	1,256	

Note: *p<0.1; **p<0.05; ***p<0.01

Table 1.2:
Loan Covenant Violations and Product Quality

This table presents an event study specification testing the relationship between firms violating loan covenants and its product quality. Observations are at the firm-year-quarter-product level. For each quarter in which at least one firm has a new loan covenant violation (the event year-quarter), I include the two quarters before and after for all new violating firms and all control firms. Control firms have no violations at or before the event year-quarter, and I only include products in categories that are listed by violating firms. The dependent variable is the average Amazon rating from reviews left that quarter. Violation is an indicator variable equal to one if a firm's ratios indicate that it has violated one of its loan covenants that quarter. The displayed independent variable is an indicator variable equal to one if the observation is after $Q = 0$ and if the firm has a new violation during the event year-quarter. Products are only included if they have at least ten reviews in each of the pre-event year-quarters and are available in all quarters. Each column is the same regression on a narrower window, where the absolute value of the minimum distance to violation the period of violation is less than or equal to the corresponding value. All regressions include firm level controls and have firm, product category-year-quarter, violation, and product fixed effects. Standard errors are clustered at the firm level.

	Dependent variable:				
	Amazon rating				
	(1)	(2)	(3)	(4)	(5)
After × violation	-0.120^{***}	-0.136^{***}	-0.141^{***}	-0.154^{***}	-0.177^{***}
	(0.028)	(0.029)	(0.033)	(0.043)	(0.046)
Window	0.7	0.6	0.5	0.4	0.3
Observations	28,080	23,304	18,032	10,272	5,652
R^2	0.696	0.703	0.699	0.680	0.696
Note:					*p<0.1; **p<0.05; ***p<0.01

Table 1.3:
Loan Covnenant Violations and Product Failure

This table presents an event study specification testing the relationship between firms violating loan covenants and product failure. Observations are at the firm-year-quarter-product level. For each quarter in which at least one firm has a new loan covenant violation (the event year-quarter), I include the two quarters before and after for all new violating firms and all control firms. Control firms have no violations at or before the event year-quarter, and I only include products in categories that are listed by violating firms. The dependent variable is the percent of Amazon reviews that mention a key phrase indicating product failure that quarter. Violation is an indicator variable equal to one if a firm's ratios indicate that it has violated one of its loan covenants that quarter. The displayed independent variable is an indicator variable equal to one if the observation is after $Q = 0$ and if the firm has a new violation during the event year-quarter. Products are only included if they have at least ten reviews in each of the pre-event year-quarters and are available in all quarters. Each column is the same regression on a narrower window, where the absolute value of the minimum distance to violation the period of violation is less than or equal to the corresponding value. All regressions include firm level controls and have firm, product category-year-quarter, violation, and product fixed effects. Standard errors are clustered at the firm level.

	Dependent variable:				
	Product failure				
	(1)	(2)	(3)	(4)	(5)
After × violation	3.142***	3.397***	3.578***	4.076***	4.056***
	(0.879)	(0.893)	(0.897)	(1.099)	(1.073)
Window	0.7	0.6	0.5	0.4	0.3
Observations	28,080	23,304	18,032	10,272	5,652
R^2	0.529	0.536	0.529	0.518	0.525
Note:			*p<0.1; **p<0.05; ***p<0.01		

Table 1.4:
Loan Covenant Violations and Product Portfolio Size

This table presents an event study specification testing the relationship between firms violating loan covenants and the number of products listed. Observations are at the firm-year-quarter-product category-brand level. For each quarter in which at least one firm has a new loan covenant violation (the event year-quarter), I include the two quarters before and after for all new violating firms and all control firms. Control firms have no violations at or before the event year-quarter, and I only include product category-brand combinations in categories that are listed by violating firms. The dependent variable is the number of products listed under that brand that quarter. Violation is an indicator variable equal to one if a firm's ratios indicate that it has violated one of its loan covenants that quarter. The displayed independent variable is an indicator variable equal to one if the observation is after $Q = 0$ and if the firm has a new violation during the event year-quarter. Observations must have at least one active product listed in each of the pre-event year-quarters. Each column is the same regression on a narrower window, where the absolute value of the minimum distance to violation the period of violation is less than or equal to the corresponding value. All regressions include firm level controls and have firm-product category-brand, product category-year-quarter, and violation fixed effects. Standard errors are clustered at the firm level.

	Dependent variable:				
	# products				
	(1)	(2)	(3)	(4)	(5)
After × violation	-1.689^{**}	-2.020^{***}	-2.584^{***}	-1.986^{***}	-1.240^{**}
	(0.773)	(0.776)	(0.752)	(0.673)	(0.603)
Window	0.7	0.6	0.5	0.4	0.3
Observations	66,895	54,340	40,374	25,720	15,786
R^2	0.591	0.649	0.742	0.761	0.835
Note:			*p<0.1; **p<0.05; ***p<0.01		

Table 1.5:
Loan Covenant Violations and Product Introduction

This table presents an event study specification testing the relationship between firms violating loan covenants and the introduction of new products. Observations are at the firm-year-quarter-product category-brand level. For each quarter in which at least one firm has a new loan covenant violation (the event year-quarter), I include the two quarters before and after for all new violating firms and all control firms. Control firms have no violations at or before the event year-quarter, and I only include product category-brand combinations in categories that are listed by violating firms. The dependent variable is the number of new products listed under that brand that were introduced that quarter. Violation is an indicator variable equal to one if a firm's ratios indicate that it has violated one of its loan covenants that quarter. The displayed independent variable is an indicator variable equal to one if the observation is after $Q = 0$ and if the firm has a new violation during the event year-quarter. Observations must have at least one active product listed in each of the pre-event year-quarters. Each column is the same regression on a narrower window, where the absolute value of the minimum distance to violation the period of violation is less than or equal to the corresponding value. All regressions include firm level controls and have firm-product category-brand, product category-year-quarter, and violation fixed effects. Standard errors are clustered at the firm level.

	Dependent variable:				
	# new products				
	(1)	(2)	(3)	(4)	(5)
After × violation	-0.377^{*}	-0.389^{**}	-0.519^{***}	-0.521^{***}	-0.309^{*}
	(0.194)	(0.197)	(0.181)	(0.196)	(0.172)
Window	0.7	0.6	0.5	0.4	0.3
Observations	66,895	54,340	40,374	25,720	15,786
R^2	0.594	0.625	0.659	0.692	0.789
Note:			*p<0.1; **p<0.05; ***p<0.01		

Table 1.6:
Loan Covenant Violations and Product Portfolio Size split by Number of Competitors

This table presents an event study specification testing the relationship between firms violating loan covenants and the number of products listed. Observations are at the firm-year-quarter-product category-brand level. For each quarter in which at least one firm has a new loan covenant violation (the event year-quarter), I include the two quarters before and after for all new violating firms and all control firms. Control firms have no violations at or before the event year-quarter, and I only include product category-brand combinations in categories that are listed by violating firms. The dependent variable is the number of products listed under that brand that quarter. Violation is an indicator variable equal to one if a firm's ratios indicate that it has violated one of its loan covenants that quarter. The first displayed independent variables is an indicator variable equal to one if the observation is after $Q = 0$ and if the firm has a new violation during the event year-quarter. The second displayed independent variable is an indicator variable equal to one if, in addition to the previously described conditions, the number of brands in that product category-brand's product category pre-event is above the median number of brands of all product categories that firm has products listed in. Observations must have at least two active product category-brands listed in each of the pre-event year-quarters. Each column is the same regression on a narrower window, where the absolute value of the minimum distance to violation the period of violation is less than or equal to the corresponding value. All regressions include firm level controls and have firm-product category-brand, product category-year-quarter, and violation fixed effects. Standard errors are clustered at the firm level.

	Dependent variable:				
	# products				
	(1)	(2)	(3)	(4)	(5)
After × violation	0.888	0.521	0.481	−1.065	0.903
	(1.380)	(1.464)	(1.355)	(1.177)	(0.979)
After × violation × more competitive	−5.256**	−5.601*	−6.060**	−2.912*	−3.487**
	(2.517)	(2.918)	(2.592)	(1.725)	(1.431)
Window	0.7	0.6	0.5	0.4	0.3
Observations	56,245	45,669	33,836	21,155	12,937
R^2	0.606	0.676	0.761	0.787	0.837
Note:					*p<0.1; **p<0.05; ***p<0.01

Table 1.7:

Loan Covenant Violations and Product Introduction split by Number of Competitors

This table presents an event study specification testing the relationship between firms violating loan covenants and the introduction of new products. Observations are at the firm-year-quarter-product category-brand level. For each quarter in which at least one firm has a new loan covenant violation (the event year-quarter), I include the two quarters before and after for all new violating firms and all control firms. Control firms have no violations at or before the event year-quarter, and I only include product category-brand combinations in categories that are listed by violating firms. The dependent variable is the number of new products listed under that brand that were introduced that quarter. Violation is an indicator variable equal to one if a firm's ratios indicate that it has violated one of its loan covenants that quarter. The first displayed independent variables is an indicator variable equal to one if the observation is after $Q = 0$ and if the firm has a new violation during the event year-quarter. The second displayed independent variable is an indicator variable equal to one if, in addition to the previously described conditions, the number of brands in that product category-brand's product category pre-event is above the median number of brands of all product categories that firm has products listed in. Observations must have at least two active product category-brands listed in each of the pre-event year-quarters. Each column is the same regression on a narrower window, where the absolute value of the minimum distance to violation the period of violation is less than or equal to the corresponding value. All regressions include firm level controls and have firm-product category-brand, product category-year-quarter, and violation fixed effects. Standard errors are clustered at the firm level.

	Dependent variable:				
	# new products				
	(1)	(2)	(3)	(4)	(5)
After × violation	0.177	0.113	0.101	−0.139	0.120
	(0.277)	(0.292)	(0.251)	(0.280)	(0.253)
After × violation × more competitive	−1.029**	−1.000**	−1.093**	−0.859**	−0.778**
	(0.401)	(0.404)	(0.436)	(0.374)	(0.357)
Window	0.7	0.6	0.5	0.4	0.3
Observations	56,245	45,669	33,836	21,155	12,937
R^2	0.610	0.649	0.674	0.714	0.788
Note:					*p<0.1; **p<0.05; ***p<0.01

Table 1.8:
Loan Covenant Violations and Product Quality split by Popularity

This table presents an event study specification testing the relationship between firms violating loan covenants and its product quality. Observations are at the firm-year-quarter-product level. For each quarter in which at least one firm has a new loan covenant violation (the event year-quarter), I include the two quarters before and after for all new violating firms and all control firms. Control firms have no violations at or before the event year-quarter, and I only include products in categories that are listed by violating firms. The dependent variable is the average Amazon rating from reviews left that quarter. Violation is an indicator variable equal to one if a firm's ratios indicate that it has violated one of its loan covenants that quarter. I define a product's review share as the number of reviews it received divided by the total number of reviews in its product category. The first displayed independent variables is an indicator variable equal to one if the observation is after $Q = 0$ and if the firm has a new violation during the event year-quarter. The second displayed independent variable is an indicator variable equal to one if, in addition to the previously described conditions, the product's review share pre-event is below the median review share for that firm's products pre-event. Products are only included if they have at least ten reviews in each of the pre-event year-quarters and are available in all quarters. Each column is the same regression on a narrower window, where the absolute value of the minimum distance to violation the period of violation is less than or equal to the corresponding value. All regressions include firm level controls and have firm, product category-year-quarter, violation, and product fixed effects. Standard errors are clustered at the firm level.

	Dependent variable:				
	Amazon rating				
	(1)	(2)	(3)	(4)	(5)
After × violation	-0.085^{**}	-0.086^{**}	-0.081^{*}	-0.082	-0.109^{*}
	(0.040)	(0.043)	(0.044)	(0.058)	(0.066)
After × violation × less popular	-0.092^{**}	-0.099^{**}	-0.132^{***}	-0.148^{***}	-0.130^{**}
	(0.044)	(0.045)	(0.043)	(0.054)	(0.057)
Window	0.7	0.6	0.5	0.4	0.3
Observations	27,068	22,572	17,544	10,028	5,532
R^2	0.695	0.701	0.696	0.672	0.692
Note:					*p<0.1; **p<0.05; ***p<0.01

Table 1.9:
Loan Covenant Violations and Product Failure split by Popularity

This table presents an event study specification testing the relationship between firms violating loan covenants and product failure. Observations are at the firm-year-quarter-product level. For each quarter in which at least one firm has a new loan covenant violation (the event year-quarter), I include the two quarters before and after for all new violating firms and all control firms. Control firms have no violations at or before the event year-quarter, and I only include products in categories that are listed by violating firms. The dependent variable is the percent of Amazon reviews that mention a key phrase indicating product failure that quarter. Violation is an indicator variable equal to one if a firm's ratios indicate that it has violated one of its loan covenants that quarter. I define a product's review share as the number of reviews it received divided by the total number of reviews in its product category. The first displayed independent variables is an indicator variable equal to one if the observation is after $Q = 0$ and if the firm has a new violation during the event year-quarter. The second displayed independent variable is an indicator variable equal to one if, in addition to the previously described conditions, the product's review share pre-event is below the median review share for that firm's products pre-event. Products are only included if they have at least ten reviews in each of the pre-event year-quarters and are available in all quarters. Each column is the same regression on a narrower window, where the absolute value of the minimum distance to violation the period of violation is less than or equal to the corresponding value. All regressions include firm level controls and have firm, product category-year-quarter, violation, and product fixed effects. Standard errors are clustered at the firm level.

	Dependent variable:				
	Product failure				
	(1)	(2)	(3)	(4)	(5)
After × violation	0.977	0.884	1.136	1.784	1.392
	(0.864)	(0.913)	(0.912)	(1.336)	(1.208)
After × violation × less popular	4.191***	4.285***	4.179***	4.310***	4.309***
	(0.956)	(0.971)	(1.011)	(1.135)	(1.220)
Window	0.7	0.6	0.5	0.4	0.3
Observations	27,068	22,572	17,544	10,028	5,532
R^2	0.527	0.533	0.528	0.517	0.523
Note:			*p<0.1; **p<0.05; ***p<0.01		

Table 1.10:
Sales Rank and Review Volume

This table presents a product level regression specification testing the relationship between the number of reviews left for a product in the prior three months and its sales rank within its product category. The sales rank is an integer, with a value of one indicating the product is the best-selling in its product category. The percentile of sales rank is done within each product category, as is the percentile of the number of reviews.

	Dependent variable:			
	Sales rank		Percentile of sales rank	
	(1)	(2)	(3)	(4)
# of reviews	$-6{,}965.493^{***}$	$-6{,}339.933^{***}$		
	(64.992)	(53.697)		
Percentile of # of reviews			-0.599^{***}	-0.599^{***}
			(0.0005)	(0.0005)
Constant	$1{,}171{,}787.000^{***}$		79.974^{***}	
	(770.220)		(0.025)	
Fixed effects?	None	Product category	None	Product category
Observations	6,394,523	6,394,523	6,394,523	6,394,523
R^2	0.002	0.320	0.214	0.214
Note:			*p<0.1; **p<0.05; ***p<0.01	

Table 1.11:
Loan Covenenat Violations and Review Volume

This table presents an event study specification testing the relationship between firms violating loan covenants and the number of reviews. Observations are at the firm-year-quarter-product level. For each quarter in which at least one firm has a new loan covenant violation (the event year-quarter), I include the two quarters before and after for all new violating firms and all control firms. Control firms have no violations at or before the event year-quarter, and I only include products in categories that are listed by violating firms. The dependent variable is the natural log of the number of Amazon reviews left that quarter. Violation is an indicator variable equal to one if a firm's ratios indicate that it has violated one of its loan covenants that quarter. The displayed independent variable is an indicator variable equal to one if the observation is after $Q = 0$ and if the firm has a new violation during the event year-quarter. Products are only included if they have at least ten reviews in each of the pre-event year-quarters and are available in all quarters. Each column is the same regression on a narrower window, where the absolute value of the minimum distance to violation the period of violation is less than or equal to the corresponding value. All regressions include firm level controls and have firm, product category-year-quarter, violation, and product fixed effects. Standard errors are clustered at the firm level.

