Product Innovation and Credit Market Disruptions*

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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 level, quality, and type 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 a firm's 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 smaller, younger, and non-publicly listed firms. Our estimates further indicate that products introduced in new categories by credit-constrained firms during the financial crisis are less successful throughout their entire life cycle 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

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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 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; Argente, Lee, and Moreira, 2018a; Akcigit and Kerr, 2018). 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 time. 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 little insight 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 such decline in product innovation during economic downturns.

In the absence of financing frictions, the decision to introduce a product should only 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 level, quality, and success 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 covers a broad sample of firms but 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) and use 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 the 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 new product attributes to the market. Radical 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. Our main result is robust to the inclusion of firm fixed effects, which implies that the documented effects are driven not by differences in product introduction rates across firms but rather by within-firm changes in their rates of product creation. 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 20% to 40% of the 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 to better evaluate whether the results are consistent with a credit market frictions channel. Consistent with such channel, our analyses suggest that the results are concentrated in subsamples of firms that derive most of their revenue from product groups belonging to 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 lack strong credit histories. Using information on public-listing status available for the subsample of firms that obtained syndicated loans, we also find that firms with access to public capital markets reduce the rate of product introduction to a lesser extent. Finally, we 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. Overall, these cross-sectional exercises support the conjecture that the decline in radical product innovation during the Great Recession can be partly attributed to credit market disruptions.

Some potential concerns exist that both our measures of credit market disruptions might be capturing the exposure of firms to unobserved shocks that are unrelated to credit market conditions rather than differences in exposure to credit supply shocks. For instance, if a bank specializes in lending to a specific industry, a demand shock to that industry might look like a credit supply shock because the impacted bank would reduce lending in all counties relative to other banks. We address this particular concern by exploiting the richness of the RMS Nielsen Dataset, which allows us to identify the predominant product groups and modules of each firm and re-estimating the main empirical specification after including Product Category×Year Fixed Effects. Thus, we ensure that our findings are robust to absorbing unobservable time-varying industry demand shocks that could bias our results. To allay similar and other concerns, we conduct a battery of additional robustness tests including using alternative definitions of the dependent variable, alternative measures of credit market disruptions, and including additional controls for local demand shocks. 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. Using the descriptions of each new product in the Nielsen RMS sample, we also 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 find that credit constrained firms not only create fewer products in new product lines during the financial crisis, but the products that they do create are less novel and more similar to other existing products. We ensure that the decline in the rate of introduction of new product characteristics is not explained by credit constrained firms cutting back on redundant characteristics that consumers do not consider valuable. In fact, credit market disruptions are associated with a decline in the "novelty" index even when we weigh each product characteristic by its respective "shadow value" obtained from a hedonic pricing regression of (log) prices on product characteristics. These results suggest that credit market disruptions not only partially explain a missing generation of new products but could also explain missing product traits.

Finally, we make use of the granular information on our dataset to ask whether credit market disruptions not only lowered the rate of introduction of products in new categories during the downturn but also impacted the overall commercial success of such products introduced during the Great Recession. The role that credit market constraints plays in shaping the outcomes of new products launched during downturns is not obvious: credit market frictions negatively impact investments in the development and promotion of products which, in turn, could hinder their potential commercial success, even conditional on entry. On the other hand, during economic downturns, constrained firms might only launch 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 revenues than similar products introduced by the same firm outside of the crisis period. We obtain this result after conditioning on firm fixed effects and product group fixed effects thereby ensuring that systematic differences across time in the average quality of firms introducing products or in the product categories that see a product introduction do not drive the results. These results are analogous to those of other papers suggesting that tight credit markets constrain the size of new firms entering in the economy (e.g. Saffie and Ates 2013; Siemer 2019).

It is not clear, however, whether these differences in the generation of revenues decay over time as the financing constraints subside and the economy recovers or whether they are path-dependent and persist long after the crisis has passed. Using a age-period-cohort empirical model, we are able to show that the differences in revenue-generating capacity of products introduced during crises by firms subject to tight credit constraints are long-lived and do not revert up to four years passed since the introduction of the new product. These results are consistent with the idea that consumer habits and demand accumulation over

the firm lifecycle (e.g. Bronnenberg, Dubé, and Gentzkow 2012; Foster, Haltiwanger, and Syverson 2016; Moreira 2016) play an important role in the capacity of firms to generate future revenues and that initial differences in reputation and brand value are not easily overcome.

The paper contributes to several strands of literature. It contributes to an important literature examining how financing constraints shape innovation activity. 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. In considering the role of financial constraints in financing innovation, an important question to ask is how firms finance innovation activities. A number of papers suggest that entrepreneurs and firms rely primarily on internal cash flows and equity markets to finance R&D investments (e.g. Brown, Fazzari, and Petersen 2009; Acharya and Xu 2017). 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. In particular, 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] Our approach and granular product-level dataset allows us to measure the impact of credit market disruption on product innovation but also to uncover what types of investment are cut following a credit supply shock.

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

[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).

[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.

the creation, quality, and long-run success 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 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. We contribute to this literature by the role that credit market distress plays in firm's decisions to launch new products to the market.

2 Data and Background Section

This study combines data from three main sources to examine the effect of credit market disruptions on product innovation. We obtain the product dataset from the Nielsen Retail Measurement 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) under the Community Reinvestment Act, 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 as barcodes 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] An alternative would be to define goods by industry classification

[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.

but such approach would potentially aggregate very heterogeneous barcodes. In fact, our data show that large firms typically sell hundreds of different products within narrowly defined categories. By using barcodes, we ensure that we observe the exact same product at different points in time and thus changes in performance cannot result from changes in the characteristics of the product.

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 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 data set 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 1070 product modules, that are organized into 104 product groups, that are then grouped into 10 major departments.[4] For

[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).

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 data set. 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]

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

[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.

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

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 the company name while requiring the state of the company to be the same. Similar to Chodorow-Reich (2013), we use Michael Blasnik's Stata ado file reclink for the described fuzzy merge. 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 local credit supply shocks across the regions 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

[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.

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 both 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 approximately 5 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 credit market follows the work of Greenstone et al. (2014), which also closely relates to the framework of Khwaja and Mian (2008) and Amiti and Weinstein (2018). Their research design uses 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.[8]

[8] 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 better uses all available information in the CRA Small Business Lending dataset by exploiting information on the evolution of small business lending for all banks in all counties.

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 shift-share approach that refines the traditional shift-share (Bartik) 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:

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

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:

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

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 shift-share approach, Greenstone et al. (2014) use the bank fixed effects estimated from equation (3) 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 (3) purge each bank's national change in lending from their exposure to unobservable demand shocks in the counties that they are located, thus addressing potential concerns that this measure captures shocks to local demand for credit or to local investment opportunities 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 some concentration in the South, Midwest, and Western regions of the United States and lower concentration in the East.

A potential concern with this modified shift-share 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. In Figure 3, we examine the possibility that firms sort on less exposed counties based on their characteristics. Panel A of 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 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 decile of our credit market disruption index such as Cass County, Michigan while others are located in counties in the bottom decile of our measure such as Monmouth, New Jersey. Thus, these specifications take advantage of the idea that firms within very narrowly-defined sectors that were exposed to similar industry demand shocks were located in areas with different exposures to our measure of credit market disruptions.

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 geographic exposure to banks that cut back their national supply of small business loans is related to product

innovation through channels other than credit supply. We can, however, use other forms of plausible variation in credit market frictions to further help with the convincing that our main results are driven by credit market disruptions.

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 better captures if an individual firm has 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.

We believe these concerns are unlikely to affect the empirical analysis. Our empirical specifications include firm fixed effects, which implies that our results are driven not by cross-sectional differences in unobservable characteristics across firms. Thus, for such concerns to come to fruition, it must be that unexpected 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. Moreover, in robustness tests, we further include module×year fixed effects to allay concerns that firms specializing in product modules that are more sensitive to the cycle may have a greater share of long-term debt coming due.[9]

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 level 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.

[9]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).

a new product in a new product module. The table also shows that firms in our sample hold on average 23.25 UPCs in their product portfolio. This distribution is, however, highly right-skewed with the median firm holding a product portfolio comprised of three 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 10% 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 150% 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 much more likely to introduce new products and, similar to the full sample, firms introduce most products in old modules. 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 .193 to .138 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 the same cyclical patterns in the subsample of Panel B despite significant differences in the levels of product innovation across the two samples. Table 2 confirms the findings of 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 canibalization 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 new product groups typically go on to 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 into three bins based on our geographic level measure of exposure to credit market constraints. Panel A of Figure 5 plots the evolution over time of the average entry rate of new products in each group, where we define entry rate of products as the number of new products introduced in year t divided by the number of products in the firm's product portfolio in year *t-1*. The entry rates in 2010 decrease at least 20% relative to their 2007 based levels for all credit shock groups but the group of firms exposed to stronger credit shocks sees a stronger decline of about 33% relative to its 2007 baseline levels. The product entry rates of all three groups return to their 2007 levels by 2012.

In Panels B and C of Figure 5, we disaggregate between the rate of new products in product modules that the firm was already operating (Panel B) and the rate of new products in new product modules (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 with the exception of a small difference in the rate of incremental product innovation in 2010. 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 more than 40% between 2007 and 2010 for the more credit-constrained group, but only 20%–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 significant 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 Figures IA.2, IA.3, and IA.4 of the internet appendix. In these figures, we repeat the analysis in Figure 5 with a focus on the extensive margin of product introduction (Figure IA.2) and using 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

(Figures IA.3 and IA.4). These plots are consistent with the results described above: the sample of firms that is more credit constrained see 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 characteristics and quality 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. Using within-firm variation also sees that our findings are not explained by a churning process where areas more exposed to financial frictions experience greater rates of exit and subsequent entry of innovative firms. Instead, the inclusion of firm fixed effects mean that our findings use only variation from the product creation decisions of incumbent firms. 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 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 double-clustered by state and year.

4.2.1 Product Introduction during the Crisis

In Panel A of 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, not statistically significant.

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 .0023 (0.084 $\times$ -0.026) in the entry rate of new products in new product modules. This negative impact compares with an overall decline in the rate of introduction of new products in new product modules from 0.044 in 2007 to 0.031 in 2010 (-0.013) 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 (.0126 = .035 × -.036) 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) the degree of dependence of a firm on external sources of finance for their growth; ii) firm characteristics that are typically associated with difficulties in obtaining access to credit, and iii) the financial health of a firm's lenders.

We begin by examining 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 expenditures. We also collect information on the average capital intensity defined as the ratio between total capital and total employment in each 4-digit SIC industry obtained from the National Bureau of Economic Research (NBER) and U.S. Census Bureau's Center

for Economic Studies (CES) Manufacturing Industry Database. Our use of this measure is predicated on the notion that sectors with greater capital intensity will more likely be dependent on external sources of finance to finance growth.

