Product Innovation and Credit Market Disruptions*

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June 2020

Abstract

We combine micro-level product barcode data for the consumer goods industry obtained from Nielsen with the Community Reinvestment Act (CRA) and Dealscan lending datasets to provide new evidence that credit market disruptions significantly affected the rate, novelty, and performance of product innovation during the recent financial crisis. We find that credit market disruptions did not affect the rate of introduction of new products on firms' existing product lines but limited their expansion to new product lines. Moreover, products created by firms experiencing credit market disruptions contain fewer novel product characteristics. Consistent with a credit frictions channel, these effects are concentrated in firms that are smaller, younger, and more dependent of external sources of finance. Our estimates further indicate that products introduced in new categories by credit-constrained firms during the financial crisis generate less revenues than products introduced in new categories by the *same* firm during normal times. Overall, our findings suggest that disrupted credit markets disrupt radical product innovation.

JEL Classification Numbers: G11, G21, G31, G32, L15, L25, O31, O32

Keywords: Innovation; Multi-Product Firms; Financial Constraints, Great Recession

*We are grateful to John Barrios, Maria Cecilia Bustamante, Christian Leuz, Diogo Mendes (discussant), Mike Minnis, Dimitris Papanikolaou, Albert Sheen (discussant), Constantine Yannelis, and workshop and conference participants at the SFS Cavalcade 2020, 9th MoFiR workshop, Chicago Entrepreneurial Finance workshop, and University of Chicago for helpful comments. We also thank Igor Kuznetsov and Fabian Nagel for stellar research assistance in this project. João Granja gratefully acknowledges support of the Jane and Basil Vasiliou Research Fund at the University of Chicago Booth School of Business. Researcher(s) own analyses calculated (or derived) based in part on data from The Nielsen Company (US), LLC and marketing databases provided through the Nielsen Datasets at the Kilts Center for Marketing Data Center at The University of Chicago Booth School of Business. The conclusions drawn from the Nielsen data are those of the researchers and do not reflect the views of Nielsen. Nielsen is not responsible for, had no role in, and was not involved in analyzing and preparing the results reported herein.

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1 Introduction

Product innovation is a pivotal element of firm growth. In order to compete against rivals, firms must continually update their own existing products and expand their sources of revenue through the introduction of new product lines. The ability of firms to survive and to grow is largely predicated on the success of their new products in preserving and broadening their customer base (e.g. Klette and Kortum, 2004; Aghion, Akcigit, and Howitt, 2015; Kogan, Papanikolaou, Seru, and Stoffman, 2017; Argente, Lee, and Moreira, 2018a; Akcigit and Kerr, 2018; Braguinsky, Ohyama, Okazaki, and Syverson, 2020). Although researchers have devoted considerable attention to understanding the margins that affect the entry, growth, and survival of firms, much less is known about the factors that shape the process of product innovation over an economic cycle. Two important exceptions are Broda and Weinstein (2010) and Argente, Lee, and Moreira (2018b) who find that there is a missing generation of new products during economic downturns. These papers, however, provide few insights about what explains the slowdown in the creation of new products during recessions. One possibility is that the slowdown in product creation reflects expectations of weak product market demand. It is possible, however, that supply-side factors such as credit market disruptions are also partly to blame for this decline in product innovation during economic downturns.

In the absence of financing frictions, the decision to introduce a product should mostly depend on its expected value. The development and introduction of a product, however, usually entails large upfront costs in the form of research and development, investment in working capital, advertising, and promotional expenses. Thus, in a world of financial frictions, difficulties in obtaining external financing could force firms to halt their product development efforts even if that entails a sacrifice in value. In this paper, we try to shed light on this question by investigating whether disruptions in the supply of credit were an important factor affecting the rate, novelty, and performance of product innovation during the Great Recession.

We develop two measures of exposure to credit market disruptions during the recent financial crisis. Because commercial lending is still predominantly local (e.g. Granja, Leuz, and Rajan, 2018), our initial approach follows Greenstone, Mas, and Nguyen (2014) and exploits preexisting *geographic* variation in the exposure of a county to lenders that significantly cut back their aggregate supply of small business loans during the 2007–2010 period. This measure builds on the shift-share approach popularized by Bartik (1991) and its main advantage in our setting is that it covers a broad sample of firms irrespective of their size. However, this measure does not discern whether an individual firm needs access to external financing. Our alternative approach addresses this limitation. We follow Almeida, Campello, Laranjeira, and Weisbenner (2012), Costello (2018), and Benmelech, Frydman, and Papanikolaou (2019) in using preexisting *firm-level* variation in the need to raise external funds at a time when syndicated lending markets saw a significant contraction. We combine these measures with detailed product- and firm-level data at the barcode level obtained from the Nielsen Retail Measurement Services (RMS) scanner dataset to evaluate the role that credit market frictions played in shaping the introduction of products during the financial crisis.

The product-level RMS dataset allows us to determine if and when a firm introduces a new product in the market. We use this dataset to evaluate whether credit market disruptions impact a firm's ability and willingness to launch products during the crisis period. The detailed nature of the dataset further allows us to look deeper into the qualitative features of the products that were introduced over time and probe what product types were more affected by shocks to the supply of credit. Here, we follow existing work (e.g. Akcigit and Kerr, 2018; Caggese, 2019; Krieger, Li, and Papanikolaou, 2018) to draw a distinction between *incremental* and *radical* product innovation. We define incremental product innovation as products introduced within a firm's existing product lines, whereas radical innovation consists of new products introduced in lines that are new to the firm.

Incremental product innovations are less likely to require significant investments in R&D, working capital, and production capacity as firms will usually be able to redeploy existing capital (both physical capital, human capital, inventories) to the production of the new product. But they are also less disruptive in that they do not broaden the scope of a firm and are less likely to unveil novel characteristics to the market. Radical product innovations are less common than incremental innovations. They are likely more costly to develop as they require greater investments in acquisition of knowledge, product development, and more likely involve new investments in production lines, machinery, employee training among other costs. But we also find that they account for a greater share of total firm revenue one year after their introduction, which is consistent with Argente et al. (2018a) and Argente et al. (2018b) who find that new products in new product lines have a higher impact on total factor productivity (TFP) and are not as likely to cannibalize existing firm products.

We find that credit market disruptions have no significant effect on the rate of *incremental* product innovation but are associated with significant declines in the rates of *radical* product innovation. The economic magnitude of the impact of credit market disruptions on radical product innovation is substantial: a one-standard deviation increase in our measures of credit market disruption results in a decline in radical product innovation that represents between 15% to 40% of the overall decline in the rate of radical product innovation between 2007 and 2010. Importantly, we find that our two main measures of credit market disruptions yield quantitatively and qualitatively similar results despite capturing distinct sources of variation and relying on markedly different samples. We interpret our main results as consistent with the conceptual framework developed in Krieger et al. (2018) that shows that in the face of credit frictions, companies are less likely to invest in high-risk/high-reward projects and could substitute toward safer projects.

We further exploit cross-sectional heterogeneity across firms and products to better evaluate whether the results are consistent with a credit market frictions channel. Our analyses indicate that the results are more pronounced in subsamples of firms that derive most of their revenue from product groups in sectors with high external finance dependence (e.g. Rajan and Zingales, 1998), as well as in subsamples of younger and smaller firms that are less likely to have established lending relationships and that lack strong credit histories. We also show that the effects on product creation are more pronounced for firms whose precrisis loan syndicate participants cut back lending to a greater extent during the crisis and were more exposed to the demise of Lehman Brothers. Finally, we exploit the broad range of products covered in the Nielsen data set to stratify firms based on whether they produce semi-durable or nondurables products. Consistent with the idea that semidurables are more capital-intensive and therefore more sensitive to financial frictions, our results indicate the impact of credit market disruptions are stronger in the subset of firms that produce semi-durable products. Overall, these cross-sectional exercises support the conjecture that the decline in radical product innovation during the Great Recession is related to disruptions in the supply of credit.

We address concerns that both our measures of credit market disruptions could capture the exposure of firms to unobserved shocks that are unrelated to supply conditions in the credit market. For instance, if a bank specializes in lending to an industry or market (e.g. Paravisini, Rappoport, and Schnabl, 2015), a demand shock to that industry might look like a credit supply shock because the bank would reduce lending in all counties relative to other banks in the same counties. We address this specific concern by exploiting the richness of the Nielsen RMS dataset to identify the predominant product groups and modules of each firm and by re-estimating the main empirical specification after including product group×year or module×year fixed effects. Thus, we ensure that our findings are robust to absorbing unobservable time-varying industry demand shocks that could bias our results. Furthermore, we conduct a battery of alternative robustness tests including using alternative definitions of the dependent variable, alternative geographic and firm-level measures of credit market disruptions, using additional controls for local demand shocks, and running our main empirical specifications in a subsample of firms whose sales come mostly from outside their state of origin. The main empirical findings are robust to all such alternative empirical strategies.

Next, we turn our attention to evaluating whether credit market disruptions could impact the characteristics of new products conditional on their introduction. This is important as the creation of highly innovative products likely shapes future firm growth differently than the addition of new products that do not contain any novel feature (e.g. Braguinsky et al., 2020). Using the descriptions of each new product in the Nielsen RMS sample, we examine whether credit market disruptions impact the average novelty of the new products of a firm. We follow Argente and Yeh (2017) and Argente, Baslandze, Hanley, and Moreira (2019) in computing "novelty" indices of all products that a firm introduces during a year. These indices measure the similarity between the characteristics of new products and existing characteristics of all available products within the same product category.

We provide new evidence that the novelty rate of characteristics embedded in new products is also procyclical, *i.e.* not only were there fewer products introduced during the Great Recession, but the fewer that were introduced were also less novel. Moreover, we find that products introduced by credit constrained firms during the crisis period were less novel than those introduced by unconstrained firms during the same period. We ensure that the decline in the rate of introduction of novel product characteristics is not explained by credit constrained firms cutting back on redundant characteristics of little value to consumers. We document that credit market disruptions are associated with a decline in the "novelty" index even when we weigh a product characteristic by its respective "shadow price" obtained from a hedonic pricing regression of (log) prices on product characteristics. These results suggest that credit market disruptions are not only partly to blame for a missing generation of new products but also for a missing generation of novel product characteristics.

Finally, we make use of the granular information on our dataset to ask whether credit market disruptions also impacted the overall commercial performance of products, conditional on their introduction during the Great Recession. The role that credit market constraints play in shaping the outcomes of new products launched during downturns is not obvious: credit market frictions could negatively impact investments in the development and promotion of products which, in turn, could hinder their potential commercial performance, even conditional on their introduction. On the other hand, during economic downturns, constrained firms might concentrate their efforts on their "very best" new products.

We provide evidence that products introduced in new categories during the crisis period by firms exposed to credit market frictions generate twenty percent less revenue. We obtain this result in an empirical specification that includes product group$\times$cohort fixed effects. This specification allows us to compare the sales performance of radical new products introduced by credit-constrained firms against the sales performance of radical new products introduced by less-constrained firms in the *same* product group and during the *same* quarter. We further condition on firm fixed effects to ensure that the results are not driven by systematic differences in the characteristics of firms introducing new product groups during the crisis period. These results are in line with those of other papers showing that tight credit markets constrain the size and growth of new firms entering in the economy (e.g. Saffie and Ates 2013; Moreira 2016; Siemer 2019).

In an effort to better understand how credit market constraints impact the ability of new product groups to generate revenues, we decompose the revenue stream of each new product group in several elements. Namely, we compute the number of products introduced in each product group, the number of Designated Market areas (DMA) where the firm sells the products in each product group, and the number of retail chains that carry these products. We then ascertain if the negative impact of credit market disruptions on revenues comes from a relatively more limited spatial, retail-chain, or product-space coverage or from lower average revenues of each product group per DMA, retail chain, and product. Our findings suggest both margins are important: the negative association of credit market disruptions with the average revenue per product, per DMA, and per retail chain accounts for most of the effect on total revenue, but credit market disruptions also negatively impact the number of products that a firm introduces in a new product group and the number of retail chains where it sells these new products. These results could, therefore, indicate that credit market disruptions limit investments in both product appeal and product availability.

The paper contributes to several strands of literature. It contributes to an important literature examining how capital structure and financing constraints shape innovation activities. A number of papers (e.g. Brown, Fazzari, and Petersen 2009; Acharya and Xu 2017) suggest that entrepreneurs and firms rely primarily on internal cash flows and equity markets to finance R&D investments. Bolton, Chen, and Wang (2011) and Bolton, Chen, and Wang (2013), however, predict cuts in investment following credit market shocks even without immediate financing needs and Benfratello, Schiantarelli, and Sembenelli (2008), Nanda and Nicholas (2014), Kerr and Nanda (2015), and Mann (2018), point to bank financing and credit shocks as important drivers of R&D investments. More related to our paper, Nanda and Nicholas (2014) finds that firms exposed to areas seeing greater rates of bank failure during the Great Depression obtain fewer patents and such patents are less impactful and original.[1] Howell (2017) and Krieger et al. (2018) find that R&D subsidies and positive shocks to net worth not only encourage firms to innovate but also affect the type of innovation and the likelihood of success of such investments. Our approach builds on these contributions by measuring the impact of credit market disruption on product innovation and by further opening the "black-box" of what types of investments in innovation get cut following a credit supply shock.

[1] Furthermore, a series of papers finds that the wave of bank deregulation of the 80s and 90s significantly impacted innovation at local firms. An incomplete list of these papers include Chava, Oettl, Subramanian, and Subramanian (2012), Amore, Schneider, and Žaldokas (2013), Cornaggia, Mao, Tian, and Wolfe (2015), and Hombert and Matray (2016).

The paper also speaks to an extensive literature that investigates the transmission of the 2007–2008 financial crisis shock to the non-financial sector. Chodorow-Reich (2013), Duygan-Bump, Levkov, and Montoriol-Garriga (2015), Giroud and Mueller (2017), Bentolila, Jansen, and Jiménez (2017), Berton, Mocetti, Presbitero, and Richiardi (2018), and Siemer (2019) show that the financial crisis significantly affected firm-level employment through the bank lending channel and this effect was particularly pronounced for smaller, younger, and more levered firms. Similarly Almeida et al. (2012), Campello, Graham, and Harvey (2010), Cingano, Manaresi, and Sette (2016), and Bucă and Vermeulen (2017) suggest that non-financial firms cut investments in capital expenditures in response to shocks to the supply of credit during the Great Recession.[2] Our paper provides evidence of a new channel mediating the relation between credit shocks and firm performance. We show that credit shocks affect the creation, novelty, and long-run performance of product innovation by firms. In doing so, we are able to better understand the relation between credit market frictions and the long-run performance of firms and shed new evidence onto how credit market frictions can meaningfully impact the real outcomes of non-financial firms.

Finally, the paper relates to a growing literature that uses the Nielsen RMS dataset and similar product-level datasets to examine the interactions between financing policies, international trade, and industrial organization. Fracassi, Previtero, and Sheen (2018) examines how private equity firms impact the product market decisions of their firms and Kim (2018), and Hyun and Kim (2018) investigate the effects of the credit crunch on the pricing policies of firms during the Great Recession. Paravisini, Rappoport, Schnabl, and Wolfenzon (2015) and Friedrich, Zator, et al. (2018) use detailed trade datasets to learn about companies adapt their product and export market mix following financial shocks. Mendes (2019) examines how the effects of credit supply shocks in the Portuguese wine industry varies with the product production cycle. We offer initial evidence that credit supply shocks play an important role in shaping the decisions of firms in the United States to launch products in a significant sector of the economy that represents approximately 14% of the consumption of goods in the United States (Argente et al., 2018b).

2 Data and Background Section

This study combines data from three sources to examine the effect of credit market disruptions on product innovation. We obtain the product dataset from the Nielsen Retail Measurement

[2]Kahle and Stulz (2013) show, nevertheless, that capital expenditures of financially-constrained firms are only lower than those of unconstrained firms late in the crisis at a time when net debt issuance of constrained and unconstrained firms is similar.

Services (RMS) scanner dataset provided by the Kilts-Nielsen Data Center at the University of Chicago Booth School of Business, the small business lending data comes from the Federal Financial Institutions Examination Council (FFIEC), and we also use the Thomson Reuters Dealscan dataset of syndicated loans.

2.1 Product Data

We use barcodes as our baseline definition of products. A barcode is a 12-digit Universal Product Code (UPC) consisting of 12 numerical digits that is uniquely assigned to each specific good available in stores. UPCs were created to allow retail outlets to determine prices and inventories accurately and improve transactions along the supply chain distribution (Basker and Simcoe, 2017).

Defining products at the level of the barcode has some important advantages. First, barcodes are unique to every product: changes in any attribute of a good (e.g. forms, sizes, package, formula) result in a new barcode.[3] A potential alternative would be to define goods and products by industry classification. Such approach, however, could aggregate very heterogeneous barcodes and neglect interesting information about new product developments within industry classifications. In fact, our data show that large firms typically sell hundreds of different products within narrowly defined categories.

Second, barcodes are so widespread that our data is likely to cover all products in the consumer goods industry (Basker and Simcoe, 2017). Producers have a strong incentive to purchase barcodes for all products that have more than a trivial amount of sales because the codes are inexpensive, and they allow sellers to access stores with scanners as well as internet sales. Further, we observe a wide range of products and we can explore several dimensions of heterogeneity because firms and products are included in the sample provided that a sale occurs.

We also provide results for an alternative definition of products that aggregates all barcodes into brands. The average brand in our data has nine different barcodes. Barcodes within a brand vary because of differences in attributes; thus, the product characteristics and quality of the same brand over time will change because of entry and exit of barcodes.

For product introduction data, we rely on the Nielsen Retail Measurement Services (RMS) scanner dataset provided by the Kilts-Nielsen Data Center at the University of Chicago Booth

[3]Firms have strong incentives not to reuse barcodes. Assigning more than one product to a single barcode can interfere with a store's inventory system and pricing policy; it is rare that a meaningful quality change occurs without resulting in an UPC change. Nonetheless, a possible concern is that a new UPC might not always represent a new product. For instance, Chevalier, Kashyap, and Rossi (2003) note that some UPCs might get discontinued only to have the same product appear with a new UPC. This is not a concern in our data set because Nielsen detects these UPCs and assigns them their prior UPC.

School of Business. The data is generated by point-of-sale systems in retail stores. Each individual store reports weekly sales and quantities sold of every barcode during that week. We use data for the 2006 to 2015 period.

The main advantage of this dataset is its size and coverage. Overall, the RMS consists of more than 100 billion unique observations at the UPC $\times$ store $\times$ week level covering approximately $2 trillion in sales. This volume represents about 53% of all sales in grocery stores, 55% in drug stores, 32% in mass merchandisers, 2% in convenience stores, and 1% in liquor stores. A key distinctive feature of this database is that the collection points include more than 40,000 distinct stores from around 90 retail chains in 371 MSAs and 2,500 counties. The dataset thus provides good coverage of the universe of products and of the full portfolio of firms in this sector.

The data covers a wide range of products both in terms of type (e.g. from non-durables such as milk to semi-durables like printers) and in terms of revenue share. The original data consist of more than one million distinct products identified by UPC, organized into a hierarchical structure. Each UPC is classified into one of the 1,070 product modules, that are organized into 104 product groups, that are then grouped into 10 major departments.[4] For example, a 31-ounce bag of Tide Pods (UPC 037000930389) is mapped to product module "Detergent-Packaged" in product group "Detergent", which belongs to the "Non-Food Grocery" department. Each UPC also contains information on the brand, size, packaging, and a rich set of product features.

We identify the period corresponding to the product introduction by observing the timing of its initial transaction in the dataset. More specifically, we define product entry as the first quarter of sales of a product. We cannot determine entry for some products. For products that are already active in the first two quarters of the sample (2006:Q1 and 2006:Q2), we classify them as incumbent products. These products can include those created just before 2006 or very established products. Moreover, in order to minimize concerns about errors in the measurement of the timing of a product's introduction, our baseline sample includes the balanced set of stores and products with at least one transaction per quarter after entering, while excluding private label products.[5]

[4]The ten major departments are: Health and Beauty aids, Dry Grocery (e.g., baby food, canned vegetables), Frozen Foods, Dairy, Deli, Packaged Meat, Fresh Produce, Non-Food Grocery, Alcohol, and General Merchandise).

[5]Our estimates of the introduction of products could be affected by the entry of stores in the sample. Therefore, we consider only a balanced sample of stores during our sample period. We consider products without missing quarters to rule out the possibility that our results are driven by seasonal products, promotional items, or products with very few sales. We exclude private label goods because Nielsen alters the UPCs associated with private label goods to protect the identity of the retailer. As a result, multiple private label items are mapped to a single UPC, which complicates the interpretation of entry patterns of these items.