	Dependent variable:				
	Log # reviews				
	(1)	(2)	(3)	(4)	(5)
After × violation	−0.116	−0.123	−0.192**	−0.303***	−0.176**
	(0.104)	(0.103)	(0.095)	(0.080)	(0.086)
Window	0.7	0.6	0.5	0.4	0.3
Observations	28,080	23,304	18,032	10,272	5,652
R^2	0.711	0.719	0.724	0.742	0.791
Note:					*p<0.1; **p<0.05; ***p<0.01

Table 1.12:
Quarterly Specifications

This table presents a quarterly event study specifications testing the impact of loan covenant violations on various product strategy measures. For each quarter in which at least one firm has a new loan covenant violation (the event year-quarter), I include the two quarters before and after for all new violating firms and all control firms. Control firms have no violations at or before the event year-quarter, and I only include products in categories that are listed by violating firms. All specifications are limited to firms whose absolute value of the minimum distance to violation is less than or equal to 0.4. The first two columns present product level results while the third and fourth columns present product portfolio-brand level results. The dependent variables measure, in order, the average Amazon rating from reviews left that quarter, the percent of Amazon reviews that mention a key phrase indicating product failure that quarter, the number of products listed under that brand that were introduced that quarter, and the number of new products listed under that brand that were introduced that quarter. Violation is an indicator variable equal to one if a firm's ratios indicate that it has violated one of its loan covenants in the event quarter. The displayed independent variables are an interaction of the quarter relative to a violation and if the firm has a new violation during the event year-quarter. For the product specifications, products are only included if they have at least ten reviews in each of the pre-event year-quarters and are available in all quarters. Observations in the product category-brand specifications must have at least one active product listed in each of the pre-event year-quarters. All regressions include firm level controls and have firm, and product category-year-quarter. The product specifications include product level fixed effects and the product portfolio specifications include product category-brand fixed effects. Standard errors are clustered at the firm level.

	Dependent variable:			
	Rating	% failure	# products	# new products
	(1)	(2)	(3)	(4)
Q-2 × Violation	0.031	−0.195	−0.119	−0.261
	(0.042)	(0.817)	(1.578)	(0.328)
Q-1 × Violation	0.064*	−0.358	−0.536	−0.297
	(0.037)	(0.885)	(1.679)	(0.342)
Q+1 × Violation	−0.100**	2.328**	−2.042	−0.795**
	(0.045)	(1.112)	(1.631)	(0.326)
Q+2 × Violation	−0.114**	3.557**	−2.600	−0.805**
	(0.048)	(1.437)	(1.719)	(0.365)
Specification?	Product	Product	Portfolio	Portfolio
Observations	10,272	10,272	25,720	25,720
R^2	0.680	0.518	0.761	0.692
Note:			*p<0.1; **p<0.05; ***p<0.01	

Table 1.13:
Control Variables and Definitions

This table defines all firm level control variables included in my parametric specifications. All Compustat data is from the Compustat Fundamentals Quarterly dataset, and CRSP data is from the CRSP Monthly Stock dataset.

Variable	Dataset	Definition
Leverage	Compustat	(dlttq + dlcq)/atq
Log market equity	Compustat	ln(mkvaltq) if available, otherwise ln(prccq × cshoq)
Return on assets	Compustat	oibdpq/atq
Log investment	Compustat	capxy/atq
Abnormal return	CRSP	3-month return - FF-12 industry return
Free cashflow	Compustat	(niq - xiq + txtq + xintq + dpq - capxy)/atq
Firm age	Compustat	Number of years since firm's first entry
Current ratio	Compustat	actq/lctq
Debt to tangible net worth	Compustat	(dlttq + dlcq)/(actq + aoq + ppentq - ltq)
Debt service coverage	Compustat	(actq + aoq + ppentq - ltq)/(dlttq + dlcq)
Debt to EBITDA	Compustat	(dlttq + dlcq)/$\left(\sum_{i=0}^{4} \text{niq}_{t-i} - \text{xiq}_{t-i} + \text{txtq}_{t-i} + \text{xintq}_{t-i} + \text{dpq}_{t-i}\right)$
Debt to equity	Compustat	(dlttq + dlcq)/(atq + prccq*cshoq - ceqq)

Table 1.14:
Phrases used to Identify Product Changes

This table defines the set of phrases search within Amazon product reviews to identify which channels drove the observed changes in product quality.

Channel	Phrase
Product failure	defective, stop work, stop working, stopped work, stopped working, doesn't work, not work, not working, died, unusable, falls apart, fell apart, broke, broken, poorly made, didn't survive, not survive, barely work, barely worked, barely working
Customer service	customer support, customer service, help line, tech support, technical support, support line, call center, help center, helpline, called help, called support, called amazon, service center, called service

Table 1.15:
Loan Covenant Violations and Product Failure with Negative Sentiment

This table presents an event study specification testing the relationship between firms violating loan covenants and product failure. Observations are at the firm-year-quarter-product level. For each quarter in which at least one firm has a new loan covenant violation (the event year-quarter), I include the two quarters before and after for all new violating firms and all control firms. Control firms have no violations at or before the event year-quarter, and I only include products in categories that are listed by violating firms. The dependent variable is the percent of Amazon reviews that mention a key phrase indicating product failure in a negative sentiment sentence that quarter. Violation is an indicator variable equal to one if a firm's ratios indicate that it has violated one of its loan covenants that quarter. The displayed independent variable is an indicator variable equal to one if the observation is after $Q = 0$ and if the firm has a new violation during the event year-quarter. Products are only included if they have at least ten reviews in each of the pre-event year-quarters and are available in all quarters. Each column is the same regression on a narrower window, where the absolute value of the minimum distance to violation the period of violation is less than or equal to the corresponding value. All regressions include firm level controls and have firm, product category-year-quarter, violation, and product fixed effects. Standard errors are clustered at the firm level.

	Dependent variable:				
	Product failure in negative sentence				
	(1)	(2)	(3)	(4)	(5)
After × violation	2.308***	2.549***	2.798***	2.969***	2.957***
	(0.863)	(0.899)	(0.906)	(1.000)	(1.055)
Window	0.7	0.6	0.5	0.4	0.3
Observations	28,080	23,304	18,032	10,272	5,652
R^2	0.467	0.472	0.464	0.449	0.450
Note:			*p<0.1; **p<0.05; ***p<0.01		

Table 1.16:
Robustness - Clustering

This table presents event study specifications testing the impact of loan covenant violations on various product strategy measures. For each quarter in which at least one firm has a new loan covenant violation (the event year-quarter), I include the two quarters before and after for all new violating firms and all control firms. Control firms have no violations at or before the event year-quarter, and I only include products in categories that are listed by violating firms. All specifications are limited to firms whose absolute value of the minimum distance to violation is less than or equal to 0.4. The first two columns present product level results while the third and fourth columns present product portfolio-brand level results. The dependent variables measure, in order, the average Amazon rating from reviews left that quarter, the percent of Amazon reviews that mention a key phrase indicating product failure that quarter, the number of products listed under that brand that were introduced that quarter, and the number of new products listed under that brand that were introduced that quarter. Violation is an indicator variable equal to one if a firm's ratios indicate that it has violated one of its loan covenants in the event quarter. The displayed independent variable is an indicator variable equal to one if the observation is after $Q = 0$ and if the firm has a new violation during the event year-quarter. For the product specifications, products are only included if they have at least ten reviews in each of the pre-event year-quarters and are available in all quarters. Observations in the product category-brand specifications must have at least one active product listed in each of the pre-event year-quarters. All regressions include firm level controls and have firm, and product category-year-quarter. The product specifications include product level fixed effects and the product portfolio specifications include product category-brand fixed effects. Standard errors are clustered at the firm level and at the year-quarter level.

	Dependent variable:			
	Rating	% failure	# products	# new products
	(1)	(2)	(3)	(4)
After × violation	-0.154^{***}	4.076^{***}	-1.986^{***}	-0.521^{**}
	(0.056)	(1.449)	(0.655)	(0.215)
Specification?	Product	Product	Portfolio	Portfolio
Observations	10,272	10,272	25,720	25,720
R^2	0.680	0.518	0.761	0.692
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 1.17:
Robustness - Winsorize

This table presents event study specifications testing the impact of loan covenant violations on various product strategy measures. For each quarter in which at least one firm has a new loan covenant violation (the event year-quarter), I include the two quarters before and after for all new violating firms and all control firms. Control firms have no violations at or before the event year-quarter, and I only include products in categories that are listed by violating firms. All specifications are limited to firms whose absolute value of the minimum distance to violation is less than or equal to 0.4. Continuous variables are winsorized at the at the 1% and 99% levels. The first two columns present product level results while the third and fourth columns present product portfolio-brand level results. The dependent variables measure, in order, the average Amazon rating from reviews left that quarter, the percent of Amazon reviews that mention a key phrase indicating product failure that quarter, the number of products listed under that brand that were introduced that quarter, and the number of new products listed under that brand that were introduced that quarter. Violation is an indicator variable equal to one if a firm's ratios indicate that it has violated one of its loan covenants in the event quarter. The displayed independent variable is an indicator variable equal to one if the observation is after $Q = 0$ and if the firm has a new violation during the event year-quarter. For the product specifications, products are only included if they have at least ten reviews in each of the pre-event year-quarters and are available in all quarters. Observations in the product category-brand specifications must have at least one active product listed in each of the pre-event year-quarters. All regressions include firm level controls and have firm, and product category-year-quarter. The product specifications include product level fixed effects and the product portfolio specifications include product category-brand fixed effects. Standard errors are clustered at the firm level.

	Dependent variable:			
	Rating	% failure	# products	# new products
	(1)	(2)	(3)	(4)
After × violation	-0.135^{***}	2.928^{***}	-1.366^{***}	-0.363^{**}
	(0.044)	(0.953)	(0.526)	(0.155)
Specification?	Product	Product	Portfolio	Portfolio
Observations	10,272	10,272	25,720	25,720
R^2	0.684	0.523	0.855	0.797
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 1.18:
Robustness - Firm-Subsidiary Structure

This table presents event study specifications testing the impact of loan covenant violations on various product strategy measures. For each quarter in which at least one firm has a new loan covenant violation (the event year-quarter), I include the two quarters before and after for all new violating firms and all control firms. Control firms have no violations at or before the event year-quarter, and I only include products in categories that are listed by violating firms. All specifications are limited to firms whose absolute value of the minimum distance to violation is less than or equal to 0.4 and to event year-quarters in 2003 or later. Continuous variables are winsorized at the at the 1% and 99% levels. The first two columns present product level results while the third and fourth columns present product portfolio-brand level results. The dependent variables measure, in order, the average Amazon rating from reviews left that quarter, the percent of Amazon reviews that mention a key phrase indicating product failure that quarter, the number of products listed under that brand that were introduced that quarter, and the number of new products listed under that brand that were introduced that quarter. Violation is an indicator variable equal to one if a firm's ratios indicate that it has violated one of its loan covenants in the event quarter. The displayed independent variable is an indicator variable equal to one if the observation is after $Q = 0$ and if the firm has a new violation during the event year-quarter. For the product specifications, products are only included if they have at least ten reviews in each of the pre-event year-quarters and are available in all quarters. Observations in the product category-brand specifications must have at least one active product listed in each of the pre-event year-quarters. All regressions include firm level controls and have firm, and product category-year-quarter. The product specifications include product level fixed effects and the product portfolio specifications include product category-brand fixed effects. Standard errors are clustered at the firm level.

	Dependent variable:			
	Rating	% failure	# products	# new products
	(1)	(2)	(3)	(4)
After × violation	-0.162^{***}	3.805^{***}	-2.031^{***}	-0.501^{**}
	(0.045)	(1.145)	(0.680)	(0.197)
Specification?	Product	Product	Portfolio	Portfolio
Observations	9,272	9,272	25,245	25,245
R^2	0.682	0.494	0.777	0.707
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 1.19:
Robustness - "Donut" Specification

This table presents event study specifications testing the impact of loan covenant violations on various product strategy measures. For each quarter in which at least one firm has a new loan covenant violation (the event year-quarter), I include the two quarters before and after for all new violating firms and all control firms. Control firms have no violations at or before the event year-quarter, and I only include products in categories that are listed by violating firms. All specifications are limited to firms whose absolute value of the minimum distance to violation is less than or equal to 0.4 and greater than or equal to 0.2. Continuous variables are winsorized at the at the 1% and 99% levels. The first two columns present product level results while the third and fourth columns present product portfolio-brand level results. The dependent variables measure, in order, the average Amazon rating from reviews left that quarter, the percent of Amazon reviews that mention a key phrase indicating product failure that quarter, the number of products listed under that brand that were introduced that quarter, and the number of new products listed under that brand that were introduced that quarter. Violation is an indicator variable equal to one if a firm's ratios indicate that it has violated one of its loan covenants in the event quarter. The displayed independent variable is an indicator variable equal to one if the observation is after $Q = 0$ and if the firm has a new violation during the event year-quarter. For the product specifications, products are only included if they have at least ten reviews in each of the pre-event year-quarters and are available in all quarters. Observations in the product category-brand specifications must have at least one active product listed in each of the pre-event year-quarters. All regressions include firm level controls and have firm, and product category-year-quarter. The product specifications include product level fixed effects and the product portfolio specifications include product category-brand fixed effects. Standard errors are clustered at the firm level.

	Dependent variable:			
	Rating	% failure	# products	# new products
	(1)	(2)	(3)	(4)
After × violation	-0.199^{***}	6.041^{***}	-2.239^{**}	-0.665^{**}
	(0.059)	(1.350)	(1.022)	(0.311)
Specification?	Product	Product	Portfolio	Portfolio
Observations	7,864	7,864	22,978	22,978
R^2	0.677	0.525	0.763	0.692
Note:			*p<0.1; **p<0.05; ***p<0.01	

Table 1.20:
Robustness - Alternate Distance to Violation

This table presents event study specifications testing the impact of loan covenant violations on various product strategy measures. For each quarter in which at least one firm has a new loan covenant violation (the event year-quarter), I include the two quarters before and after for all new violating firms and all control firms. Control firms have no violations at or before the event year-quarter, and I only include products in categories that are listed by violating firms. All specifications are limited to firms whose absolute value of the minimum alternative distance to violation is less than or equal to 1.0. The first two columns present product level results while the third and fourth columns present product portfolio-brand level results. The dependent variables measure, in order, the average Amazon rating from reviews left that quarter, the percent of Amazon reviews that mention a key phrase indicating product failure that quarter, the number of products listed under that brand that were introduced that quarter, and the number of new products listed under that brand that were introduced that quarter. Violation is an indicator variable equal to one if a firm's ratios indicate that it has violated one of its loan covenants in the event quarter. The displayed independent variable is an indicator variable equal to one if the observation is after $Q = 0$ and if the firm has a new violation during the event year-quarter. For the product specifications, products are only included if they have at least ten reviews in each of the pre-event year-quarters and are available in all quarters. Observations in the product category-brand specifications must have at least one active product listed in each of the pre-event year-quarters. All regressions include firm level controls and have firm, and product category-year-quarter. The product specifications include product level fixed effects and the product portfolio specifications include product category-brand fixed effects. Standard errors are clustered at the firm level.

	Dependent variable:			
	Rating	% failure	# products	# new products
	(1)	(2)	(3)	(4)
After × violation	-0.122^{***}	2.774^{**}	-2.532^{***}	-0.598^{***}
	(0.035)	(1.182)	(0.654)	(0.180)
Specification?	Product	Product	Portfolio	Portfolio
Observations	6,316	6,316	15,979	15,979
R^2	0.686	0.530	0.773	0.735
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 1.21:
Robustness - Distribution of Ratings

This table presents event study specifications testing the impact of loan covenant violations on the distribution of Amazon product ratings. For each quarter in which at least one firm has a new loan covenant violation (the event year-quarter), I include the two quarters before and after for all new violating firms and all control firms. Control firms have no violations at or before the event year-quarter, and I only include products in categories that are listed by violating firms. All specifications are limited to firms whose absolute value of the minimum distance to violation is less than or equal to 0.4. The dependent variables are the percent of Amazon ratings received that quarter equal to the corresponding rating. Violation is an indicator variable equal to one if a firm's ratios indicate that it has violated one of its loan covenants in the event quarter. The displayed independent variable is an indicator variable equal to one if the observation is after $Q = 0$ and if the firm has a new violation during the event year-quarter. Products are only included if they have at least ten reviews in each of the pre-event year-quarters and are available in all quarters. All regressions include firm level controls and have firm, product category-year-quarter, and product fixed effects. Standard errors are clustered at the firm level.