In Panel A of Table 5, we repeat the analysis of column (6) in Table 3 after stratifying the full sample based on the median of the external financial dependence measure computed following Rajan and Zingales (1998) (columns (1) and (2)) and based on the median average capital intensity from the NBER-CES database (columns (3) and (4)). 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. Similarly, the impact of credit market disruptions on the rates of introduction of new products in new product modules is more pronounced in industries with greater average capital intensity.

Next, we examine 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 become 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 Panel B of 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 in 2006:Q1 and 2006:Q2, were negatively but not significantly affected by the local credit shocks. The results of Column (2) show that new firms, whose products first appeared on our sample after 2006:Q2, experienced a strong 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 exceed \$250,000.[10] Consistent with the idea that smaller firms are more credit constrained, we find that the effects are

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

concentrated in the subset of small firms.

Next, we turn our attention to the Dealscan-matched sample of firms and to the empirical analyses using the firm measure of credit shocks. Using information obtained from the Dealscan dataset, we split the sample based on the public listing status of the company. The results presented in columns (1) and (2) of Panel A of Table 6 suggest that private firms that see a greater portion of their debt coming due during the crisis cut back on product innovation more than public firms in the same conditions. These results are consistent with the notion that public firms are more transparent as they are subject to greater monitoring and regulatory scrutiny, which increases their ability to find alternative sources of financing (e.g. Sufi (2007)). In columns (3) and (4) of the same Table, we repeat the analysis after stratifying 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 in the sample between 2006 and 2008 exceed $3,000,000. We find statistically significant results for the subsample of small firms but not for the subset of large firms.

In Panel B of Table 6 we evaluate if our results vary 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 banks were healthier.

In columns (1) and (2) of Panel B of Table 6, 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 between the periods October 2005 to June 2007 and 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 shares as weights. Consistent with a bank balance sheet channel, we find that the impact of our firm-level credit shock on the rates of introduction of new products on new product modules are 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 the Lehman's demise and therefore were more liquidity constrained. Our findings, reported in columns (3)

and (4), 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 contracted their supply of credit to a larger extent.

4.2.3 Robustness - Product Introduction during the Crisis

Next, we conduct a battery of robustness tests to further ensure that our empirical 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 identified as a credit supply shock because in the modified shift-share approach the impacted bank reduces lending in all counties relative to other banks. To deal with this concern, in Table 7, we reestimate the empirical specifications of columns (5) and (6) after including Department×Year, Group×Year, and Module×Year fixed effects, respectively. Thus, in these specifications, we absorb any industry-specific shocks at a very narrow module level. In this specification, our identifying variation comes from comparing the product introduction outcomes of a firm in a specific product module such as "First Aid - Thermometers" whose headquarters are located in a high credit market disruption county such as Cass County, Michigan against the product introduction outcomes of another firm specializing in "First Aid - Thermometers" whose headquarters are located in a county with low credit market disruptions such as Monmouth, New Jersey.

We present the results of this analysis in Panels A and B of Table 7. In Panel A, we assess the robustness of the results of Table 3 to the inclusion of these alternative fixed effects structures. The coefficients obtained from estimating these empirical specifications are quantitatively and qualitatively similar when we include these granular fixed effects. In fact, as we include more demanding Product Group×Year and Prod. Module×Year fixed effects, the estimated magnitude of the estimated coefficients increase suggesting that, if anything, industry composition effect might have been working against our findings. 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 and we exclude them from the analysis following Correia (2015). Despite this reduced number of observations, the results remain statistically significant.

A related concern is that the shift-share 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 shift-share 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, 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 8. 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 states other their own headquarter's (HQ) state. As we move from the subsample that derives at least 66% of sales from outside HQ states to the subsample that derives more than 90% of sales from outside HQ states, the estimated coefficients continue to suggest that credit market disruptions the coefficients remain economically and statistically significant. Overall, these results allay concerns that the results might be driven by local economic shocks.

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.5 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 (2013)) finds that investments decreases sharply following a covenant violation as creditors use the threat of accelerating the loan to intervene in management. n our sample of Dealscan-matched CPG borrowers, however, we find that only six companies violate a covenant between 2008 and 2010. Instead, as an alternative measure, 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 to breaching a covenant will be more likely to take precautionary measures and reduce discretionary spending especially during the crisis. 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, in Table IA.7 we further control for local economic conditions, (log) unemployment rate and county income *per capita* in the county where each company's headquarters is located.

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 conditional on product introduction, 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 data set. 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:

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

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.[11] We assume that each attribute is equally weighted in order to remain agnostic about the relative importance of each attribute to the degree of novelty of a product. We refer to Argente et al. (2018a) for more information and detailed statistics about the distribution of the novelty across sectors and product attributes.

Our basic novelty index counts the number of new characteristics (within each attribute) that each new product brings to the market. Alternatively, we could determine if a product brings a combination of characteristics for the first time to the market. For example, in the carbonated beverages, a new soft drink will not be the first fusing drink or the first soda with cherry flavor, but the first cherry flavor fusing drink. To account for new products that do not appear with a new characteristic (within a given attribute) but rather a new combination of characteristics, we developed an alternative index. Let c_{jkt} denote the combination of characteristics of UPC j (e.g. container: can, flavor: orange, brand: Coca-Cola, formula: no calories) and let Θ_{kt} contain all the possible combinations of attributes observed up until

[11] 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.

period t in product module k. Using this information we define an alternative novelty index that not only accounts for new characteristics within product attributes but also for new combinations of characteristics:

$$\text{NIC}^k_{jt} = \frac{1}{N_k + 1}\left[\sum_{i=1}^{N_k} \mathbb{1}[v_{kji} \notin \Omega_{kt}] + \mathbb{1}[c_{kj} \notin \Theta_{kt}]\right] \tag{6}$$

In this case, we add to the numerator of the baseline novelty index one if a new product brings a new combination of characteristics to the market. By definition, if a new product brings a new characteristic within an attribute, it will also bring a new combination. However, new products that may not bring a new characteristic within an attribute to the market might bring a new combination if 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 and orange flavor low calorie soda). The advantage of this index, relative to our baseline index, is that it differentiates more clearly products that bring new characteristics to the market (even if marginal) with those that do not.

A potential pitfall of the two "novelty" indices utilized above is that they just count new 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.

Specifically, we for each module, we estimate the following equation by non-negative least squares:

$$p_{it} = \sum_j \pi^j a_i^j + \lambda_t + \epsilon_{it} \tag{7}$$

where i denotes the product, j is the characteristic, and t is the time period (years). a_i^j is an indicator that equals one if a given characteristic j is present in product i, and the shadow price of a given characteristics is denoted by π^j.

We define a product i in product module m as a vector of characteristics $V_{mi} = [v_{mi1}, v_{mi2}, .., v_{miA_m}]$ where A_m denotes the number of attributes we observe in product module m in our data. Let Ω_{mt} contain the set of product characteristics for each product ever sold in product module m at time t, then the *hedonic novelty index* of a product i in product module m, launched at time t is defined as follows:

$$\text{NIH}_{it}^{m} = \sum_{k=1}^{A^m} \omega_k^m \mathbb{1}[v_{mik} \notin \Omega_{mt}].$$

where ω_k^m is the average of the estimated $\hat{\pi}^j$ for attribute k and ω_k^m is normalized so that $\sum_k \omega_k^m = 1$.

We report the time-series evolution of the "novelty" indices that we use on our empirical analysis in Table 9. 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 .149 in 2007 to .139 in 2010 while the hedonic "novelty" index declines from .296 in 2007 to .275 in 2010. In all cases, the indices bounce back after 2010 and reach the 2007 levels prior to the end of the sample period.

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 10. Overall, the results 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 in columns (5) and (6) show our results are robust to using a measure of "novelty" of product attributes weighed by the shadow prices of such characteristics. Thus, this result suggests that consumers had positive valuations on these "missing" product characteristics. 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. Our back-of-the-envelope computations imply that the economic magnitude of the results are substantial. The credit market disruption accounts for a significant portion of the decline in "novelty" of the generation of products introduced during the crisis. A standard-deviation increase in the exposure to local credit shocks lowers the main "novelty" index of products by (-0.0035 = .084 × - 0.043), which corresponds to approximately 40% of the decline in the "novelty" index between 2007 and 2010 period. In Tables IA.8 and IA.9, 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

5.1 Credit Market Disruptions and Aggregate Product Sales

The rich micro-level data available in the RMS dataset offers an opportunity to further explore how credit market disruptions shape the performance of new products over their entire lifecycle. Thus our data allows us to say something about the impact of credit market disruptions not only on the rate of introduction of new products but also on their relative success 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 constrain amounts invested in the development and promotion of new products. These differences in initial investments in product development could stunt their potential commercial success and future growth. On the other hand, during economic downturns, the opportunity cost of an investment in product introduction and development is higher, which should prompt firms to focus their investment efforts in their best and most promising products, i.e. those with higher expected value. This selection effect would suggest that products introduced in recessionary cohorts by firms exposed to credit market disruptions (henceforth "crisis-cohort products") 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 product group level because of computational reasons but, in the internet appendix, we show that this is without loss of generality as the rates of product introduction in new product groups are also highly procyclical and affected by credit market disruptions. This dataset allows us to identify when an existing firm expands to a new product group and, crucially, to observe the evolution of total sales generated in all product groups of the firm over their respective lifecycles. 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:

$$Rev_{i,g,c} = \alpha_i + \theta_g + \gamma_c + \beta Shock_i \times Crisis\ Cohort_c + \epsilon_{i,g,c} \tag{8}$$

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, ensure that 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 created during normal times. The inclusion of these fixed effects imply that the results are not driven by unobservable differences in the quality of firms launching products in crisis and non-crisis periods. The product-group fixed effects, θ_g, control for overall differences in total volume of sales across product groups and ensure that the results are not driven by differences in the composition of product groups introduced in crisis periods. Finally, γ_c is a cohort fixed-effect that controls for overall fluctuations in demand for new product groups over time. All regressions are estimated with heteroskedasticity-robust standard errors clustered by state.

We report the results of this analysis in Table 11. In column (1), we report results of estimating the specification of equation (8) 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 22% 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 and suggest that credit market shocks are associated with a reduction of 20% in revenues of new product groups over the first four years of life. In columns (3) and (4), we repeat the analysis of the previous columns using the natural logarithm of the average revenue of products in the new product group, and in columns (5) and (6) we do the same using the average share of firm revenues accounted by the new product group over its initial four years. The results of columns (3)–(6) indicate that exposure to credit market disruption at inception significantly impacts the overall performance of these new product groups. 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.