2.2 Firm Data and Measures of Credit Market Disruption

To compute firm-level measures of product introduction and credit market disruptions we link firms and products with information obtained from GS1 US, the single official source of UPCs. The GS1 US data contains all of the company prefixes generated in the US and we combine these prefixes with the UPC codes in the RMS.[6] By linking firms to products, we can characterize their portfolio. With this dataset, we can identify the revenue, price, and quantity of each product in a firm's portfolio and aggregate them to the level of the firm. We mostly focus on measures of product introduction (frequency, number, and revenue). The product-firm baseline data allows us to study how measures of credit market disruption affected product innovation during the Great Recession.

We measure county-level exposure to credit market disruptions based on small business lending information obtained from the CRA dataset. This dataset is made publicly available by the FFIEC pursuant to Regulations 12 parts 25, 228, 345, and 195 of the CRA. The dataset contains information on the total number and volume of small business loans originated by each reporting financial institution in each county of the United States during a calendar year.[7] Since 2005, all commercial and savings banks with total assets exceeding $1 billion are required to report their originations of small business loans by county of the borrower. According to Greenstone et al. (2014) and Nguyen (2019), CRA-eligible banks account for approximately 86% of all loans originated in this market, thus mitigating concerns that the sample is not representative of this market. We use the CRA dataset to compute measures of local bank shocks at the county level. We match the geography-based measure of credit market disruption with our baseline dataset using each firm's location data available in the GS1 data.

To compute our firm-level measure of credit market disruptions, we link the GS1 dataset with loan market data from the Thomson Reuters Dealscan database. Dealscan collects loan-level information on syndicated loans from a variety of sources including regulatory filings, media reports, and company briefs. The dataset includes detailed information on the identities and characteristics of the borrowers and lenders in the dataset as well as other loan characteristics such as the principal amount, interest rates, and information on the origination and maturity dates of each loan. We link the Dealscan and GS1 datasets through a multi-step merging procedure. First, we merge the two databases using their exact company names and location information. Second, we match the remaining companies in the product database to the Thomson Reuters Dealscan database using a bigram string comparator for

[6] Argente et al. (2018a) provide more details on these data and their advantages compared to alternative sources.

[7] The county corresponding to a small business loan is where the main business facility is located or where the loan proceeds otherwise will be applied, as indicated by the borrower.

the company name while requiring the state of the company to be the same.[8] We keep observations with the same state headquarters and a name-matching score greater than 0.97. Finally, we hand-match the remaining companies in the GS1 database whose names are an exact match to those of the Thomson Reuters Dealscan database but that for some reason list different addresses. We conduct a thorough check of these matches to ensure that they refer to the same company by performing extensive online searches about the company and we retain only those observations whose addresses listed in both datasets can be traced back to the same company.

3 Measuring Credit Market Disruptions

We measure the exposure of firms to credit market frictions during the financial crisis using two distinct approaches. We begin by using *geographic* variation in the extent of the local credit supply shocks in the counties where firms are located. This approach allows us to measure credit market frictions for a broader sample of firms irrespective of their size and characteristics. This measure, however, captures variation in the health of banks across the locations where firms operate rather than direct information on firm's need to access external finance. To address this limitation, we use an alternative *firm-level* measure that captures preexisting variation in the fraction of long term debt that comes due during the financial crisis. This measure is a better indicator of external financing needs but covers a smaller sample of generally larger firms. In spite of capturing distinct sources of variation, both measures yield similar results suggesting that they pick up meaningful dimensions of credit market frictions. Below, we explain the computation of these measures in greater detail.

3.1 County-level Measure of Exposure to Credit Market Disruptions

The aggregate amount of small business loans originated in the United States experienced a significant decline between 2007 and 2010. Panel A of Figure 1 shows that the total volume of small business lending originated in the United States went from a peak of $320 billion to less than half of that amount in just three years. The aggregate decline in small business lending conceals substantial heterogeneity in the change in small business lending across U.S. counties between 2007 and 2010. Panel B of Figure 1 shows that more than 25 percent of all counties in the U.S. experienced declines in small business lending that exceeded 60%, whereas

[8] Similar to Chodorow-Reich (2013), we use Michael Blasnik's Stata ado file reclink for the described fuzzy merge.

approximately five percent of U.S. counties actually saw an increase in small business lending over this period. Naturally, the severity of this decline in small business lending conflates restrictions in the supply of credit from banks operating in the area and lower demand for external financing from local business.

Our initial approach to isolate a firm's exposure to disruptions in the supply of credit market follows the work of Greenstone et al. (2014), which also closely relates to the frameworks of Khwaja and Mian (2008) and Amiti and Weinstein (2018). The idea is to use preexisting variation in bank market shares across counties to compute a measure of the exposure of each county to banks that registered significant contractions in small business lending during the financial crisis at a national level. Intuitively, this measure exploits the notion that some banks (e.g. JP Morgan Chase, Citibank) significantly cut back their originations of small business loans relative to the rest of the banking sector and that some counties were more exposed to such banks through their preexisting branch footprint.[9]

This approach hinges on the assumptions that small business lending is inherently local and that borrowers cannot easily obtain financing from other sources. We believe that these assumptions are plausible: Granja et al. (2018) show that more than 75% of all small business loans are originated between borrowers and lenders that are located in the same county. An extensive literature (e.g. Petersen and Rajan 1994; Berger and Udell 1995; Liberti and Petersen 2018; Nguyen 2019) further suggest that long-term relationships are an important factor in overcoming important information asymmetries and that such relationships are not easily replaceable.

To compute their measure of local credit market disruptions, Greenstone et al. (2014) develop a modified Bartik approach that refines the traditional approach by exploiting the granularity of the CRA small business lending dataset. In line with Greenstone et al. (2014), we use available data on the total amount of small business loans originated by each bank to borrowers located in each county to estimate the following equation:

$$\Delta SBL_{b,c}^{07-10} = \gamma_b + \delta_c + \epsilon_{b,c} \tag{1}$$

where the outcome variable is the percent change in small business lending originated by bank b in county c between 2007 and 2010, γ_b are bank fixed effects, and δ_c are county fixed effects. The measure of local exposure to credit supply shocks at the county level is then computed as:

[9] Chen, Hanson, and Stein (2017) directly explore the idea that the top-4 banks in the economy largely pulled out from the small business lending market and areas that were more exposed to branches of Top-4 banks prior to the crisis were economically affected by this change in lending strategy. Our approach is in the same spirit as Chen et al. (2017) but uses all available information in the CRA Small Business Lending dataset by exploiting the evolution of small business lending for all banks in all counties.

$$SBL\ Shock_c = -\sum_b (\hat{\gamma}_b \times s_{b,c}^{07}) \tag{2}$$

where $s_{b,c}^{07}$ is the share of small business loans originated by b in county c during 2007. Note that relative to the traditional Bartik approach, Greenstone et al. (2014) use the bank fixed effects estimated from equation (1) rather than each bank's national change in lending to construct the measure of local exposure to shocks. The difference is that the county fixed effects in equation (1) purge each bank's national change in lending from their exposure to unobservable demand shocks in the counties where they are located, thus addressing potential concerns that this measure captures the bank's exposure to local demand shocks rather than shocks to the credit supply of local banks.

Figure 2 plots the spatial distribution of our county-level measure of credit market disruptions. The figure suggests that there is broad dispersion in the pattern of distress with greater exposure in the South, Midwest, and Western regions of the United States and lower exposure to credit supply shocks in the East.

A potential concern with this modified Bartik approach is that the bank supply and firm demand parameters might not be well identified if the world is better described by a more general class of models where the change in small business lending is determined by:

$$\Delta SBL_{b,c} = \gamma_b + \delta_c + \gamma \times Z_{b,c} + \epsilon_{b,c} \tag{3}$$

where $Z_{b,c}$ is a bank-firm interaction term. This could be the case if banks specialize in specific industries and unobservable national demand shocks to these industries are identified as a credit supply shock because the impacted bank reduces lending in all counties relative to other banks.

One way to evaluate this specific concern is to investigate if the composition of firms in a county correlates with our measure of credit market disruptions (e.g. Goldsmith-Pinkham, Sorkin, and Swift, 2018). In Figure 3, we examine the possibility that firms sort on less exposed counties based on their characteristics. Panel A of Figure 3 shows that there is no relation between the severity of county-level distress in credit markets and the size of the firms and panel B of the same figure shows that our measure of local credit market disruption is also not related to the size of the portfolio of products of the firm. Furthermore, we partition all counties in the analysis in percentile bins based on their exposure to our measure of credit market disruptions and we plot the share of firms in the Food Groceries, Non-Food Groceries, Health & Beauty, and General Merchandise Departments in each percentile bin. Figure IA.1 suggests that the sectoral composition of our sample does not change significantly with changes in the exposure to our measure of credit market disruptions.

To further address this specific concern, we run additional empirical specifications that include fixed effects at the very granular module×year level. By including these fixed effects, we absorb variation in industry demand shocks across very narrowly defined industries. For concreteness, we take advantage of the fact that within the set of firms that specialize in a specific product module such as "First Aid - Thermometers" some firms are located in counties in the upper deciles of our credit market disruption index such as Cass County, Michigan while others are located in counties in the bottom deciles of our measure such as Monmouth, New Jersey. Thus, we explore the notion that firms within very narrowly-defined sectors were exposed to similar industry-wide demand shocks but happened to be located in areas with different exposures to banks that cut their supply of credit.

Finally, the Greenstone et al. (2014) empirical strategy does not guarantee that the bank shocks are orthogonal to local conditions but only that they are orthogonal to contemporaneous local demand in the case when bank lending is described by an additively separable decomposition into bank supply and firm demand. We further try to ensure that our results are not driven by the exposure of firms to local demand by reestimating our results in a subsample of firms that originate most of their sales from outside their state headquarters.

We acknowledge that we cannot entirely rule out the possibility that channels other than credit supply drive the results obtained using this approach. To help with the convincing that we are measuring the effects of credit supply disruptions we use an alternative measure of credit market disruption that draws on a very different source of variation.

3.2 Firm-level Measure of Exposure to Credit Market Disruptions

The county-level measure of credit market disruption covers all firms in our dataset but does not directly capture whether firms need external financing. Next, we describe an alternative approach to measuring financing frictions that is better able to ascertain whether a specific firm had external financing needs during the financial crisis.

This alternative approach closely follows Almeida et al. (2012) and other recent papers (e.g. Benmelech et al., 2019; Costello, 2018) that use preexisting variation in the fraction of long-term debt that was prescheduled to come due during the initial phase of the financial crisis. The approach builds on the well-documented notion that the seeds of the recent crisis were sown in the subprime mortgage market but that its troubles later spilled to the corporate debt market in the fall of 2007. A series of papers (e.g. Ivashina and Scharfstein, 2010; Almeida et al., 2012; Chodorow-Reich, 2013) show that banks significantly cut back their supply of corporate loans relative to the peak of the boom and that these cuts are related to runs by short-term creditors and from problems emanating from other areas of their loan portfolio. This firm-level measure of credit market disruptions captures whether a firm was prescheduled to refinance their existing debt during the 2007–2008 period. The idea is that firms that had to refinance during this period likely experienced greater financial constraints as costs of financial intermediation increased substantially (Santos, 2010) and credit markets became highly illiquid (Ivashina and Scharfstein, 2010).

We follow Costello (2018) and compute the fraction of syndicated loans that came due during the initial stages of the financial crisis. More specifically, for each firm, we compute the total principal amount of its syndicated loans that were initiated before July 2006 and were expiring between July 2007 and August 2008. Using similar maturity and loan initiation requirements, we also compute the total amount of debt each firm had outstanding in July 2007. Similar to Costello (2018) we use the fraction of syndicated loans coming due between between July 2007 and August 2008 as our firm-level measure of financial constraints. The maturity restrictions that we impose on the sample of loans used in the analysis ensure that firms' ability to obtain long- vs. short-term debt does not drive the results.

The critical identification assumption in this analysis is that the fraction of syndicated lending coming due during the crisis is orthogonal to shocks in the expected value of investing in new products during the crisis. The idea is that by using the fraction of loans coming due during the financial crisis, we tease out variation in financial constraints that is plausibly unrelated to systematic differences in the expected outcomes of new products that the firm is developing or to systematic differences in firms' exposure to demand shocks. A potential caveat of this approach is that "better" quality firms are more likely to proactively manage risks by extending the maturities of their syndicated loans (e.g. Mian and Santos, 2018). Our findings, therefore, could be driven by unobserved differences in firm quality that may be correlated both with the likelihood that the firm experiences a loan coming due during the 2007–2008 period and with the expected value of its new product innovation *during* the crisis.

Our empirical specifications include firm fixed effects, which slightly allays such concerns by controlling for time-invariant differences in firm quality that could affect their overall rate of innovation. Thus, for such concerns to come to fruition, it must be that shocks to the expected outcomes of potential products introduced during the crisis are correlated with the fraction of long-term debt coming due during that time. In further robustness tests, we implement a tighter matching of treatment and control firms. Our preferred strategy is to include granular module×year fixed effects to ensure that we use only variation across firms specializing in same product modules. This strategy means that the results are driven not by systematic differences in the share of long-term debt coming due across product modules with different sensitivities to the economic cycle.[10]

[10] We also gauge the sensitivity of results to using variation in credit constraints based on the closeness to covenant thresholds (e.g., Chava and Roberts, 2008; Demerjian and Owens, 2016; and Chodorow-Reich and Falato, 2017).

Overall, while we cannot entirely dismiss alternative explanations for our results, we believe that the fact that we find consistent results across our two measures of credit market disruptions covering very different samples and using different sources of variation indicates that we are capturing the effects of credit market disruptions rather than unobservable factors that correlate with the treatment status.

4 Credit Market Disruption and Product Innovation

This section documents the main empirical patterns in the relation between credit market disruptions and the rate and characteristics of product innovation before, during, and after the recent financial crisis.

4.1 Summary Statistics

We begin our empirical analysis by presenting descriptive statistics for key variables in our sample. Panel A of Table 1 reports that approximately one third of the observations in our sample introduce new products over the course of a year. Most new products are incremental product innovations, i.e. new products in modules where a firm already had a product. By contrast, only 10% of the firm-year observations introduce radical product innovations, i.e. a new product in a new product module. The table also shows that firms in our sample hold on average 25.7 UPCs in their product portfolio. This distribution is, however, highly right-skewed with the median firm holding a product portfolio comprised of four UPCs. Most firms are focused on a few types of products: the average firm operates in three modules (out of 1,070 distinct modules) and two product groups (out of 114 distinct product groups). The revenues generated by new products in the year following their introduction represent approximately 8.33% of the total firm revenues in the previous year for the median firm. This distribution is, once again, right-skewed as the revenues of new products of the average firm represents approximately 115% of its total revenue in the prior year.

In Panel B of Table 1, we repeat the exercise for the subset of firms that we were able to match to the Thomson Reuters Dealscan database. These firms are typically larger than the firms in the full sample in terms of their total annual revenues and number of products. They are also twice as likely to introduce new products during a year and almost three times as likely to introduce a new product in a new module relative to the full sample in the previous panel. In spite of the significant differences in the characteristics of the samples used in panels A and B, we will see below that the results of the main empirical analyses largely agree across the two samples.

In Table 2, we present basic information about the evolution of product innovation over the 2007 to 2015 sample period. In Panel A, we show that all measures of product introduction see a decline between 2007 and 2010. In particular, the entry rate of new products, which we define as the ratio of new products to existing products in the prior period declined from .161 to .116 during this period. Importantly, this ratio recovered to its 2007 levels in the subsequent years and has remained approximately at those levels since 2012. We find similar cyclical patterns in panel B where we present these statistics for the subsample of firms matched to Dealscan. Overall, Table 2 confirms the findings of Broda and Weinstein (2010) and Argente et al. (2018b) of a significant slowdown in the rate of product introduction in the years around the Great Recession.

An important component of our empirical strategy is predicated on the idea that there is a meaningful distinction between introducing a new product in a product line that the firm already occupies and introducing a new product in a product line that is new to the firm. In particular, we conjecture that incremental product innovation carries fewer risks but also fewer rewards. Radical product innovation, on the other hand, almost by definition will entail greater investments but will typically imply greater market disruption, less cannibalization of existing products (e.g. Argente et al., 2018a), and potentially greater future revenues. We empirically examine this conjecture in Figure 4. Here, for each type of product innovation, we boxplot the respective ratio between the one-year ahead revenue generated by new products and total revenues of the firm in the year of product introduction. The main takeaway of the figure is consistent with our prediction: new products introduced in new product modules and in new product groups become a larger share of total product revenue of the firm, suggesting that these products are associated with greater rewards from the incremental revenue standpoint.

Next, we provide a simple cut of the raw data suggesting that the slowdown in product innovation in the years that immediately followed the crisis was more pronounced for firms exposed to greater disruptions in their local credit markets. In Figure 5, we sort firms based on our geographic level measure of exposure to credit market constraints and we plot the evolution of the average entry rate of new products of firms in the upper and bottom quartiles of exposure to the credit market disruption measure. In Panel A of Figure 5 we measure the average product introduction rate using all new products. The entry rates declined relative to their 2007 base levels for both groups but the group of firms exposed to greater credit market disruptions saw a stronger decline of about 33% relative to its 2007 baseline levels.

In Panels B and C of Figure 5, we plot the average product introduction rate in product modules that already existed in firms' product portfolios (Panel B) and the average product introduction rate of products that expand the set of product modules of the firm (Panel C).

The plots offer initial evidence that credit market disruptions play a more significant role in shaping the slowdown of radical product innovation. The plot of Panel B suggests that the rates of incremental innovation are similar across the entire period. By contrast, Panel C suggests that credit constraints play an important role in explaining the decline in radical product innovation. The entry rate of new products in new product modules declined by more than 45% between 2007 and 2010 for the more credit-constrained group, but only 25% for the less credit-constrained groups. An interesting feature of this plot is that the differences between high local credit shock and the medium/low credit shocks groups are substantial in 2009 and 2010 but not in 2008. An explanation for this pattern could be that the crunch in the small business lending market materialized mostly in 2009 as can be seen in Figure 1. Also, the "time-to-build" a new product could last some months, which explains that in some cases the effects on product innovation might only be felt a few months after the onset of the crisis.

We further explore the evolution of the rates of product innovation in Figure IA.2 of the internet appendix. In this figure, we repeat the analysis in Figure 5 in the Dealscan-matched firm sample after splitting the firms based on whether they have more or less than one third of their outstanding debt coming due in the early stages of the crisis. These plots are consistent with the results described above: the sample of firms that is more credit constrained sees a more pronounced reduction in the rates of radical product innovation during the Great Recession relative to the rates of incremental product innovation.

4.2 Empirical Results

In this section, we formally examine whether credit market disruptions induced changes in the rate of introduction and in the novelty of new products introduced during the crisis period. We estimate ordinary-least-squares (OLS) specifications of several outcomes related to the introduction of new products as a function of the exposure to credit market disruptions during the crisis. Specifically, we estimate the following specification:

$$Y_{i,t} = \alpha_i + \theta_t + \beta Shock_i \times Crisis_t + \Gamma X_{i,t} + \epsilon_{i,t} \tag{4}$$

where i indexes observed outcomes of a firm during year t. The dependent variable $Y_{i,t}$ represents an outcome of the firm during the year such as the entry rate of new products or the novelty of the product characteristics of the products introduced during the year. The main variable of interest, $Shock_i \times Crisis_t$, is the interaction between a measure of credit market disruption, which could be the *geographic-* or *firm-level* measure described above, and a dummy variable that takes the value of one throughout the crisis period: 2008, 2009, and 2010. Our main coefficient of interest, β, measures the impact that an increase in our measures of credit market disruption has on product innovation outcomes during the crisis.

Our main specification also includes firm and year fixed effects. The firm fixed effects ensure that our results are driven not by cross-sectional differences in unobservable firm characteristics but rather by within-firm changes in the decisions to introduce new products during the crisis period. The year fixed effects absorb overall trends in the evolution of product innovation rates over time. In some specifications we further include a vector of firm-level characteristics that include the natural logarithm of the total revenue of the firm in the sample, the Herfindahl index of revenue concentration across a firm's products, the natural logarithm of average firm revenue per product, and a set of indicator variables that take the value of one for each decile of the number of products in the portfolio and the total revenue of the firm. All regressions are estimated with heteroskedasticity-robust standard errors clustered at the level of the state.