	Dependent variable:				
	% 1 star	% 2 stars	% 3 stars	% 4 stars	% 5 stars
	(1)	(2)	(3)	(4)	(5)
After × violation	3.611^{***}	-0.226	0.618	0.376	-4.379^{*}
	(1.070)	(0.378)	(0.802)	(2.482)	(2.556)
Observations	10,272	10,272	10,272	10,272	10,272
R^2	0.600	0.348	0.342	0.392	0.652
Note:					*p<0.1; **p<0.05; ***p<0.01

Table 1.22:
Loan Covenant Violations and Quality

This table presents an event study specification testing the relationship between firms violating loan covenants and its product quality. Observations are at the firm-year-quarter-product-review level. For each quarter in which at least one firm has a new loan covenant violation (the event year-quarter), I include the two quarters before and after for all new violating firms and all control firms. Control firms have no violations at or before the event year-quarter, and I only include products in categories that are listed by violating firms. The dependent variable is the Amazon rating of each review. Violation is an indicator variable equal to one if a firm's ratios indicate that it has violated one of its loan covenants that quarter. The displayed independent variable is an indicator variable equal to one if the observation is after $Q = 0$ and if the firm has a new violation during the event year-quarter. Reviews are only included if the firm has at least one review in all event year-quarters. Each column is the same regression on a narrower window, where the absolute value of the minimum distance to violation the period of violation is less than or equal to the corresponding value. All regressions include firm level controls and have firm, product-year-quarter, violation, and product fixed effects. Standard errors are clustered at the firm level.

	Dependent variable:				
	Amazon rating				
	(1)	(2)	(3)	(4)	(5)
After × violation	-0.052^{***}	-0.047^{***}	-0.044^{***}	-0.051^{***}	-0.046^{***}
	(0.011)	(0.010)	(0.010)	(0.012)	(0.012)
Window	0.7	0.6	0.5	0.4	0.3
Observations	7,396,494	6,148,019	4,459,015	2,800,405	1,733,426
R^2	0.188	0.190	0.184	0.181	0.179
Note:			*p<0.1; **p<0.05; ***p<0.01		

Table 1.23:
Loan Covenant Violations and Failure Frequency

This table presents an event study specification testing the relationship between firms violating loan covenants and product failure. Observations are at the firm-year-quarter-product-review level. For each quarter in which at least one firm has a new loan covenant violation (the event year-quarter), I include the two quarters before and after for all new violating firms and all control firms. Control firms have no violations at or before the event year-quarter, and I only include products in categories that are listed by violating firms. The dependent variable is an indicator variable equal to one if the review has a key phrase indicating product failure that quarter. Violation is an indicator variable equal to one if a firm's ratios indicate that it has violated one of its loan covenants that quarter. The displayed independent variable is an indicator variable equal to one if the observation is after $Q = 0$ and if the firm has a new violation during the event year-quarter. Reviews are only included if the firm has at least one review in all event year-quarters. Each column is the same regression on a narrower window, where the absolute value of the minimum distance to violation the period of violation is less than or equal to the corresponding value. All regressions include firm level controls and have firm, product-year-quarter, violation, and product fixed effects. Standard errors are clustered at the firm level.

	Dependent variable:				
	Product failure				
	(1)	(2)	(3)	(4)	(5)
After × violation	0.003	0.003	0.004**	0.005**	0.004
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Window	0.7	0.6	0.5	0.4	0.3
Observations	7,396,494	6,148,019	4,459,015	2,800,405	1,733,426
R^2	0.089	0.091	0.087	0.086	0.089
Note:			*p<0.1; **p<0.05; ***p<0.01		

1.8 Bibliography

Amazon (2018a). *About Amazon Best Sellers Rank*. URL: https://www.amazon.com/gp/help/customer/display.html?nodeId=525376 (visited on 08/14/2018).

Amazon (2018b). *Community Guidelines*. URL: https://www.amazon.com/gp/help/customer/display.html?nodeId=201929730 (visited on 08/14/2018).

Chava, S. and M. R. Roberts (2008). "How Does Financing Impact Investment? The Role of Debt Covenants". *The Journal of Finance* 63.5, pp. 2085–2121. eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.1540-6261.2008.01391.x.

Chen, K. C. W. and K. C. J. Wei (1993). "Creditors' Decisions to Waive Violations of Accounting-Based Debt Covenants". *The Accounting Review* 68.2, pp. 218–232.

Choi, J. P. (1998). "Brand Extension as Informational Leverage". *The Review of Economic Studies* 65.4, pp. 655–669.

Denis, D. J. and J. Wang (2014). "Debt covenant renegotiations and creditor control rights". *Journal of Financial Economics* 113.3, pp. 348–367.

Falato, A. and N. Liang (2016). "Do creditor rights increase employment risk? Evidence from loan covenants". *The Journal of Finance* 71.6, pp. 2545–2590.

Ferreira, D., M. A. Ferreira, and B. Mariano (2018). "Creditor Control Rights and Board Independence". *The Journal of Finance* 0.ja. eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/jofi.12692.

Frieder, L. and A. Subrahmanyam (2005). "Brand Perceptions and the Market for Common Stock". *The Journal of Financial and Quantitative Analysis* 40.1, pp. 57–85.

Harmon, A. (2004). "Amazon glitch unmasks war of reviewers". *The New York Times* 14.8.

He, R. and J. McAuley (2016). "Ups and Downs: Modeling the Visual Evolution of Fashion Trends with One-Class Collaborative Filtering". *CoRR* abs/1602.01585. arXiv: 1602.01585.

Holderness, C. G. (2016). "Problems using aggregate data to infer individual behavior: Evidence from law, finance, and ownership concentration". *Critical Finance Review* 5.1, pp. 1–40.

Hortaçsu, A., G. Matvos, C. Syverson, and S. Venkataraman (2013). “Indirect Costs of Financial Distress in Durable Goods Industries: The Case of Auto Manufacturers”. *The Review of Financial Studies* 26.5, pp. 1248–1290. eprint: /oup/backfile/content_public/journal/rfs/26/5/10.1093_rfs_hht006/1/hht006.pdf.

Huang, J. (2018). “The customer knows best: The investment value of consumer opinions”. *Journal of Financial Economics* 128.1, pp. 164–182.

J.H., G. S., H. Galen, M. A. C., and M. A. Fila (2013). “The USPTO Trademark Case Files Dataset: Descriptions, Lessons, and Insights”. *Journal of Economics & Management Strategy* 22.4, pp. 669–705. eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/jems.12035.

Kini, O., J. Shenoy, and V. Subramaniam (2017). “Impact of Financial Leverage on the Incidence and Severity of Product Failures: Evidence from Product Recalls”. *The Review of Financial Studies* 30.5, pp. 1790–1829. eprint: /oup/backfile/content_public/journal/rfs/30/5/10.1093_rfs_hhw092/6/hhw092.pdf.

Maksimovic, V. and S. Titman (1991). “Financial Policy and Reputation for Product Quality”. *The Review of Financial Studies* 4.1, pp. 175–200.

Manning, C., M. Surdeanu, J. Bauer, J. Finkel, S. Bethard, and D. McClosky (2014). “The Stanford CoreNLP natural language processing toolkit”. *Proceedings of 52nd annual meeting of the association for computational linguistics: system demonstrations*, pp. 55–60.

McAuley, J. J., C. Targett, Q. Shi, and A. van den Hengel (2015). “Image-based Recommendations on Styles and Substitutes”. *CoRR* abs/1506.04757. arXiv: 1506.04757.

Nini, G., D. C. Smith, and A. Sufi (2009). “Creditor control rights and firm investment policy”. *Journal of Financial Economics* 92.3, pp. 400–420.

Nini, G., D. C. Smith, and A. Sufi (2012). “Creditor Control Rights, Corporate Governance, and Firm Value”. *The Review of Financial Studies* 25.6, pp. 1713–1761. eprint: /oup/backfile/content_public/journal/rfs/25/6/10.1093_rfs_hhs007/2/hhs007.pdf.

Patent, U. S. and T. Office (2018). *Trademark basics*. URL: https://www.uspto.gov/trademarks-getting-started/trademark-basics (visited on 08/14/2018).

Phillips, G. and G. Sertsios (2013). "How Do Firm Financial Conditions Affect Product Quality and Pricing?" *Management Science* 59.8, pp. 1764–1782. eprint: https://doi.org/10.1287/mnsc.1120.1693.

Roberts, M. R. (2015). "The role of dynamic renegotiation and asymmetric information in financial contracting". *Journal of Financial Economics* 116.1, pp. 61–81.

Roberts, M. R. and A. Sufi (2009). "Control Rights and Capital Structure: An Empirical Investigation". *The Journal of Finance* 64.4, pp. 1657–1695. eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.1540-6261.2009.01476.x.

Rogerson, W. P. (1983). "Reputation and Product Quality". *The Bell Journal of Economics* 14.2, pp. 508–516.

Sheen, A. (2014). "The real product market impact of mergers". *The Journal of Finance* 69.6, pp. 2651–2688.

Snyder, T. J. (1990). "Trademark Law Revision Act of 1988 and the Gatekeeper Role of the PTO: Heading Abuse Off at the Pass". *Washington University Law Review* 68, p. 753.

Thomas, L. (Jan. 2018). *Amazon grabbed 4 percent of all US retail sales in 2017, new study says*. Ed. by CNBC. [Online; posted 3-January-2018].

Tirunillai, S. and G. J. Tellis (2012). "Does chatter really matter? Dynamics of user-generated content and stock performance". *Marketing Science* 31.2, pp. 198–215.

Titman, S. (1984). "The effect of capital structure on a firm's liquidation decision". *Journal of Financial Economics* 13.1, pp. 137–151.

Wernerfelt, B. (1988). "Umbrella Branding as a Signal of New Product Quality: An Example of Signalling by Posting a Bond". *The RAND Journal of Economics* 19.3, pp. 458–466.

CHAPTER 2

Trade Competition and Product Quality: Evidence from Amazon Reviews

China's rapid growth and transition to a market economy has fueled its rise as a major trading partner around the world. In the United States, Chinese imports increased as a percentage of total imports from 7.3% to 20.2% between 1997 and 2014. Foreign goods from low-income trading partners, such as China, represent a form of competition for the products of domestic manufacturers. As a result, trade with China has received a large amount of attention. The empirical literature finds trade competition negatively affects employment and earnings in the US (e.g. Acemoglu et al. (2016), David, Dorn, and Hanson (2013), and Autor et al. (2014)) as well as operating performance of US firms (e.g. Hombert and Matray (2018)). Political debate also swirls around trade with China evidenced by President Donald Trump recently targeting China through increased tariffs, sparking concerns about a trade war.

Despite the empirical and political attention on the effects of international competition on firms and employees that are directly affected, we have little evidence on how import competition affects product quality. Product quality underlies many of the interactions firms have with their customers. For firms, maintaining high product quality builds reputational capital with customers, allowing firms to sell their products for a premium and reduce frictions associated with product introductions (e.g. Rogerson (1983), Wernerfelt (1988), and Choi (1998)). A product's quality, along with its price, drives most consumer purchase decisions. Unanticipated changes to product quality can be costly for consumers, resulting in reduced functionality, defective products, warranty claims, or unanticipated replacement purchases.

The effect of import competition shocks on product quality are not well understood. Under standard economic theory, competition leads to lower prices for firms' products and higher consumer surplus. How domestic firms respond to this competition is unclear. International firms often have an inherent advantage due to lower operational costs. Domestic firms may try to maintain their short-term cashflows by reducing product quality, changing the physical product itself, cutting customer service, or enacting more stringent warranty honoring (e.g. Titman (1984)). Alternatively, domestic firms may respond to competition through product differentiation (e.g. Moreira (2007)). Improving product quality allows firms to earn a premium on sales and insulates them against future shocks. In this research, we investigate the effect of import competition from China on the quality of the products produced by US firms.

Using detailed product level data from Amazon in a two-staged least squared specification, we find that increases in competition cause domestic firms to improve product quality. We quantify product quality using Amazon product ratings and show that a one standard deviation increase in import competition leads to an increase in average product rating of 0.089, an increase of 14.7% of its standard deviation. This change in rating is driven by a decrease in low-quality evaluations, as the rate of one star ratings decreases by 1.678%. We use textual analysis on written product reviews to identify a decrease in the rate of product failures, indicating firms actively change the quality of their products.

We pay particular attention to whether the observed effects are driven by improvements in product quality within firms or by variation across firms. Distinguishing between the intensive and extensive margin helps us interpret the response to import competition. We find that product quality improves on the intensive margin with an alternative specification using firm level fixed effects. We extend this question to firms' product portfolios. Increasing average product quality can be achieved by improving the quality of existing products and by both introducing higher quality products and discontinuing lower quality products. We find significant improvement in the quality of existing products in response to import competition, indicating both firm level and product portfolio level changes occur on the intensive margin. Our results align with those of Matsa (2011), who finds that supermarkets invest in product quality in response to competition from Walmart. The search costs on Amazon are lower than in traditional retail stores, creating even strong incentives for firms to differentiate their products.

We find that domestic firms' product portfolio size mitigates the improvements in their average product quality. We run an alternative specification with an interaction term on product portfolios size and import competition and find that firms with smaller product portfolios have larger increases in average product quality. Firms with smaller product portfolios have less diversified cashflows. Differentiating their products may be more important, as any competition put a larger fraction of their portfolio at risk.

Our research is part of a wider literature investigating product quality at the firm level. Sheen (2014) finds that firms merge in order to achieve operational synergies, resulting in lower costs and higher product quality. Kini, Shenoy, and Subramaniam (2017) find that financial distress leads to worsening of product quality through a higher product recall probability. In my first chapter, I find that product quality decreases after firms violate their loan covenants. Though import competition has been shown to lead to worse operating performance of domestic firms, we find that it leads to an average improvement in product quality. At the firm level, increased product differentiation may allow a firm to mitigate the effects of competition and improve operating performance (e.g. Hoberg and Phillips (2010)). We argue that product quality is a form of product differentiation. We contribute to the literature by showing that foreign competition is an important consideration for domestic product quality.

Papers studying the effects of import competition have focused on the effects on employment or firm performance in the particular industries involved (e.g. Autor et al. (2014), Bloom, Draca, and Van Reenen (2016), Acemoglu et al. (2016), and Hombert and Matray (2018)), the geographies where these industries are concentrated (e.g. David, Dorn, and Hanson (2013)), and the effects on executive compensation (e.g. Lie and Yang (2018)). We present the first research, to the best of our knowledge, using detailed consumer review data to gauge the effect of import competition on product quality in the US.

The paper most similar to ours is Fernandes and Paunov (2009), who investigate the effect of Chinese import competition on product quality in Chile. Our study offers a key advantage over theirs. Their study uses prices as a measure of quality. This is problematic since price changes may reflect the changing cost nature across industries, which may be related to import competition. Our study is immune to this concern as the Amazon product rating system is uniform across all product categories. Moreover, we use product reviews which are appraisals on quality directly from customers, rather than indirect measures such as prices.

The remainder of the chapter is as follows: Section 2.1 describes the data, Section 2.2 describes the empirical methodology, Section 2.3 describes the results, and Section 2.4 concludes.

2.1 Data

Annual accounting data is from Compustat and firm stock return data is from the Center for Research in Security Prices. Product quality measures are calculated using Amazon data and import competition data is from UN Comtrade dataset. Our final sample runs from 1997 to 2014.

2.1.1 Amazon Data

Amazon review data was kindly provided by Julian McAuley. The dataset, as used in He and J. McAuley (2016) and J. J. McAuley et al. (2015), contains Amazon reviews and product meta-data from 1996 to 2014 for 9.4 million products. Each Amazon product has a unique identifier, the ASIN (Amazon Standard Identification Number), and product metadata collected at the end of the sample. This product metadata includes the product's brand, the product category it is listed under, and its sales rank within that product category. Products are classified into one of 31 product categories, which span the set of products available on

Amazon.[1] Within each product category, products are given a sales rank. How this sales rank is determined is not clearly defined by Amazon, but a lower ranking is a "good indicator" that the product has higher sales (Amazon (2018a)). Along with product metadata, we have every review left on Amazon for these products. Each review is time-stamped, has a written review, and a numerical product rating of 1, 2, 3, 4, or 5. Amazon does not provide guidelines to reviewers regarding what each numerical rating is meant to signify. For the written review, Amazon provides the prompt "What did you like or dislike? What did you use this product for?" (Amazon (2018b)).