5.2 Credit Market Disruptions and the Lifecycle of Product Sales

After documenting that firms with high exposure to credit market disruptions generate fewer sales from new product groups that they introduce in their portfolio during the crisis

period, we examine how these differences in initial conditions impact the evolution of sales of these "crisis-cohort products" over their lifecycles. In particular, we examine whether these differences are relatively short lived or whether they persist over long periods of time. One possibility is that the wedge in aggregate total sales of "crisis-cohort products" is driven by lower than optimal initial investments in product development and promotion. If this is the case, then this wedge should gradually disappear once firms become unconstrained in the credit market and adjust their investments in the marketing and promotion of such products. On the other hand, a growing literature (e.g. Bronnenberg et al. 2012; Foster et al. 2016; Moreira 2016) suggests that consumer habits and dynamic processes of demand accumulation through consumer reputation and brand awareness play an important role in the capacity of firms to generate future demand. Lower initial investments in product development and promotion could then have persistent effects as initial differences in reputation and brand value are not easily overcome. This scenario would indicate that temporary differences in initial exposure to credit market conditions are highly persistent and that the product lifecycle dynamics is path-dependent.

We use our data and information about the ages of new product groups to study how their sales evolve as a function of the initial exposure to credit market disruptions. To properly isolate the effect of age we must account for the fact that we observe products in different quarters and want to capture the effect of age irrespective of the particular period at which a product is observed. Similarly, we want to account for the fact that otherwise comparable products, might behave differently depending on the timing of their introduction. To examine these questions, we estimate age effects by implementing age-period-cohort models. These specifications allow us to estimate the role that credit market disruptions play in shaping the evolution of revenue since the product's inception, while accounting for cohort-specific differences in outcomes and any calendar effects specific to the moment when we measure the outcomes (e.g., business cycles affecting all products).

Following Argente et al. (2018a), we estimate the natural logarithm of total revenues, $Rev_{i,g,c,t}$, of firm i in product group g during quarter t as a function of age (a), interacted period and product group (gt), and cohort fixed effects (c). Because there is an exact linear relation between the three effects, we normalize the cohort effect as suggested in Deaton (1997). The normalization averages the cohort effects to zero over the sample period and orthogonalizes the cohort trends such that all growth is attributed to age and time effects. Specifically, we run the following specification:

$$Rev_{i,g,c,t} = \lambda_{g,t} + \theta_c + \gamma_i + \sum_{a=1}^{A} \beta_a^0 \times D_a + \sum_{a=1}^{A} \beta_a^1 \times D_a \times Shock_i + \sum_{a=1}^{A} \beta_a^2 \times D_a \times Shock_i \times Crisis_c + \epsilon_{i,g,c,t} \tag{9}$$

we are interested in the set of coefficients, β_a^0, β_a^1, and β_a^2 that capture the average evolution of the aging process of the product group across different levels of initial exposure to credit market disruptions relative to the baseline level of the outcome in the last full quarter of activity.

We estimate equation (9) using the level of quarterly revenue (in logs) as the dependent variable for product groups that were active for at least 16 quarters. We plot estimated coefficients in Figure 6. The blue line represents the evolution of revenues over the lifecycle for a product group that was introduced by a firm that was exposed to an average level of credit market disruptions. By contrast, the red line represents the evolution of revenues over the lifecycle for a product group that was introduced during the crisis period by a firm that was highly exposed to credit market disruptions. Similar to Argente et al. (2018a), revenues of products mostly decline with age except for the first four to five quarters. But most importantly, we find that the product groups introduced during the crisis period by firms with strong exposure to credit market disruptions generate lower revenues not only in the first few quarters of operation but also throughout the lifecycle of the product.

The results in this section suggest that credit market disruptions not only affect the intensity and type of innovation during crises periods but also leave permanent scars in the revenue and performance profile of new products that are introduced during the crisis.

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, quality, and type 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.

Our estimates further indicate that products introduced in new product groups during the financial crisis by firms exposed to credit market disruptions are less successful throughout their entire life cycle than products introduced in new groups by the *same* firm during normal times. Thus, our findings not only indicate that the credit market disruptions partially account for a missing generation of new products but also suggest that credit market constraints carry a negative and persistent effect in the performance of new products introduced during the financial crisis.

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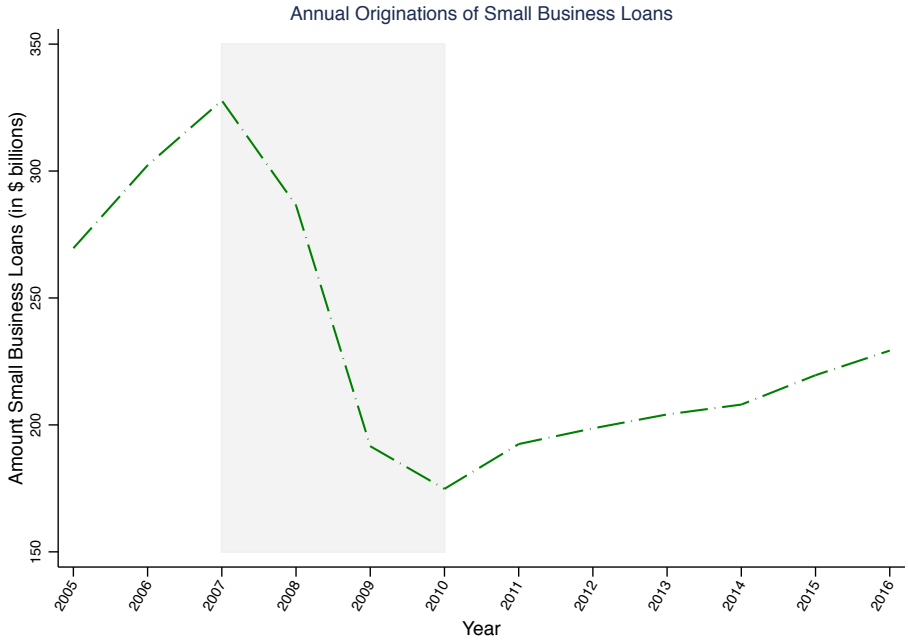
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Figure 1: Evolution of Small Business Lending (2007–2010)

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)

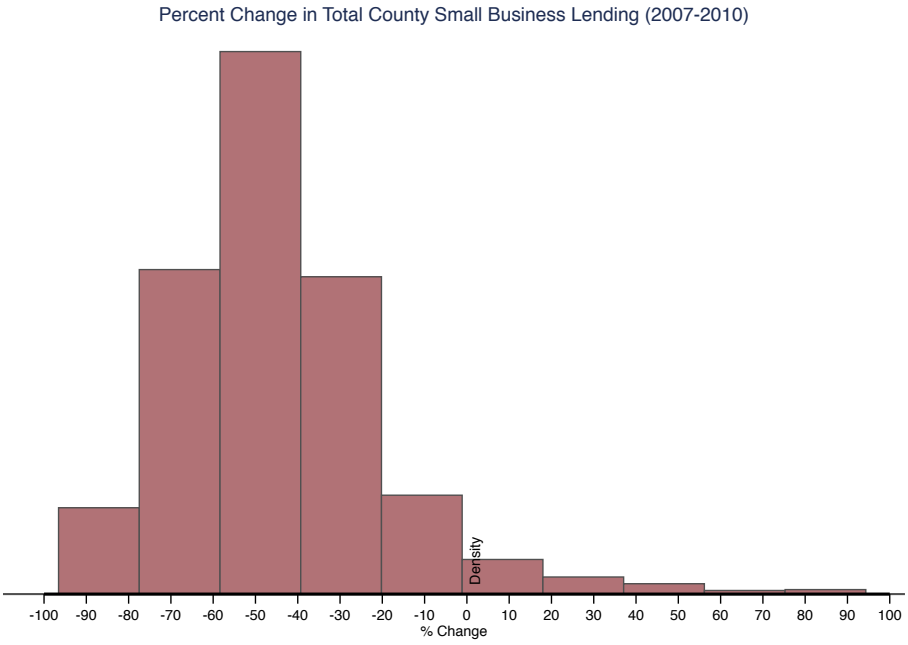


Figure 2: Spatial Distribution of County-Level Measure of Credit Market Disruption

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.