4.2.1 Product Introduction during the Crisis

In Table 3, we present the results of estimating the empirical specification of equation (4) using our *geographic* measure of credit market disruption as the main variable of interest and the entry rate of new products as the dependent variable. Columns (1) and (2) present results using the entry rate of all products as the main dependent variable. The main coefficient of interest, β, indicates that an increase in the exposure to local financial institutions that cut back their aggregate supply of small business lending is associated with a lower overall rate of product introduction. The results are, however, only statistically significant when we include additional control variables in column (2).

Next, in columns (3)–(6), we disaggregate the entry rate of new products into the entry rate of new products in old product modules (Columns (3) and (4)) and the entry rate of new products in new product modules (Columns (5) and (6)). This distinction is economically meaningful: new products (barcodes) introduced in old product modules (incremental product innovation) most likely require less significant investments in R&D, working capital and production capacity because firms will be able to redeploy their existing capital (both physical capital and human capital) and their existing inventories of raw materials to the production of the new product. The results of columns (3) and (4) suggest that an increase in our geographic measure of credit market disruption does not significantly affect the rate of incremental innovation.

By contrast, new products introduced in new product modules (radical product innovation) require greater investments in acquisition of knowledge, product development, and more likely involve new investments in production lines, machinery, employee training among other operating costs. The results of columns (5) and (6) suggest that an increase in the exposure to credit market disruptions significantly reduced the rate of radical innovation. The results are also economically significant: A standard deviation increase in the geographic measure of credit market disruption is associated with a negative impact of .0018 (0.085 $\times$ -0.021) in the entry rate of new products in new product modules. This negative impact is approximately 15% of the overall decline in the rate of introduction of new products in new product modules from 0.036 in 2007 to 0.024 in 2010 (-0.012) reported in Table 2.

Because our *geographic* measure of credit market disruption cannot assess whether a specific firm needs external financing, we repeat the analysis using a *firm* measure of credit market disruption that follows Almeida et al. (2012) and captures whether a firm needed to refinance some of its long-term debt during the crisis period. We report results of this analysis in Table 4. We find that firms with a larger share of their debt prescheduled to mature during the financial crisis were significantly more likely to cut back on their adoption of radical product innovations (columns (5) and (6)) but not on their overall rates of product innovation (columns (1) and (2)) or their adoption of incremental product innovation (columns (3) and (4)). The coefficients in columns (5) and (6) indicate that firms having to refinance all their outstanding debt during the crisis reduced their entry rate by 3.6 basis points. To put this number in context, it indicates that a standard deviation increase in the share of outstanding debt that a firm must refinance during the crisis is associated with a reduction in the rate of introduction of new products of 1.2 basis points (.012 = .035 $\times$ -.035) or approximately 40% of the average decline in the rate of radical product innovation between 2007 and 2010. Overall, the empirical findings of Table 4 are very reassuring in that we find similar empirical patterns when we use an alternative proxy that covers a different subset of firms while picking up a very different source of variation in credit market disruptions.

Overall, these results are consistent with a conceptual framework developed in Krieger et al. (2018) that suggests that credit constrained firms that are either credit rationed or have to incur high costs to access external sources of financing reduce their investment in high-risk/high reward projects. Our results are consistent with the notion that expansions of the product portfolio to new product lines carry greater risks in the form of greater fixed costs and that credit constrained firms decided either to cut their plans to expand their product portfolio to new product lines or to substitute toward less risky projects in the form of new product varieties within their existing product lines.

4.2.2 The Role of Credit Market Disruptions: Cross-Sectional Heterogeneity

To further validate the idea that credit market disruptions distort the decisions of firms to introduce new products, we investigate whether the impact of credit shocks during the crisis period varies based on: i) firm characteristics that are typically associated with difficulties in obtaining access to credit; ii) the degree of dependence of a firm on external sources of finance; and iii) the financial health of a firm's relationship lenders.

We begin by examining whether the effects of credit market disruptions on product innovation are more pronounced for firms whose characteristics hinder their ability to access external finance. A large literature that started with Petersen and Rajan (1994) and Berger and Udell (1995) suggest that smaller and younger firms are more likely to be credit constrained as they lack established lending relationships and strong credit histories. Furthermore, these information frictions in lending relationships are typically amplified during times of crisis (e.g. Dell'Ariccia and Marquez, 2006; Chodorow-Reich, 2013; Duygan-Bump et al., 2015; Siemer, 2019) as credit conditions become tighter and lenders less willing to make credits based on the prospect of future cash flows and without the security of collateral (e.g. Granja et al., 2018, Jiménez, Ongena, Peydró, and Saurina, 2014).

In Table 5 we examine the role that firm age and size play in shaping the effects of credit market disruptions. We stratify the sample based on firm age (columns (1) and (2)) and on size of the firm at the beginning of the crisis (columns (3) and (4)). Column (1) shows that old firms, defined as those whose products were already covered in the RMS dataset since the beginning of the sample were negatively and significantly affected by the local credit shocks. The results of Column (2), however, show that new firms experienced a stronger and statistically significant impact of credit market disruptions on the rates of product innovation. The magnitude of the coefficient of credit market disruption on young firms is six times as large as that of old firms. In columns (3) and (4), we stratify the firms in the sample based on whether their average annual total sales between 2006 and 2008 are above or below the third quartile of the distribution of these average sales in the sample.[11] Consistent with the idea that smaller firms are more credit constrained, we find that the effects are concentrated in the subset of small firms.

Next, we examine whether the effects of credit market disruptions on product innovation were more pronounced for firms whose sales come primarily from sectors that are more dependent on external sources of finance. The idea is that the transmission of credit shocks to the decision to launch new products should be more pronounced for firms whose sectors are more likely to depend on external financing sources to finance growth. To compute the measure of sectoral external financial dependence, we follow Rajan and Zingales (1998) and compute the median (at the 3-digit standard industrial classification (SIC) level) of the difference between capital expenditures and net cash from operations divided by the capital

[11] In this analysis, we drop firms with no sales between 2006 and 2008, hence explaining the lower number of observations relative to Table 3.

expenditures. In columns (5) and (6) of Table 5, we stratify the full sample based on the median of the external financial dependence measure computed following Rajan and Zingales (1998). The results suggest that firms in industries with high dependence of external sources of finance see a more pronounced decline in the entry rate of new products in new product modules than firms in industries that do not depend as much on external sources of finance.

The Nielsen data set covers an extraordinarily broad range of products from microwaves, telephone accessories, and other electric goods to frozen vegetables and other frozen foods. We exploit heterogeneity in product characteristics across the broad spectrum of products covered in the data set to further assess whether credit market disruptions distort the decisions of firms to introduce new products during a crisis. Specifically, we exploit the fact that semi-durable products such as electric goods are more likely to be capital-intensive and therefore more sensitive to capital market disruptions than nondurables. We approximate the durability of each product module by using the Nielsen Consumer Panel Data to count the average number of shopping trips made by households in a given year to purchase products in that module. We classify a firm as a producer of semi-durable products if its main product line involves few consumer trips per year.[12] We present the results of this analysis in Table 6. Consistent with the notion that semidurables are more sensitive to capital market disruptions, we find that producers of semi-durable products scale back the introduction of new products in new product modules to a larger extent than producers of non-durables. In fact, the impact of exposure to credit market disruptions on the aggregate product innovation rate is substantially more pronounced for semi-durables (column 1) than nondurables (column 2).

Next, we turn our attention to the Dealscan-matched sample of firms. In columns (1) and (2) of Table 7, we stratify the sample based on firm size. Because the subset of firms that we match to Dealscan is comprised of larger firms relative to the full sample, we define large firms as those whose average annual total sales between 2006 and 2008 exceed the median of the distribution in the sample. We find statistically significant results for the subsample of small firms but not for the subset of large firms. In columns (3)–(6), we evaluate if our results vary predictably with the financial health of a firm's lenders. Chodorow-Reich (2013) finds that lending relationships in the syndicated loan market are sticky, which implies incremental costs to borrowers that are forced to switch lenders. We rely on this previously established finding to examine whether firms that see a greater portion of their debt coming due during the crisis and that, at the same time, had precrisis lending relationships with less healthy lenders cut back on their radical product innovation efforts more significantly than other firms whose precrisis syndicate lenders were healthier.[13]

[12] Examples of semi-durable products are sun-exposure trackers, bathroom scales, and printers. Examples of nondurable firms are refrigerated milk, cigarettes, and fresh bread.

[13] This strategy is closely aligned to the work of Chodorow-Reich and Falato (2017) who find that a covenant

In columns (3) and (4) of Table 7, we split our sample based on the change in lending of a firm's lenders between the crisis and pre-crisis period. More specifically, we follow Chodorow-Reich (2013) and, for each bank in the sample, we compute the annualized change in the total volume of loans originated between October 2005 to June 2007 and between October 2008 to June 2009. We then compute a firm-specific measure of lender health by taking the weighted average of the change in lending over all members of each firm's last precrisis syndicate using that syndicate's lender shares as weights. Consistent with a bank-balance sheet channel, we find that the impact of our firm-level credit shock on the rate of radical product innovation is more pronounced when the firm is exposed to a precrisis syndicate that is less financially sound. Following Ivashina and Scharfstein (2010) and Chodorow-Reich (2013), we further split the sample based on the pre-crisis co-syndication share of a firm's lenders with Lehman Brothers. The idea is that banks that co-syndicated credit lines with Lehman Brothers were more likely to experience larger credit-line drawdowns after Lehman's demise and therefore were more liquidity constrained. Our findings, reported in columns (5) and (6), are consistent with this conjecture and indicate that the effects associated with the need to refinance during the crisis are more pronounced if the firms were exposed to lenders with a greater co-syndication share with Lehman Brothers.

Overall, this section strongly supports our conjecture that a credit-supply channel is responsible for the association between our measure of credit market disruptions and the decline in the introduction of new products that would diversify their product portfolio to new product lines. Consistent with this idea, our findings suggest that the impact of credit market disruption on product innovation is more pronounced for firms that are more dependent on external sources of finance for growth, firms exposed to information frictions that hinder their ability to obtain finance and for firms with existing banking relationships with lenders that cut back their supply of credit more significantly.

4.2.3 Robustness - Product Introduction during the Crisis

Next, we conduct a battery of robustness tests to further ensure that our headline findings are driven not by unobservable local or industry shocks, but rather by the impact of credit market disruptions on product innovation.

A potential concern is that banks specialize in lending to specific industries and demand shocks to these industries are misidentified as credit supply shocks because banks specializing in these industries cut lending in all counties relative to other banks. To deal with this concern, in Table 8, we reestimate the empirical specifications of columns (5) and (6) of Tables 3 and 4

violation is more likely to trigger a decline in the volume of lending when the lender is in worse financial health.

after including Department×Year, Group×Year, and Module×Year fixed effects, respectively. Thus, in the most stringent specification, we absorb any year-industry-specific shocks at a very fine level. Here, the identifying variation comes from comparing the evolution over the crisis of product introduction outcomes of a firm that specializes in a specific product module such as "First Aid - Thermometers" and is headquartered in high-credit market disruption county such as Cass County, Michigan against the evolution of product introduction outcomes of another firm specializing in the *same* product module such as "First Aid - Thermometers" whose headquarters happened to be located in Monmouth, New Jersey – a low credit market disruption county.

We present the results of this analysis in Panels A and B of Table 8. In Panel A, we assess the robustness of the results of Tables 3 to the inclusion of these alternative fixed effects structures. Despite the potential concerns about the role of bank-industry specialization, the coefficients obtained from estimating these empirical specifications are quantitatively and qualitatively similar when we include these granular fixed effects. In Panel B, we repeat the analysis, using the Dealscan-matched sample of firm and our firm-level measure of credit market disruption. Similarly, our results remain quantitatively and qualitatively similar. We should note that when we include Module×Year fixed effects we lose a substantial number of observations in the analysis because many firms are the only ones in their respective modules. Following Correia (2015) we exclude these observations from the analysis. Despite this reduced number of observations, the results remain statistically significant.

A related concern is that the modified Bartik design only guarantees that the bank shocks are orthogonal to local conditions in the case in which bank lending is described by an additively separable decomposition into bank supply and firm demand. To further address the possibility that our geographic measure of credit market disruption captures shocks to local economic conditions that are not subsumed by the additively separable decomposition in the modified Bartik design à la Greenstone et al. (2014), we repeat the empirical specifications of columns (5) and (6) of Table 3 in the subsample of firms that make more than 66%, 75%, and 90% of their total sales outside their headquarters' state (henceforth, outside states), respectively. The idea is that firms in those subsamples are exposed to local credit shocks because bank financing is local (e.g. Petersen and Rajan, 1994; Granja et al., 2018; and Nguyen, 2019), but less exposed to shocks to local economic conditions because they source their revenues from a wide geographic footprint through their relations with regional or national retail chains.

We report the results of this analysis in Table 9. We find that the estimated negative impact of credit market disruption on the introduction of products in *new* modules are not sensitive to using subsamples of firms that derive most of their sales from outside states. As we move from the subsample that derives at least 66% to the sample that derives more than 90% of sales from outside states, the estimated coefficients continue to suggest that credit market disruptions have an economically and statistically significant negative impact on product introduction. These results are comforting because one would think that if our measure of credit market disruption was capturing local demand shocks, the estimated coefficients would lose significance as we moved toward subsamples that are less and less exposed to local demand conditions.

We implement many other robustness tests to gauge the sensitivity of the main results to alternative empirical strategies. We examine whether the results are robust to using alternative definition of the dependent variables such as an indicator variable that takes the value of one if the firm introduces a new product during the year (Table IA.1) or the natural logarithm of the number of products introduced by a firm during a year (Table IA.2). In Figure IA.3 and Table IA.3, we use an alternative definition of new product that focuses on new brands rather than on new barcodes. The results are robust to using these alternative dependent variables.

Second, we test the sensitivity of the results to alternative measures of credit market disruptions. We begin by using an alternative time-varying *geographic* measure of the local exposure of each county to idiosyncratic bank supply shocks. Unlike our main measure that focuses on the county exposure to a bank supply shock during the 2007–2010 period, here we estimate: $\Delta SBL_{b,c,t} = \gamma_{b,t} + \delta_{c,t} + \epsilon_{b,c,t}$ for every year in the sample and we compute the local credit shock measure of county c in year t as: $SBL\ Shock_{c,t} = -\sum_b(\hat{\gamma_{b,t}} \times s_{b,c}^{t-1})$. Table IA.4 shows that the results are not driven by this particular research design choice. In Table IA.5 we show that the rates of radical product innovation *during* the crisis are not sensitive to placebo credit market shocks measured *outside* of the crisis during the 2005–2008, 2011–2014, and 2012–2015 periods.

We also use an alternative firm-specific measure of financial constraints based on how close a firm is to violating a covenant in a loan package. A long literature (e.g. Chava and Roberts, 2008 and Chodorow-Reich and Falato, 2017) finds that investments decrease sharply following a covenant violation as creditors use the threat of accelerating the loan to intervene in management. After matching the Roberts and Sufi (2009) dataset of covenant violations to our sample of Dealscan-matched CPG borrowers, however, we find only six companies violating a covenant between 2008 and 2010. This small number of matched- and treated-observations precludes us from using covenant violations as an alternative shock to credit supply. Instead, we use the likelihood that a firm will breach a covenant in a loan package, obtained from the work of Demerjian and Owens (2016). The idea is that firms that are closer, in a probabilistic sense, to breaching a covenant will be more likely to take precautionary measures and reduce discretionary spending especially during the crisis (Bolton et al., 2013). In Table IA.6 we find that firms with higher likelihood of covenant violation significantly reduce their rate of introduction of new products in new product modules. Furthermore, the results suggest that these results are even more pronounced in response to increases in the probability of violation of an earnings-based/performance-based covenant suggesting that companies could be avoiding R&D or marketing expenses that lower reported earnings and could trigger violations of this type of covenants.

Finally, we gauge whether our results are sensitive to the inclusion of indicators of local economic conditions. In Table IA.7 we find that our results are robust to including controls for the (log) unemployment rate and (log) county income *per capita* in the county where the firm's headquarters is located. In Table IA.8, we draw from the work in Mian, Rao, and Sufi (2013) and Saiz (2010) to examine if the impact of our measure of credit supply disruption is subsumed after the inclusion of measures of house price shocks, local household net worth shocks, and household leverage at the start of the Great Recession. The results suggest that the association between our main measure of credit supply shocks and radical product innovation remains statistically significant even after conditioning on the interaction between these measures of local household shocks and the indicator variable for the crisis period. In fact, the measures of local household net worth shocks are not statistically significant in explaining the lower rates of product introduction in new product modules following the financial crisis. A possible explanation for this result is that most companies in our sample sell products in more than one state and therefore are not so exposed to local demand shocks. Moreover, Mian et al. (2013) show that the impact of household net worth shocks in explaining changes in spending in groceries and other non-durables is small relative to the impact of those shocks on the consumption of other goods such as durables and autos.

4.3 Credit Market Disruption and Characteristics of New Products

In the previous section, we determined that firms are less willing to expand to new product lines during the crisis. Next, we explore whether greater exposure to a credit market shock also induces changes in the qualitative characteristics of all new products introduced during the crisis period. We focus on a critical element of product innovation: the level of novelty associated with the new product. We examine whether firms not only are less willing to expand to new product modules but also whether new products are more likely to be "me-too" products that do not bring novel characteristics to the marketplace.

In order to quantify the novelty of a product, we follow Argente and Yeh (2017) and compute a *novelty index* using detailed information about the characteristics of each UPC provided in the Nielsen RMS dataset. The index counts the number of new and unique attributes of a product at the time of its introduction relative to all other products ever sold within the same product module. Our measure assigns a higher value to products that introduce "never before seen" features to the market. We define a product j in product module k as a vector of characteristics $V_{kj} = [v_{j1}, v_{j2}, .., v_{jN_k}]$ where N_k denotes the number of attributes we observe in product module k in our data. For example, the product module "soft drinks - carbonated" consists of $N_{\text{soft drinks}} = 8$ attributes for each barcode: brand, flavor, firm, size, type (sparkling soda or natural soda), container (e.g. can or bottle), formula, generic (i.e. private label). Let Ω_{kt} contain the set of product characteristics for each product ever sold in product module k at time t, then the *novelty index* of a product j in product module k, launched at time t is defined as follows:

$$\mathrm{NI}_{jt}^{k} = \frac{1}{N_k} \sum_{i=1}^{N_k} \mathbb{1}[v_{kji} \notin \Omega_{kt}]. \tag{5}$$

For example, if a new product within the soft drinks category enters with a flavor and size that has never been sold in any store before, its novelty index is $(1+1)/N_{\text{soft drinks}} = 2/8$. On average, we observe 7.2 product characteristics in each product module.[14] This index equal weights each characteristic and, therefore, is implicitly agnostic about the relative importance of each attribute to the degree of novelty of a product.

Our basic novelty index counts the number of new characteristics (within each attribute) of each new product. Alternatively, we could consider a product as "novel" if it brings a never before seen combination of characteristics. For example, in the carbonated beverages module, a new soft drink may be neither the first fusing drink nor the first cherry-flavored soda, but might be the first cherry-flavored fusing drink. To account for new products that do not innovate with a new characteristic (within a given attribute) but rather with a new combination of characteristics, we also use an alternative index whose scoring function is identical to that of the numerator of equation (5) with the exception that it adds one to this numerator if the new product introduces a new combination of characteristics.[15]

[14] Comparing the novelty index of different products across distinct modules depends not only on the number of new attributes of each product but also on the total amount of observable characteristics the Nielsen data provides for each module. The minimum characteristics we observe for each module is 5 and the maximum is 12.

[15] By definition, if a new product brings a new characteristic within an attribute, it will also bring a new combination. However, new products that do not bring a new characteristic within an attribute to the market might bring a new combination of characteristics (e.g. not the first time we observe a soda with orange flavor or the first time we observe a low calorie soda, but the first time we observe an orange-flavored low-calorie soda).

Finally, a potential pitfall of the two "novelty" indices introduced above is that they just count new characteristics or new combinations of characteristics irrespective of how consumers value these novel product characteristics or of how much they are willing to pay for them. To overcome this possible criticism, we follow Argente et al. (2019) in creating a "novelty" index that weighs each characteristic by their respective shadow prices obtained from regressions of (log) prices on a set of product attributes and a sequence of time-dummies. The "hedonic novelty index" largely follows the computation of equation (5) with the exception that we weigh each product characteristic by the shadow price of each characteristic. We refer to Argente et al. (2019) for further details on the computation of this measure.

We report the time-series evolution of the "novelty" indices that we use on our empirical analysis in Table 10. The evolution of the "novelty" measures indicates that new products introduced over the crisis were less novel and more similar to existing products than products introduced during normal times. For example, in the full sample the main "novelty" index declines from .129 in 2007 to .121 in 2010 while the hedonic "novelty" index declines from .250 in 2007 to .236 in 2010. Thus, we offer initial evidence that consumers saw a decline of approximately five percent in the rate of arrival of never-before-seen characteristics in new products in the product markets covered by the RMS dataset. The novelty indices subsequently bounced back after 2010 and reached the 2007 levels prior to the end of the sample period suggesting that the novelty indices are procyclical.