Matching Amazon products to CRSP firms requires several intermediate steps. At each point in time, we link Amazon product brands to valid trademarks using data from the United States Patent and Trademark Office. We link trademarks owned by corporations to CorpWatch's firm parent-subsidiary dataset and match the ultimate parent company to CRSP. To ensure match quality, we only keep exact matches. We also only keep matches that uniquely link, at any point in time, one firm to each brand. This allows us to observe if and when a brand moves from one firm to another. We discuss our matching methodology in more detail in Section 2.5.

Table 2.1 gives summary statistics for our final sample, which runs from 1997 to 2014. The average firm in our sample has a market value of $13.1 billion. The average Amazon rating for firms in our sample is 4.14 out of 5. Five is the modal rating, given in 60% of the reviews in our sample. The average firm sold 79 unique products on Amazon within a fiscal year and received 580 reviews across its entire product portfolio. The number of unique products sold on Amazon has a large amount of variation across firms with the lowest being one product and the largest being 6,953 products.

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[1] Data includes products in the following product categories: Books, Software, Video Games, Cell Phones & Accessories, Grocery & Gourmet Food, Electronics, Toys & Games, Automotive, Health & Personal Care, Music, Magazines, Pet Supplies, Camera & Photo, Sports & Outdoors, Kitchen & Dining, Musical Instruments, Shoes, Home & Kitchen, Jewelry, Clothing, Beauty, Office Products, Industrial & Scientific, Computers & Accessories, Patio, Lawn & Garden, Arts, Crafts & Sewing, Home Improvement, Movies & TV, Watches, Gift Cards Store, Baby, Appliances, Prime Pantry.

2.1.2 Trade Data

UN Comtrade data on dollar imports from China for the US and other high-income countries (Germany, Japan, Australia, New Zealand, Denmark, Spain, Finland, and Switzerland) are kindly provided by Gordon Hanson. The data, which is a continuation of the data used in David, Dorn, and Hanson (2013), measures the annual dollar amount of Chinese imports at the four-digit SIC level from 1991 to 2014. We begin our analysis in 1997 to match the availability of our product quality measures. During this period, the dollar value of US imports from China (in 2014 dollars) increased by 389%. As a share of US total dollar imports this represents an increase from 7.3% to 20.2%.

Our measure of import competition is the import penetration measured used in Hombert and Matray (2018). We calculate import penetration as dollar imports (in $000s of 2014 dollars) divided by four-digit SIC employment in the US obtained from the U.S. Census Bureau County Business Pattern data. Therefore an increase in import penetration by one represents a $1000 (in 2014 dollars) increase in imports per worker in that particular four-digit SIC industry. As with Hombert and Matray (2018) we use the year before our sample period starts (1996) for employment data. This is motivated by the likely endogenous relationship between import penetration and employment (e.g. Acemoglu et al. (2016), David, Dorn, and Hanson (2013), and Autor et al. (2014)).

$$\text{import penetration}_{j,t} = \frac{\text{imports (2014 \$000s)}_{j,t}}{\text{employment}_{j,1996}}$$

where j and t reference industry and year respectively. We restrict attention in our analysis to SIC codes between 1000 and 3999, though 99% of SIC codes in our sample are between 2000 and 3999 (manufacturing firms). Table 2.2 gives summary statistics for import penetration at the 2-digit SIC level. The ordering of industries by import penetration is almost identical for the US and the other high income countries. Import penetration has been highest in durable goods, such as leather products, electronic equipment, and industrial machinery rather than nondurables such as food and paper. This makes sense as durables do not spoil over time and are more likely to survive transportation.

The empirical literature has found inconsistencies between SIC codes from Compustat and those from CRSP (e.g. Guenther and Rosman (1994)). We choose to merge import penetration data to Compustat using CRSP four-digit SIC codes. Compustat SIC codes are self-reported and consistent with the list provided by the Corporate Finance Division of the Securities and Exchange Commission (SEC).[2] This list does not have much granularity at the fourth digit level as around two-thirds of SIC codes in the Compustat data have a fourth digit of zero. In contrast, SIC codes provided by the North American Industry Classification System (NAICS) have a much more granular fourth digit.[3] Given the matching of the trade data to SIC codes is based on the crosswalk between ten-digit Harmonized (HS) codes used to classify products in international trade data and the SIC and NAICS industry codes (e.g. Pierce and Schott (2012)), we use SIC codes provided by CRSP. Inspection of SIC codes in the trade data reveals a level of granularity equivalent to that of SIC codes in CRSP.

2.1.3 External Validity

An additional consideration is to what extent our results can be generalized. Amazon is the largest online retailer but has a relatively small share of the overall retail market (Thomas (2018)). It is possible that the set of products firms sell on Amazon does not reflect their full portfolios, as Amazon historically focused on consumer products. We study the impact of import shocks from China. China is the largest source of imports in the US, the country with which the US operates the largest trade deficit, and is subject to intense political scrutiny. In our setting, China represents an international competitor with lower costs. David, Dorn, and Hanson (2013) find that China accounted for 91.5% of low-wage country imports in the US between 2000 and 2007. Golub (1998) states China's labor costs may be as little as 5% of US levels. This makes competing through reducing costs difficult for domestic firms. We expect that our results generalize to import competition from other low wage countries, as the relative constraints on domestic firms would remain the same.

[2] https://www.sec.gov/info/edgar/siccodes.htm

[3] https://www.naics.com/sic-codes-industry-drilldown/

2.2 Empirical Methodology

We use import penetration in year t to predict product quality in the following year $t+1$. In our analysis we report OLS estimates from the following specification

$$Y_{i,j,t} = \alpha_j + \gamma_t + \beta \text{Import Penetration}_{j,t-1} + \psi' X_{i,j,t-1} + \epsilon_{i,j,t} \tag{2.1}$$

where i, j, and t reference firm, industry (four-digit SIC), and time respectively. X is a vector of firm level control variables that controls for book assets, market equity, Q ratio, return on assets, leverage, cash flow, sales growth, and annual stock return (variable definitions included in Table 2.13). Standard errors from estimated specifications are clustered at the industry level to account for dependence between observations within state both within and across time.[4] We normalize import penetration by its standard deviation so the coefficient of interest β measures the change in the dependent variable for a one standard deviation change in import penetration. Import penetration in the US has a standard deviation of \$100.8 thousand 2014 dollars per worker.

Each specification controls for variables that are cross-sectionally invariant within a given year by including year fixed effects. We also control for time-invariant variables at the four-digit SIC level. Though we report results using unwinsorized data, our results are robust to winsorization of accounting variables at the 1% and 99% levels.

The above specification is not free of endogeneity concerns. Though we predict product quality one year ahead, the expectation of favorable reviews may influence current levels of imports. Moreover, an industry's performance in the United States may jointly explain customer reviews and imports. Due to these concerns we adopt an identification strategy that is widely-used in the international trade literature where import penetration in the US is instrumented by import penetration in other high-income countries.[5] This strategy relies

[4] We also run the analysis clustering by industry and year. Our results are economically and statistically similar.

[5] This methodology has been used in studies such as Bloom, Draca, and Van Reenen (2016), David, Dorn, and Hanson (2013), Acemoglu et al. (2016), and Autor et al. (2014), Hombert and Matray (2018), and Lie and Yang (2018).

on the assumption that commonality between imports from China in the US and imports from China in these other high-income countries is driven by factors internally related to China. Table 2.2 suggests this commonality is large as the two-digit SIC ordering of import penetration for the US and other countries is near identical.[6] Though not formally testable, we believe the instrument satisfies the exclusion restriction i.e. that it only correlates with product quality through its correlation with import penetration in the US. As discussed in David, Dorn, and Hanson (2013), China's export growth has been driven by its transition to a market-oriented economy rather than US outsourcing. In addition, industries in China have recently began to gain access to technologies previously subject to long-term bans. Finally, joining the World Trade Organization (WTO) in 2001 further improved China's standing as a trade partner.

The second condition an instrument must satisfy is the relevance condition. This requires non-zero correlation between US import penetration and import penetration in the other high-income countries. Table 2.2 suggests a strong correlation between Chinese import penetration in the US and Chinese import penetration in the other high-income countries. Fortunately, the relevance condition is formally testable. The first stage of the 2SLS specification regresses import penetration in the US on import penetration in the other high-income countries.

$$\text{Import Penetration}_{i,j,t} = \theta_j + \delta_t + \phi \text{Import Penetration (Other)}_{i,j,t-1} + \rho' X_{i,j,t-1} + \eta_{i,j,t} \quad (2.2)$$

A significant ϕ coefficient satisfies the relevance condition. The fitted value from this regression is used as the independent variable in Equation 2.1.[7]

[6] Imports in the non-US countries are also normalized by US industry employment.

[7] Most statistical packages run this analysis in one step in order to ensure correct estimation of the standard errors.

2.3 Results

We begin by investigating if the relevance condition is satisfied by estimating a variant (four-digit SIC-year level rather than firm-year level) of Equation 2.2.[8] We regress import penetration from China in the US on our instrument. Table 2.3 confirms a positive and both an economically and statistically strong relationship, with a coefficient of 1.137.

For our baseline test, we investigate the effect of import penetration on the weighted average rating for a firm's products over the next fiscal year. Each product is weighted by the number of reviews it receives over that fiscal year. We run the analysis with and without control variables.[9] Table 2.4 presents our baseline results. Both OLS and 2SLS specifications suggest a positive effect of Chinese import penetration on product quality for US firms. A one standard deviation increase in import penetration leads to a 0.089 increase in the weighted average product rating of a firm's product portfolio.[10] This increase is 14.7% of the standard deviation of the weighted average rating and is statistically significant with a t-statistic of 2.83. The result is highly invariant to the exclusion of firm level control variables. Our results suggest that firms respond to increased import competition by product differentiation through quality. We additionally find a negative relationship between leverage and product quality, consistent with the results of Kini, Shenoy, and Subramaniam (2017). Interestingly, cash flow does not appear to be an important determinant of product quality, as the coefficient is negative and statistically insignificant.

It is worth noting that a valid concern with any instrumental variable test is external validity due to the fact that the effect is identified by "conformers" i.e. industries with higher import penetration that also have high import penetration in other countries. Given Table 2.2 shows the ordering is nearly the same between the US and other the high-income countries, external validity of the result within the sample is not a concern.

[8] In the 2SLS analysis, we estimate Equation 2.2 exactly.

[9] See Table 2.13

[10] This effect is identified using industry, rather than firm, fixed effects. Thus the identified effect may be within industry across firms. In later tests we present evidence that this effect holds within firm.

Amazon ratings take on discrete values between one and five, where five is best. With our baseline results in hand, we investigate the source of the ratings increase in the firm's product rating distribution. To do so, we replace our dependent variable with the percentage of ratings receiving one, two, and five stars within the next fiscal year. Table 2.5 shows that a one standard deviation increase in import penetration leads to a decrease in the percentage of one-star reviews by 1.678 percentage points. This effect is statistically significant with a t-statistic of -2.456. There is also evidence of a decrease in two star reviews, though not statistically significant. At the top end, we find weak evidence of an increase in the percentage of five-star reviews by 2.183 percentage points. Given a decrease in one star reviews it is not surprising that the changes elsewhere in the rating distribution are not statistically significant as the decrease in one star reviews may be relatively evenly redistributed amongst higher ratings. In unreported analysis, exclusion of the control variables yields economically and statistically similar results. Our results show that import competition has a positive effect on a firm's average product quality and this is reflected in a smaller left tail of its product rating distribution.

To understand the increase in product quality, we analyze the text of reviews received by products. The prompt given to Amazon customers when leaving a written product review is broad, allowing reviewers a large degree of latitude. This allows customers the freedom to write about the aspects of product quality that are most salient to them. We take advantage of this by searching for key phrases corresponding to different channels in each written review and seeing how the frequency of these phrases is related to import penetration. We measure the percentage of reviews that state the word "quality". We also measure the percentage of reviews that mention product failures, a common reason for products receiving one star reviews on Amazon. This is through looking for key phrases in reviews that would indicate a product is in some way defective. These phrases include "stopped working", "fell apart", and "broke". Though Table 2.6 does not show a change in the percentage of reviews stating the word "quality", we find a decrease in complaints about defective products. A one standard deviation increase in import penetration leads to a decrease in the percentage of reviews with words indicative of defective products by 1.158 percentage points. This effect is statistically significant with a t-statistic of -2.692.[11] Given defective products is typical for a one-star rating, an increase in product quality is consistent with less reviews stating product defectiveness, less one star reviews, and a shift toward higher ratings.

At this point, it is useful to point out that our results are obtained controlling for time-invariant variables at the four-digit SIC level. Though this is much more granular than the definition of industry typically used for industry fixed effects (e.g. Fama and French 48 industries, 2-digit SIC, 2-digit NAICS, etc) we have not identified whether the observed effect is due to within firm variation in import penetration and product quality. This can only be achieved using firm fixed effects. Though we find economically similar results using firm fixed effects, our results are not statistically significant. We believe this is due to losing a large degree of variation in the data with firm fixed effects. Given our sample starts in 1997 and firms only enter the Amazon data due to selling products rather than offering products on Amazon, firms enter and exit the sample in earlier years due to a lack of sales. Nevertheless, it is important to understand if results are driven by within-firm variation or within-industry across-firm variation. If the results are due to the latter, a possible explanation is that a high level of import penetration causes firms with low quality products to exit the sample and additionally requires new firms to have high quality products in order to be competitive. We therefore investigate how import penetration is related to exit and entry from our sample. Table 2.7 sorts all firms into quartiles every year by the level of import penetration in their industry. We then calculate the average product rating for firms in their last year in the Amazon data (excluding the end of the sample) by import penetration quartile. For firms exiting the sample, those in the highest quartile of import penetration do not have the highest product rating (4.02 for quartile four vs. 4.20 for quartile two). For firms entering the sample, this is also the case, as the average product rating for firms entering the highest import penetration quartile is the third highest among the four quartiles. The percentage of

[11] Our results show that import penetration leads to an improvement in product quality, driven by a decrease in the occurrence of product defectiveness. Though consumers benefit from import penetration through product quality, it is not clear if this is accompanied by higher prices charged for these products. Though we cannot observe historical prices charged to customers in the Amazon data, as an alternative, in Table 2.12 we find no increase in cost of goods sold nor an increase in selling and general expenses.

firms within each quartile entering and exiting the sample also exhibits very little variation across quartiles. These results are inconsistent with low quality firms no longer selling on Amazon due to import penetration. We find no evidence that entry and exit are driving our results. Table 2.8 provides further support of the results of Table 2.7. Import penetration does not predict a higher chance of exit from the sample, in fact the relationship is negative.

We confirm that our results are not driven by entry to and exit from the sample by finding the effect within firms. We use an alternate specification using firm fixed effects on the last three years of our sample to find that domestic firms' product quality increases after increases in import penetration (2011 to 2013, given we study product quality in the next fiscal year). Given the early sample has less observations, firm fixed effects remove a lot of variation from the sample. Though the 2011-2013 subsample is only three years, it represents over one third of the firm-years in our sample and 82% of the firms from the full sample. This is due to the increase in popularity over time of Amazon for purchases as an alternative to brick and mortar stores. Table 2.9 gives results consistent with those for the full sample in terms of sign and statistical significance. Economically the effects are stronger. A one standard deviation increase in import penetration leads to a statistically significant increase in average rating by 0.234. Given that Amazon has reduced search costs for finding alternative products due to its wide product offering, a decrease in product quality may be increasingly costly for firms in more recent times. Our results are consistent with this as the effect of import penetration is larger in this recent subsample. The effect is driven by a decrease in two star ratings though there is weak evidence of a decrease in one star ratings and an increase in five star ratings. The results in the subsample are consistent with that of the full sample; we find that import competition results in a shorter left tail in the distribution of product ratings.