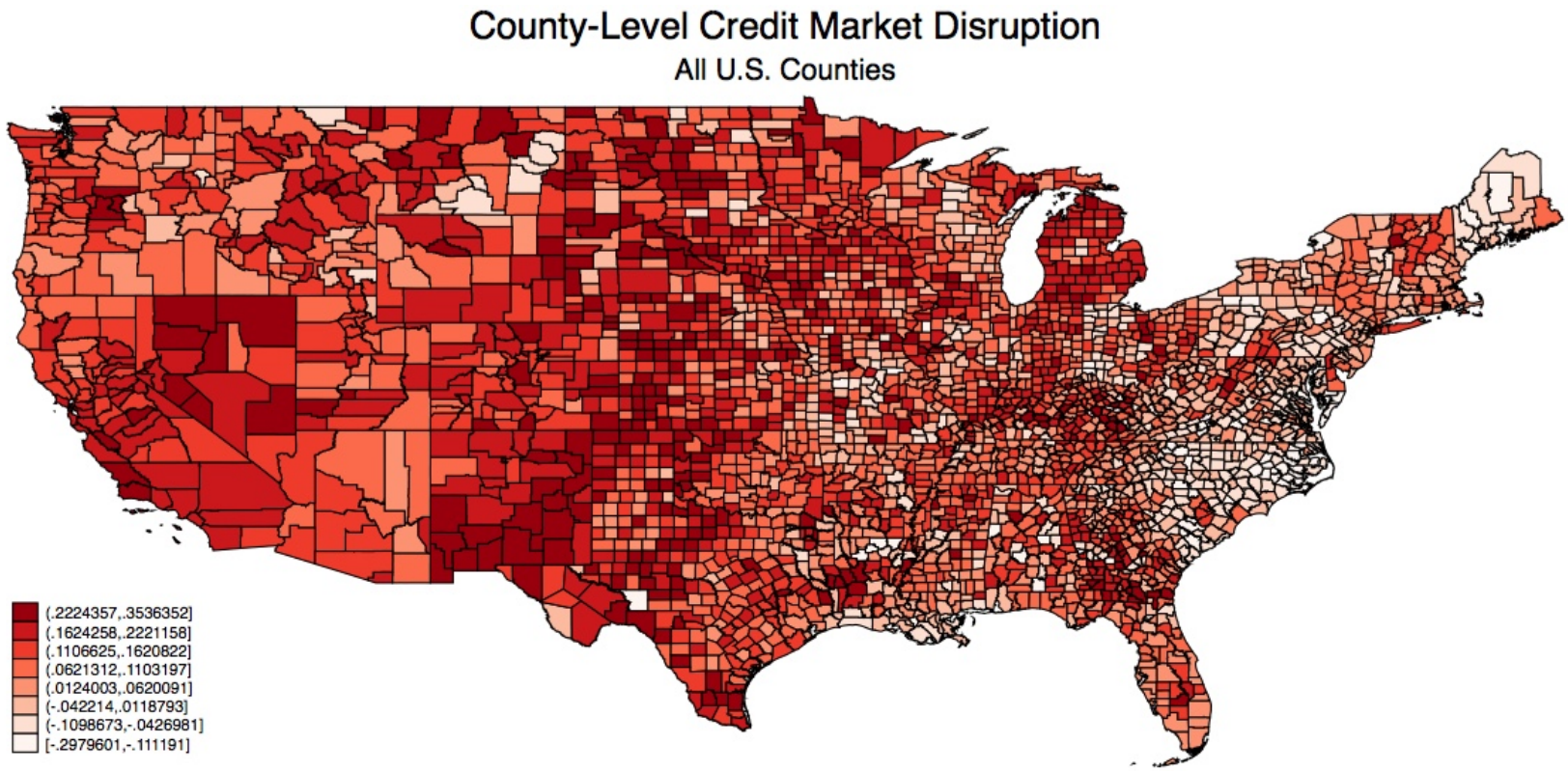
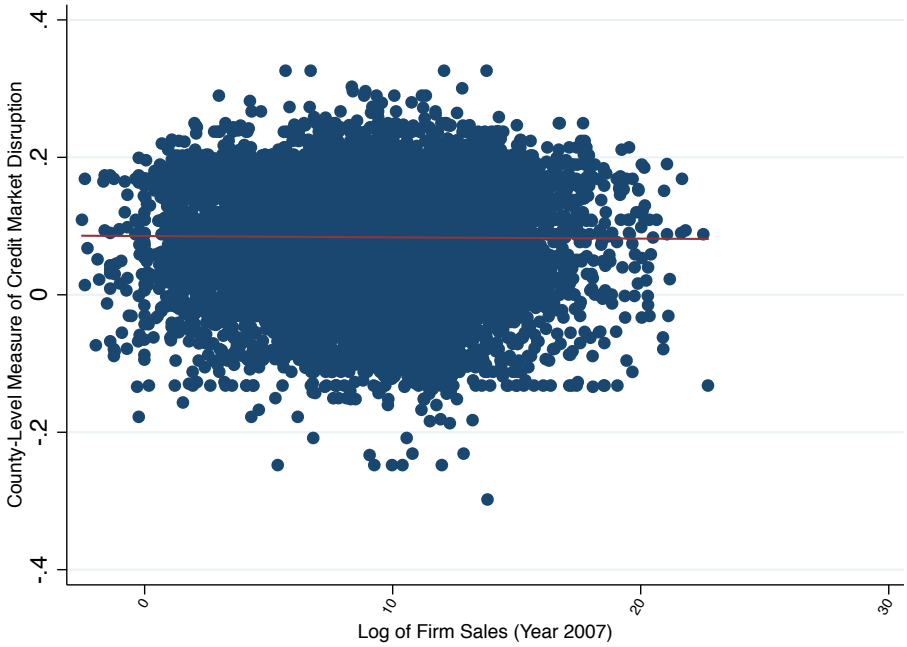


Figure 3: Sorting of Firms into Counties

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)

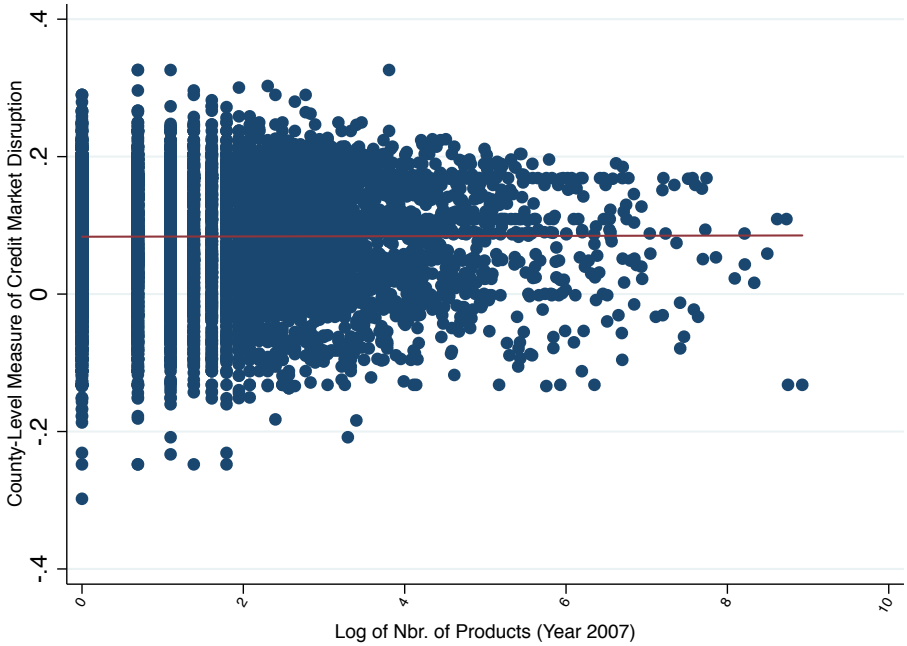


Figure 4: Type of Product Innovation and Product Revenue Share

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.

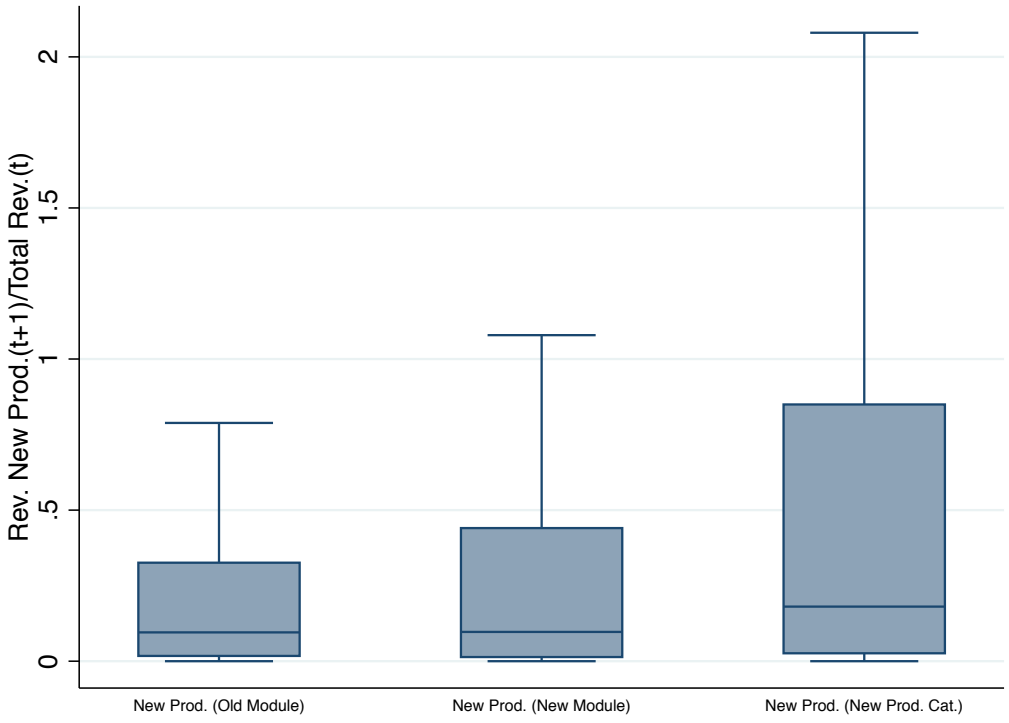


Figure 5: : Product Innovation and Credit Market Disruption: Entry Rate

Figure 5 plots the evolution of the average firm 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 the 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 tercile of firms that are located in counties that were more exposed to our geographic measure of credit market disruptions. The red line represents the evolution of the average firm entry rate of new products for the tercile of firms that are located in counties with medium exposure to our geographic measure of credit market disruptions. The blue line represents the evolution of the average firm entry rate of new products for the tercile of firms that are located in counties with low exposure 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 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.

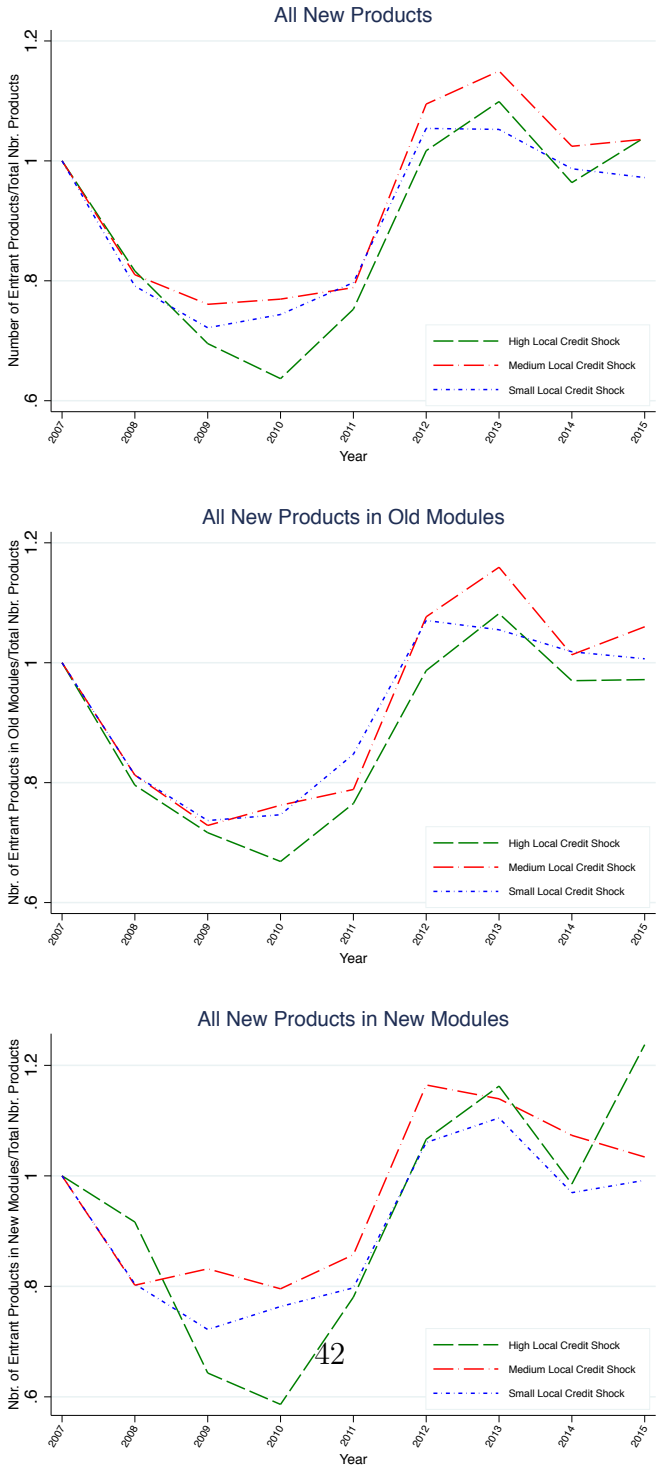


Figure 6: : Credit Market Disruptions and Product Outcomes: Total Sales over Product Lifecycle

Figure 6 represents the lifecycle evolution of revenues generated by new product groups introduced in crisis vs non-crisis cohorts and by severity of exposure to credit market disruption. Specifically, the plot represents the series of coefficients from estimating equation (9) $\beta_a^0; \beta_a^1; \beta_a^2$ and respective coefficients evaluated at $D_a = 0$ and $Shock = 0$ (blue line) and at $D_a = 1$ and $Shock = 2\sigma$, where σ represents one standard deviation of our geographic measure of credit market disruption. Data for all figures is obtained from the CRA and Nielsen datasets.