To further understand the role of credit market disruptions in shaping this decline in "product novelty" during the crisis, we estimate the specification of equation (4) using the novelty indices as our dependent variables. We report the results in Table 11. Panel A shows results using the full sample of firms and our *geographic* measure of credit market disruption and Panel B reports similar findings using our Dealscan-matched firm dataset with our *firm*-level measure of credit market shock. Overall, the results of this table suggest that when firms are more exposed to credit market disruptions during periods of crisis they introduce new products that contain fewer novel attributes than other products introduced by the same firm during normal periods. The results of columns (1) through (4) of both panels suggest that credit market disruptions negatively impact product novelty regardless of whether we are measuring novelty as only never-before-seen product characteristics or also with never-before-seen combinations of characteristics. The results in columns (5) and (6) show our results are robust to using the "hedonic novelty index". This result likely suggests that consumers had positive valuations on the "missing" product characteristics that were cut during recessions. In Tables IA.9 and IA.10, we show that these results are robust when we employ alternative fixed effect structures and use a subsample of firms whose sales are mostly outside their HQ's state, respectively.

Overall, these results are consistent with the notion that when firms face financial constraints they introduce fewer products in new product lines and, conditional on introducing new products, these products contain fewer novel product characteristics. Moreover, our results suggest that the decline in the rate of introduction of novel characteristics is not explained by a decline in the introduction of characteristics with low consumer valuations. Thus our results could indicate that consumers are missing out on valuable characteristics and that they may be worse off as a result of these credit frictions.

5 Credit Market Disruptions and Product Outcomes

The rich micro-level data available in the RMS dataset offers an opportunity to follow the revenues generated by each product over time. Thus, the dataset allows us to say something about the impact of credit market disruptions not only on the rate of introduction of products and their novelty, but also on their performance conditional on introduction.

The role that credit market constraints play in shaping the outcomes of new products launched during downturns is not obvious: credit market frictions could limit amounts invested in the development and promotion of new products and such lower initial investments in product development could stunt both their initial performance and future growth potential. On the other hand, during economic downturns, the opportunity cost of an investment in product introduction and development is higher, which could prompt firms to focus their investments in their best and most promising products, i.e. those with higher expected value. This selection effect would suggest that products introduced in crisis cohorts by firms exposed to credit market disruptions are relatively more promising.

To study these questions, we develop a dataset that follows the evolution of a firm in each product group over time. Here, we collapse the empirical analysis at the firm-product group level for computational reasons. This dataset allows us to identify when an existing firm expands to a new product group and, crucially, to observe the total sales that a firm generates in each of its product groups. To shed more light on the link between credit market disruptions and the relative performance of products introduced during the crisis period, we estimate the following specification:

$$Rev_{i,g,c} = \alpha_i + \theta_{gc} + \beta Shock_i \times Crisis\ Cohort_c + \epsilon_{i,g,c} \tag{6}$$

where Rev is a measure of the cumulative total sales that the firm i generated in product group g launched during period c in its first four years of operation. It, thus, measures total sales performance over the initial years of a firm's new product group. The main variable of interest, $Shock_i \times Crisis\ Cohort_c$, is the interaction between our *geographic* measure of credit market disruption and a dummy variable that takes the value of one if firm i launched the new product group g between 2008:Q3 and 2010:Q4. The firm fixed effect, α_i, ensures we are comparing the revenue performance of a new product group created during the crisis period with the revenue performance of a new product group of the *same* firm that was introduced during normal times. Thus, the results are not driven by a selection effect whereby firms launching products in crisis periods are systematically different from firms introducing products in normal times. The product-group $\times$ cohort fixed effects, θ_{gc}, ensure that we are comparing the revenue performance of new products introduced by different firms within the same product group during the same quarter. The idea is to take distinct firms that expand to the same product group during the same quarter, therefore, facing very similar economic conditions at inception, and to ask if the revenue performance of their new product group varies systematically with the exposure of each firm to credit supply disruptions.

We report the results of this analysis in Table 12. In column (1), we report results of estimating the specification of equation (6) using the natural logarithm of the total revenues generated by the product group during its four initial years of life as our dependent variable. Our dataset includes only new product groups that that were created after the beginning of the sample, i.e. that did not exist yet at the beginning of the sample. The results suggest that a one-standard deviation increase in our measure of exposure to credit market shocks is associated with a 20% reduction in the total sales generated by a new product group. In column (2), we repeat the analysis after restricting the sample to new product groups launched by incumbent firms. The results are not sensitive to the exclusion of the product groups launched by new firms. In columns (3) and (4), we find that products groups introduced in crises cohorts by firms exposed to credit market disruptions account for a smaller share of firm revenues over their initial four years. Overall, these results are in line with those of other papers suggesting that (e.g. Saffie and Ates 2013; Siemer 2019) differences in initial economic and financial conditions have strong impacts on initial investment and explain variation across time in the average size of start-up firms.

To further enhance our understanding of the above findings we attempt to investigate what are some of the potential channels that shape the negative relation between credit market disruptions and revenue performance of the new product groups. Namely, we examine whether credit constrained firms roll out fewer product varieties in their crisis-cohort product groups, whether they sell these crisis-cohort products in fewer geographies, or even whether they invest less in securing a large network of retailers for their new products. To that effect, we decompose the total revenues generated by a product group into: (i) average number of products sold within the product group and average revenue per product; (ii) average number of DMAs where products are sold and average revenues per DMA; and (iii) average number of retail chains that carry the products and average revenue per retail chain.

We report the results of this analysis in Panels A and B of Table 13. In columns (1), (3), and (5) we estimate the impact of credit market disruptions on the average revenue per product, per DMA, and per retail chain, respectively. The estimated coefficients suggest that the negative association between credit market disruptions and these variables account for most of the observed negative association between credit supply shocks and total revenue performance. We interpret this result as being consistent with the idea that products introduced by credit constrained firms during the crisis period have less appeal than other products introduced by less constrained firms in the same product group during the same period. The results of column (2) of both panels suggest that credit market disruptions also negatively impact the number of products that a firm introduces in a new product group. This pattern could indicate that credit constraints limit the ability of firms to invest in new varieties within a product group. In column (4) indicates that credit constraints are associated, albeit non-significantly in Panel A, with lower availability of new products groups in terms of their geographic coverage. Finally, in column (6) of both panels, we document a significant negative association between credit supply shocks and the number of retail chains that carry new product groups launched by firms exposed to credit supply shocks.

6 Conclusion

Recent theory models in the Schumpeterian tradition increasingly model the process through which investments in R&D translate in improvements of existing products that allow firms to keep an edge over competitors or in the development of new products that expand a firm's product portfolio and potentially displace the products of competitors (e.g. Klette and Kortum, 2004; Akcigit and Kerr, 2018; Argente et al., 2018a). These models, however, are silent about the importance of the credit market constraints channel in mediating this process.

We conduct an initial empirical investigation of the role that credit market disruptions played in shaping the rate, novelty, and performance of product innovation during the recent financial crisis. We find that credit market disruptions did not affect the rate at which a incumbent firm introduces new products in its own product lines but constrains its expansion to new product lines or product groups. This fact entails important implications for firm and aggregate economic growth: Akcigit and Kerr (2018) estimate that 54.5 percent of aggregate growth due to innovations is accounted by investments of incumbent firms in new products outside its current scope of operations, whereas only 19.8 percent of aggregate growth through innovations is due to investments in internal innovation efforts. In the context of the Akcigit and Kerr (2018) results, our empirical findings suggest that credit market disruptions affect the margin of innovation that most contributes for growth and uncovers a new channel through which credit market disruptions could have long-run growth consequences.

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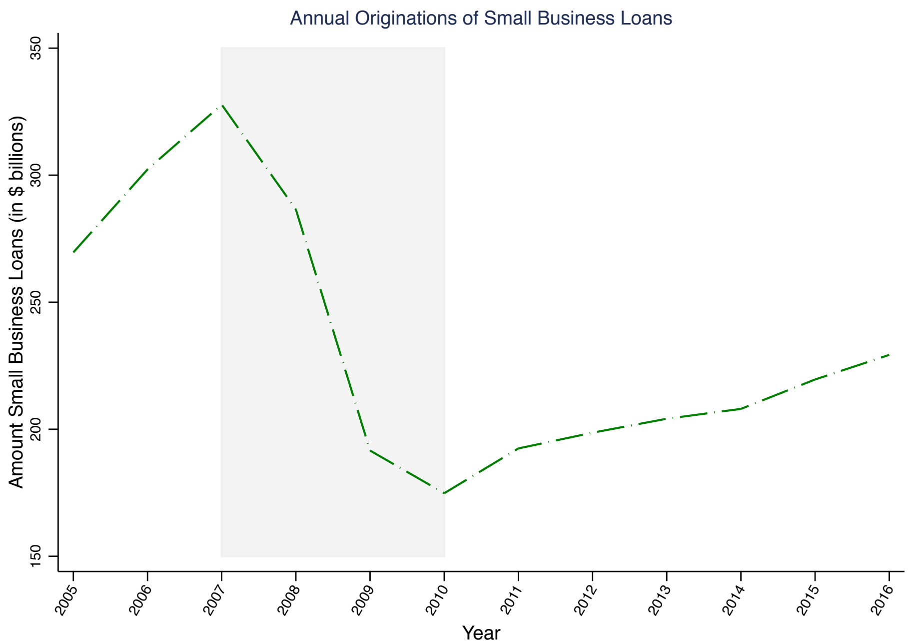
Figure 1: Evolution of Small Business Lending (2007–2010)

Panel A of Figure 1 represents the time-series of the aggregate small business lending over the 2005 to 2016 period. Panel B is a histogram of the county-level percent change in total county small business lending between 2007 and 2010. Data for both panels is obtained from the CRA small business lending dataset.

Panel A: Evolution of Total U.S. Small Business Lending (2005–2016)



Panel B: Change in Total County Small Business Lending (2007–2010)

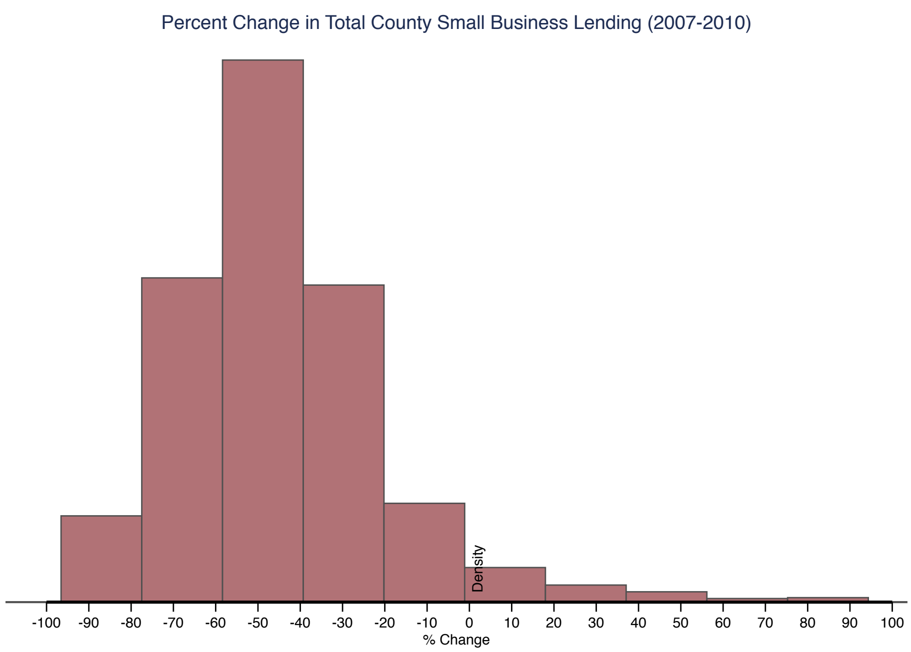


Figure 2: Spatial Distribution of County-Level Measure of Credit Market Disruption

The map of Figure 2 plots the exposure of each county to credit market disruptions, where our measure of credit market disruption is obtained from estimating the models of equations (2) and (4). Data for the figure comes from the CRA small business lending dataset.

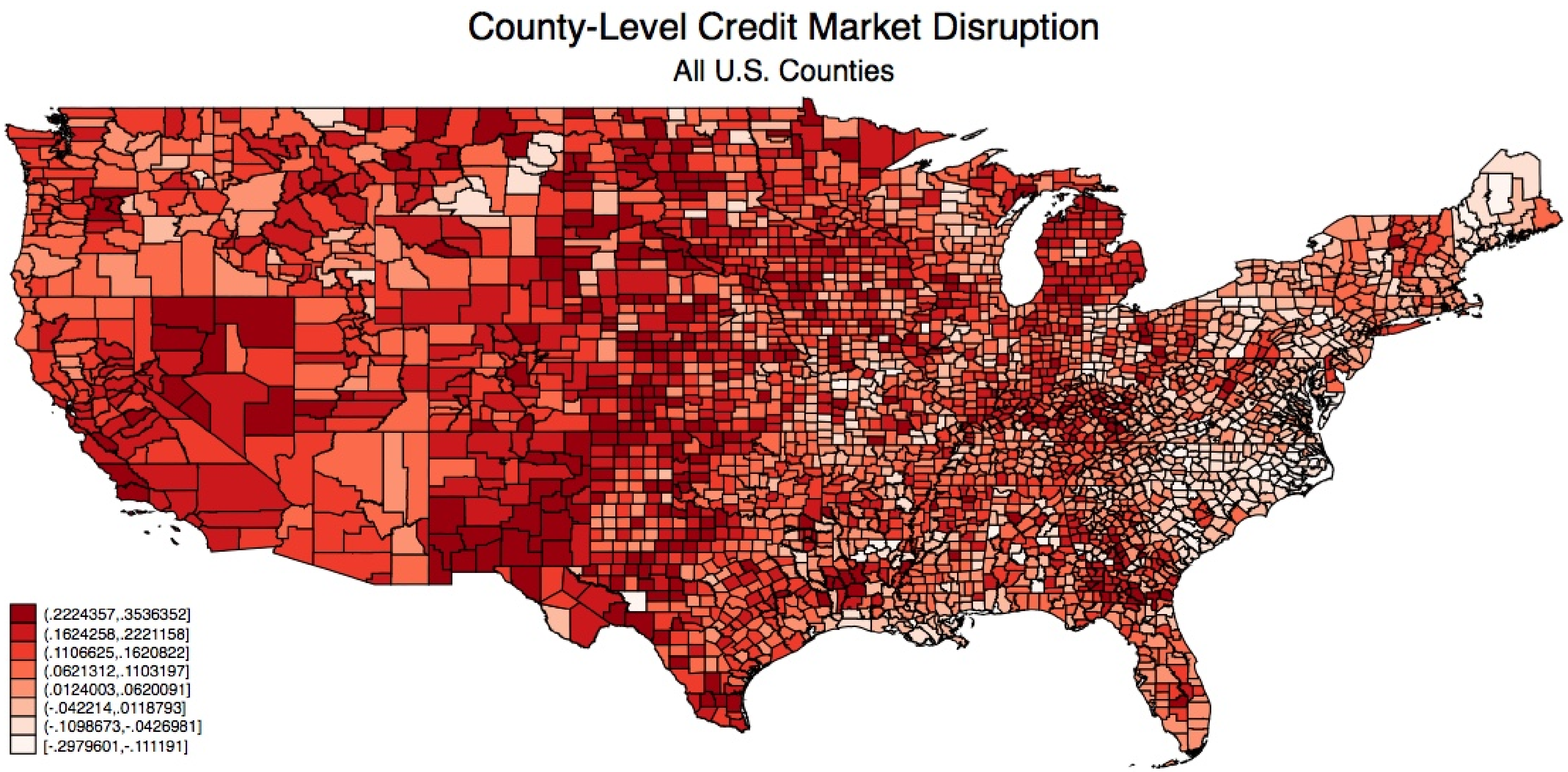
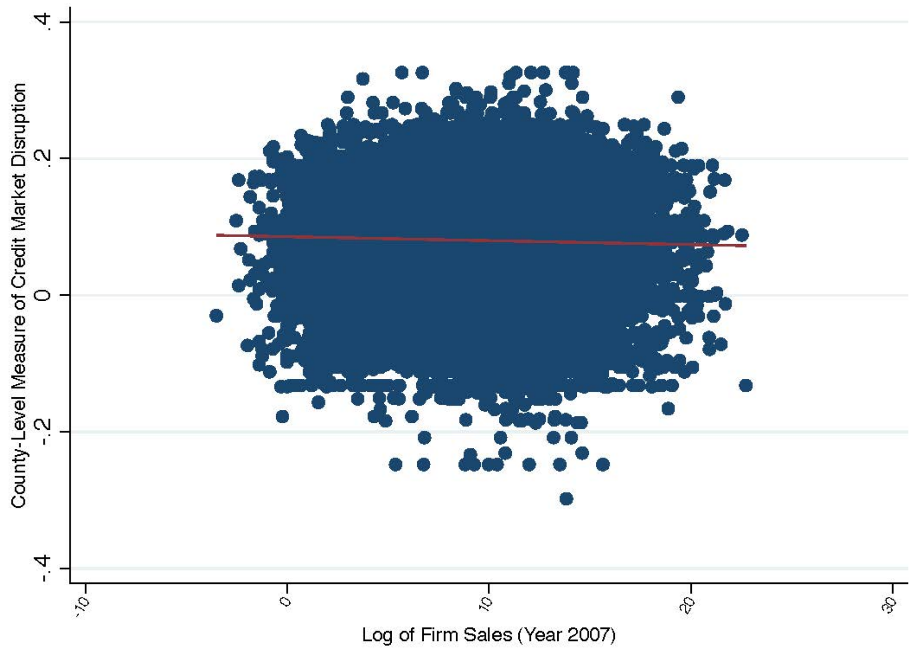


Figure 3: Sorting of Firms into Counties

Figure 3 are scatterplots (blue dots) and linear fit (red line) between our geographic measure of exposure to credit market disruptions and the pre-existing level of total firm sales of firms located in the county (Panel A) and between our geographic measure of exposure to credit market disruptions and the pre-existing level of the total number of products of firms located in the county (Panel B). Data for all figures is obtained from the CRA and Nielsen datasets.

Panel A: Credit Market Disruption and Firm Sales (2007)



Panel B: Credit Market Disruption and Total Number of Products (2007)

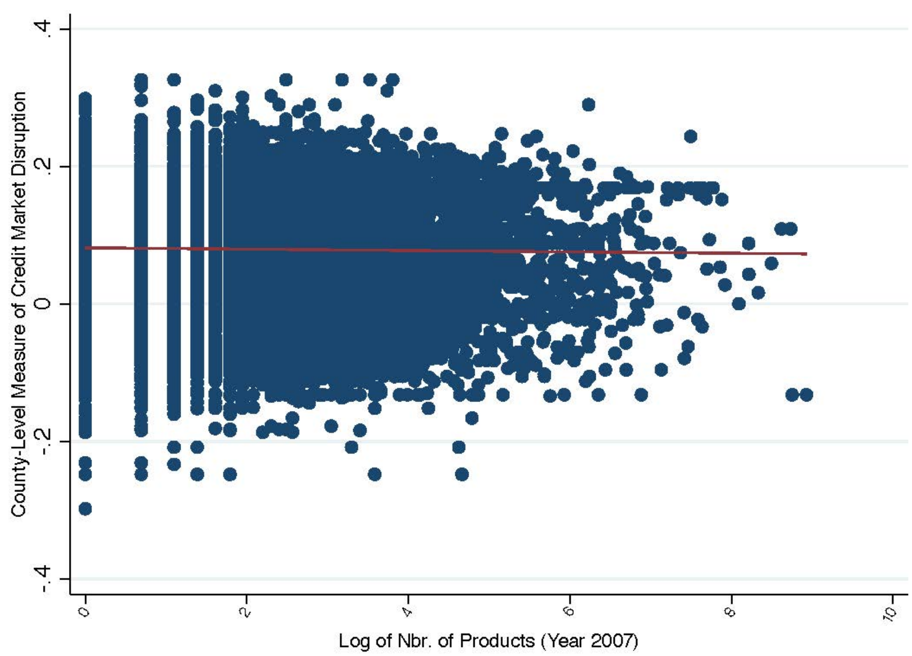


Figure 4: Type of Product Innovation and Product Revenue Share

Figure 4 represents a box-plot chart of the ratio between the total firm revenue generated by products that the firm introduced in the previous year and the total firm revenue from all products. We present box-plot charts for products introduced in product lines in which the firm is already operating (left), products introduced in modules that are new to the firm (center), products introduced in product groups that are new to the firm (right) Data for the figure is from the Nielsen datasets.