We now focus on whether product quality improvements are a result of product changes or changes to product portfolio composition. We isolate the intensive margin in an alternative specification by restricting analysis to the set of products that are available in year t and year $t+1$. The dependent variable is the ratings over the next fiscal year for products that are currently in a firm's product portfolio. Table 2.10 presents the results. The results are consistent with the full portfolio results of Table 2.4 and Table 2.9. A one standard deviation increase in import penetration leads to a 0.078 and 0.214 increase in average product rating in the full sample and 2011-2013 subsample respectively. Firms respond to import competition by increasing the quality of their existing products, rather than differentiating by creating new products. Our results are direct evidence that firms respond to import competition by differentiating their existing products by improving their quality.

Given the literature's evidence that import penetration negatively affects operating performance (e.g. Hombert and Matray (2018)), firms have an incentive to respond to increase import competition through product differentiation, especially if competing through lower prices and quality adversely affects sales. This incentive may be stronger for firms with a smaller product portfolio due to the reliance on a smaller set of products for sales and hence operating performance. We therefore investigate how import penetration affects product quality in the cross-section. We interact import penetration with the number of products in a firm's current product portfolio. We also instrument for this interaction by instead using the import penetration in the other high-income countries in this interaction, rather than import penetration in the US. We do not include the uninteracted import penetration variable in the regression since we use industry-year fixed effects. Consistent with our hypothesis, Table 2.11 shows that the effect of import penetration on product quality is attenuated by product portfolio size. That is, the effect is larger for firms with smaller product portfolios. Given that firms respond to competition through product differentiation, the incentives appear to be higher for firms with a smaller product offering.

2.4 Conclusion

In the past two decades, countries around the world have experienced a increase in trade with China. Due to China's emergence as a superpower and the size of trade with the US, it is important to understand the implications of this trade. In economic theory, an increase in competition increases consumer surplus while decreasing prices and firm profits. Firms may respond by cutting costs and potentially quality in order to maintain margins. However, if firms cannot lower costs and/or prices or lowering quality increases the risk of potential customers switching to alternative products, their sales and performance may suffer. Hence an alternative route in response to competition is product differentiation.

We investigate the effect of low-income import competition from China on product quality for US firms using detailed customer reviews from Amazon as a proxy for product quality. We use an instrumental variables approach widely used in the international trade economics literature. Our results show that import competition leads to an increase in product quality. An increase in average ratings is driven by a decrease in the percentage of one and two-star ratings with weak evidence of an increase of five-star ratings. In textual analysis we find that this improvement in product quality is through a decreased incidence of reviews mentioning defective products. We find that the increase in product quality holds within firm and for existing product portfolios. Furthermore, firms reliant on a smaller set of products explain the results due to a reliance on a smaller set of products.

Our research is part of a wider literature exploring the effects of increased import competition from China. Though existing studies have considered the effects on employees and firms operating in industries directly impacted by import competition, there has been little evidence of the effects on product quality and hence the offerings to consumers in the US as a whole. An increase in product quality is beneficial to households through greater certainty with respect to purchases.

Though we find an increase in average product quality across a firm's product portfolio as a result of import competition, we are not concluding that the effect will hold for every product within a firm's portfolio. We cannot say why a particular product in a firm's portfolio would experience a product quality increase given our data. Data on product level margins, variable costs, production complementarities across products, and prices may be more revealing. Finally, though we find no evidence of a cost increase for domestic firms, due to data limitations we cannot directly test if consumers pay for the quality increase through higher prices. If consumers benefit through higher quality products at no increased cost, import competition may improve consumer surplus. We leave these matters to future research.

2.5 Appendix 1: Amazon to CRSP Match Methodology

We first attempt to match each Amazon product's brand name to that brand's trademark.[12] Trademark data is downloaded from USPTO's 2017 Trademark Case Files dataset, which contains information on 8.6 million trademark applications filed from January 1870 forward. Our trademark selection methodology is guided by the discussion of J.H. et al. (2013), who document and discuss the Trademark Case Files dataset in detail.

Each trademark has an entry, which is updated throughout the trademark's life. As our goal is to link Amazon products to public firms, we only include registered text trademarks owned by corporations. For dead trademarks, we use the provided expiration date. For trademarks that were last updated as living, we define the expiration date as twenty years after the registration date if the trademark was filed before November 16, 1989. If the trademark was filed on or after November 16, 1989, we define the patent expiration date as ten years after the registration date. This difference in expiration date is due to the Trademark Law Revision Act of 1988, which eliminated the requirement of commercial use of a trademark prior to registration (Snyder (1990)). We require an exact match between the Amazon brand and the trademark's text, and that product reviews occur within the trademark's life.

We then try to link each matched trademark's owner to a subsidiary corporation, using data collected by CorpWatch. CorpWatch's dataset extracts firm subsidiary information listed in Exhibit 21 of firms' 10-K filings. Using this, we build a parent-subsidiary hierarchy and identify an ultimate parent company for each subsidiary firm. Firm subsidiary data is only available from 2003 onward, so we assume the 2003 subsidiary structure for all years prior. We attempt to standardize common firm name endings (for example, we replace the words "international", "intrntnl", and "internl" with "intl") before doing an exact match between the trademark owner name and firm subsidiary name. We require all exact matches to be overlapping in time.

[12] A trademark, as defined by the US Patent and Trademark Office, is "... any word, name, symbol, device, or any combination, used or intended to be used to identify and distinguish the goods/services of one seller or provider from those of others, and to indicate the source of the goods/services" (Patent and Office (2018)).

Finally, we match the firm subsidiary to its CRSP ultimate parent firm. Like in the previous step, we first standardize common firm name endings. We then do an exact match between the subsidiary's ultimate parent firm's name, defined with the CorpWatch dataset, to the CRSP firm name at that time using the CRSP Names dataset.

Table 2.1:
Import Competition Summary Statistics

Summary statistics for variables used throughout this research. *Avg. Amazon Rating* is the the weighted (by number of reviews) average Amazon rating for the firm's products over the fiscal year. *Number of Products* is the number of Amazon products for the firm over the fiscal year. *Number of Reviews* is the number of Amazon reviews for the firm over the fiscal year. *% n Star* is the percentage of Amazon reviews that are *n* stars for the firm's products over the fiscal year.

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Total Assets ($m)	3,459	12,796.43	50,936.70	4.05	646.37	7,035.00	797,769.00
Market Equity ($m)	3,459	13,110.32	37,797.20	0.86	560.04	8,093.76	626,550.30
Tobin's Q	3,459	1.88	1.11	0.38	1.23	2.15	20.27
ROA	3,458	0.12	0.14	−2.56	0.09	0.18	0.91
Leverage	3,456	0.24	0.20	0.00	0.11	0.34	2.18
Cash Flow	3,457	0.08	0.15	−1.52	0.05	0.14	2.69
Sales Growth	3,451	8.37	35.21	−100.00	−1.75	14.21	1,145.97
Annual Return	3,399	0.18	0.64	−0.96	−0.11	0.35	13.65
Avg. Amazon Rating	3,459	4.14	0.65	1	3.9	4.5	5
Number of Products	3,459	79.14	274.64	1	2	45	6,953
Number of Reviews	3,459	580.48	2,566.61	1	4	176.5	49,251
% One Star	3,459	9.30	13.43	0	0	12.5	100
% Two Star	3,459	5.26	9.93	0	0	6.6	100
% Three Star	3,459	7.76	11.96	0	0	9.6	100
% Four Star	3,459	17.96	17.12	0	7.8	22.6	100
% Five Star	3,459	59.71	24.01	0	50	71.4	100

Table 2.2:
Import Penetration by 2-Digit SIC: 1996–2014

Import penetration from China for 1997 to 2014 per 2-digit SIC code. Mean import penetration is defined as the mean level of 2-digit SIC imports (in $000 of 2014 dollars) divided by 1996 US employment at the 2-digit SIC level. Change variables are defined as the change (from 1997 to 2014) in imports (in $000 of 2014 dollars) divided by 1996 employment at the 2-digit SIC level.

2-digit SIC		Mean US	Change US	Mean Other	Change Other
31	Leather and leather products	49.86	23.85	19.42	18.00
39	Miscellaneous manufacturing industries	24.89	15.15	12.08	10.80
36	Electronic and other electronic equipment	14.97	25.63	11.81	19.98
23	Apparel and other textile products	10.22	11.42	15.02	10.23
35	Industrial machinery and equipment	8.82	15.52	6.16	11.18
25	Furniture and fixtures	8.42	10.87	3.17	5.64
33	Primary metal industries	2.79	3.75	3.81	4.37
28	Chemicals and allied products	2.72	5.19	3.80	5.98
32	Stone, clay, and glass products	2.72	2.38	2.03	2.51
34	Fabricated metal products	2.62	4.11	2.20	3.79
30	Rubber and miscellaneous plastics products	2.27	3.19	1.64	2.62
38	Instruments and related products	2.00	3.87	2.05	3.78
26	Paper and allied products	1.39	1.91	0.98	1.68
24	Lumber and wood products	1.38	1.82	1.24	0.89
37	Transportation equipment	1.04	2.56	0.98	1.77
22	Textile mill products	0.69	1.68	1.39	1.41
29	Petroleum and coal products	0.54	0.55	0.47	0.63
20	Food and kindred products	0.48	0.66	1.67	0.74
27	Printing and publishing	0.40	0.40	0.16	0.23
10	Metal mining	0.31	0.07	0.43	0.12
12	Nonmetallic minerals, except fuels	0.00	0.00	3.54	-2.36

Table 2.3:
Relevance Condition

Predicting United States imports from China with imports from China in other high-income countries (Australia, Denmark, Finland, Germany, Japan, New Zealand, Spain, and Switzerland). *Import Penetration* is imports (in $000s of 2014 dollars) at the four-digit SIC level divided by 1996 four-digit SIC level employment in the United States. T-statistics calculated using standard errors clustered at the four-digit SIC level are given in parentheses. First stage regressions in instrumental variables analysis include all second stage variables as controls.

	Dependent variable:
	Import Penetration
	(1)
Import Penetration in Other Countries	1.137***
	(7.586)
Industry FE	Yes
Year FE	Yes
Observations	1563
Adjusted R^2	0.970
Note:	*p<0.1; **p<0.05; ***p<0.01

Table 2.4:
Import Competition and Product Quality

The dependent variable is the weighted (by number of reviews) average rating for the firm's products over the next fiscal year. *Import Penetration* is imports (in $000s of 2014 dollars) at the four-digit SIC level divided by 1996 four-digit SIC level employment in the United States. *Import Penetration* is standardized by its standard deviation. T-statistics calculated using standard errors clustered at the four-digit SIC level are given in parentheses.

	Dependent variable:			
	Weighted Average Rating			
	(1)	(2)	(3)	(4)
Import Penetration	0.073***		0.073***	
	(2.627)		(2.610)	
Import Penetration (fitted)		0.086***		0.089***
		(2.636)		(2.830)
log(Assets)			0.075**	0.074**
			(2.076)	(2.058)
log(Market Equity)			−0.061*	−0.060*
			(−1.856)	(−1.832)
Tobin's Q			0.010	0.009
			(0.389)	(0.366)
ROA			0.393*	0.391*
			(1.900)	(1.889)
Leverage			−0.193*	−0.193*
			(−1.945)	(−1.945)
Cash Flow			−0.338	−0.339
			(−1.038)	(−1.043)
Sales Growth			0.000	0.000
			(1.086)	(1.069)
Annual Return			−0.019	−0.018
			(−0.808)	(−0.773)
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	3464	3464	3392	3392
Adjusted R^2	0.109	0.109	0.116	0.116
Note:		*p<0.1; **p<0.05; ***p<0.01		

Table 2.5:
Import Competition and the Distribution of Ratings

The dependent variable is the percentage of Amazon reviews that are n stars across a firm's product portfolio over the next fiscal year. *Import Penetration* is imports (in $000s of 2014 dollars) at the four-digit SIC level divided by 1995 four-digit SIC level employment in the United States. *Import Penetration* is standardized by its standard deviation. T-statistics calculated using standard errors clustered at the four-digit SIC level are given in parentheses.

	Dependent variable:					
	% 1 star		% 2 star		% 5 star	
	OLS	2SLS	OLS	2SLS	OLS	2SLS
	(1)	(2)	(3)	(4)	(5)	
Import Penetration	-1.138^{**}		-0.787		2.205^{*}	
	(-1.976)		(-1.492)		(1.696)	
Import Penetration (fitted)		-1.678^{**}		-0.971		2.183
		(-2.456)		(-1.526)		(1.629)
log(Assets)	-1.577^{**}	-1.561^{**}	-0.776^{*}	-0.771^{*}	1.118	1.119
	(-2.139)	(-2.112)	(-1.809)	(-1.796)	(0.783)	(0.783)
log(Market Equity)	1.605^{**}	1.578^{**}	0.413	0.404	-0.495	-0.497
	(2.408)	(2.367)	(1.045)	(1.023)	(-0.377)	(-0.377)
Tobin's Q	-0.501	-0.482	0.263	0.270	0.192	0.192
	(-1.132)	(-1.088)	(0.749)	(0.766)	(0.224)	(0.225)
ROA	-11.197^{*}	-11.127^{*}	1.121	1.146	7.329	7.332
	(-1.903)	(-1.889)	(0.655)	(0.668)	(1.280)	(1.279)
Leverage	2.886^{*}	2.884^{*}	3.394^{**}	3.393^{**}	-4.159	-4.159
	(1.778)	(1.778)	(2.548)	(2.546)	(-1.113)	(-1.113)
Cash Flow	7.184	7.227	0.282	0.297	-10.176	-10.174
	(0.806)	(0.811)	(0.207)	(0.218)	(-1.422)	(-1.423)
Sales Growth	0.000	0.001	-0.009	-0.009	0.019	0.019
	(0.045)	(0.068)	(-1.446)	(-1.437)	(1.184)	(1.185)
Annual Return	0.601	0.578	-0.151	-0.159	-0.286	-0.287
	(1.228)	(1.180)	(-0.573)	(-0.607)	(-0.420)	(-0.416)
Industry FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3392	3392	3392	3392	3392	3392
Adjusted R^2	0.096	0.096	0.029	0.029	0.109	0.109
Note:						*p<0.1; **p<0.05; ***p<0.01

Table 2.6:
Import Competition and Aspects of Product Quality

Import Penetration is imports (in $000s of 2014 dollars) at the four-digit SIC level divided by 1995 four-digit SIC level employment in the United States. *Import Penetration* is standardized by its standard deviation. *Defective Products* is the probability a review contains key phrases that would indicate a product is in some way defective. *"Quality"* is the probability a review contains the word "quality." T-statistics calculated using standard errors clustered at the four-digit SIC level are given in parentheses.

	Dependent variable:			
	% Defective Products		% "Quality"	
	OLS	2SLS	OLS	2SLS
	(1)	(2)	(3)	(4)
Import Penetration	−0.850**		−0.706	
	(−2.305)		(−1.220)	
Import Penetration (fitted)		−1.158***		−0.231
		(−2.692)		(−0.456)
log(Assets)	0.008	0.014	−1.078	−1.087
	(0.015)	(0.026)	(−1.132)	(−1.134)
log(Market Equity)	0.043	0.031	1.116	1.135
	(0.080)	(0.057)	(1.370)	(1.380)
Tobin's Q	−0.188	−0.177	−0.587	−0.603
	(−0.688)	(−0.647)	(−1.486)	(−1.512)
ROA	−0.572	−0.524	1.270	1.197
	(−0.439)	(−0.404)	(0.812)	(0.760)
Leverage	1.939	1.940	0.704	0.703
	(1.554)	(1.552)	(0.504)	(0.503)
Cash Flow	3.327*	3.338*	2.001	1.985
	(1.751)	(1.757)	(0.984)	(0.980)
Sales Growth	−0.001	−0.001	−0.007	−0.007
	(−0.278)	(−0.245)	(−1.313)	(−1.342)
Annual Return	0.092	0.075	−0.511	−0.483
	(0.275)	(0.221)	(−1.381)	(−1.324)
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	2995	2995	2995	2995
Adjusted R^2	0.075	0.075	0.129	0.129
Note:		*p<0.1; **p<0.05; ***p<0.01		

Table 2.7:
Market Entry/Exit Summary Statistics

This table presents average Amazon ratings for firms entering and exiting the Amazon data by import penetration quartile (1=lowest, 4=highest). *Exit Rating* is the average Amazon rating for firms in their last year in the Amazon data (i.e. firms that exit the sample before 2014). *Entry Rating* is the average Amazon rating for firms in their first year in the Amazon data (i.e. firms that enter the sample after 1997). *% Exit* is the percentage of firms in the quartile that exit the Amazon data before the end of the sample. *% Entry* is the percentage of firms in that quartile that enter the Amazon data after the start of the sample.