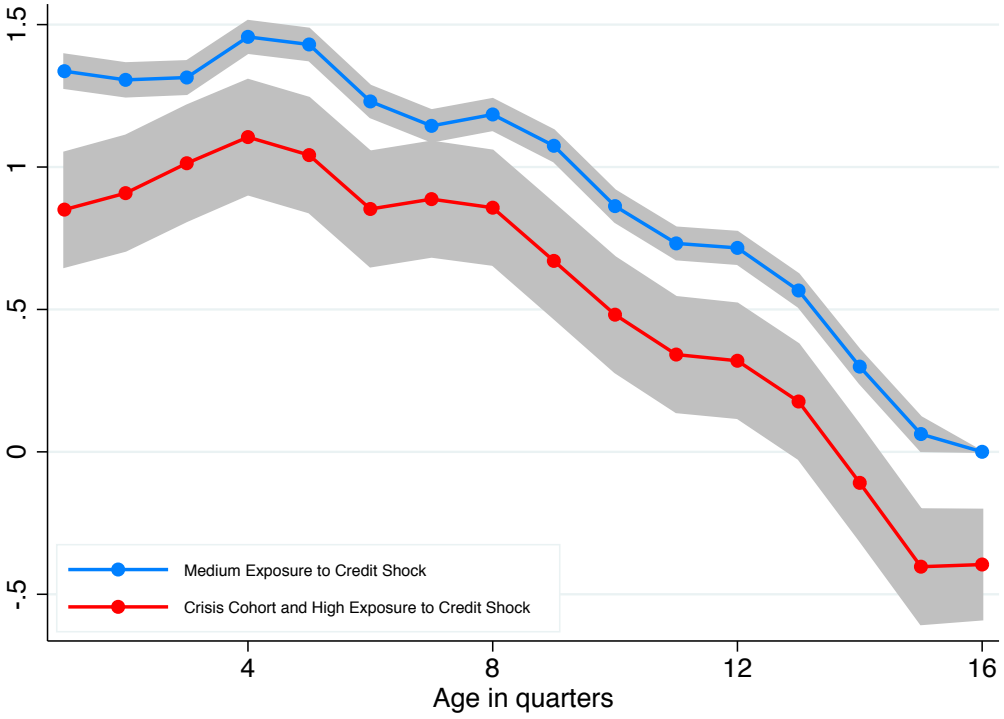


Table 1: Summary Statistics

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

	count	mean	sd	p25	p50	p75
Nbr. of New Products	103886	3.759	28.59	0	0	1
Nbr. of New Products (Old Modules)	103886	3.404	28.13	0	0	1
Nbr. of New Products (New Modules)	103886	0.355	2.172	0	0	0
I(New Prod. =1)	103886	0.333	0.471	0	0	1
I(New Prod. =1) (Old Modules)	103886	0.295	0.456	0	0	1
I(New Prod. =1) (New Modules)	103886	0.109	0.312	0	0	0
Total Nbr. of Products	103886	23.25	166.0	1	3	10
Total Nbr. of Distinct Modules	103886	3.079	8.002	1	1	3
Total Nbr. of Distinct Prod. Cat.	103886	1.910	2.782	1	1	2
Total Annual Revenues	103886	5980152.3	109729834.9	478.6	14936.8	178734.6
Rev. New Prod.(t+1)/Total Rev.(t)	27350	1.423	64.19	0.0239	0.117	0.379

Panel B: Firms Matched to Dealscan

	count	mean	sd	p25	p50	p75
Nbr. of New Products	2555	40.32	136.2	0	3	22
Nbr. of New Products (Old Modules)	2555	39.06	135.1	0	2	20
Nbr. of New Products (New Modules)	2555	1.268	4.149	0	0	1
I(New Prod. =1)	2555	0.677	0.468	0	1	1
I(New Prod. =1) (Old Modules)	2555	0.631	0.483	0	1	1
I(New Prod. =1) (New Modules)	2555	0.286	0.452	0	0	1
Total Nbr. of Products	2555	273.9	820.8	4	27	157
Total Nbr. of Distinct Modules	2555	14.45	33.90	2	4	12
Total Nbr. of Distinct Prod. Cat.	2555	5.622	8.816	1	2	6
Total Annual Revenues	2555	120123477.9	615129596.8	24630.1	2228816.5	28558470
Rev. New Prod.(t+1)/Total Rev.(t)	1453	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	0.193	0.134	0.044	0.350	0.309	0.121
2008	0.155	0.108	0.037	0.301	0.264	0.101
2009	0.140	0.097	0.032	0.289	0.255	0.094
2010	0.138	0.097	0.031	0.281	0.249	0.087
2011	0.150	0.107	0.035	0.304	0.269	0.097
2012	0.203	0.140	0.048	0.361	0.321	0.121
2013	0.212	0.147	0.049	0.379	0.340	0.128
2014	0.191	0.134	0.044	0.359	0.317	0.115
2015	0.196	0.136	0.047	0.357	0.318	0.116

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 natural logarithm of the firm's total sales in the previous year. 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)	-0.016	-0.019	0.012	0.010	-0.026**	-0.027**
	(0.028)	(0.034)	(0.038)	(0.039)	(0.011)	(0.011)
Ln(Firm Revenue)		0.025***		0.016***		0.006**
		(0.005)		(0.003)		(0.002)
Observations	100958	100958	100958	100958	100958	100958
Adjusted R^2	0.260	0.264	0.224	0.227	0.166	0.168
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 natural logarithm of the firm's total sales in the previous year. 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	-0.035	0.014	0.009	-0.035***	-0.038***
	(0.040)	(0.038)	(0.032)	(0.032)	(0.012)	(0.005)
Ln(Firm Revenue)		0.027		0.025**		-0.002
		(0.021)		(0.010)		(0.010)
Observations	1744	1744	1744	1744	1744	1744
Adjusted R^2	0.308	0.315	0.293	0.298	0.229	0.228
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 external finance dependence impact the effect of credit market disruptions on firms' decisions to launch new products on the market. Panel A explores cross-industry variation in the external finance dependence of the industrial sector that corresponds to the main product module of the firm. Panel B explores cross-sectional variation in the age and size of each firm. *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 natural logarithm of the firm's total sales in the previous year. In columns (1) and (2) of Panel A, 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. In columns (3) and (4) of Panel A, we stratify firms in the sample based on the average capital intensity of the 4-digit SIC industry that corresponds to its main product module. Average capital intensity is computed as the ratio (in logs) between the total real capital stock and total employment in the industry (obtained from the NBER-CES Manufacturing Industry Database). *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) of Panel B, we stratify firms based on whether they report average annual total sales between 2006 and 2008 above or below $250,000. 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: Heterogeneity across External Finance Dependence (Geography-Based Measure)

	Low Ext.Fin.Dep.	Hi Ext.Fin.Dep	Low Cap. Int	Hi Cap. Int
	Entry Rate (New Modules)			
Local Credit Shock × I(Crisis)	-0.015	-0.037*	-0.004	-0.036*
	(0.015)	(0.017)	(0.015)	(0.017)
Ln(Firm Revenue)	0.005*	0.007***	0.008**	0.003
	(0.003)	(0.002)	(0.002)	(0.003)
Observations	54202	53304	46619	47312
Adjusted R^2	0.191	0.181	0.181	0.187
Year Fixed-Effects	Yes	Yes	Yes	Yes
Firm Fixed-Effects	Yes	Yes	Yes	Yes

Panel B: Heterogeneity across Size and Age (Geography-Based Measure)

	Old Firms	New Firms	Large Firms	Small Firms
	Entry Rate (New Modules)			
Local Credit Shock × I(Crisis)	-0.015*	-0.094*	0.006	-0.025*
	(0.008)	(0.044)	(0.023)	(0.013)
Ln(Firm Revenue)	0.006***	0.004	0.000	0.005*
	(0.001)	(0.005)	(0.001)	(0.002)
Observations	69268	31690	20092	62013
Adjusted R^2	0.091	0.198	0.127	0.088
Year Fixed-Effects	Yes	Yes	Yes	Yes
Firm Fixed-Effects	Yes	Yes	Yes	Yes

Table 6: Product Innovation and Credit Market Disruptions: Access to Finance

Table 6 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 natural logarithm of the firm's total sales in the previous year. Columns (1) and (2) of Panel A stratify the sample based on whether it is a publicly listed company. Columns (3) and (4) of Panel A stratify the sample based on whether the average annual total sales between 2006 and 2008 were above or $3,000,000. *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.