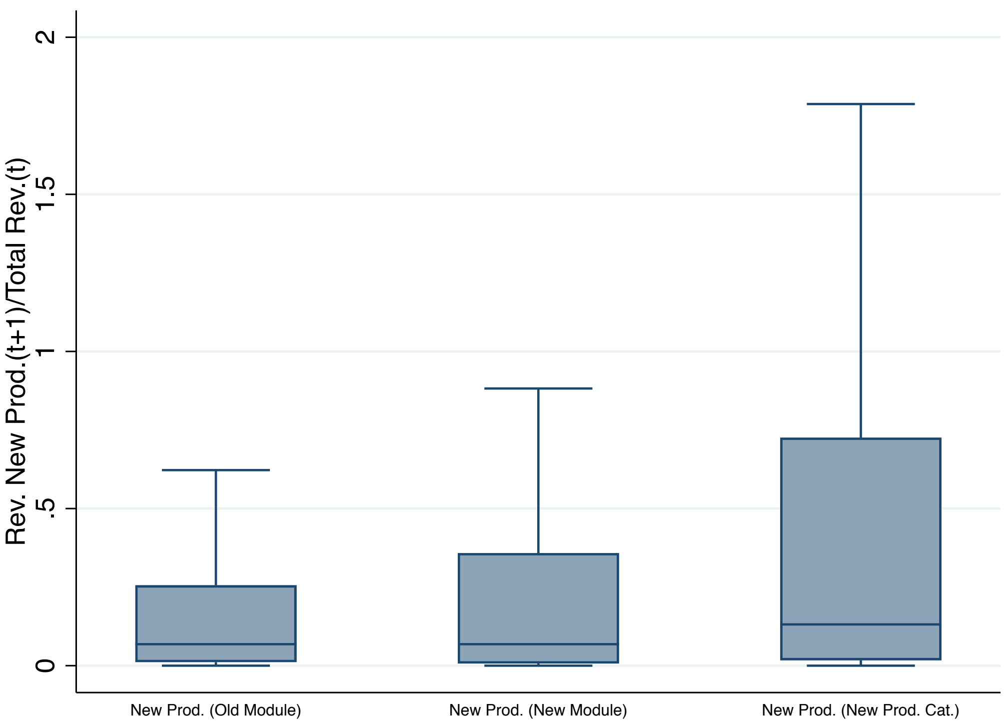
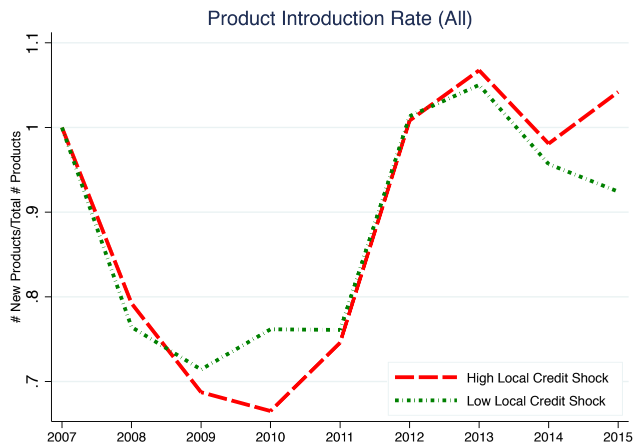


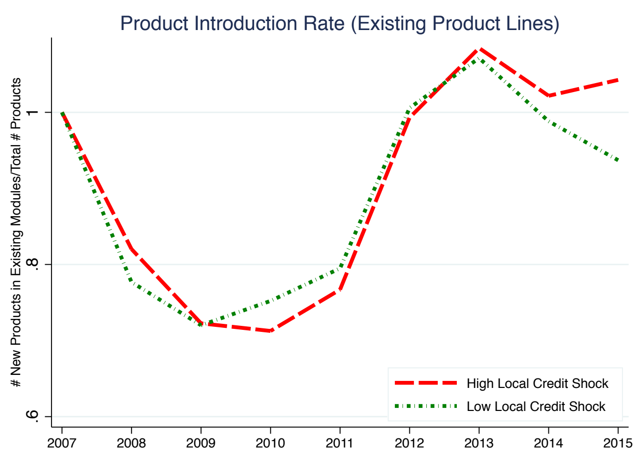
Figure 5: : Product Innovation and Credit Market Disruption: Entry Rate

Figure 5 plots the evolution of the average entry rate of new products during a calendar year over time. We stratify the sample based on the exposure of each firm to our geographic measure of credit market disruption. The entry rate of new products is defined as the ratio between the number of new products introduced during a year and the total number of products at the beginning of the year. The green line represents the evolution of the average firm entry rate of new products for the quartile of firms located in counties that were least exposed to our geographic measure of credit market disruptions. The red line represents the evolution of the average entry rate of new products for the quartile of firms located in counties most exposed to our geographic measure of credit market disruptions. The plot on the top panel represents the average entry rate of new products of all types. The second plot represents the evolution of the average entry rate of new products in product lines that already existed in a firm's product portfolio. The plot on the bottom represents the evolution of the average entry rate of new products that expand the set of product modules of the firm. All time series plotted are normalized such that 2007 = 100. Data for all figures is obtained from the CRA and Nielsen datasets.

Panel A: Average Entry Rate of New Products



Panel B: Average Entry Rate of New Products in Existing Product Lines



Panel C: Average Entry Rate of New Products in New Product Lines

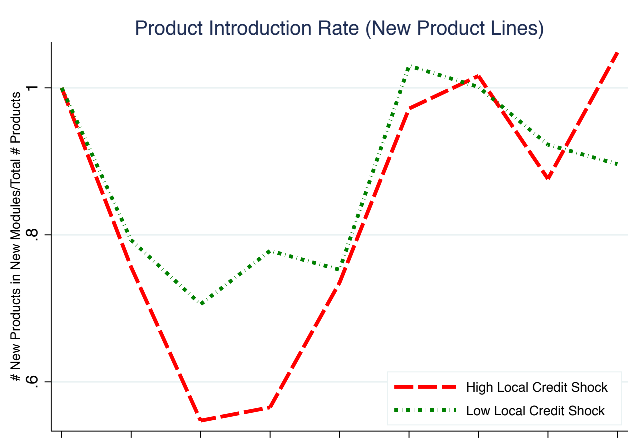


Table 1: Summary Statistics

Table 1 reports the coefficients of OLS regressions investigating the effect of credit market disruptions on firms' decisions to launch new products on the market. *Nbr. of New Products (All Modules)* is the number of new products (barcodes) that a firm introduces during a year. *Nbr. of New Products (Old Modules)* is the number of new products (barcodes) that a firm introduces during a year in product modules that it was already occupying. *Nbr. of New Products (New Modules)* is the number of new products (barcodes) that a firm introduces during a year in new product modules. *I(New Prod=1) (All)* is an indicator variable that assumes the value of one if a firm introduces a new barcode during the year. *I(New Prod=1) (Old Modules)* is an indicator variable that assumes the value of one if a firm introduces a new barcode in a product module that it already occupied. *I(New Prod=1) (New Modules)* is an indicator variable that assumes the value of one if a firm introduces a new barcode in a new product module during the year. *Total Nbr. of Products* is the number of products (barcodes) that a firm keeps in its product portfolio at the beginning of the year. *Total Nbr. of Distinct Modules* is the number of distinct product modules in which a firm sells a product. *Total Nbr. of Distinct Prod. Groups* is the number of distinct product groups in which a firm sells a product. *Total Annual Revenues* are the total revenues that a firm generates in the stores covered by our sample during a year. *Rev. New Prod.(t+1)/Total Rev.(t)* is the ratio of total revenues generated by new products in the year following their introduction and the total revenues generated by the firm in the year of the products' introduction.

Panel A: Full Sample

	N	Mean	St. Dev.	p25	p50	p75
Nbr. of New Products	177,517	3.704	25.03	0	0	1
Nbr. of New Products (Old Modules)	177,517	3.387	24.64	0	0	1
Nbr. of New Products (New Modules)	177,517	0.317	1.972	0	0	0
I(New Prod. =1)	177,517	0.343	0.475	0	0	1
I(New Prod. =1) (Old Modules)	177,517	0.307	0.461	0	0	1
I(New Prod. =1) (New Modules)	177,517	0.106	0.308	0	0	0
Total Nbr. of Products	177,517	25.70	143.1	1	4	13
Total Nbr. of Distinct Modules	177,517	3.401	7.646	1	1	3
Total Nbr. of Distinct Prod. Cat.	177,517	2.047	2.822	1	1	2
Total Annual Revenues	177,517	6,751,895	93,975,186	668	23,939	326,849
Rev. New Prod.(t+1)/Total Rev.(t)	48,405	1.152	52.73	0.0152	0.0833	0.296

Panel B: Firms Matched to Dealscan

	N	Mean	St. Dev.	p25	p50	p75
Nbr. of New Products	2,555	40.32	136.2	0	3	22
Nbr. of New Products (Old Modules)	2,555	39.06	135.1	0	2	20
Nbr. of New Products (New Modules)	2,555	1.268	4.149	0	0	1
I(New Prod. =1)	2,555	0.677	0.468	0	1	1
I(New Prod. =1) (Old Modules)	2,555	0.631	0.483	0	1	1
I(New Prod. =1) (New Modules)	2,555	0.286	0.452	0	0	1
Total Nbr. of Products	2,555	273.9	820.8	4	27	157
Total Nbr. of Distinct Modules	2,555	14.45	33.90	2	4	12
Total Nbr. of Distinct Prod. Cat.	2,555	5.622	8.816	1	2	6
Total Annual Revenues	2,555	120,123,477	615,129,596	24,630	2,228,816	28,558,470
Rev. New Prod.(t+1)/Total Rev.(t)	1,453	0.336	1.234	0.0274	0.0941	0.249

Table 2: Product Innovation: Evolution over Time

Table 2 reports the evolution of the means of main dependent variables over time for the full sample (Panel A) and for the smaller sample of firms that we match to the Dealscan Dataset. *Entry Rate (All Modules)* is the number of new products (barcodes) that a firm introduces during a year divided by the number of products at the beginning of that year. *Entry Rate (Old Modules)* is the number of new products (barcodes) that a firm introduces during a year in product modules that it was already occupying divided by the number of products at the beginning of that year. *Entry Rate (New Modules)* is the number of new products (barcodes) that a firm introduces during a year in new product modules divided by the number of products at the beginning of that year. *I(New Prod=1) (All)* is an indicator variable that assumes the value of one if a firm introduces a new barcode during the year. *I(New Prod=1) (Old Modules)* is an indicator variable that assumes the value of one if a firm introduces a new barcode in a product module that it already occupied. *I(New Prod=1) (New Modules)* is an indicator variable that assumes the value of one if a firm introduces a new barcode in a new product module during the year.

Panel A: Full Sample

Year	Entry Rate (All Mod.)	Entry Rate (Old Mod.)	Entry Rate (New Mod.)	I(New Prod=1) (All)	I(New Prod=1) (Old Mod.)	I(New Prod=1) (New Mod.)
2007	0.161	0.115	0.036	0.379	0.335	0.128
2008	0.127	0.091	0.028	0.319	0.285	0.100
2009	0.115	0.083	0.025	0.306	0.275	0.091
2010	0.116	0.084	0.024	0.301	0.271	0.087
2011	0.125	0.091	0.028	0.316	0.284	0.097
2012	0.164	0.116	0.037	0.363	0.326	0.115
2013	0.169	0.121	0.037	0.377	0.341	0.120
2014	0.156	0.114	0.033	0.361	0.324	0.109
2015	0.158	0.115	0.035	0.359	0.323	0.108

Panel B: Firms Matched to Dealscan

Year	Entry Rate (All Mod.)	Entry Rate (Old Mod.)	Entry Rate (New Mod.)	I(New Prod=1) (All)	I(New Prod=1) (Old Mod.)	I(New Prod=1) (New Mod.)
2007	0.244	0.169	0.056	0.727	0.675	0.349
2008	0.182	0.131	0.038	0.675	0.633	0.322
2009	0.178	0.126	0.032	0.689	0.629	0.286
2010	0.149	0.111	0.029	0.639	0.590	0.236
2011	0.198	0.126	0.044	0.656	0.591	0.268
2012	0.159	0.119	0.030	0.633	0.602	0.253
2013	0.205	0.161	0.030	0.692	0.652	0.287
2014	0.181	0.145	0.035	0.696	0.674	0.289
2015	0.176	0.125	0.036	0.686	0.639	0.281

Table 3: Product Innovation and Credit Market Disruptions (Geography-Based Measure)

Table 3 reports the coefficients of OLS regressions investigating the effect of credit market disruptions on firms' decisions to launch new products on the market. *Entry Rate (All Modules)* is the number of new products (barcodes) that a firm introduces during a year divided by the number of products at the beginning of that year. *Entry Rate (Old Modules)* is the number of new products (barcodes) that a firm introduces during a year in product modules that it was already occupying divided by the number of products at the beginning of that year. *Entry Rate (New Modules)* is the number of new products (barcodes) that a firm introduces during a year in new product modules divided by the number of products at the beginning of that year. *Local Credit Shock* is a measure of the magnitude of the credit market disruption between 2007 and 2010 in the county where each firm's headquarter is located. *I(Crisis)* is an indicator variable that takes the value of one for the crises years: 2008, 2009, and 2010. *Ln(Firm Revenue)* is the natural logarithm of the firm's total sales in the previous year. *Rev. Concentration index* is the Herfindahl index of revenue concentration across a firm's products. *Ln(Rev. per Product)* is the natural logarithm of the firm's average revenue per product. The specifications (2), (4), and (6) control for the size of the firm non-parametrically by including fixed-effects for the deciles of the total number of products of the firm in the previous year. Standard errors are presented in parentheses, and are clustered at the level of the firm's state headquarters. ***, **, and *, represent statistical significance at 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Entry Rate (All Modules)		Entry Rate (Old Modules)		Entry Rate (New Modules)	
Local Credit Shock × I(Crisis)	-0.042	-0.045*	-0.011	-0.013	-0.020***	-0.021***
	(0.027)	(0.024)	(0.022)	(0.020)	(0.007)	(0.007)
Ln(Firm Revenue)		-0.176***		-0.114***		-0.044***
		(0.012)		(0.006)		(0.003)
Rev. Concentration Index		-0.194***		-0.125***		-0.041***
		(0.006)		(0.004)		(0.002)
Ln(Rev. per Product)		0.198***		0.128***		0.050***
		(0.011)		(0.006)		(0.004)
Observations	173447	173447	173447	173447	173447	173447
Adjusted R^2	0.248	0.269	0.218	0.234	0.156	0.163
Year Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes

Table 4: Product Innovation and Credit Market Disruptions (Individual Firm Measure)

Table 4 reports the coefficients of OLS regressions investigating the effect of firm-specific credit market disruptions on firms' decisions to launch new products on the market. *Entry Rate (All Modules)* is the number of new products (barcodes) that a firm introduces during a year divided by the number of products at the beginning of that year. *Entry Rate (Old Modules)* is the number of new products (barcodes) that a firm introduces during a year in product modules that it was already occupying divided by the number of products at the beginning of that year. *Entry Rate (New Modules)* is the number of new products (barcodes) that a firm introduces during a year in new product modules divided by the number of products at the beginning of that year. *Firm Credit Shock* is a measure of the credit market disruption that follows Almeida et al. (2012) and capture the share of long-term debt of the firm that came due between June 2007 and August 2008. *I(Crisis)* is an indicator variable that takes the value of one for the crises years: 2008, 2009, and 2010. *Ln(Firm Revenue)* is the natural logarithm of the firm's total sales in the previous year. *Rev. Concentration index* is the Herfindahl index of revenue concentration across a firm's products. *Ln(Rev. per Product)* is the natural logarithm of the firm's average revenue per product. The specifications (2), (4), and (6) control for the size of the firm non-parametrically by including fixed-effects for the deciles of the total number of products of the firm in the previous year. Standard errors are presented in parentheses, and are clustered at the level of the firm's state headquarters. ***, **, and *, represent statistical significance at 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Entry Rate (All Modules)		Entry Rate (Old Modules)		Entry Rate (New Modules)	
Firm Credit Shock × I(Crisis)	-0.029	-0.026	0.014	0.014	-0.035***	-0.035***
	(0.044)	(0.039)	(0.028)	(0.025)	(0.012)	(0.012)
Ln(Firm Revenue)		-0.148***		-0.056		-0.047**
		(0.041)		(0.038)		(0.020)
Rev. Concentration Index		-0.199***		-0.108***		-0.048*
		(0.063)		(0.037)		(0.024)
Ln(Rev. per Product)		0.176***		0.082**		0.046**
		(0.048)		(0.037)		(0.022)
Observations	1744	1744	1744	1744	1744	1744
Adjusted R^2	0.309	0.330	0.293	0.309	0.229	0.233
Year Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes

Table 5: Product Innovation and Credit Market Disruptions: External Financial Dependence

Table 5 reports the coefficients of OLS regressions that investigative how differences in the age, size, and external finance dependence of firms impact the effect of credit market disruptions on firms' decisions to launch new products on the market. *Entry Rate (New Modules)* is the number of new products (barcodes) that a firm introduces during a year in new product modules divided by the number of products at the beginning of that year. *Local Credit Shock* is a measure of the magnitude of the credit market disruption between 2007 and 2010 in the county where each firm's headquarter is located. *I(Crisis)* is an indicator variable that takes the value of one for the crises years: 2008, 2009, and 2010. *Ln(Firm Revenue)* is the natural logarithm of the firm's total sales in the previous year. *Rev. Concentration index* is the Herfindahl index of revenue concentration across a firm's products. *Ln(Rev. per Product)* is the natural logarithm of the firm's average revenue per product. *Old Firms* are firms that entered the market prior to 2006. *New Firms* are firms that entered the market after 2006. In columns (3) and (4), we stratify firms based on whether they are above or below the third quartile of sales, measured as a total amount of annual total sales between 2006 and 2008. We chose to stratify at the third quartile, because the distribution of size is very skewed and, at the median of the distribution, firms are relatively small, generating only approximately $20,000 of total revenues in stores covered in the Nielsen dataset. In columns (5) and (6), firms are stratified based on a measure of external financial dependence, *Ext.Fin.Dep*, of the 3-digit SIC industry to which their main product module belongs. To compute the external financial dependence measure we follow Rajan and Zingales (1998) and take the sample of public firms in Compustat between 2000 and 2008 and we compute the difference between capital expenditures and net cash from operations divided by capital expenditures. The external financial dependence measure is the median of this ratio at the 3-digit SIC level. Standard errors are presented in parentheses, and are clustered at the level of the firm's state headquarters. ***, **, and *, represent statistical significance at 1%, 5%, and 10% levels, respectively.

	Old Firms	New Firms	Large Firms	Small Firms	Low Ext.Fin.Dep.	Hi Ext.Fin.Dep
	Entry Rate (New Modules)					
Local Credit Shock × I(Crisis)	-0.012*	-0.095***	-0.007	-0.018*	-0.014**	-0.024**
	(0.006)	(0.031)	(0.009)	(0.010)	(0.006)	(0.010)
Ln(Firm Revenue)	-0.031***	-0.123***	-0.037***	-0.037***	-0.049***	-0.037***
	(0.003)	(0.015)	(0.004)	(0.004)	(0.005)	(0.004)
Rev. Concentration Index	-0.032***	-0.060***	-0.053***	-0.033***	-0.042***	-0.033***
	(0.002)	(0.004)	(0.004)	(0.002)	(0.005)	(0.005)
Ln(Rev. per Product)	0.035***	0.127***	0.037***	0.041***	0.054***	0.042***
	(0.003)	(0.014)	(0.004)	(0.005)	(0.005)	(0.005)
Observations	135372	38075	39766	111355	90145	89358
Adjusted R^2	0.101	0.195	0.125	0.095	0.184	0.179
Year Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes

Table 6: Product Innovation and Credit Market Disruptions: Product Durability

Table 6 reports the coefficients of OLS regressions that investigate how differences in the product durability of firms's main product line mediate the effect of credit market disruptions on firms' decisions to launch new products in the market. *Entry Rate (New Modules)* is the number of new products (barcodes) that a firm introduces during a year in new product modules divided by the number of products at the beginning of that year. *Local Credit Shock* is a measure of the magnitude of the credit market disruption between 2007 and 2010 in the county where each firm's headquarter is located. *I(Crisis)* is an indicator variable that takes the value of one for the crises years: 2008, 2009, and 2010. *Ln(Firm Revenue)* is the natural logarithm of the firm's total sales in the previous year. *Rev. Concentration index* is the Herfindahl index of revenue concentration across a firm's products. *Ln(Rev. per Product)* is the natural logarithm of the firm's average revenue per product. *Old Firms* are firms that entered the market prior to 2006. *New Firms* are firms that entered the market after 2006. Standard errors are presented in parentheses, and are clustered at the level of the firm's state headquarters. ***, **, and *, represent statistical significance at 1%, 5%, and 10% levels, respectively.