Import Competition Quartile	Exit Rating	% Exit	Entry Rating	% Entry
1	3.90	0.02	4.39	0.14
2	4.20	0.02	4.15	0.14
3	3.69	0.01	4.21	0.15
4	4.02	0.03	4.20	0.15

Table 2.8:
Import Competition and Market Entry/Exit

This table predicts dummy variables for exit and entry into the sample with import penetration. *Import Penetration* is imports (in $000s of 2014 dollars) at the four-digit SIC level divided by 1995 four-digit SIC level employment in the United States. *Import Penetration* is standardized by its standard deviation. T-statistics calculated using standard errors clustered at the four-digit SIC level are given in parentheses.

	Dependent variable:			
	Last year in Amazon data		First year in Amazon data	
	OLS	2SLS	OLS	2SLS
	(1)	(2)	(3)	(4)
Import Penetration	−0.007		0.010	
	(−1.624)		(0.778)	
Import Penetration (fitted)		−0.010*		−0.000
		(−1.648)		(−0.005)
log(Assets)	0.013	0.014	−0.030	−0.030
	(1.497)	(1.505)	(−1.288)	(−1.283)
log(Market Equity)	−0.017*	−0.017*	0.002	0.002
	(−1.776)	(−1.788)	(0.083)	(0.067)
Tobin's Q	0.015**	0.015**	0.003	0.003
	(2.255)	(2.272)	(0.168)	(0.186)
ROA	−0.154***	−0.154***	−0.011	−0.010
	(−4.514)	(−4.512)	(−0.266)	(−0.241)
Leverage	0.016	0.016	−0.055	−0.055
	(0.717)	(0.719)	(−1.312)	(−1.311)
Cash Flow	0.075*	0.075*	−0.035	−0.034
	(1.783)	(1.785)	(−0.470)	(−0.459)
Sales Growth	0.000	0.000	−0.000	−0.000
	(0.915)	(0.924)	(−0.433)	(−0.418)
Annual Return	−0.005	−0.005	−0.001	−0.001
	(−1.299)	(−1.355)	(−0.065)	(−0.100)
Industry FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	3847	3847	3847	3847
Adjusted R^2	0.114	0.114	0.126	0.126
Note:			*p<0.1; **p<0.05; ***p<0.01	

Table 2.9:
Import Competition, Product Quality, and the Distribution of Ratings from 2011-2013

The dependent variable is the weighted (by number of reviews) average rating for the firm's products over the next fiscal year or the percentage of Amazon reviews that are n stars across a firm's product portfolio over the next fiscal year. *Import Penetration* is imports (in \$000s of 2014 dollars) at the four-digit SIC level divided by 1996 four-digit SIC level employment in the United States. *Import Penetration* is standardized by its standard deviation. T-statistics calculated using standard errors clustered at the four-digit SIC level are given in parentheses.

	Dependent variable:							
	Weighted Average Rating		% 1 star		% 2 star		% 5 star	
	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Import Penetration	0.210**		−2.013		−1.426**		7.431*	
	(2.053)		(−1.455)		(−2.147)		(1.769)	
Import Penetration (fitted)		0.234**		−2.988		−2.015*		6.993
		(2.178)		(−1.496)		(−1.849)		(1.594)
log(Assets)	−0.017	−0.016	−0.347	−0.365	0.804	0.794	−2.564	−2.572
	(−0.145)	(−0.142)	(−0.167)	(−0.175)	(0.437)	(0.430)	(−0.476)	(−0.478)
log(Market Equity)	−0.135*	−0.133*	1.755	1.699	1.057	1.023	−4.709	−4.734
	(−1.808)	(−1.778)	(1.071)	(1.039)	(0.540)	(0.520)	(−1.342)	(−1.354)
Tobin's Q	0.016	0.015	−0.973	−0.964	0.574	0.580	0.301	0.306
	(0.302)	(0.297)	(−1.176)	(−1.167)	(0.725)	(0.732)	(0.148)	(0.150)
ROA	0.332	0.333	−4.909	−4.923	−4.061	−4.070	13.934	13.928
	(1.365)	(1.369)	(−0.969)	(−0.979)	(−1.538)	(−1.538)	(1.256)	(1.255)
Leverage	−0.184	−0.184	−1.415	−1.440	0.434	0.419	−16.977	−16.988
	(−0.622)	(−0.619)	(−0.182)	(−0.185)	(0.119)	(0.114)	(−1.218)	(−1.219)
Cash Flow	−0.017	−0.018	0.518	0.548	0.935	0.952	−0.460	−0.447
	(−0.182)	(−0.191)	(0.183)	(0.196)	(0.831)	(0.849)	(−0.150)	(−0.146)
Sales Growth	−0.000	−0.000	−0.002	−0.001	0.001	0.002	−0.015	−0.015
	(−0.103)	(−0.133)	(−0.145)	(−0.101)	(0.114)	(0.152)	(−0.617)	(−0.609)
Annual Return	0.003	0.003	1.012	1.009	−0.405	−0.406	0.942	0.941
	(0.080)	(0.082)	(0.826)	(0.825)	(−0.295)	(−0.296)	(0.709)	(0.709)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1145	1145	1145	1145	1145	1145	1145	1145
Adjusted R^2	0.616	0.616	0.575	0.574	0.380	0.379	0.555	0.555
Note:								*p<0.1; **p<0.05; ***p<0.01

Table 2.10:
Import Competition and Quality of Existing Products

The dependent variable is the weighted (by number of reviews) average rating for the firm's current products over the next fiscal year. *Import Penetration* is imports (in $000s of 2014 dollars) at the four-digit SIC level divided by 1996 four-digit SIC level employment in the United States. *Import Penetration* is standardized by its standard deviation. T-statistics calculated using standard errors clustered at the four-digit SIC level are given in parentheses.

	Dependent variable:							
	Weighted Average Rating							
	Full Sample				2011-2013			
	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Import Penetration	0.070**		0.065**		0.211***		0.200**	
	(2.438)		(2.180)		(2.692)		(2.217)	
Import Penetration (fitted)		0.078**		0.074*		0.218**		0.214*
		(1.975)		(1.841)		(2.303)		(1.890)
log(Assets)			0.109**	0.109**			0.037	0.037
			(2.211)	(2.209)			(0.246)	(0.248)
log(Market Equity)			−0.100**	−0.099**			−0.145	−0.144
			(−2.183)	(−2.179)			(−1.153)	(−1.155)
Tobin's Q			0.027	0.026			0.000	0.000
			(0.930)	(0.915)			(0.003)	(0.001)
ROA			0.724***	0.723***			0.263	0.263
			(2.665)	(2.660)			(0.846)	(0.847)
Leverage			−0.378***	−0.378***			−0.149	−0.149
			(−3.245)	(−3.245)			(−0.512)	(−0.513)
Cash Flow			−0.396	−0.397			0.005	0.005
			(−1.270)	(−1.272)			(0.063)	(0.055)
Sales Growth			−0.000	−0.000			0.000	0.000
			(−0.134)	(−0.145)			(0.304)	(0.296)
Annual Return			−0.006	−0.005			0.041	0.041
			(−0.184)	(−0.170)			(0.488)	(0.488)
Industry FE	Yes	Yes	Yes	Yes	Absorbed	Absorbed	Absorbed	Absorbed
Firm FE	No	No	No	No	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3090	3090	3028	3028	1123	1123	1105	1105
Adjusted R^2	0.098	0.098	0.113	0.113	0.605	0.605	0.601	0.601
Note:								*p<0.1; **p<0.05; ***p<0.01

Table 2.11:
Import Competition and Product Quality split by Product Portfolio Size

The dependent variable is the weighted (by number of reviews) average rating for the firm's products over the next fiscal year. *Number of Products* is the number of Amazon products a firm has in its portfolio in the current fiscal year. *Import Penetration* is imports (in $000s of 2014 dollars) at the four-digit SIC level divided by 1996 four-digit SIC level employment in the United States. *Import Penetration* is standardized by its standard deviation. T-statistics calculated using standard errors clustered at the four-digit SIC level are given in parentheses.

	Dependent variable:			
	Weighted Average Rating			
	Full Sample		2011-2013	
	OLS	2SLS	OLS	2SLS
	(1)	(2)	(3)	(4)
log(Number of Products)× Import Penetration	−0.017**		−0.064*	
	(−2.002)		(−1.841)	
log(Number of Products)× Import Penetration (fitted)		−0.017*		−0.091**
		(−1.751)		(−2.484)
log(Number of Products)	0.032*	0.032*	0.006	0.024
	(1.772)	(1.721)	(0.055)	(0.213)
log(Assets)	0.077	0.077	0.112	0.106
	(1.187)	(1.184)	(0.498)	(0.487)
log(Market Equity)	−0.068	−0.068	−0.255	−0.256
	(−1.074)	(−1.071)	(−1.244)	(−1.267)
Tobin's Q	0.010	0.010	0.073	0.076
	(0.231)	(0.229)	(0.642)	(0.669)
ROA	0.467	0.466	0.416	0.435
	(1.502)	(1.505)	(1.231)	(1.266)
Leverage	−0.227*	−0.227*	−0.128	−0.125
	(−1.790)	(−1.789)	(−0.280)	(−0.274)
Cash Flow	−0.414	−0.414	−0.020	−0.020
	(−0.831)	(−0.832)	(−0.140)	(−0.138)
Sales Growth	−0.000	−0.000	−0.000	−0.000
	(−0.036)	(−0.036)	(−0.461)	(−0.412)
Annual Return	−0.001	−0.001	0.024	0.021
	(−0.032)	(−0.033)	(0.337)	(0.291)
Firm FE	No	No	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes
Observations	3392	3392	1145	1145
Adjusted R^2	0.089	0.089	0.599	0.598
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 2.12:
Import Penetration and Firm Costs

The dependent variable is either the cost of goods sold or selling, general, and administrative expenses (both divided by lagged book assets). *Import Penetration* is imports (in \$000s of 2014 dollars) at the four-digit SIC level divided by 1996 four-digit SIC level employment in the United States. *Import Penetration* is standardized by its standard deviation. *COGS* is cost of goods sold and *SGA* is selling and general expenses. T-statistics calculated using standard errors clustered at the four-digit SIC level are given in parentheses.

	Dependent variable:							
	COGS		SGA		COGS		SGA	
	Full Sample				2011-2013			
	OLS	2SLS	OLS	2SLS	OLS	2SLS	OLS	2SLS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Import Penetration	−0.002		−0.007		0.007		0.001	
	(−0.071)		(−0.971)		(0.324)		(0.099)	
Import Penetration (fitted)		−0.010		−0.001		0.023		0.003
		(−0.403)		(−0.110)		(1.129)		(0.301)
log(Assets)	−0.055**	−0.055**	−0.051***	−0.051***	−0.333***	−0.332***	−0.139***	−0.139***
	(−2.039)	(−2.038)	(−3.567)	(−3.586)	(−4.314)	(−4.297)	(−4.663)	(−4.658)
log(Market Equity)	−0.021	−0.021	0.015	0.015	0.023	0.023	0.004	0.004
	(−0.863)	(−0.873)	(1.172)	(1.192)	(0.643)	(0.654)	(0.185)	(0.187)
Tobin's Q	0.004	0.004	0.066***	0.066***	0.023	0.023	0.044***	0.044***
	(0.248)	(0.261)	(5.853)	(5.882)	(1.340)	(1.352)	(2.800)	(2.802)
ROA	0.453***	0.454***	−0.393***	−0.394***	0.049	0.048	−0.042	−0.043
	(3.521)	(3.508)	(−3.331)	(−3.349)	(0.392)	(0.383)	(−0.598)	(−0.600)
Leverage	−0.056	−0.056	−0.035	−0.035	0.056	0.054	0.148*	0.148*
	(−0.657)	(−0.656)	(−0.636)	(−0.638)	(0.558)	(0.531)	(1.768)	(1.762)
Cash Flow	−0.068	−0.067	−0.040	−0.041	−0.062	−0.062	−0.034	−0.035
	(−0.588)	(−0.583)	(−0.777)	(−0.787)	(−1.021)	(−1.030)	(−0.567)	(−0.567)
Sales Growth	0.000	0.000	0.001*	0.001*	0.000	0.000	−0.000	−0.000
	(1.125)	(1.133)	(1.836)	(1.830)	(0.160)	(0.152)	(−1.106)	(−1.113)
Annual Return	0.026**	0.026**	−0.020**	−0.020**	0.015	0.015	−0.007	−0.007
	(2.563)	(2.529)	(−2.393)	(−2.362)	(0.849)	(0.851)	(−1.069)	(−1.068)
Industry FE	Yes	Yes	Yes	Yes	Absorbed	Absorbed	Absorbed	Absorbed
Firm FE	No	No	No	No	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3722	3722	3677	3677	1501	1501	1488	1488
Adjusted R^2	0.591	0.591	0.614	0.614	0.953	0.953	0.960	0.960
Note:								*p<0.1; **p<0.05; ***p<0.01

Table 2.13:
Variable Construction

Construction of variables used in our research. Amazon data is obtained from Julian McAuley and import data is obtained from Gordon Hanson.

Variable	Definition	Source
Weighted Average Rating	$\frac{\sum_k \#\text{reviews}_k \times \text{avg. rating}_k}{\sum_k \#\text{reviews}_k}$	Amazon data
% n stars	$\frac{\sum_k \#\text{reviews}_k \times \%n\text{star}_k}{\sum_k \#\text{reviews}_k}$	Amazon data
Import penetration	$\frac{\text{imports (2014 \$000s)}}{\text{employment}_{1996}}$	UN Comtrade & Census Bureau
Book Equity	first available of seq, $ceq + pstk$, or $at - lt$ minus the first available of $pstkl$, $pstkrv$, or $pstk$ plus $txditc$ (if available) minus $prba$ (if available)	Compustat
Tobin's Q	$\frac{at - ceq + mkvalt}{at}$	Compustat
Leverage	$\frac{dltt + dlc}{at}$	Compustat
log(Assets)	$\log(at)$	Compustat
log(Equity)	$\log(prcc * shrout)$	CRSP
ROA	ni/at	Compustat
Cash Flow	$(ib + dp)/at(-1)$	Compustat
Sales Growth	$(sale/sale(-1)) - 1$	Compustat
COGS	$cogs/at(-1)$	Compustat
SGA	$xsga/at(-1)$	Compustat

2.6 Bibliography

Acemoglu, D., D. Autor, D. Dorn, G. H. Hanson, and B. Price (2016). "Import competition and the great US employment sag of the 2000s". *Journal of Labor Economics* 34.S1, S141–S198.

Amazon (2018a). *About Amazon Best Sellers Rank*. URL: https://www.amazon.com/gp/help/customer/display.html?nodeId=525376 (visited on 08/14/2018).

Amazon (2018b). *Community Guidelines*. URL: https://www.amazon.com/gp/help/customer/display.html?nodeId=201929730 (visited on 08/14/2018).

Autor, D. H., D. Dorn, G. H. Hanson, and J. Song (2014). "Trade adjustment: Worker-level evidence". *The Quarterly Journal of Economics* 129.4, pp. 1799–1860.

Bloom, N., M. Draca, and J. Van Reenen (2016). "Trade induced technical change? The impact of Chinese imports on innovation, IT and productivity". *The Review of Economic Studies* 83.1, pp. 87–117.

Choi, J. P. (1998). "Brand Extension as Informational Leverage". *The Review of Economic Studies* 65.4, pp. 655–669.

David, H., D. Dorn, and G. H. Hanson (2013). "The China syndrome: Local labor market effects of import competition in the United States". *American Economic Review* 103.6, pp. 2121–68.

Fernandes, A. M. and C. Paunov (2009). *Does tougher import competition foster product quality upgrading?* The World Bank.

Golub, S. S. (1998). "Does trade with low-wage countries hurt American workers?" *Federal Reserve Bank of Philadelphia Business Review* 1998.