Panel A: Heterogeneity across Access to Finance (Firm Level)

	Private Firms	Public Firms	Large Firms	Small Firms
	Entry Rate (New Modules)			
Firm Credit Shock × I(Crisis)	-0.044***	-0.037***	0.006	-0.068***
	(0.006)	(0.008)	(0.004)	(0.019)
Ln(Firm Revenue)	0.004	-0.013	0.019	-0.004
	(0.016)	(0.011)	(0.012)	(0.010)
Observations	906	763	844	821
Adjusted R^2	0.228	0.222	0.279	0.199
Year Fixed-Effects	Yes	Yes	Yes	Yes
Firm Fixed-Effects	Yes	Yes	Yes	Yes

Panel B: Heterogeneity across Firms in Exposure to Change in Bank Supply (Firm Level)

	Low Δ^- Loans	Hi Δ^- Loans	Hi. Lehman	Low Lehman
	Entry Rate (New Modules)			
Firm Credit Shock × I(Crisis)	-0.030*	-0.048***	-0.059***	-0.031***
	(0.014)	(0.008)	(0.015)	(0.009)
Ln(Firm Revenue)	-0.005	0.001	0.000	-0.007
	(0.017)	(0.014)	(0.014)	(0.014)
Observations	809	935	674	1070
Adjusted R^2	0.211	0.236	0.168	0.265
Year Fixed-Effects	Yes	Yes	Yes	Yes
Firm Fixed-Effects	Yes	Yes	Yes	Yes

Table 7: Robustness: Product Innovation and Credit Market Disruption – Alternative Fixed-Effects

Table 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. *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 natural logarithm of the firm's total sales 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 (New Modules)					
Local Credit Shock × I(Crisis)	-0.022*	-0.023*	-0.025**	-0.025**	-0.029*	-0.029*
	(0.010)	(0.011)	(0.010)	(0.010)	(0.014)	(0.014)
Ln(Firm Revenue)		0.005**		0.005**		0.005**
		(0.002)		(0.002)		(0.002)
Observations	100956	100956	100945	100945	99577	99577
Adjusted R^2	0.168	0.170	0.171	0.172	0.200	0.201
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***	-0.038***	-0.065***	-0.064***	-0.065*	-0.069*
	(0.011)	(0.006)	(0.017)	(0.019)	(0.031)	(0.036)
Ln(Firm Revenue)		-0.003		-0.008		-0.022
		(0.009)		(0.007)		(0.012)
Observations	1740	1740	1445	1445	825	825
Adjusted R^2	0.236	0.235	0.290	0.289	0.210	0.209
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 8: Robustness: Product Innovation and Credit Market Disruption – Large Share of Sales Outside Home State

Table 8 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 natural logarithm of the firm's total sales in the previous year. 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)	-0.042**	-0.042**	-0.044**	-0.045**	-0.048**	-0.049**
	(0.016)	(0.016)	(0.018)	(0.018)	(0.017)	(0.017)
Ln(Firm Revenue)		0.005**		0.005**		0.005*
		(0.002)		(0.002)		(0.002)
Observations	56588	56588	53804	53804	44711	44711
Adjusted R^2	0.111	0.113	0.111	0.112	0.108	0.110
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 9: Novelty Index: Evolution over Time

Table 9 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. *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	0.149	0.227	0.296
2008	0.140	0.218	0.275
2009	0.143	0.221	0.289
2010	0.139	0.219	0.275
2011	0.142	0.220	0.284
2012	0.147	0.226	0.300
2013	0.147	0.226	0.302
2014	0.149	0.227	0.302
2015	0.152	0.231	0.301

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 10: Credit Market Disruptions and Novelty of Product Innovation

Table 10 reports the coefficients of OLS regressions investigating the effect of credit market disruptions on firms' decisions to launch new products on 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 natural logarithm of the firm's total sales in the previous year. 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)
	Novelty Index		Novelty Index (Combination)		Novelty Index (Hedonic)	
Local Credit Shock × I(Crisis)	-0.042**	-0.042**	-0.060***	-0.061***	-0.096***	-0.097***
	(0.013)	(0.013)	(0.014)	(0.014)	(0.026)	(0.026)
Ln(Firm Revenue)		-0.001		-0.002		-0.002
		(0.002)		(0.002)		(0.003)
Observations	29693	29693	29693	29693	26936	26936
Adjusted R^2	0.332	0.332	0.389	0.389	0.345	0.345
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)
	Novelty Index		Novelty Index (Combination)		Novelty Index (Hedonic)	
Firm Credit Shock × I(Crisis)	-0.018**	-0.018**	-0.024***	-0.023***	-0.048	-0.055*
	(0.006)	(0.007)	(0.006)	(0.007)	(0.028)	(0.028)
Ln(Firm Revenue)		0.003		0.005		0.003
		(0.011)		(0.012)		(0.023)
Observations	1161	1161	1161	1161	856	856
Adjusted R^2	0.346	0.347	0.435	0.435	0.292	0.301
Year Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes

Table 11: Credit Market Disruptions and Outcomes of New Products

Table 11 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 quarterly revenues 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(Av. Revenues)* 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). *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), (3), and (5) include all firm observations and the specifications of columns (2), (4), and (6) exclude observations representing 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)	(5)	(6)
	Ln(Total Revenues)		Ln(Av. Revenues)		Share Firm Rev.	
Local Credit Shock × I(Crisis Cohort)	-0.221**	-0.209*	-0.132**	-0.167**	-0.017*	-0.010*
	(0.092)	(0.123)	(0.060)	(0.082)	(0.009)	(0.006)
Observations	12489	7537	12489	7537	12850	7808
Adjusted R^2	0.402	0.358	0.448	0.403	0.332	0.352
Product Group Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes
Cohort Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes

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.

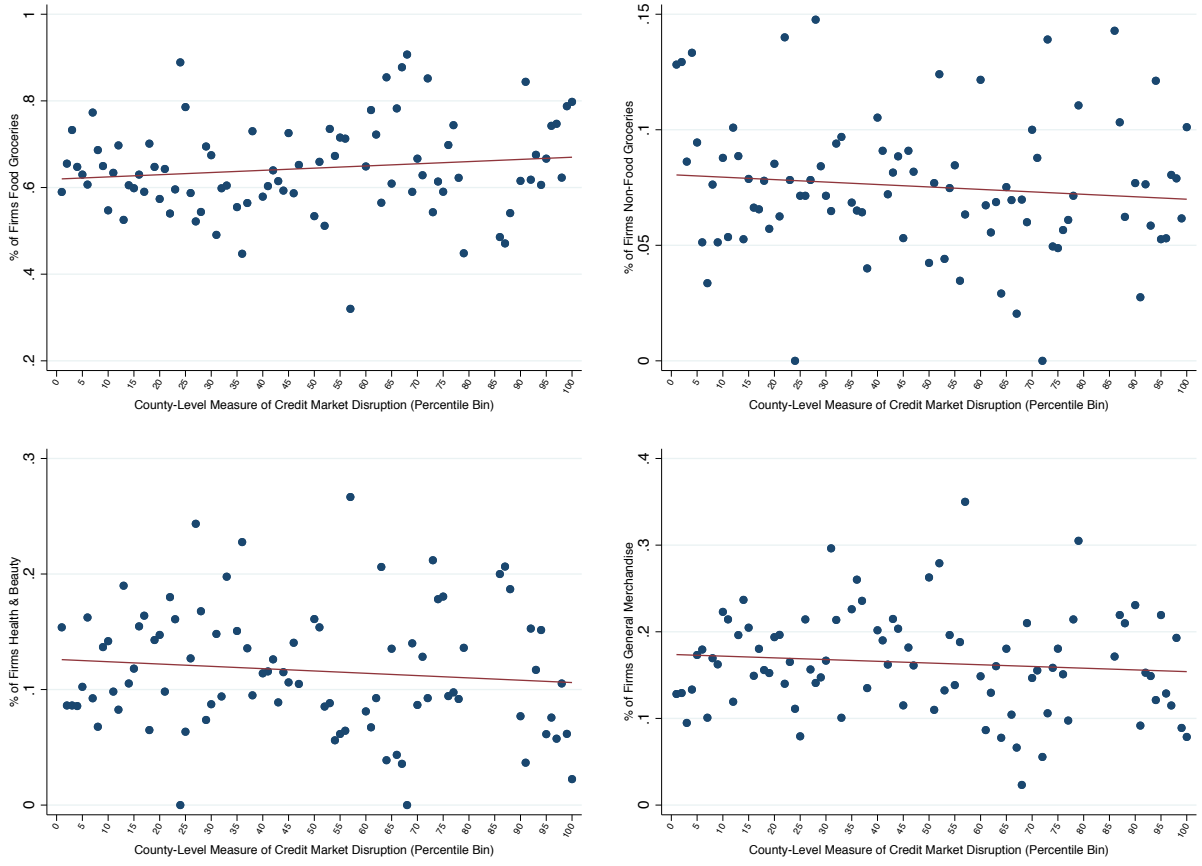


Figure IA.2: : Product Innovation and Credit Market Disruption: Product Introduction

Figure IA.2 plots the evolution of the average firm propensity to introduce products during a calendar year over time. We stratify the sample based on terciles of exposure of each firm to our geographic measure of credit market disruption. The propensity to introduce products during a calendar year is defined as an indicator variable that takes the value of one if a firm introduces a new product during the calendar year. The green line represents the evolution of the propensity to introduce products during a calendar year for the tercile of firms that are located in counties that were more exposed to our geographic measure of credit market disruptions. The red line represents the evolution of the propensity to introduce products during a calendar year for the tercile of firms that are located in counties with medium exposure to our geographic measure of credit market disruptions. The blue line represents the evolution of the propensity to introduce products during a calendar year for the tercile of firms that are located in counties with low exposure to our geographic measure of credit market disruptions. The plot on the top panel represents the propensity to introduce products of all types during a calendar year. The second plot represents the evolution of the propensity to introduce products during a calendar year in product modules where the firm already operated. The plot on the bottom represents the evolution of the propensity to introduce products during a calendar year 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.

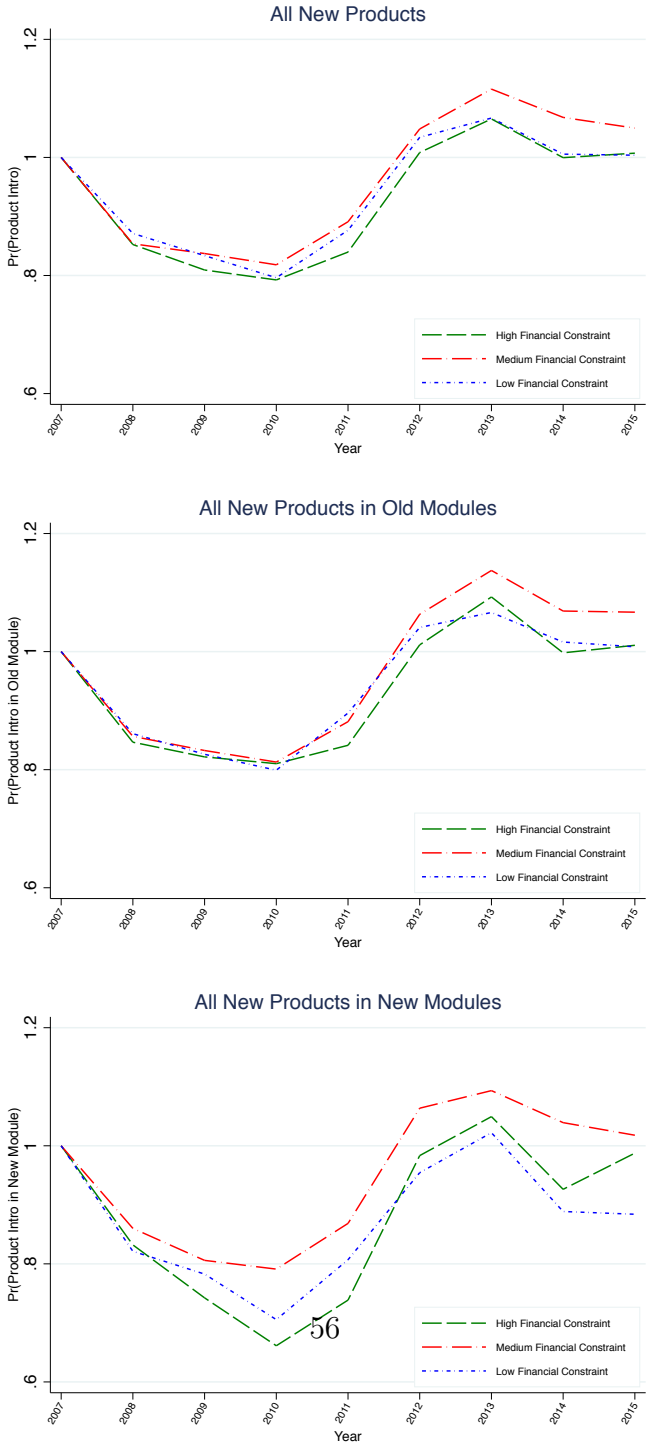


Figure IA.3: : Product Innovation and Credit Market Disruption: Entry Rate (Firm-Level Analysis)

Figure IA.3 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.