	Hi. Dur	Low Dur.	Hi. Dur	Low Dur.	Hi. Dur	Low Dur.
	Entry Rate (All)		Entry Rate (Old Modules)		Entry Rate (New Modules	
Local Credit Shock × I(Crisis)	-0.073**	-0.020	-0.031	-0.000	-0.026***	-0.015*
	(0.030)	(0.028)	(0.026)	(0.023)	(0.009)	(0.008)
Ln(Firm Revenue)	-0.173***	-0.195***	-0.112***	-0.131***	-0.043***	-0.046***
	(0.014)	(0.014)	(0.008)	(0.009)	(0.005)	(0.005)
Rev. Concentration Index	-0.181***	-0.180***	-0.120***	-0.121***	-0.036***	-0.035***
	(0.009)	(0.009)	(0.005)	(0.006)	(0.003)	(0.003)
Ln(Rev. per Product)	0.187***	0.222***	0.121***	0.149***	0.046***	0.052***
	(0.012)	(0.014)	(0.008)	(0.009)	(0.004)	(0.005)
Observations	78802	93370	78802	93370	78802	93370
Adjusted R^2	0.279	0.287	0.243	0.241	0.176	0.191
Year Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes

Table 7: Product Innovation and Credit Market Disruptions: Access to Finance

Table 7 reports the coefficients of OLS regressions investigating the effect of cross-sectional differences in credit availability and access to finance in the impact of credit market disruptions on firms' decisions to launch new products on the market. *Entry Rate (New Modules)* is the number of new products (barcodes) that a firm introduces during a year in new product modules divided by the number of products at the beginning of that year. *Firm Credit Shock* is a measure of the credit market disruption that follows Almeida et al. (2012) and capture the share of long-term debt of the firm that came due between June 2007 and August 2008. *I(Crisis)* is an indicator variable that takes the value of one for the crises years: 2008, 2009, and 2010. *Ln(Firm Revenue)* is the natural logarithm of the firm's total sales in the previous year. *Rev. Concentration index* is the Herfindahl index of revenue concentration across a firm's products. *Ln(Rev. per Product)* is the natural logarithm of the firm's average revenue per product. Columns (1) and (2) stratify the sample based on whether the average annual total sales between 2006 and 2008 exceeded the median of the distribution of average firm annual sales between 2006 and 2008. *Low* Δ^- indicates that the firm is in a lending relationship with a financial institution with a below-median contraction in the syndicated lending market during the crisis. *Hi* Δ^- indicates that the firm is in a lending relationship with a financial institution with an above-median contraction in the syndicated lending market during the crisis. *Hi Lehman* indicates that the firm is in a lending relationship with a bank that has an above median share of co-syndication with Lehman prior to its demise. *Hi Lehman* indicates that the firm is in a lending relationship with a bank that has a below-median share of co-syndication with Lehman prior to its demise. Standard errors are presented in parentheses, and are clustered at the level of the firm's state headquarters. ***, **, and *, represent statistical significance at 1%, 5%, and 10% levels, respectively.

	Large Firms	Small Firms	Low Δ^- Loans	Hi Δ^- Loans	Hi. Lehman	Low Lehman
	Entry Rate (New Modules)					
Firm Credit Shock × I(Crisis)	0.010	-0.067***	-0.030*	-0.047**	-0.061***	-0.026
	(0.006)	(0.018)	(0.017)	(0.021)	(0.019)	(0.017)
Ln(Firm Revenue)	-0.017	-0.062*	-0.028	-0.062*	-0.038	-0.068***
	(0.014)	(0.032)	(0.019)	(0.035)	(0.044)	(0.025)
Rev. Concentration Index	-0.087***	-0.040	-0.080	-0.017	0.008	-0.091*
	(0.020)	(0.028)	(0.050)	(0.035)	(0.028)	(0.050)
Ln(Rev. per Product)	0.041*	0.057*	0.025	0.062	0.036	0.061**
	(0.018)	(0.027)	(0.027)	(0.041)	(0.053)	(0.024)
Observations	844	821	809	935	674	1070
Adjusted R^2	0.294	0.201	0.218	0.239	0.168	0.276
Year Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes

Table 8: Product Innovation and Credit Market Disruption: Alternative Fixed-Effects

Table 8 reports the coefficients of OLS regressions investigating the effect of credit market disruptions on the entry rate of new products. *Entry Rate (All Modules)* is the number of new products (barcodes) that a firm introduces during a year divided by the number of products at the beginning of that year. *Entry Rate (Old Modules)* is the number of new products (barcodes) that a firm introduces during a year in product modules that it was already occupying divided by the number of products at the beginning of that year. *Entry Rate (New Modules)* is the number of new products (barcodes) that a firm introduces during a year in new product modules divided by the number of products at the beginning of that year. *Local Credit Shock* is a measure of the magnitude of the credit market disruption between 2007 and 2010 in the county where each firm's headquarter is located. *Firm Credit Shock* is a measure of the credit market disruption that follows Almeida et al. (2012) and capture the share of long-term debt of the firm that came due between July 2007 and August 2008. *I(Crisis)* is an indicator variable that takes the value of one for the crises years: 2008, 2009, and 2010. *Ln(Firm Revenue)* is the natural logarithm of the firm's total sales in the previous year. *Rev. Concentration index* is the Herfindahl index of revenue concentration across a firm's products. *Ln(Rev. per Product)* is the natural logarithm of the firm's average revenue per product. Standard errors are presented in parentheses, and are clustered at the level of the firm's state headquarters. ***, **, and *, represent statistical significance at 1%, 5%, and 10% levels, respectively.

Panel A: Geography-Based Measure of Credit Market Disruption

	(1)	(2)	(3)	(4)	(5)	(6)
	Entry Rate (New Modules)					
Local Credit Shock × I(Crisis)	-0.018**	-0.019***	-0.021***	-0.021***	-0.019**	-0.019**
	(0.007)	(0.007)	(0.007)	(0.007)	(0.008)	(0.008)
Ln(Firm Revenue)		-0.045***		-0.046***		-0.047***
		(0.003)		(0.004)		(0.003)
Rev. Concentration Index		-0.040***		-0.040***		-0.039***
		(0.002)		(0.002)		(0.002)
Ln(Rev. per Product)		0.050***		0.051***		0.052***
		(0.004)		(0.004)		(0.003)
Observations	173445	173445	173445	173445	172285	172285
Adjusted R^2	0.157	0.164	0.160	0.166	0.180	0.186
Firm Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes
Department × Year Fixed-Effects	Yes	Yes	No	No	No	No
Prod. Group × Year Fixed-Effects	No	No	Yes	Yes	No	No
Prod. Module × Year Fixed-Effects	No	No	No	No	Yes	Yes

Panel B: Firm-Level Measure of Credit Market Disruption

	(1)	(2)	(3)	(4)	(5)	(6)
	Entry Rate (New Modules)					
Firm Credit Shock × I(Crisis)	-0.036***	-0.037***	-0.065***	-0.059***	-0.065*	-0.070*
	(0.011)	(0.006)	(0.017)	(0.017)	(0.031)	(0.035)
Ln(Firm Revenue)		-0.059**		-0.076***		-0.067
		(0.018)		(0.020)		(0.040)
Rev. Concentration Index		-0.048**		-0.089**		0.018
		(0.019)		(0.035)		(0.045)
Ln(Rev. per Product)		0.056***		0.070***		0.043
		(0.014)		(0.015)		(0.050)
Observations	1740	1740	1445	1445	825	825
Adjusted R^2	0.236	0.240	0.290	0.300	0.210	0.208
Firm Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes
Department × Year Fixed-Effects	Yes	Yes	No	No	No	No
Prod. Group × Year Fixed-Effects	No	No	Yes	Yes	No	No
Prod. Module × Year Fixed-Effects	No	No	No	No	Yes	Yes

Table 9: Robustness: Product Innovation and Credit Market Disruption – Large Share of Sales Outside Home State

Table 9 reports the coefficients of OLS regressions investigating the effect of credit market disruptions on firms' decisions to launch new products on the market. We repeat the results of columns (5) and (6) of Table 3 after restricting the sample to firms that originate more than 2/3, 75%, and 90% of their sales during 2007, 2008, and 2009 in states other than their HQ's state. *Entry Rate (New Modules)* is the number of new products (barcodes) that a firm introduces during a year in new product modules divided by the number of products at the beginning of that year. *Local Credit Shock* is a measure of the magnitude of the credit market disruption between 2007 and 2010 in the county where each firm's headquarter is located. *I(Crisis)* is an indicator variable that takes the value of one for the crises years: 2008, 2009, and 2010. *Ln(Firm Revenue)* is the natural logarithm of the firm's total sales in the previous year. *Rev. Concentration index* is the Herfindahl index of revenue concentration across a firm's products. *Ln(Rev. per Product)* is the natural logarithm of the firm's average revenue per product. The specifications (2), (4), and (6) control for the size of the firm non-parametrically by including fixed-effects for the deciles of the total number of products of the firm in the previous year. Standard errors are presented in parentheses, and are clustered at the level of the firm's state headquarters. ***, **, and *, represent statistical significance at 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Entry Rate (New Modules)					
Local Credit Shock × I(Crisis)	-0.033***	-0.033***	-0.038***	-0.039***	-0.037***	-0.037***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Ln(Firm Revenue)		-0.036***		-0.036***		-0.037***
		(0.003)		(0.004)		(0.004)
Rev. Concentration Index		-0.035***		-0.034***		-0.032***
		(0.002)		(0.002)		(0.002)
Ln(Rev. per Product)		0.041***		0.041***		0.041***
		(0.003)		(0.003)		(0.004)
Observations	101817	101817	96853	96853	80471	80471
Adjusted R^2	0.113	0.119	0.113	0.119	0.110	0.116
Year Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes
Subsample (% Sales Outside HQ State)	>66%	>66%	>75%	>75%	>90%	>90%

Table 10: Novelty Index: Evolution over Time

Table 10 reports the evolution of the indices of product novelty over time for the full sample (Panel A) and for the smaller sample of firms that we match to the Dealscan Dataset (Panel B). *Novelty Index* is the average ratio for a firm across all products introduced during the year between the number of the number of new and unique attributes of a product at the time of its introduction relative to all other products ever sold within the same product module and total number of product attributes in that product module. *Novelty Index (Combination)* is the number of new products of a firm during a calendar year that introduce a never before seen combination of product characteristics divided by the total number of products introduced by the firm. *Novelty Index (Hedonic)* is a weighted average ratio for a firm across all products introduced during the year between the number of the number of new and unique attributes of a product at the time of its introduction relative to all other products ever sold within the same product module and total number of product attributes in that product module. The weights are given from hedonic price regressions of (log) prices on a set of product attributes and a sequence of time-dummies.

Panel A: Full Sample

Year	Novelty Index	Novelty Index (Combination)	Novelty Index (Hedonic)
2007	0.129	0.209	0.250
2008	0.119	0.199	0.230
2009	0.123	0.203	0.242
2010	0.121	0.201	0.236
2011	0.125	0.204	0.248
2012	0.131	0.210	0.261
2013	0.132	0.211	0.265
2014	0.132	0.210	0.263
2015	0.135	0.214	0.264

Panel B: Firms Matched to Dealscan

Year	Novelty Index	Novelty Index (Combination)	Novelty Index (Hedonic)
2007	0.096	0.173	0.185
2008	0.087	0.162	0.174
2009	0.090	0.165	0.173
2010	0.085	0.159	0.177
2011	0.097	0.170	0.195
2012	0.086	0.159	0.181
2013	0.088	0.162	0.183
2014	0.087	0.161	0.174
2015	0.093	0.169	0.166

Table 11: Credit Market Disruptions and Novelty of Product Innovation

Table 11 reports the coefficients of OLS regressions investigating the effect of credit market disruptions on the novelty characteristics of new products that the firm introduces in the market. *Novelty Index* is the natural logarithm of the average ratio for a firm across all products introduced during the year between the number of the number of new and unique attributes of a product at the time of its introduction relative to all other products ever sold within the same product module and total number of product attributes in that product module. *Novelty Index (Combination)* is the natural logarithm of the number of new products of a firm during a calendar year that introduce a never before seen combination of product characteristics divided by the total number of products introduced by the firm. *Novelty Index (Hedonic)* is the natural logarithm of the weighted average ratio for a firm across all products introduced during the year between the number of the number of new and unique attributes of a product at the time of its introduction relative to all other products ever sold within the same product module and total number of product attributes in that product module. The weights are given from hedonic price regressions of (log) prices on a set of product attributes and a sequence of time-dummies. *Local Credit Shock* is a measure of the magnitude of the credit market disruption between 2007 and 2010 in the county where each firm's headquarter is located. *I(Crisis)* is an indicator variable that takes the value of one for the crises years: 2008, 2009, and 2010. *Ln(Firm Revenue)* is the natural logarithm of the firm's total sales in the previous year. *Rev. Concentration index* is the Herfindahl index of revenue concentration across a firm's products. *Ln(Rev. per Product)* is the natural logarithm of the firm's average revenue per product. The specifications (2) and (4) control for the total revenue of the firm non-parametrically by including board size fixed-effects . Standard errors are presented in parentheses, and are clustered at the level of the firm's state headquarters. ***, **, and *, represent statistical significance at 1%, 5%, and 10% levels, respectively.

Panel A: Geography-Based Measure of Credit Market Disruption

	(1)	(2)	(3)	(4)	(5)	(6)
	Ln(Novelty Index)		Ln(Novelty Index (Combination))		Ln(Novelty Index (Hedonic))	
Local Credit Shock × I(Crisis)	-0.015*	-0.015*	-0.024**	-0.025**	-0.025*	-0.026*
	(0.008)	(0.008)	(0.008)	(0.008)	(0.011)	(0.012)
Ln(Firm Revenue)		-0.009***		-0.011***		-0.015***
		(0.002)		(0.002)		(0.004)
Rev. Concentration Index		0.015***		0.017***		0.023***
		(0.004)		(0.004)		(0.006)
Ln(Rev. per Product)		0.008***		0.011***		0.014**
		(0.002)		(0.002)		(0.004)
Observations	52728	52728	52728	52728	50295	50295
Adjusted R^2	0.329	0.330	0.394	0.395	0.333	0.333
Year Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Firm-Level Measure of Credit Market Disruption

	(1)	(2)	(3)	(4)	(5)	(6)
	Ln(Novelty Index)		Ln(Novelty Index (Combination))		Ln(Novelty Index (Hedonic))	
Firm Credit Shock × I(Crisis)	-0.015**	-0.014**	-0.019***	-0.019***	-0.031	-0.035*
	(0.005)	(0.006)	(0.005)	(0.006)	(0.021)	(0.018)
Ln(Firm Revenue)		-0.025*		-0.029**		-0.034**
		(0.012)		(0.012)		(0.014)
Rev. Concentration Index		0.009		0.038		0.031
		(0.027)		(0.030)		(0.067)
Ln(Rev. per Product)		0.027*		0.034**		0.034**
		(0.012)		(0.013)		(0.014)
Observations	1159	1159	1159	1159	854	854
Adjusted R^2	0.376	0.381	0.461	0.468	0.315	0.327
Year Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes

Table 12: Credit Market Disruptions and Outcomes of New Products

Table 12 reports the coefficients of OLS regressions investigating the effect of credit market disruptions on the outcomes of new products. *Ln(Total Revenues)* is the natural logarithm of the sum of the total revenues that the new product group generated in its first four years of activity (excluding the first quarter of activity to account for within quarter differences in the timing of the launch). *Share Firm Rev.* is the average share of firm revenue that the new product group represented in its first four years of activity (excluding the first quarter of activity to account for within quarter differences in the timing of the launch). *Local Credit Shock* is a measure of the magnitude of the credit market disruption between 2007 and 2010 in the county where each firm's headquarter is located. *I(Crisis Cohort)* is an indicator variable that takes the value of one if the firm launched the new product group in 2008, 2009, or 2010. The specifications of columns (1) and (3) include all firm observations and the specifications of columns (2) and (4), exclude new product groups introduced by new firms entering the sample. Standard errors are presented in parentheses, and are clustered at the level of the firm's state headquarters. ***, **, and *, represent statistical significance at 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)
	Ln(Total Revenues)		Share Firm Rev.	
Local Credit Shock × I(Crisis Cohort)	-0.200**	-0.219**	-0.026***	-0.015***
	(0.093)	(0.093)	(0.007)	(0.005)
Observations	13110	8464	13110	8464
Adjusted R^2	0.448	0.431	0.412	0.423
Product Group×Cohort Fixed-Effects	Yes	Yes	Yes	Yes
Firm Fixed-Effects	Yes	Yes	Yes	Yes

Table 13: Credit Market Disruptions and Outcomes of New Products: Potential Channels

Table 13 reports the coefficients of OLS regressions investigating the effect of credit market disruptions on the outcomes of new products. *Ln(Rev. per Prod.)* is the natural logarithm of the average quarterly revenues per product that the firm produced in the new product group in its first four years of activity (excluding the first quarter of activity to account for within quarter differences in the timing of the launch). *Ln(Products)* is the natural logarithm of the average number of products that the firm carried in that product group during the first four years of activity. *Ln(Rev. per DMA)* is the natural logarithm of the average quarterly revenues per DMA where firm sold in its first four years of activity . *Ln(DMA)* is the natural logarithm of the average number of DMAs where the firm made sales in that product group during the first four years of activity. *Ln(Rev. per Chain.)* is the natural logarithm of the average quarterly revenues per state where firm sold in its first four years of activity . *Ln(Retail Chains)* is the natural logarithm of the average number of states that the firm where the firm made sales in that product group during the first four years of activity. *Local Credit Shock* is a measure of the magnitude of the credit market disruption between 2007 and 2010 in the county where each firm's headquarter is located. *I(Crisis Cohort)* is an indicator variable that takes the value of one if the firm launched the new product group in 2008, 2009, or 2010. The specifications include all firm observations. Standard errors are presented in parentheses, and are clustered at the level of the firm's state headquarters. ***, **, and *, represent statistical significance at 1%, 5%, and 10% levels, respectively.

Panel A: All New Product Groups

	(1) Ln(Rev. per Prod.)	(2) Ln(Products)	(3) Ln(Rev. per DMA)	(4) Ln(DMA)	(5) Ln(Rev. per Chain.)	(6) Ln(Retail Chains)
Local Credit Shock × I(Crisis Cohort)	-0.161**	-0.039**	-0.146**	-0.054	-0.151*	-0.049**
	(0.079)	(0.019)	(0.061)	(0.045)	(0.078)	(0.024)
Observations	13110	13110	13110	13110	13110	13110
Adjusted R^2	0.464	0.199	0.440	0.600	0.453	0.504
Product Group×Cohort Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Excluding New Product Groups of New Entrants

	(1) Ln(Rev. per Prod.)	(2) Ln(Products)	(3) Ln(Rev. per DMA)	(4) Ln(DMA)	(5) Ln(Rev. per Chain.)	(6) Ln(Retail Chains)
Local Credit Shock × I(Crisis Cohort)	-0.183**	-0.036**	-0.146**	-0.073*	-0.183**	-0.036*
	(0.081)	(0.017)	(0.065)	(0.042)	(0.081)	(0.021)
Observations	8464	8464	8464	8464	8464	8464
Adjusted R^2	0.446	0.166	0.415	0.568	0.432	0.466
Product Group×Cohort Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes

Internet Appendix for "Product Innovation and Credit Market Disruptions"

A Table of Contents:

Figure IA.1: : Sorting: Credit Market Disruptions and Industry Composition

Figure IA.1 presents a scatterplot of percentile bins of the exposure to the county-level measure of credit market disruption against the proportion of firms in the Food Groceries Departments (Dry Grocery, Frozen Foods, Deli, Packaged Meat, Fresh Produce, and Alcoholic Beverages), Non-Food Groceries Department, Health & Beauty Products Department, and General Merchandise Departments, respectively. Each dot represents the proportion of firms within each bin that receive the major share of their revenues from each category. Data for all figures is obtained from the CRA and Nielsen datasets.