Guenther, D. A. and A. J. Rosman (1994). "Differences between COMPUSTAT and CRSP SIC codes and related effects on research". *Journal of Accounting and Economics* 18.1, pp. 115–128.

He, R. and J. McAuley (2016). "Ups and Downs: Modeling the Visual Evolution of Fashion Trends with One-Class Collaborative Filtering". *CoRR* abs/1602.01585. arXiv: 1602.01585.

Hoberg, G. and G. Phillips (2010). “Product market synergies and competition in mergers and acquisitions: A text-based analysis”. *The Review of Financial Studies* 23.10, pp. 3773–3811.

Hombert, J. and A. Matray (2018). “Can innovation help US manufacturing firms escape import competition from China?” *The Journal of Finance*.

J.H., G. S., H. Galen, M. A. C., and M. A. Fila (2013). “The USPTO Trademark Case Files Dataset: Descriptions, Lessons, and Insights”. *Journal of Economics & Management Strategy* 22.4, pp. 669–705. eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/jems.12035.

Kini, O., J. Shenoy, and V. Subramaniam (2017). “Impact of Financial Leverage on the Incidence and Severity of Product Failures: Evidence from Product Recalls”. *The Review of Financial Studies* 30.5, pp. 1790–1829. eprint: /oup/backfile/content_public/journal/rfs/30/5/10.1093_rfs_hhw092/6/hhw092.pdf.

Lie, E. and K. Yang (2018). “Import Penetration and Executive Compensation”.

Matsa, D. A. (2011). “Competition and product quality in the supermarket industry”. *The Quarterly Journal of Economics* 126.3, pp. 1539–1591.

McAuley, J. J., C. Targett, Q. Shi, and A. van den Hengel (2015). “Image-based Recommendations on Styles and Substitutes”. *CoRR* abs/1506.04757. arXiv: 1506.04757.

Moreira, M. M. (2007). “Fear of China: is there a future for manufacturing in Latin America?” *World Development* 35.3, pp. 355–376.

Patent, U. S. and T. Office (2018). *Trademark basics*. URL: https://www.uspto.gov/trademarks-getting-started/trademark-basics (visited on 08/14/2018).

Pierce, J. R. and P. K. Schott (2012). “A concordance between ten-digit U.S. harmonized system codes and SIC/NAICS product classes and industries”. *Journal of Economic and Social Measurement* 37, pp. 61–96.

Rogerson, W. P. (1983). “Reputation and Product Quality”. *The Bell Journal of Economics* 14.2, pp. 508–516.

Sheen, A. (2014). “The real product market impact of mergers”. *The Journal of Finance* 69.6, pp. 2651–2688.

Snyder, T. J. (1990). “Trademark Law Revision Act of 1988 and the Gatekeeper Role of the PTO: Heading Abuse Off at the Pass”. *Washington University Law Review* 68, p. 753.

Thomas, L. (Jan. 2018). *Amazon grabbed 4 percent of all US retail sales in 2017, new study says*. Ed. by CNBC. [Online; posted 3-January-2018].

Titman, S. (1984). “The effect of capital structure on a firm’s liquidation decision”. *Journal of Financial Economics* 13.1, pp. 137–151.

Wernerfelt, B. (1988). “Umbrella Branding as a Signal of New Product Quality: An Example of Signalling by Posting a Bond”. *The RAND Journal of Economics* 19.3, pp. 458–466.

CHAPTER 3

Initial Public Offerings and Product Quality

The decision to list equity securities on a public exchange, or to "go public", is consequential for firms. Completing an initial public offering allows firms to issue equity on public markets, a significant source of financing. Going public also adds regulatory burdens on firms; publicly listed firms are required to make regular "business and financial" disclosures.[1] As Jensen and Meckling (1976) highlight, changes in capital structure in general, and equity issuance in particular, have associated agency costs. Given these different tensions, it is important to identify how initial public offerings ultimately affect firms.

The lack of disclosures for private firms has made identifying the effects of initial public offerings difficult. Requiring publicly listed firms to disclose certain information helps inform outside stakeholders. These same disclosures are not required of private firms. This regulatory difference often makes defining financial and performance measures that are commonly used when analyzing public firms impossible for private firms. In this chapter, I overcome this limitation by using product level data spanning both private and public firms. This allows me to identify and quantify changes within firms both before and after their initial public offerings.

After firms go public, I find that their product quality decreases. I use Amazon product data in an event study framework and show that the average rating of existing products decreases after firms complete their initial public offerings. I identify that an increase in the rate of negative customer service experiences corresponds to the decline in quality. I also find that brand recognition increases for firms after going public, consistent with the increased attention given to firms around their initial public offerings.

[1] Securities and Commission (2019)

I quantify firms' product strategies using Amazon product metadata and Amazon product reviews. This data allows me to identify differences in various aspects of individual products over time. To measure the effects of initial public offerings on firms' products, I use an event study specification on the two quarters before and the two quarters after firms' initial public offerings. I control for time-invariant product characteristics by including product fixed effects.

After firms complete their initial public offerings, I find that the quality of their products decreases. The average rating of firms' existing products decreases by 2.4% after firms go public. This decline is also significant when ratings are adjusted relative to those of their product markets. I explore how the distribution of product ratings changes and find significantly more one star ratings and significantly fewer five star ratings after firms complete their initial public offerings.

I use textual analysis to find which aspects of product quality change after firms complete their initial public offerings. I identify key phrases in review texts that correspond to different aspects of product quality and measure their frequency over time. I find an increase in the rate of brand mentions after firms go public. I determine that this increase is driven by an increase in the rate of negative brand mentions. I also find a significant increase in the rate of negative customer service experiences.

My research makes several contributions to the literature. I add to the literature on firm level changes resulting from initial public offerings. Several papers document declines in measures of firm performance post-IPO, including operational performance and profitability (Jain and Kini (1994) and Pástor, Taylor, and Veronesi (2008), respectively). Chemmanur, S. He, and Nandy (2009) find that productivity and sales growth increase prior to firms going public and decline after the initial public offering concludes. I find that product quality decrease after firms go public, a possible precursor to a decrease in sales growth. My work also relates to Bernstein (2015), who finds that patent novelty decreases post-IPO. I do not find changes in the composition of products, but rather the quality of the individual products. My results also add to the literature exploring the role of firm reputation and customers (e.g. Rogerson (1983), Wernerfelt (1988) and Choi (1998)), and build on the use of product reviews to understand firm level changes (e.g. Tirunillai and Tellis (2012), Sheen (2014), and Huang (2018)).

This chapter proceeds as follows. In Section 3.1, I describe my data. I define my empirical methodology in Section 3.2. Section 3.3 presents my results and Section 3.4 concludes.

3.1 Data

My sample data begins with Amazon product metadata and reviews. I use available metadata to identify the CRSP firm that owns each product. Quarterly firm level characteristics are from Compustat, and stock returns are from CRSP. I identify initial public offerings using Compustat.

Amazon data was kindly provided by Julian McAuley. The dataset, as used in R. He and J. McAuley (2016) and J. J. McAuley et al. (2015), contains Amazon reviews and product metadata from 1996 to 2014 for 9.4 million products. Each Amazon product has a unique identifier, the ASIN (Amazon Standard Identification Number), and product metadata collected at the end of the sample. The product metadata includes the product's brand, the product category it is listed under, and its sales rank within that product category. Products are classified into one of 31 product categories, which span the set of products available on Amazon.[2] Within each product category, products are given a sales rank. Amazon does not clearly define how sales ranks are determined, but states that lower rankings are a "good indicator" that products have higher sales Amazon (2018a). Along with product metadata, I have every Amazon review of these products. Each review is time-stamped, has a written review, and a numerical product rating of 1, 2, 3, 4, or 5. Amazon does not provide guidelines to reviewers regarding what each numerical rating is meant to signify. For the written review, Amazon provides the prompt "What did you like or dislike? What did you use this

[2]Data includes products in the following product categories: Books, Software, Video Games, Cell Phones & Accessories, Grocery & Gourmet Food, Electronics, Toys & Games, Automotive, Health & Personal Care, Music, Magazines, Pet Supplies, Camera & Photo, Sports & Outdoors, Kitchen & Dining, Musical Instruments, Shoes, Home & Kitchen, Jewelry, Clothing, Beauty, Office Products, Industrial & Scientific, Computers & Accessories, Patio, Lawn & Garden, Arts, Crafts & Sewing, Home Improvement, Movies & TV, Watches, Gift Cards Store, Baby, Appliances, Prime Pantry.

product for?" Amazon (2018b).

Matching Amazon products to CRSP firms requires several intermediate steps. At each point in time, I link Amazon product brands to valid trademarks using data from the United States Patent and Trademark Office. I link trademarks owned by corporations to CorpWatch's firm parent-subsidiary dataset and match the ultimate parent companies to CRSP. To ensure match quality, I only keep exact matches. I also only keep matches that uniquely link, at any point in time, one firm to each brand. This procedure allows me to observe if and when a brand moves from one firm to another. I discuss my matching methodology in more detail in Section 3.5.

For each firm-year-quarter, I define several product level measures. I define each product's average rating as the average numerical rating in that year-quarter (every review is required to include a numerical rating). I also count the number of reviews left for each product that year-quarter. Each Amazon product is listed in a single product category and is sold under a single brand.

Initial public offerings are identified using Compustat's Company dataset. I define the date of the initial public offering (IPO) using the IPODATE variable. Given that I do not have any firm level data prior to the initial public offering, I define firm-year-quarters as three month intervals relative to the three months ending in the month of the initial public offering.

To what extent my results can be generalized is important to consider. Amazon is the largest online retailer but has a relatively small share of the overall retail market (Thomas (2018)). The set of products that firms sell on Amazon does not necessarily reflect their full product portfolios, as Amazon historically focused on consumer markets. In addition, my current method of linking Amazon product portfolios to firms does not allow me to identify firms that are not publicly listed. Unlike the analysis in my first chapter, this limits the extent to which I can test for changes in the product portfolio composition of firms that go public. Because of this limitation, I focus my analysis on products that were available both before firms go public and after firms go public, which I define as existing products.

3.2 Empirical Approach

The objective of my empirical design is to measure the effects of initial public offerings on firms' existing products. The ideal experiment would have identical private firms randomly assigned to an initial public offering. An empirical challenge when studying these events is the relative lack of data on private firms. By using product level data from Amazon, I can identify the product portfolios of public firms and see how the set of products that also existed before the firms went public changed as a result of the initial public offering.

I utilize an event study framework so that I can contrast the trend before the initial public offering (pre-IPO) with the trend after the initial public offering (post-IPO). For each IPO year-quarter, I include the two year-quarters before the IPO year-quarter and the two year-quarters after the IPO year-quarter while dropping the IPO year-quarter itself. My results use the product level event study specification

$$y_{i,k,t,\tau} = \beta \times \mathbb{1}\left(t > \tau\right) + \alpha_k + \varepsilon_{i,k,t,\tau}. \tag{3.1}$$

The subscripts represent firm i and product k in year-quarter t. For each IPO year-quarter τ, I only include observations where $t - \tau \in \{-2, -1, 1, 2\}$. The unit of observation is at the firm-year-quarter-product level. The dependent variable $y_{i,k,t,\tau}$ is a product level measure. The coefficient of interest is β. The first term is a post-IPO indicator variable $\mathbb{1}\left(t > \tau\right)$. I include product fixed effects α_k. Due to the way I build my sample, products are uniquely linked to a single firm, so product fixed effects subsume firm fixed effects. Since firms in my sample only IPO once, the product fixed effects also subsume cohort fixed effects. I cluster standard errors at the firm level.

To identify changes in the product quality of firms that go public, I run my regressions at the product level. Using product level observations allows me to include product fixed effects, capturing time-invariant product characteristics. I add several restrictions to the set of products included in my sample to better identify how average product quality changes after firms complete their initial public offerings. I only include products that are reviewed both before and after their IPO year-quarter. This allows me to quantify measures of product quality before firms go public and identify how going public changes these measures. I also require products to have five or more reviews in each of the year-quarters in my window.

One important limitation of my empirical approach is the inability to account for the selection bias associated with the decision to pursue and complete an initial public offering. As noted in Jain and Kini (1994), firms choose when to complete their initial public offerings. While I am able to look within firms and identify how changes occur at the product-level, it is possible that unobservable firm level factors drive both the decision to go public and the product level changes I find. Unfortunately, my current method of linking firms to Amazon products does not allow me to identify "counter-factual" firms, such as firms that withdrew their IPO filings (e.g. Bernstein (2015)). Addressing this limitation should be the focus of future work in this area of research.

Table 3.1 presents summary statistics of product level and firm level measures both before the initial public offering and after the initial public offering. I include average values of variables at the product level and the firm level two year-quarters prior to the IPO year-quarter and two year-quarters after the IPO year-quarter. I also show the difference between the pre-IPO product level measures and the post-IPO product level measures, as well as the p-values of the corresponding difference-in-means tests. As I do not observe firm level measures for private firms, I only include firm level statistics post-IPO. Both the average product rating and the average abnormal rating (the average product rating minus the average product ratings of all products in that product category) decrease after firms go public. The distribution of ratings shifts as well. Consistent with the change in the average product rating, the percent of one star reviews increases and the percent of four and five star reviews decreases after firms go public.

3.3 Results

I first establish that product quality decreases after firms go public. My parametric tests use the product level event study regression specification defined in Equation 3.1.

I identify a decrease in product quality after initial public offerings in Table 3.2. The first dependent variable is the average rating of all reviews a product received during that year-quarter. The second dependent variable is the average rating of all reviews a product received during that year-quarter minus the average rating of all products in its product category that year-quarter. I find that both the average product rating and the average abnormal product rating decrease significantly after firms complete their initial public offerings. The coefficient corresponding to the change in abnormal product ratings is smaller in magnitude than that of the change in the product rating. The first coefficient, -0.11, should be interpreted as the change in firms' average product rating, measured in stars. Alternatively, by dividing the coefficient by the average product rating of pre-IPO firms, I find that the average product rating decreases by 2.4% post-IPO. The coefficient represents 19% of one standard deviation of average product ratings before firms went public.

Table 3.2 shows no significant changes in either the number of product reviews or the market share of firms' existing products after firms complete their initial public offerings. The third dependent variable is the number of reviews a product received during that year-quarter. The fourth dependent variable is the number of reviews a product received during that year-quarter as a percent of the total number of reviews in that product category during that year-quarter. As discussed in my first chapter, review volume within each product category can be used as a proxy for sales volume. The decrease in product quality does not see a correspondingly significant decline in product sales, at least in the studied time horizon.

I explore how the underlying distribution of product ratings change as a result of firms going public in Table 3.3. The five dependent variables correspond to the percent of ratings a product received in that year-quarter equal to one star, two star, three star, four star, and five star respectively. Consistent with the decrease in product quality I show in Table 3.2, I find an increase in the percent of one star ratings that is significant at the 1% level. I also find a significant decrease in the percent of five star ratings, though it is only significant at the 10% level.

Both the decrease in product quality identified in Table 3.2 and the change in the distribution of product ratings found in Table 3.3 reflect the raw differences in means seen in

Table 3.1. After firms complete their initial public offerings, the quality of their existing products decreases significantly. This change in average product quality seems to be a shift in the tails of product quality distribution. There is a significantly higher proportion of extreme negative product ratings and a significantly lower proportion of extreme positive ratings, while the rest of the distribution stays similar. This suggests that the modal post-IPO customer does not receive a product of significantly worse quality, but that the change in quality is driven by relatively few customer experiences.

To identify what causes firms' product quality to decline after going public, I analyze the review text of those firms' products. As mentioned in Section 3.1, the prompt given by Amazon when leaving a written product review is broad, allowing reviewers the freedom to write about the aspects of product quality that are most salient to them. I take advantage of this by searching for key phrases that correspond to different aspects of product quality in each written review and measure if the frequency of these phrases changes after firms go public.