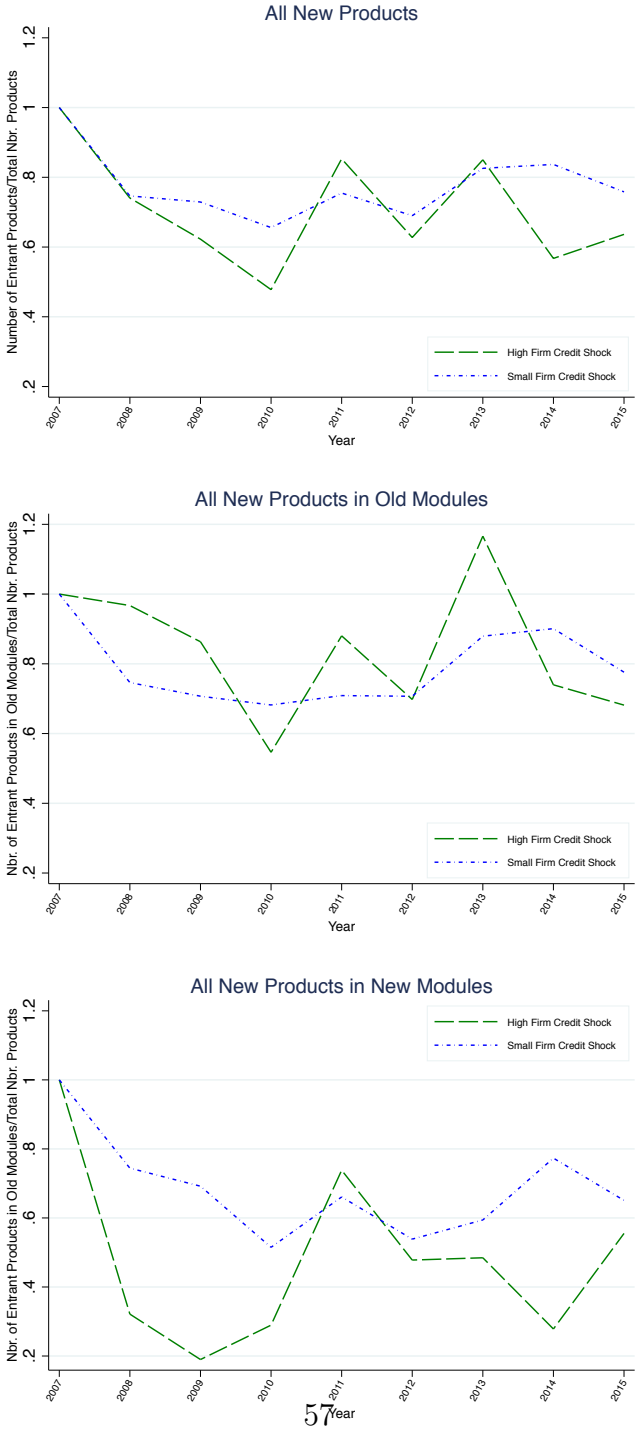


Figure IA.4: : Product Innovation and Credit Market Disruption: Entry Rate (Firm-Level Analysis)

Figure IA.4 plots the evolution of the average firm propensity to introduce products during a calendar year over time. The propensity to introduce products during a calendar year is defined as an indicator variable that takes the value of one if a firm introduces a new product during the calendar year. The green (blue) line represents the evolution of the of the average firm propensity to introduce 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 firm propensity to introduce products new products of all types. The second plot represents the evolution of the average firm propensity to introduce new products in product modules where the firm already operated. The plot on the bottom represents the evolution of the average firm propensity to introduce 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.

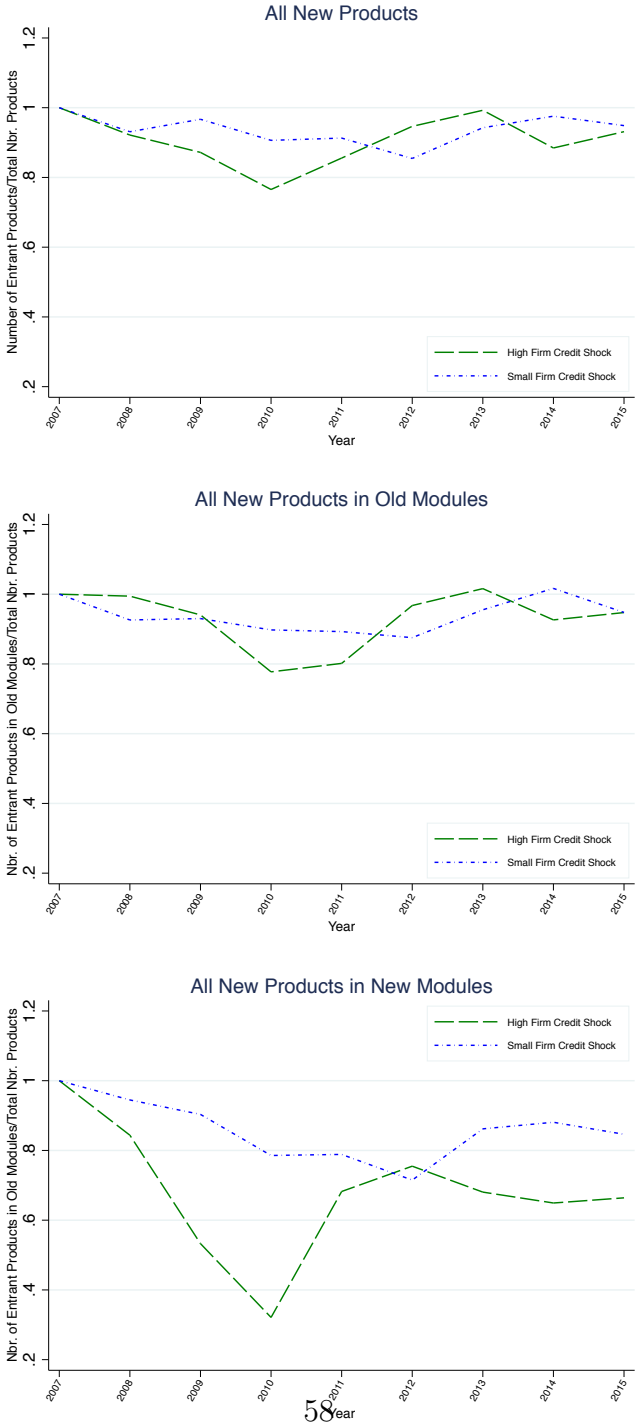
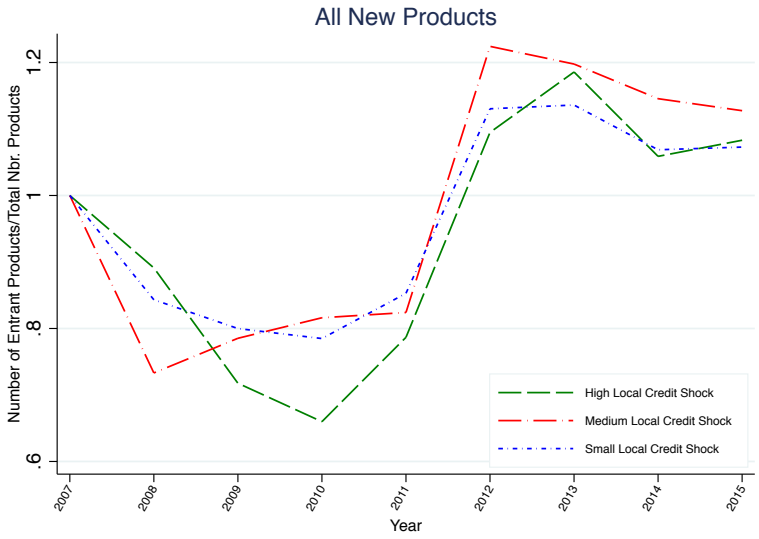
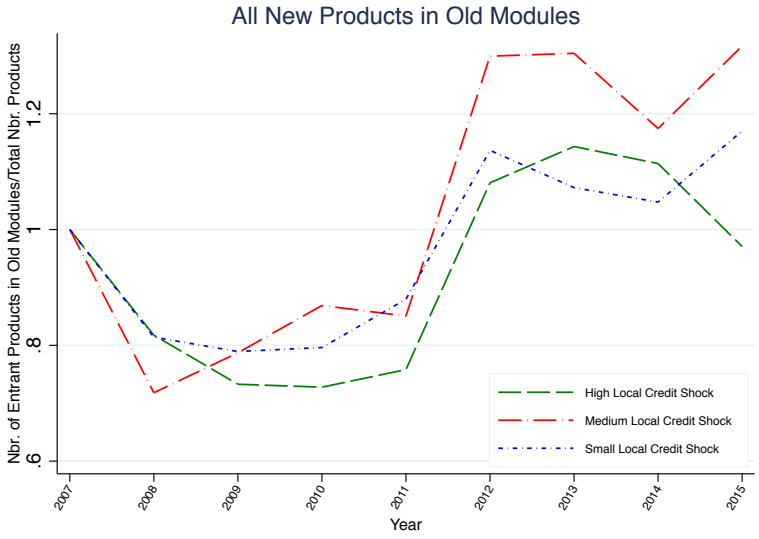


Figure IA.5: : Product Innovation and Credit Market Disruption: Entry Rate (Brand-Level Analysis)

Figure IA.5 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.