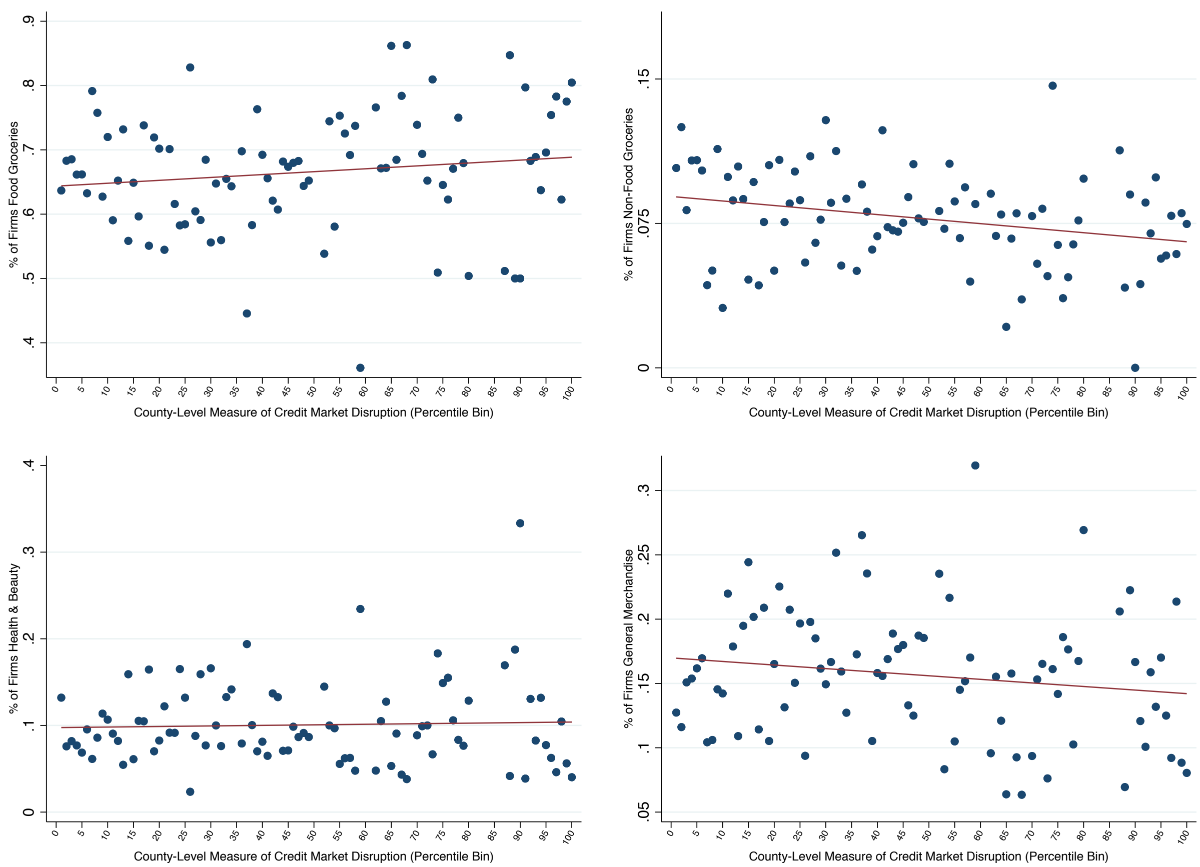
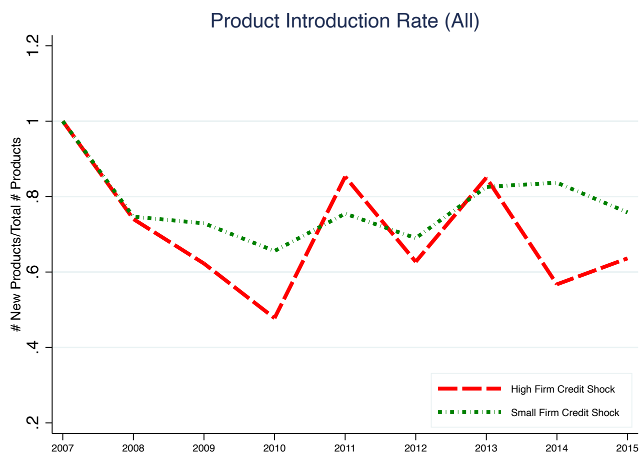
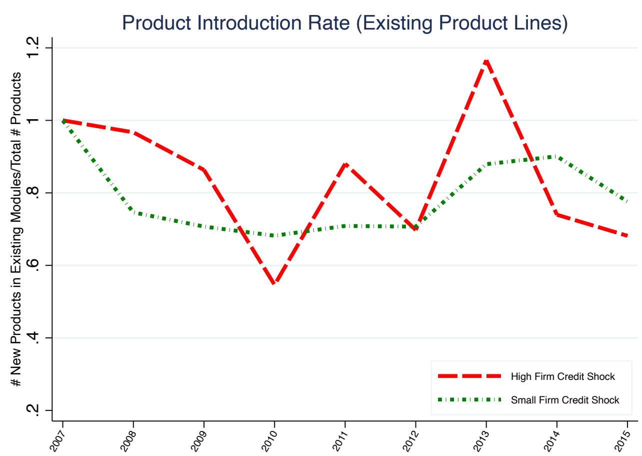


Figure IA.2: : Product Innovation and Credit Market Disruption: Entry Rate (Firm-Level Analysis)

Figure IA.2 plots the evolution of the average firm entry rate of new products during a calendar year over time. The entry rate of new products is defined as the ratio between the number of new products introduced during the year and the total number of products at the beginning of the year. The green (blue) line represents the evolution of the average firm entry rate of new products for the group of firms that saw more than (less than) one third of their long-term syndicated debt come due between June 2007 and August 2008 . The plot on the top panel represents the average entry rate of new products of all types. The second plot represents the evolution of the average entry rate of new products in product modules where the firm already operated. The plot on the bottom represents the evolution of the average entry rate of new products in product modules that are new to the firm. All time series plotted are normalized such that 2007 = 100. Data for all figures is obtained from the CRA and Nielsen datasets.





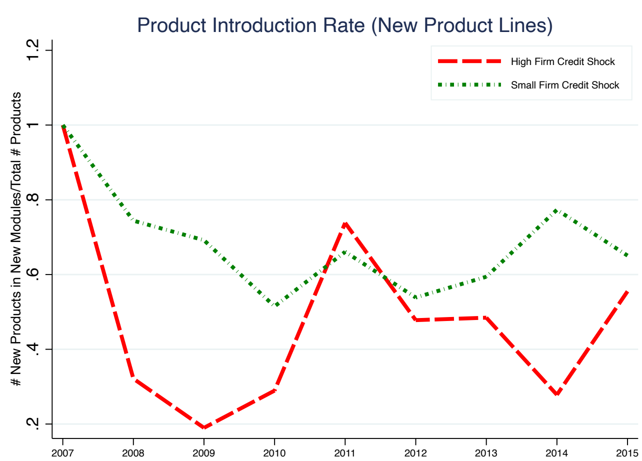


Figure IA.3: : Product Innovation and Credit Market Disruption: Entry Rate (Brand-Level Analysis)

Figure IA.3 repeats the analysis of figure 5 using brand as our definition of product. Data for all figures is obtained from the CRA and Nielsen datasets.

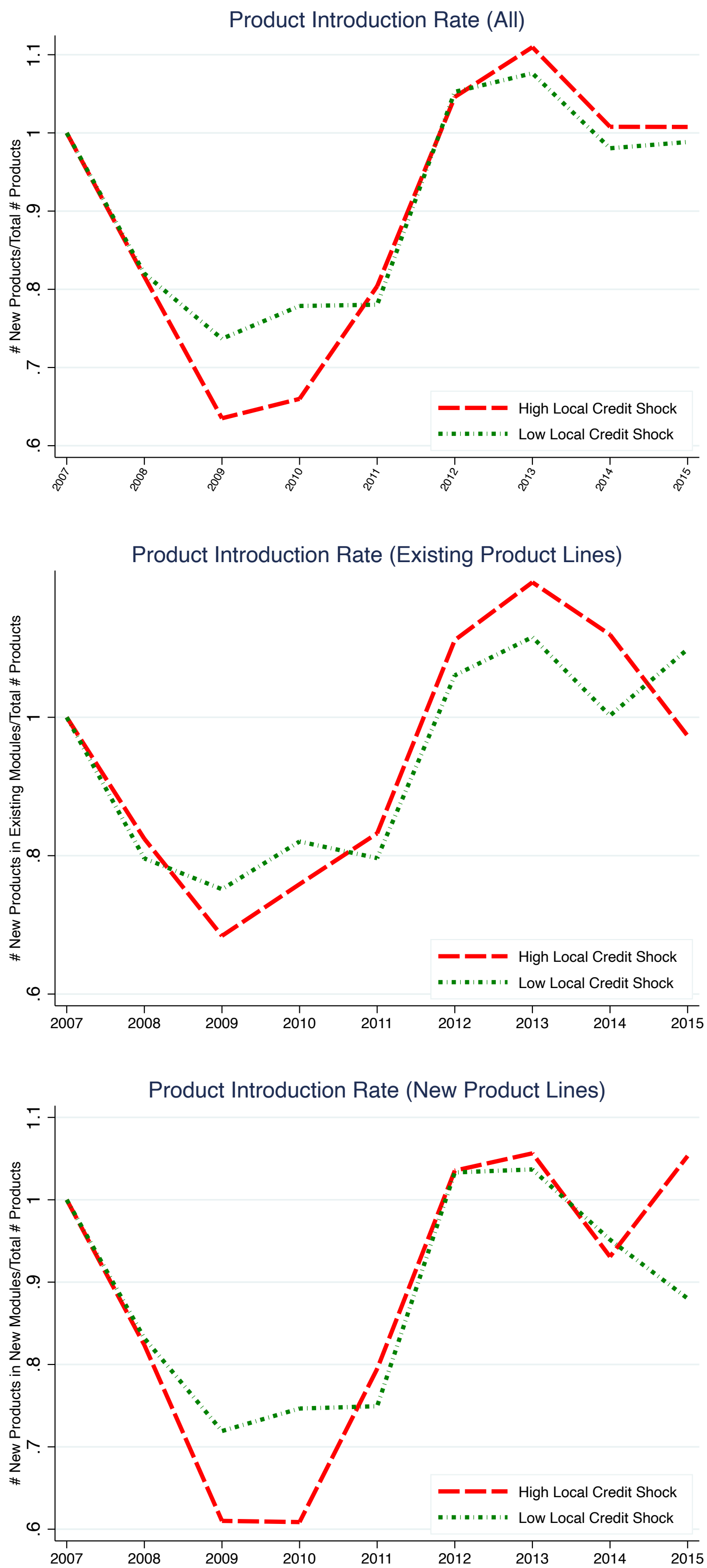


Table IA.1: Product Innovation and Credit Market Disruption (Dummy Variable Introduction of New Products)

Table IA.1 reports the coefficients of OLS regressions investigating the effect of credit market disruptions on whether companies introduce new products or not. *I(New Prod=1) (All)* is an indicator variable that assumes the value of one if a firm introduces a new barcode during the year. *I(New Prod=1) (Old Modules)* is an indicator variable that assumes the value of one if a firm introduces a new barcode in a product module that it already occupies during the year. *I(New Prod=1) (New Modules)* is an indicator variable that assumes the value of one if a firm introduces a new barcode in a new product module during the year. *Local Credit Shock* is a measure of the magnitude of the credit market disruption between 2007 and 2010 in the county where each firm's headquarter is located. *Firm Credit Shock* is a measure of the credit market disruption that follows Almeida et al. (2012) and capture the share of long-term debt of the firm that came due between July 2007 and August 2008. *I(Crisis)* is an indicator variable that takes the value of one for the crises years: 2008, 2009, and 2010. *Ln(Firm Revenue)* is the natural logarithm of the firm's total sales in the previous year. *Rev. Concentration index* is the Herfindahl index of revenue concentration across a firm's products. *Ln(Rev. per Product)* is the natural logarithm of the firm's average revenue per product. The specifications (2), (4), and (6) control for the size of the firm non-parametrically by including fixed-effects for the deciles of the total number of products of the firm in the previous year. Standard errors are presented in parentheses, and are clustered at the level of the firm's state headquarters. ***, **, and *, represent statistical significance at 1%, 5%, and 10% levels, respectively.

Panel A: Geography-Based Measure of Credit Market Disruption

	(1)	(2)	(3)	(4)	(5)	(6)
	I(New Prod=1) (All)		I(New Prod=1) (Old Modules)		I(New Prod=1) (New Modules)	
Local Credit Shock × I(Crisis)	-0.049*	-0.049*	-0.028	-0.027	-0.032**	-0.032**
	(0.028)	(0.026)	(0.029)	(0.026)	(0.014)	(0.013)
Ln(Firm Revenue)		0.066***		0.076***		-0.004
		(0.006)		(0.006)		(0.007)
Rev. Concentration Index		-0.143***		-0.135***		-0.068***
		(0.004)		(0.004)		(0.003)
Ln(Rev. per Product)		-0.035***		-0.048***		0.015**
		(0.006)		(0.005)		(0.006)
Observations	173447	173447	173447	173447	173447	173447
Adjusted R^2	0.453	0.460	0.464	0.470	0.210	0.213
Year Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Firm-Level Measure of Credit Market Disruption

	(1)	(2)	(3)	(4)	(5)	(6)
	I(New Prod=1) (All)		I(New Prod=1) (Old Modules)		I(New Prod=1) (New Modules)	
Firm Credit Shock × I(Crisis)	-0.060	-0.065	0.015	0.009	-0.130*	-0.135*
	(0.034)	(0.036)	(0.039)	(0.041)	(0.058)	(0.061)
Ln(Firm Revenue)		-0.006		0.025		0.039
		(0.039)		(0.047)		(0.057)
Rev. Concentration Index		-0.178**		-0.156**		-0.100*
		(0.066)		(0.067)		(0.047)
Ln(Rev. per Product)		0.044		0.016		-0.016
		(0.035)		(0.041)		(0.048)
Observations	1744	1744	1744	1744	1744	1744
Adjusted R^2	0.531	0.536	0.580	0.584	0.347	0.348
Year Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes

Table IA.2: Product Innovation and Credit Market Disruption (Number of New Products)

Table IA.2 reports the coefficients of OLS regressions investigating the effect of credit market disruptions on the natural logarithm of new products launched by the firm. *Ln(1+New Prod.) (All)* is the natural logarithm of one plus the number of new products (barcodes) that a firm introduces in the market over a particular year. *Ln(1+New Prod.) (Old Modules)* is the natural logarithm of one plus the number of new products (barcodes) that a firm introduces in product modules where it already operated during a year. *Ln(1+New Prod.) (New Modules)* is the natural logarithm of one plus the number of new products (barcodes) that a firm introduces in new product modules during a year. *Local Credit Shock* is a measure of the magnitude of the credit market disruption between 2007 and 2010 in the county where each firm's headquarter is located. *Firm Credit Shock* is a measure of the credit market disruption that follows Almeida et al. (2012) and capture the share of long-term debt of the firm that came due between July 2007 and August 2008. *I(Crisis)* is an indicator variable that takes the value of one for the crises years: 2008, 2009, and 2010. *Ln(Firm Revenue)* is the natural logarithm of the firm's total sales in the previous year. *Rev. Concentration index* is the Herfindahl index of revenue concentration across a firm's products. *Ln(Rev. per Product)* is the natural logarithm of the firm's average revenue per product. The specifications (2), (4), and (6) control for the size of the firm non-parametrically by including fixed-effects for the deciles of the total number of products of the firm in the previous year. Standard errors are presented in parentheses, and are clustered at the level of the firm's state headquarters. ***, **, and *, represent statistical significance at 1%, 5%, and 10% levels, respectively.

Panel A: Geography-Based Measure of Credit Market Disruption

	(1)	(2)	(3)	(4)	(5)	(6)
	Ln(1+New Prod.) (All)		Ln(1+New Prod.) (Old Modules)		Ln(1+New Prod.) (New Modules)	
Local Credit Shock × I(Crisis)	-0.064	-0.057	-0.028	-0.020	-0.047***	-0.048***
	(0.050)	(0.046)	(0.049)	(0.046)	(0.014)	(0.013)
Ln(Firm Revenue)		0.289***		0.345***		-0.069***
		(0.019)		(0.017)		(0.010)
Rev. Concentration Index		-0.308***		-0.246***		-0.113***
		(0.008)		(0.007)		(0.005)
Ln(Rev. per Product)		-0.213***		-0.275***		0.080***
		(0.017)		(0.014)		(0.009)
Observations	173447	173447	173447	173447	173447	173447
Adjusted R^2	0.714	0.723	0.730	0.738	0.282	0.286
Year Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Firm-Level Measure of Credit Market Disruption

	(1)	(2)	(3)	(4)	(5)	(6)
	Ln(1+New Prod.) (All)		Ln(1+New Prod.) (Old Modules)		Ln(1+New Prod.) (New Modules)	
Firm Credit Shock × I(Crisis)	-0.008	-0.011	0.076	0.075	-0.174**	-0.184**
	(0.094)	(0.085)	(0.084)	(0.073)	(0.083)	(0.082)
Ln(Firm Revenue)		0.298**		0.374**		0.028
		(0.112)		(0.145)		(0.097)
Rev. Concentration Index		-0.435***		-0.314***		-0.192***
		(0.095)		(0.082)		(0.063)
Ln(Rev. per Product)		-0.215*		-0.305**		-0.000
		(0.113)		(0.143)		(0.085)
Observations	1744	1744	1744	1744	1744	1744
Adjusted R^2	0.890	0.894	0.903	0.906	0.447	0.449
Year Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes

Table IA.3: Product Innovation and Credit Market Disruptions (Brand-Level Analysis)

Table IA.3 reports the coefficients of OLS regressions investigating the effect of credit market disruptions on firms' decisions to launch new brands on the market. *Entry Rate (All Modules)* is the number of new products (brands) that a firm introduces during a year divided by the number of products at the beginning of that year. *Entry Rate (Old Modules)* is the number of new products (brands) that a firm introduces during a year in product modules that it was already occupying divided by the number of products at the beginning of that year. *Entry Rate (New Modules)* is the number of new products (brands) that a firm introduces during a year in new product modules divided by the number of products at the beginning of that year. *Local Credit Shock* is a measure of the magnitude of the credit market disruption between 2007 and 2010 in the county where each firm's headquarter is located. *Firm Credit Shock* is a measure of the credit market disruption that follows Almeida et al. (2012) and capture the share of long-term debt of the firm that came due between July 2007 and August 2008. *I(Crisis)* is an indicator variable that takes the value of one for the crises years: 2008, 2009, and 2010. *Ln(Firm Revenue)* is the natural logarithm of the firm's total sales in the previous year. *Rev. Concentration index* is the Herfindahl index of revenue concentration across a firm's products. *Ln(Rev. per Product)* is the natural logarithm of the firm's average revenue per product. The specifications (2), (4), and (6) control for the size of the firm non-parametrically by including fixed-effects for the deciles of the total number of products of the firm in the previous year. Standard errors are presented in parentheses, and are clustered at the level of the firm's state headquarters. ***, **, and *, represent statistical significance at 1%, 5%, and 10% levels, respectively.