I define four different aspects of product quality by searching for phrases corresponding to each of these aspect in the written reviews. The first aspect of product quality I search for is the customer service experience. I identify mentions of the customer service experience by finding key phrases that relate to customer service, including "customer support", "technical support", and "called Amazon". The second aspect of product quality I search for is explicit discussion of product quality, specifically mentions of the word "quality". The third aspect of product quality I search for is product failure. I look for key phrases in reviews that would indicate products are in some way defective, such as "stopped working", "fell apart", and "broke". A full list of all key phrases for these aspects of product quality is included in Table 3.6. The fourth aspect of product quality I define is brand name recognition. I search for explicit mentions of the brand name associated with the product. Most of the product brands in my sample share their names with their parent companies.[3] Therefore, changes in brand name recognition correlate to changes in firm name recognition.

[3] Brands with names shared by their parent firms in my sample include Sling Media, Kingston, Skullcandy and Nature's Bounty.

I test for changes in the frequency of different aspects of product quality in Table 3.4. The dependent variables are the percent of reviews a product received that quarter that include at least one key phrase associated with customer service, product quality, product failure, and brand recognition, respectively. I find that the average rate of brand mentions increases significantly after firms go public. This may be due to the increased salience of the parent firms' names to consumers from popular and business media regarding the initial public offerings, as most of the brand names in my sample are the same as that of the parent firms. Interestingly, this increase in salience does not seem to correspond to a significant change in sales volume, as seen in Table 3.2.

To better understand how these aspects of product quality change, I interact their corresponding key phrases with sentiment analysis. Specifically, I define the percent of Amazon reviews a product received that quarter that mention a key phrase for each aspect of product quality in a negative sentiment sentence. A review still needs to have one of the key phrases indicating that aspect of product quality. In addition, at least one key phrase must be in a negative sentiment sentence. I define sentence level sentiment using Stanford's CoreNLP software (e.g. Manning et al. (2014)). Calculating sentiment at the sentence level, as opposed to word by word, allows for the ordering of words, as well as capitalization and punctuation of the sentence, to be factored into the overall sentence sentiment.

Table 3.5 tests for changes in the frequency of negative mentions of different aspects of product quality. I define the dependent variables as the percent of Amazon reviews a product received that quarter that mention a key phrase relating to customer service, product quality, product failures, and brand recognition, in a negative sentiment sentence. I find a significant increase in the percent of negative customer service mentions, though the coefficient is not large in magnitude (0.19%). There is also a significant increase in the frequency of negative brand mentions after the initial public offering. The coefficient for the change in negative brand mentions is 2.53%, larger in magnitude than the coefficient for the change in frequency of all brand mentions (1.19%). This is due to positive and neutral brand mentions being dropped when the negative brand recognition variable is defined.

3.4 Conclusion

The quality of a firm's products is affected by its access to public equity markets. Compared to the two quarters prior to going public, the average product quality of firms that complete their initial public offerings decreases significantly in the two quarters after going public. This decrease in quality is driven by a shift in the distribution of reviews, with more one star reviews and less five star reviews. When identifying which aspects of product quality change post-IPO, I find significant increases in the rate of negative customer service mentions and the rate of negative brand recognition.

Existing research shows that initial public offerings negatively impact firm performance. By observing changes in firms' product portfolios, I am able to contribute a more nuanced understanding of this phenomenon. For many firms, product sales are the primary source of revenue. Changes in individual products will appear before any corresponding changes in sales can be observed at the firm level. High product quality allows firms to sell products at a relative premium. While a change in product quality may not be immediately observed by consumers, it will eventually be factored in to consumer evaluations and lead to a decrease in sales, all else held equal (e.g. Maksimovic and Titman (1991)). The decrease in product quality I identify is consistent with the eventual decrease in sales growth found after firms go public by Chemmanur, S. He, and Nandy (2009).

The results presented here offer a preliminary understanding of what causes changes in firm level performance measures after completing their initial public offerings. The method of financing when frictions exist is important, not only to firms and their shareholders, but to consumers as well. Identifying the impact on customers, the stakeholder responsible for generating revenue for many firms, is important when evaluating initial public offerings.

3.5 Appendix 1: Amazon to CRSP Match Methodology

I first attempt to match each Amazon product's brand name to that brand's trademark.[4] Trademark data is downloaded from USPTO's 2017 Trademark Case Files dataset, which contains information on 8.6 million trademark applications filed from January 1870 forward. My trademark selection methodology is guided by the discussion of J.H. et al. (2013), who document and discuss the Trademark Case Files dataset in detail.

Each trademark has an entry, which is updated throughout the trademark's life. As my goal is to link Amazon products to public firms, I only include registered text trademarks owned by corporations. For dead trademarks, I use the provided expiration date. For trademarks that were last updated as living, I define the expiration date as twenty years after the registration date if the trademark was filed before November 16, 1989. If the trademark was filed on or after November 16, 1989, I define the patent expiration date as ten years after the registration date. This difference in expiration date is due to the Trademark Law Revision Act of 1988, which eliminated the requirement of commercial use of a trademark prior to registration (Snyder (1990)). I require an exact match between the Amazon brand and the trademark's text, and that product reviews occur within the trademark's life.

I then try to link each matched trademark's owner to a subsidiary corporation, using data collected by CorpWatch. CorpWatch's dataset extracts firm subsidiary information listed in Exhibit 21 of firms' 10-K filings. Using this, I build a parent-subsidiary hierarchy and identify an ultimate parent company for each subsidiary firm. Firm subsidiary data is only available from 2003 onward, so I assume the 2003 subsidiary structure for all years prior. I attempt to standardize common firm name endings (for example, I replace the words "international", "intrntnl", and "internl" with "intl") before doing an exact match between the trademark owner name and firm subsidiary name. I require all exact matches to be overlapping in time.

[4] A trademark, as defined by the US Patent and Trademark Office, is "... any word, name, symbol, device, or any combination, used or intended to be used to identify and distinguish the goods/services of one seller or provider from those of others, and to indicate the source of the goods/services" (Patent and Office (2018)).

Finally, I match the firm subsidiary to its CRSP ultimate parent firm. Like in the previous step, I first standardize common firm name endings. I then do an exact match between the subsidiary's ultimate parent firm's name, defined with the CorpWatch dataset, to the CRSP firm name at that time using the CRSP Names dataset.

Table 3.1:
Initial Public Offering Summary Statistics

This table presents product level and firm level summary statistics for firms in my sample. Pre-IPO values are measured two year-quarters prior to the IPO year-quarter and post-IPO values are measured two year-quarters after the IPO quarter. Firm level measures are not available pre-IPO. The difference p-value is calculated using a two-sample t-test for equal means.

Panel A: Product level			
	Pre-IPO	Post-IPO	Difference
Rating	4.35	4.22	0.13
Abnormal Rating	1.06	1.03	0.03
# Reviews	19.4	23.6	-4.3
% Market Share	0.0474	0.0281	0.0194
% 1 star	5.16	8.66	-3.50**
% 2 star	4.57	4.55	0.02
% 3 star	7.75	8.20	-0.45
% 4 star	15.0	13.5	1.4
% 5 star	67.5	65.0	2.5
# observations	100	100	

Panel B: Firm level			
	Pre-IPO	Post-IPO	Difference
Leverage		0.407	
Market cap		1,980	
B/M ratio		0.468	
RoA		0.0500	
Investments		0.0172	
Excess return		-0.0579	
FCF		0.0330	
# observations		14	

Note: *p<0.1; **p<0.05; ***p<0.01

Table 3.2:
Initial Public Offerings, Product Quality, and Review Volume

This table presents an event study specification testing the relationship between firms going public and their products. Observations are at the firm-year-quarter-product level. I include the two year-quarters before the initial public offering and the two year-quarters after the initial public offering for all firms with initial public offerings. The first dependent variable is the average Amazon rating from reviews left that quarter. The second dependent variable is the average Amazon rating from reviews left that quarter minus the average Amazon rating from reviews left that quarter of all products in its product market. The third dependent variable is the number of reviews left that quarter. The fourth dependent variable is the market share of a product, measured as the number of reviews left that quarter divided by the total number of reviews left that quarter in its product market. The displayed independent variable is an indicator variable equal to one if the observation is after the IPO year-quarter. Products are only included if they have at least five reviews in each of the year-quarters in the event window. All regressions have product fixed effects. Standard errors are clustered at the firm level.

	Dependent variable:			
	Rating	Abnormal Rating	# Reviews	Market Share
	(1)	(2)	(3)	(4)
IPO	-0.105^{***}	-0.019^{***}	1.015	-0.034
	(0.033)	(0.007)	(2.189)	(0.044)
Observations	400	400	400	400
R^2	0.611	0.612	0.900	0.365
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 3.3:
Initial Public Offerings and the Distribtuion of Ratings

This table presents an event study specification testing the relationship between firms going public and the distribution of their product quality. Observations are at the firm-year-quarter-product level. I include the two year-quarters before the initial public offering and the two year-quarters after the initial public offering for all firms with initial public offerings. The dependent variables are the percent of Amazon ratings received that quarter equal to the corresponding rating. The displayed independent variable is an indicator variable equal to one if the observation is after the IPO year-quarter. Products are only included if they have at least five reviews in each of the year-quarters in the event window. All regressions have product fixed effects. Standard errors are clustered at the firm level.

	Dependent variable:				
	% 1 star	% 2 star	% 3 star	% 4 star	% 5 star
	(1)	(2)	(3)	(4)	(5)
IPO	2.284***	0.750	0.176	−1.203	−2.008*
	(0.584)	(0.893)	(0.680)	(0.855)	(1.125)
Observations	400	400	400	400	400
R^2	0.566	0.344	0.338	0.327	0.544
Note:					*p<0.1; **p<0.05; ***p<0.01

Table 3.4:
Initial Public Offerings and Aspects of Product Quality

This table presents an event study specification testing the relationship between firms going public and various aspects of product quality. Observations are at the firm-year-quarter-product level. I include the two year-quarters before the initial public offering and the two year-quarters after the initial public offering for all firms with initial public offerings. The dependent variables are the percent of Amazon reviews that mention a key phrase indicating different aspects of quality that quarter. The dependent variables measures mentions of customer service, quality, product failures, and product brand respectively. The displayed independent variable is an indicator variable equal to one if the observation is after the IPO year-quarter. Products are only included if they have at least five reviews in each of the year-quarters in the event window. All regressions have product fixed effects. Standard errors are clustered at the firm level.

	Dependent variable:			
	% CS	% Quality	% Failure	% Brand
	(1)	(2)	(3)	(4)
IPO	−0.118	0.325	−1.320	1.188^{**}
	(0.291)	(0.621)	(0.846)	(0.593)
Observations	400	400	400	400
R^2	0.418	0.642	0.526	0.616
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 3.5:
Initial Public Offerings and Negative Aspects of Product Quality

This table presents an event study specification testing the relationship between firms going public and various negative aspects of product quality. Observations are at the firm-year-quarter-product level. I include the two year-quarters before the initial public offering and the two year-quarters after the initial public offering for all firms with initial public offerings. The dependent variables are the percent of Amazon reviews that mention a key phrase indicating different aspects of quality in negative sentiment sentences that quarter. The dependent variables measures negative mentions of customer service, quality, product failures, and product brand respectively. The displayed independent variable is an indicator variable equal to one if the observation is after the IPO year-quarter. Products are only included if they have at least five reviews in each of the year-quarters in the event window. All regressions have product fixed effects. Standard errors are clustered at the firm level.

	Dependent variable:			
	% Negative CS	% Negative Quality	% Negative Failure	% Negative Brand
	(1)	(2)	(3)	(4)
IPO	0.189**	0.299	−1.123	2.525***
	(0.093)	(0.362)	(0.924)	(0.600)
Observations	400	400	400	400
R^2	0.526	0.531	0.486	0.450
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 3.6:
Phrases used to Identify Product Changes

This table defines the set of phrases search within Amazon product reviews to identify which channels drove the observed changes in product quality.

Channel	Phrase
Product failure	defective, stop work, stop working, stopped work, stopped working, doesn't work, not work, not working, died, unusable, falls apart, fell apart, broke, broken, poorly made, didn't survive, not survive, barely work, barely worked, barely working
Customer service	customer support, customer service, help line, tech support, technical support, support line, call center, help center, helpline, called help, called support, called amazon, service center, called service

3.6 Bibliography

Amazon (2018a). *About Amazon Best Sellers Rank*. URL: https://www.amazon.com/gp/help/customer/display.html?nodeId=525376 (visited on 08/14/2018).

Amazon (2018b). *Community Guidelines*. URL: https://www.amazon.com/gp/help/customer/display.html?nodeId=201929730 (visited on 08/14/2018).

Bernstein, S. (2015). "Does Going Public Affect Innovation?" *The Journal of Finance* 70.4, pp. 1365–1403. eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/jofi.12275.

Chemmanur, T. J., S. He, and D. K. Nandy (Dec. 2009). "The Going-Public Decision and the Product Market". *The Review of Financial Studies* 23.5, pp. 1855–1908. eprint: http://oup.prod.sis.lan/rfs/article-pdf/23/5/1855/24436187/hhp098.pdf.

Choi, J. P. (1998). "Brand Extension as Informational Leverage". *The Review of Economic Studies* 65.4, pp. 655–669.

He, R. and J. McAuley (2016). "Ups and Downs: Modeling the Visual Evolution of Fashion Trends with One-Class Collaborative Filtering". *CoRR* abs/1602.01585. arXiv: 1602.01585.

Huang, J. (2018). "The customer knows best: The investment value of consumer opinions". *Journal of Financial Economics* 128.1, pp. 164–182.

J.H., G. S., H. Galen, M. A. C., and M. A. Fila (2013). "The USPTO Trademark Case Files Dataset: Descriptions, Lessons, and Insights". *Journal of Economics & Management Strategy* 22.4, pp. 669–705. eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/jems.12035.

Jain, B. A. and O. Kini (1994). "The Post-Issue Operating Performance of IPO Firms". *The Journal of Finance* 49.5, pp. 1699–1726. eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.1540-6261.1994.tb04778.x.

Jensen, M. C. and W. H. Meckling (1976). "Theory of the firm: Managerial behavior, agency costs and ownership structure". *Journal of Financial Economics* 3.4, pp. 305–360.

Maksimovic, V. and S. Titman (1991). "Financial Policy and Reputation for Product Quality". *The Review of Financial Studies* 4.1, pp. 175–200.

Manning, C., M. Surdeanu, J. Bauer, J. Finkel, S. Bethard, and D. McClosky (2014). "The Stanford CoreNLP natural language processing toolkit". *Proceedings of 52nd annual meeting of the association for computational linguistics: system demonstrations*, pp. 55–60.

McAuley, J. J., C. Targett, Q. Shi, and A. van den Hengel (2015). "Image-based Recommendations on Styles and Substitutes". *CoRR* abs/1506.04757. arXiv: 1506.04757.

Pástor, Ľ., L. A. Taylor, and P. Veronesi (Aug. 2008). "Entrepreneurial Learning, the IPO Decision, and the Post-IPO Drop in Firm Profitability". *The Review of Financial Studies* 22.8, pp. 3005–3046. eprint: http://oup.prod.sis.lan/rfs/article-pdf/22/8/3005/24429747/hhn082.pdf.

Patent, U. S. and T. Office (2018). *Trademark basics*. URL: https://www.uspto.gov/trademarks-getting-started/trademark-basics (visited on 08/14/2018).

Rogerson, W. P. (1983). "Reputation and Product Quality". *The Bell Journal of Economics* 14.2, pp. 508–516.

Securities, U. and E. Commission (2019). *Public Companies*. URL: https://www.investor.gov/introduction-investing/basics/how-market-works/public-companies (visited on 04/11/2019).

Sheen, A. (2014). "The real product market impact of mergers". *The Journal of Finance* 69.6, pp. 2651–2688.

Snyder, T. J. (1990). "Trademark Law Revision Act of 1988 and the Gatekeeper Role of the PTO: Heading Abuse Off at the Pass". *Washington University Law Review* 68, p. 753.

Thomas, L. (Jan. 2018). *Amazon grabbed 4 percent of all US retail sales in 2017, new study says*. Ed. by CNBC. [Online; posted 3-January-2018].

Tirunillai, S. and G. J. Tellis (2012). "Does chatter really matter? Dynamics of user-generated content and stock performance". *Marketing Science* 31.2, pp. 198–215.

Wernerfelt, B. (1988). "Umbrella Branding as a Signal of New Product Quality: An Example of Signalling by Posting a Bond". *The RAND Journal of Economics* 19.3, pp. 458–466.