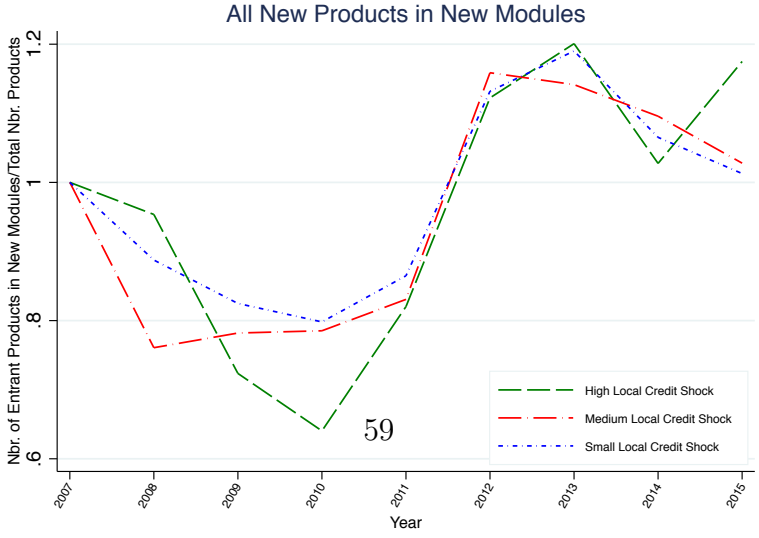


Table IA.1: Product Innovation and Credit Market Disruption (Dummy Variable Introduction of New Products)

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 natural logarithm of the firm's total sales in the previous year. 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)	0.001	-0.001	0.031	0.029	-0.030**	-0.031**
	(0.018)	(0.022)	(0.034)	(0.036)	(0.012)	(0.012)
Ln(Firm Revenue)		0.022***		0.019***		0.007**
		(0.004)		(0.003)		(0.002)
Observations	100958	100958	100958	100958	100958	100958
Adjusted R^2	0.435	0.438	0.438	0.441	0.229	0.229
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	-0.073*	0.015	0.001	-0.130*	-0.140**
	(0.034)	(0.035)	(0.039)	(0.042)	(0.058)	(0.060)
Ln(Firm Revenue)		0.033***		0.036**		0.018
		(0.010)		(0.014)		(0.010)
Observations	1744	1744	1744	1744	1744	1744
Adjusted R^2	0.531	0.532	0.580	0.581	0.347	0.347
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 natural logarithm of the firm's total sales in the previous year. 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)	0.008	0.005	0.043	0.042	-0.037**	-0.039**
	(0.062)	(0.065)	(0.072)	(0.074)	(0.013)	(0.014)
Ln(Firm Revenue)		0.051***		0.048***		0.007*
		(0.010)		(0.009)		(0.004)
Observations	100958	100958	100958	100958	100958	100958
Adjusted R^2	0.697	0.701	0.712	0.715	0.304	0.304
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	-0.032	0.076	0.059	-0.174*	-0.193**
	(0.100)	(0.105)	(0.095)	(0.100)	(0.080)	(0.081)
Ln(Firm Revenue)		0.058***		0.045**		0.021
		(0.011)		(0.019)		(0.016)
Observations	1744	1744	1744	1744	1744	1744
Adjusted R^2	0.890	0.891	0.903	0.904	0.447	0.447
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 natural logarithm of the firm's total sales in the previous year. 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)	-0.023	-0.024	0.006	0.006	-0.026***	-0.026**
	(0.018)	(0.019)	(0.011)	(0.011)	(0.008)	(0.008)
Ln(Firm Revenue)		0.007**		0.003*		0.003**
		(0.003)		(0.001)		(0.001)
Observations	99046	99046	99046	99046	99046	99046
Adjusted R^2	0.230	0.233	0.152	0.154	0.177	0.178
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	-0.042**	0.010	0.007	-0.038***	-0.048***
	(0.016)	(0.017)	(0.025)	(0.025)	(0.009)	(0.011)
Ln(Firm Revenue)		0.022		0.014*		0.007
		(0.015)		(0.008)		(0.015)
Observations	1708	1708	1708	1708	1708	1708
Adjusted R^2	0.190	0.192	0.171	0.177	0.168	0.167
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 $SBL\ Shock_{c,t} = -\sum_b (\gamma_{\hat{b},t} \times s_{b,c}^{t-1})$. *I(Crisis)* is an indicator variable that takes the value of one for the crises years: 2008, 2009, and 2010. *Ln(Firm Revenue* is natural logarithm of the firm's total sales in the previous year. 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	0.065***	0.064	0.016	0.015	0.032	0.032
	(0.014)	(0.117)	(0.098)	(0.096)	(0.022)	(0.022)
Local Credit Shock × I(Crisis)	-0.129	-0.133	-0.021	-0.023	-0.073**	-0.074***
	(0.176)	(0.106)	(0.100)	(0.092)	(0.022)	(0.018)
Ln(Firm Revenue)		0.025***		0.016***		0.006**
		(0.006)		(0.004)		(0.002)
Observations	100958	100958	100958	100958	100958	100958
Adjusted R^2	0.260	0.264	0.224	0.227	0.166	0.168
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 investigating 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 (brands) that a firm introduces during a year in new product module 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. The idea is that exposure to idiosyncratic bank supply shocks between 2005 and 2008 should *not* explain product innovation during the crisis period. *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. The idea is that exposure to idiosyncratic bank supply shocks between 2011 and 2014 should *not* explain product innovation during the crisis period. *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. The idea is that exposure to idiosyncratic bank supply shocks between 2012 and 2015 should *not* explain product innovation during the crisis period. *I(Crisis)* is an indicator variable that takes the value of one for the crises years: 2008, 2009, and 2010. *Ln(Firm Revenue* is natural logarithm of the firm's total sales in the previous year. 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	-0.000				
	(0.023)	(0.023)				
Local Credit Shock (2011–2014) × I(Crisis)			-0.025	-0.024		
			(0.024)	(0.025)		
Local Credit Shock (2012–2015) × I(Crisis)					-0.012	-0.012
					(0.028)	(0.028)
Ln(Firm Revenue)		0.006**		0.006**		0.006**
		(0.002)		(0.002)		(0.002)
Observations	100958	100958	100958	100958	100958	100958
Adjusted R^2	0.166	0.168	0.166	0.168	0.166	0.168
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 natural logarithm of the firm's total sales 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: 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	-0.091	-0.030	-0.030	-0.037**	-0.040***
	(0.055)	(0.055)	(0.051)	(0.049)	(0.012)	(0.010)
Ln(Firm Revenue)		0.024		0.025		-0.004
		(0.031)		(0.015)		(0.011)
Observations	982	982	982	982	982	982
Adjusted R^2	0.272	0.276	0.294	0.300	0.212	0.216
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*	-0.108*	-0.037	-0.037	-0.042***	-0.043***
	(0.055)	(0.055)	(0.047)	(0.044)	(0.012)	(0.010)
Ln(Firm Revenue)		0.024		0.025		-0.004
		(0.031)		(0.015)		(0.011)
Observations	982	982	982	982	982	982
Adjusted R^2	0.273	0.277	0.294	0.300	0.213	0.216
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. *Cnty Inc. pc* is the income per capital of the residents of the county where the firm's headquarters is located. *Ln(Firm Revenue* is natural logarithm of the firm's total sales 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)	-0.030	-0.034	0.002	-0.000	-0.028***	-0.029***
	(0.031)	(0.035)	(0.038)	(0.040)	(0.008)	(0.009)
Ln(Unemployment Rate)	-0.049**	-0.044**	-0.009	-0.006	-0.027***	-0.026***
	(0.020)	(0.018)	(0.015)	(0.015)	(0.005)	(0.005)
Cnty Inc. pc	-0.000***	-0.000***	-0.000**	-0.000**	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Ln(Firm Revenue)		0.025***		0.016***		0.006**
		(0.005)		(0.003)		(0.002)
Observations	100251	100251	100251	100251	100251	100251
Adjusted R^2	0.260	0.264	0.224	0.227	0.167	0.168
Year Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes

Table IA.8: Credit Market Disruptions and Novelty of Product Innovation (Alternative Fixed-Effects Structures)

Table IA.8 reports the coefficients of OLS regressions investigating the effect of credit market disruptions on firms' decisions to launch new products on 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 natural logarithm of the firm's total sales 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)	(7)	(8)	(9)
	Novelty Index			Novelty Index (Combination)			Novelty Index (Hedonic)		
Local Credit Shock × I(Crisis)	-0.040***	-0.046***	-0.046**	-0.060***	-0.067***	-0.075***	-0.094***	-0.119***	-0.130***
	(0.011)	(0.013)	(0.016)	(0.012)	(0.013)	(0.016)	(0.023)	(0.024)	(0.035)
Ln(Firm Revenue)	-0.002	-0.002	-0.002	-0.003	-0.003*	-0.003	-0.003	-0.003	-0.003
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.004)
Observations	29691	29651	27811	29691	29651	27811	26936	26898	25050
Adjusted R^2	0.333	0.339	0.357	0.390	0.393	0.404	0.346	0.352	0.357
Firm Fixed-Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Department × Year Fixed-Effects	Yes	Yes	Yes	No	No	No	No	No	No
Prod. Group × Year Fixed-Effects	No	No	No	Yes	Yes	Yes	No	No	No
Prod. Module × Year Fixed-Effects	No	No	No	No	No	No	Yes	Yes	Yes

Table IA.9: Credit Market Disruptions and Novelty of Product Innovation – Large Share of Sales Outside Home State

Table IA.9 reports the coefficients of OLS regressions investigating the effect of credit market disruptions on firms' decisions to launch new products on 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 natural logarithm of the firm's total sales 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)	(7)	(8)	(9)
	Novelty Index			Novelty Index (Combination)			Novelty Index (Hedonic)		
Local Credit Shock × I(Crisis)	-0.030*	-0.028*	-0.022	-0.044***	-0.042***	-0.040**	-0.064*	-0.065*	-0.075
	(0.014)	(0.015)	(0.018)	(0.009)	(0.010)	(0.016)	(0.033)	(0.031)	(0.046)
Ln(Firm Revenue)	-0.001	-0.001	-0.003	-0.002	-0.003	-0.005*	-0.002	-0.002	-0.006
	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)	(0.002)	(0.003)	(0.003)	(0.004)
Observations	19260	18316	11448	19260	18316	11448	16981	16102	10140
Adjusted R^2	0.328	0.328	0.323	0.398	0.398	0.381	0.326	0.326	0.325
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%	>95%	>66%	>75%	>95%	>66%	>75%	>95%