Panel A: Geography-Based Measure of Credit Market Disruption

	(1)	(2)	(3)	(4)	(5)	(6)
	Entry Rate (All Modules)		Entry Rate (Old Modules)		Entry Rate (New Modules)	
Local Credit Shock × I(Crisis)	-0.044***	-0.046***	-0.011	-0.012	-0.027***	-0.028***
	(0.012)	(0.010)	(0.008)	(0.007)	(0.008)	(0.007)
Ln(Firm Revenue)		-0.132***		-0.054***		-0.074***
		(0.005)		(0.003)		(0.004)
Rev. Concentration Index		-0.097***		-0.043***		-0.049***
		(0.003)		(0.002)		(0.002)
Ln(Rev. per Product)		0.142***		0.058***		0.079***
		(0.005)		(0.003)		(0.004)
Observations	170216	170216	170216	170216	170216	170216
Adjusted R^2	0.207	0.220	0.141	0.148	0.160	0.167
Year Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Firm-Level Measure of Credit Market Disruption

	(1)	(2)	(3)	(4)	(5)	(6)
	Entry Rate (All Modules)		Entry Rate (Old Modules)		Entry Rate (New Modules)	
Firm Credit Shock × I(Crisis)	-0.028	-0.039**	0.010	0.008	-0.038***	-0.047***
	(0.016)	(0.017)	(0.025)	(0.025)	(0.009)	(0.012)
Ln(Firm Revenue)		-0.252**		-0.046**		-0.206*
		(0.083)		(0.016)		(0.090)
Rev. Concentration Index		-0.205**		-0.068***		-0.138
		(0.081)		(0.018)		(0.080)
Ln(Rev. per Product)		0.270***		0.061***		0.209**
		(0.070)		(0.015)		(0.076)
Observations	1708	1708	1708	1708	1708	1708
Adjusted R^2	0.190	0.204	0.171	0.183	0.168	0.175
Year Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes

Table IA.4: Product Innovation and Credit Market Disruptions (Alternative Geography-Based Measure)

Table IA.4 reports the coefficients of OLS regressions investigating the effect of credit market disruptions on firms' decisions to launch new products on the market. *Entry Rate (All Modules)* is the number of new products (barcodes) that a firm introduces during a year divided by the number of products at the beginning of that year. *Entry Rate (Old Modules)* is the number of new products (barcodes) that a firm introduces during a year in product modules that it was already occupying divided by the number of products at the beginning of that year. *Entry Rate (New Modules)* is the number of new products (barcodes) that a firm introduces during a year in new product modules divided by the number of products at the beginning of that year. *Local Credit Shock* is a measure of the local exposure of each firm's county to idiosyncratic bank supply shocks. Unlike the measure used in the main analysis that focuses on the bank supply shock in the period 2007–2010, to compute this measure we run the following specification: $\Delta SBL_{b,c,t} = \gamma_{b,t} + \delta_{c,t} + \epsilon_{b,c,t}$ for every year in the sample and then compute the local credit shock measure as $SBL\ Shock_{c,t} = -\sum_b (\hat{\gamma_{b,t}} \times s_{b,c}^{t-1})$. *I(Crisis)* is an indicator variable that takes the value of one for the crises years: 2008, 2009, and 2010. *Ln(Firm Revenue)* is the natural logarithm of the firm's total sales in the previous year. *Rev. Concentration index* is the Herfindahl index of revenue concentration across a firm's products. *Ln(Rev. per Product)* is the natural logarithm of the firm's average revenue per product. The specifications (2), (4), and (6) control for the size of the firm non-parametrically by including fixed-effects for the deciles of the total number of products of the firm in the previous year. Standard errors are presented in parentheses, and are clustered at the level of the firm's state headquarters. ***, **, and *, represent statistical significance at 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Entry Rate (All Modules)		Entry Rate (Old Modules)		Entry Rate (New Modules)	
Local Credit Shock	0.037***	0.032	0.004	0.000	0.020*	0.019
	(0.000)	(0.072)	(0.060)	(0.056)	(0.012)	(0.012)
Local Credit Shock × I(Crisis)	-0.084	-0.086	-0.018	-0.019	-0.043***	-0.044***
	(0.098)	(0.055)	(0.053)	(0.049)	(0.012)	(0.012)
Ln(Firm Revenue)		-0.175***		-0.114***		-0.044***
		(0.020)		(0.014)		(0.003)
Rev. Concentration Index		-0.194***		-0.125***		-0.041***
		(0.016)		(0.010)		(0.002)
Ln(Rev. per Product)		0.198***		0.128***		0.050***
		(0.019)		(0.013)		(0.004)
Observations	173447	173447	173447	173447	173447	173447
Adjusted R^2	0.248	0.269	0.218	0.234	0.156	0.163
Year Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes

Table IA.5: Product Innovation and Credit Market Disruptions (Placebo Analysis)

Table IA.5 reports the coefficients of OLS regressions using placebo credit supply shocks. The idea is that exposure to idiosyncratic bank supply shocks over these triennial periods *outside* of the crisis period should be unlikely to deter product innovation *during* the crisis period. *Entry Rate (New Modules)* is the number of new products (barcodes) that a firm introduces during a year in new product modules divided by the number of products at the beginning of that year. *Local Credit Shock (2005–2008)* is a measure of the local exposure of each firm's county to idiosyncratic bank supply shocks during the 2005–2008 periods. *Local Credit Shock (2011–2014)* is a measure of the local exposure of each firm's county to idiosyncratic bank supply shocks during the 2011–2014 periods. *Local Credit Shock (2012–2015)* is a measure of the local exposure of each firm's county to idiosyncratic bank supply shocks during the 2012–2015 periods. *I(Crisis)* is an indicator variable that takes the value of one for the crises years: 2008, 2009, and 2010. *Ln(Firm Revenue)* is the natural logarithm of the firm's total sales in the previous year. *Rev. Concentration index* is the Herfindahl index of revenue concentration across a firm's products. *Ln(Rev. per Product)* is the natural logarithm of the firm's average revenue per product. The specifications (2), (4), and (6) control for the size of the firm non-parametrically by including fixed-effects for the deciles of the total number of products of the firm in the previous year. Standard errors are presented in parentheses, and are clustered at the level of the firm's state headquarters. ***, **, and *, represent statistical significance at 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Entry Rate (New Modules)					
Local Credit Shock (2005–2008) × I(Crisis)	-0.000	-0.001				
	(0.012)	(0.012)				
Local Credit Shock (2011–2014) × I(Crisis)			-0.012	-0.013		
			(0.009)	(0.009)		
Local Credit Shock (2012–2015) × I(Crisis)					-0.010	-0.010
					(0.010)	(0.010)
Ln(Firm Revenue)		-0.044***		-0.044***		-0.044***
		(0.003)		(0.003)		(0.003)
Rev. Concentration Index		-0.041***		-0.041***		-0.041***
		(0.002)		(0.002)		(0.002)
Ln(Rev. per Product)		0.050***		0.050***		0.050***
		(0.004)		(0.004)		(0.004)
Observations	173447	173447	173447	173447	173447	173447
Adjusted R^2	0.156	0.163	0.156	0.163	0.156	0.163
Year Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes

Table IA.6: Product Innovation and Credit Market Disruption (Alternative Firm-Based Measure)

Table IA.6 reports the coefficients of OLS regressions investigating the effect of credit market disruptions on the entry rate of new products. *Entry Rate (New Modules)* is the number of new products (barcodes) that a firm introduces during a year in new product modules divided by the number of products at the beginning of that year. *Prob(Cov. Violation)* is a measure of the probability that a firms violate a covenant obtained from Demerjian and Owens (2016). *Prob(Earn. Cov. Violation)* is a measure of the probability that a firms violate a performance-based (also known as earnings-based) covenant obtained from Demerjian and Owens (2016). *I(Crisis)* is an indicator variable that takes the value of one for the crises years: 2008, 2009, and 2010. *Ln(Firm Revenue)* is the natural logarithm of the firm's total sales in the previous year. *Rev. Concentration index* is the Herfindahl index of revenue concentration across a firm's products. *Ln(Rev. per Product)* is the natural logarithm of the firm's average revenue per product. Standard errors are presented in parentheses, and are clustered at the level of the firm's state headquarters. ***, **, and *, represent statistical significance at 1%, 5%, and 10% levels, respectively.

Panel A: Probability of Violation of All Covenants

	(1)	(2)	(3)	(4)	(5)	(6)
	Entry Rate (All Modules)		Entry Rate (Old Modules)		Entry Rate (New Modules)	
Prob(Cov. Violation) × I(Crisis)	-0.088	-0.082	-0.030	-0.024	-0.037**	-0.038***
	(0.055)	(0.053)	(0.051)	(0.049)	(0.012)	(0.010)
Ln(Firm Revenue)		-0.044		0.015		-0.039
		(0.088)		(0.048)		(0.040)
Rev. Concentration Index		-0.235**		-0.142***		-0.057
		(0.088)		(0.041)		(0.037)
Ln(Rev. per Product)		0.075		0.016		0.037
		(0.087)		(0.040)		(0.041)
Observations	982	982	982	982	982	982
Adjusted R^2	0.272	0.287	0.294	0.310	0.212	0.219
Firm Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes

Panel B: Probability of Violation of Earnings-Based Covenants

	(1)	(2)	(3)	(4)	(5)	(6)
	Entry Rate (All Modules)		Entry Rate (Old Modules)		Entry Rate (New Modules)	
Prob(Earn. Cov. Violation) × I(Crisis)	-0.106*	-0.100*	-0.037	-0.031	-0.042***	-0.042***
	(0.055)	(0.051)	(0.047)	(0.045)	(0.012)	(0.009)
Ln(Firm Revenue)		-0.045		0.014		-0.040
		(0.088)		(0.048)		(0.040)
Rev. Concentration Index		-0.235**		-0.141***		-0.056
		(0.088)		(0.042)		(0.037)
Ln(Rev. per Product)		0.076		0.016		0.037
		(0.087)		(0.040)		(0.041)
Observations	982	982	982	982	982	982
Adjusted R^2	0.273	0.288	0.294	0.310	0.213	0.220
Firm Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes

Table IA.7: Product Innovation and Credit Market Disruption (Controlling for local economic conditions)

Table IA.7 reports the coefficients of OLS regressions investigating the effect of credit market disruptions on the entry rate of new products. *Entry Rate (All Modules)* is the number of new products (barcodes) that a firm introduces during a year divided by the number of products at the beginning of that year. *Entry Rate (Old Modules)* is the number of new products (barcodes) that a firm introduces during a year in product modules that it was already occupying divided by the number of products at the beginning of that year. *Entry Rate (New Modules)* is the number of new products (barcodes) that a firm introduces during a year in new product modules divided by the number of products at the beginning of that year. *Local Credit Shock* is a measure of the magnitude of the credit market disruption between 2007 and 2010 in the county where each firm's headquarter is located. *I(Crisis)* is an indicator variable that takes the value of one for the crises years: 2008, 2009, and 2010. *Ln(Unemployment Rate)* is the natural logarithm of the unemployment rate in the county where the firm's headquarters is located. *Ln(Cnty Inc. pc)* is the natural logarithm of income per capita in the county where the firm's headquarters is located. *Ln(Firm Revenue)* is the natural logarithm of the firm's total sales in the previous year. *Rev. Concentration index* is the Herfindahl index of revenue concentration across a firm's products. *Ln(Rev. per Product)* is the natural logarithm of the firm's average revenue per product. Standard errors are presented in parentheses, and are clustered at the level of the firm's state headquarters. ***, **, and *, represent statistical significance at 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
	Entry Rate (All Modules)		Entry Rate (Old Modules)		Entry Rate (New Modules)	
Local Credit Shock × I(Crisis)	-0.046*	-0.050**	-0.018	-0.020	-0.019***	-0.020***
	(0.026)	(0.024)	(0.021)	(0.019)	(0.007)	(0.006)
Ln(Unemployment Rate) × I(Crisis)	0.014*	0.014*	0.014**	0.013**	0.001	0.001
	(0.008)	(0.008)	(0.006)	(0.006)	(0.003)	(0.002)
Ln(Cnty Inc. pc) × I(Crisis)	0.026***	0.022***	0.018***	0.016***	0.004**	0.003**
	(0.005)	(0.005)	(0.004)	(0.004)	(0.002)	(0.002)
Ln(Unemployment Rate)	-0.032***	-0.031***	-0.009	-0.009	-0.016***	-0.015***
	(0.011)	(0.010)	(0.009)	(0.009)	(0.004)	(0.004)
Ln(Cnty Inc. pc)	-0.007	-0.013	0.010	0.006	-0.015	-0.017
	(0.029)	(0.028)	(0.018)	(0.017)	(0.014)	(0.014)
Ln(Firm Revenue)		-0.175***		-0.113***		-0.044***
		(0.012)		(0.006)		(0.003)
Rev. Concentration Index		-0.195***		-0.126***		-0.041***
		(0.006)		(0.004)		(0.002)
Ln(Rev. per Product)		0.198***		0.128***		0.050***
		(0.011)		(0.006)		(0.004)
Observations	172189	172189	172189	172189	172189	172189
Adjusted R^2	0.248	0.269	0.218	0.234	0.156	0.163
Year Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes

Table IA.8: Product Innovation and Credit Market Disruption (Controlling for Household Wealth Shocks)

Table IA.8 reports the coefficients of OLS regressions investigating the effect of credit market disruptions on the entry rate of new products. *Entry Rate (New Modules)* is the number of new products (barcodes) that a firm introduces during a year in new product modules divided by the number of products at the beginning of that year. *Local Credit Shock* is a measure of the magnitude of the credit market disruption between 2007 and 2010 in the county where each firm's headquarter is located. *I(Crisis)* is an indicator variable that takes the value of one for the crises years: 2008, 2009, and 2010. Δ *Cnty. HPI* is the percentage change in the Federal Housing Finance Agency (FHFA) county-house price index between 2006 and 2009 *Ln(Debt to Income Ratio, 2006)* is the natural logarithm of the household debt to income ratio at the county level obtained from the work of Mian et al. (2013). *Ln(Housing Supply Elasticity, Saiz)* is the natural logarithm of the housing supply elasticity measure obtained form the work of Saiz (2010). *Housing Net Worth Shock, 2006–2009* is the Housing Net Worth Shock at the CBSA-level obtained from the work of Mian et al. (2013). *Ln(Firm Revenue)* is the natural logarithm of the firm's total sales in the previous year. *Rev. Concentration index* is the Herfindahl index of revenue concentration across a firm's products. *Ln(Rev. per Product)* is the natural logarithm of the firm's average revenue per product. Standard errors are presented in parentheses, and are clustered at the level of the firm's state headquarters. ***, **, and *, represent statistical significance at 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Entry Rate (New Modules)							
Local Credit Shock × I(Crisis)	-0.020**	-0.020**	-0.017*	-0.017*	-0.026***	-0.027***	-0.019**	-0.019**
	(0.009)	(0.009)	(0.010)	(0.009)	(0.009)	(0.009)	(0.008)	(0.007)
Δ Cnty. HPI × I(Crisis)	-0.000	0.001						
	(0.005)	(0.005)						
Ln(Debt to Income Ratio, 2006) × I(Crisis)			-0.001	-0.002				
			(0.002)	(0.002)				
Ln(Housing Supply Elasticity, Saiz) × I(Crisis)					-0.003	-0.002		
					(0.002)	(0.002)		
Housing Net Worth Shock, 2006–2009 × I(Crisis)							0.007	0.008
							(0.006)	(0.006)
Ln(Firm Revenue)		-0.044***		-0.044***		-0.042***		-0.043***
		(0.003)		(0.003)		(0.003)		(0.004)
Rev. Concentration Index		-0.041***		-0.041***		-0.041***		-0.041***
		(0.002)		(0.002)		(0.003)		(0.003)
Ln(Rev. per Product)		0.050***		0.050***		0.047***		0.047***
		(0.004)		(0.004)		(0.004)		(0.004)
Observations	171466	171466	170387	170387	136546	136546	132925	132925
Adjusted R^2	0.156	0.163	0.157	0.164	0.162	0.168	0.162	0.168
Year Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Table IA.9: Credit Market Disruptions and Novelty of Product Innovation: Alternative Fixed-Effects Structures

Table IA.9 reports the coefficients of OLS regressions investigating the effect of credit market disruptions on the novelty characteristics of new products that the firm introduces in the market. *Novelty Index* is the average ratio for a firm across all products introduced during the year between the number of the number of new and unique attributes of a product at the time of its introduction relative to all other products ever sold within the same product module and total number of product attributes in that product module. *Novelty Index (Combination)* is the number of new products of a firm during a calendar year that introduce a never before seen combination of product characteristics divided by the total number of products introduced by the firm. *Novelty Index (Hedonic)* is a weighted average ratio for a firm across all products introduced during the year between the number of the number of new and unique attributes of a product at the time of its introduction relative to all other products ever sold within the same product module and total number of product attributes in that product module. The weights are given from hedonic price regressions of (log) prices on a set of product attributes and a sequence of time-dummies. *Local Credit Shock* is a measure of the magnitude of the credit market disruption between 2007 and 2010 in the county where each firm's headquarter is located. *I(Crisis)* is an indicator variable that takes the value of one for the crises years: 2008, 2009, and 2010. *Ln(Firm Revenue)* is the natural logarithm of the firm's total sales in the previous year. *Rev. Concentration index* is the Herfindahl index of revenue concentration across a firm's products. *Ln(Rev. per Product)* is the natural logarithm of the firm's average revenue per product. Standard errors are presented in parentheses, and are clustered at the level of the firm's state headquarters. ***, **, and *, represent statistical significance at 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Ln(Novelty Index)			Ln(Novelty Index (Combination))			Ln(Novelty Index (Hedonic))		
Local Credit Shock × I(Crisis)	-0.012	-0.017*	-0.016*	-0.022**	-0.028***	-0.028**	-0.021	-0.027*	-0.028
	(0.007)	(0.007)	(0.008)	(0.007)	(0.008)	(0.010)	(0.011)	(0.014)	(0.016)
Ln(Firm Revenue)	-0.008***	-0.008***	-0.008***	-0.011***	-0.011***	-0.011***	-0.015***	-0.015***	-0.015***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.004)	(0.004)	(0.004)
Rev. Concentration Index	0.016***	0.015***	0.012**	0.017***	0.017***	0.014**	0.024***	0.023***	0.022***
	(0.004)	(0.004)	(0.005)	(0.004)	(0.004)	(0.005)	(0.006)	(0.006)	(0.006)
Ln(Rev. per Product)	0.009***	0.009***	0.009***	0.011***	0.011***	0.011***	0.014***	0.014***	0.014***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)	(0.004)	(0.004)	(0.004)
Observations	52726	52706	50969	52726	52706	50969	50293	50268	48488
Adjusted R^2	0.331	0.334	0.348	0.397	0.399	0.409	0.334	0.337	0.345
Firm Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Department × Year Fixed-Effects	Yes	No	No	Yes	No	No	Yes	No	No
Prod. Group × Year Fixed-Effects	No	Yes	No	No	Yes	No	No	Yes	No
Prod. Module × Year Fixed-Effects	No	No	Yes	No	No	Yes	No	No	Yes

Table IA.10: Credit Market Disruptions and Novelty of Product Innovation – Large Share of Sales Outside Home State

Table IA.10 reports the coefficients of OLS regressions investigating the effect of credit market disruptions on the novelty characteristics of new products that the firm introduces in the market. *Novelty Index* is the average ratio for a firm across all products introduced during the year between the number of the number of new and unique attributes of a product at the time of its introduction relative to all other products ever sold within the same product module and total number of product attributes in that product module. *Novelty Index (Combination)* is the number of new products of a firm during a calendar year that introduce a never before seen combination of product characteristics divided by the total number of products introduced by the firm. *Novelty Index (Hedonic)* is a weighted average ratio for a firm across all products introduced during the year between the number of the number of new and unique attributes of a product at the time of its introduction relative to all other products ever sold within the same product module and total number of product attributes in that product module. The weights are given from hedonic price regressions of (log) prices on a set of product attributes and a sequence of time-dummies. *Local Credit Shock* is a measure of the magnitude of the credit market disruption between 2007 and 2010 in the county where each firm's headquarter is located. *I(Crisis)* is an indicator variable that takes the value of one for the crises years: 2008, 2009, and 2010. *Ln(Firm Revenue)* is the natural logarithm of the firm's total sales in the previous year. *Rev. Concentration index* is the Herfindahl index of revenue concentration across a firm's products. *Ln(Rev. per Product)* is the natural logarithm of the firm's average revenue per product. Standard errors are presented in parentheses, and are clustered at the level of the firm's state headquarters. ***, **, and *, represent statistical significance at 1%, 5%, and 10% levels, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	Novelty Index			Novelty Index (Combination)			Novelty Index (Hedonic)		
Local Credit Shock × I(Crisis)	-0.012*	-0.011	-0.010	-0.019***	-0.017***	-0.018**	-0.025**	-0.024**	-0.022**
	(0.006)	(0.006)	(0.009)	(0.002)	(0.003)	(0.006)	(0.008)	(0.008)	(0.008)
Ln(Firm Revenue)	-0.008***	-0.008***	-0.007***	-0.011***	-0.011***	-0.009***	-0.016***	-0.014***	-0.010*
	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.004)	(0.004)	(0.005)
Rev. Concentration Index	0.016***	0.015***	0.018***	0.018***	0.017***	0.021***	0.025***	0.023***	0.027***
	(0.005)	(0.004)	(0.004)	(0.005)	(0.004)	(0.004)	(0.006)	(0.006)	(0.007)
Ln(Rev. per Product)	0.009***	0.008***	0.007**	0.011***	0.011***	0.009***	0.014***	0.013**	0.010*
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.004)	(0.004)	(0.005)
Observations	35774	34049	27021	35774	34049	27021	33610	31943	25341
Adjusted R^2	0.331	0.331	0.331	0.410	0.411	0.408	0.321	0.321	0.323
Firm Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed-Effects	Yes	Yes	Yes	No	No	No	No	No	No
Subsample (% Sales Outside HQ State)	>66%	>75%	>90%	>66%	>75%	>90%	>66%	>75%	>90%