New Products*

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March 2021

Abstract

We introduce a new measure of innovation based on important product launches by public firms in the US. Our measure is based on stock-market reactions to media articles – classified by a convolutional neural network approach as referring to new product introductions – and has two distinct advantages. First, it covers the entire spectrum of industries and is not limited to products sold by retail firms. Second, we rely on collective wisdom about product value expressed through financial markets. This lends a forward-looking aspect to our measure, and helps avoid issues associated with valuing new types of output in a changing economy. Using our measure, we derive a few stylized facts. We show that product innovations are highly persistent, both at the firm- and at the industry-level. Firms that launch more new products are larger, and they typically operate in industries that are more competitive. New product introductions correlate with productivity measures at the aggregate level. However, most of these new products are launched in industries that are not among the largest employers; moreover, employment falls further following product launches.

Keywords: New Products, Innovation, Competition, Labor Share, Productivity

JEL Classification: D24, E01, E24, O31

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1 Introduction

This paper introduces a new way to value product innovation by public firms. While R&D expenditures quantify innovation inputs and granted patents capture intermediate innovation output, we instead focus on new product announcements, which pertains to the final stage of innovation and directly affects consumers.

Our approach is based on a forward-looking way of measuring the market value of new product introductions. We first extract all media articles from Dow Jones' Factiva database that involve firms traded on US stock exchanges, and that Factiva has filed under New Products/Services category over 1989-2015. Next, we classify these articles using a convolutional neural network approach. We then estimate abnormal returns on the mentioned firm's stock in the two days surrounding the publication of the media articles, and consider only those firms with a positive stock price reaction. This ensures that our procedure captures new product releases that are important enough to move firms' stock prices.

The advantages that our measure brings in are as follows. First, our approach covers all industries in a systematic way. While separate industry-specific studies can capture new product introductions in that industry, e.g., by using scanner data in the retail sector or FDA data for pharmaceuticals, our measure enables cross-industry comparisons in product innovation in a broader way, allowing future research to explore a more complete link to the macroeconomy. This approach, given its reliance on media sources, is also able to capture the new product introductions that are not directly observed by the end consumer, i.e, those occurring in the B2B sector. Second, it is challenging to identify important innovation. We rely on financial markets to value the expected profitability of new products or services, which lends a forward-looking aspect to our approach. Using such a market-based measure of value also helps avoid typical issues associated with measuring changing sources of value in the new economy (e.g., the difficulty in valuing services an economy derives from, say, Uber or Facebook). Our measure is flexible in that sense – it allows the *market* to estimate a profitability measure for any type of good, service, or activity that might be useful to the economy. To the extent that expected profits for the innovating firm reflects the aggregate willingness-to-pay for that good or service by consumers, short-horizon returns around product launches can be thought of as a measure of the value created by that particular innovation.

Armed with this method to capture new product introductions, we explore the landscape of product innovations in the US economy in the last 25 years. We study general trends, and derive stylized facts. In general, we see that there has been a growth in new products over time with a small slump in early 2000s and after 2010. We also see that the distribution of top innovating industries and states have been changing over time with California notably increasing in importance in the geography of new product introductions.

Next, we study firm and industry characteristics that are correlated with new product introductions. We examine five different aspects our measure can be useful for. First, we study whether our new products measure is correlated with other measures of innovation, such as patents or R&D. Second, we try to disentangle the importance of the firm versus the industry in innovation. Third, we study how new products relate to the competitiveness of the industry. Fourth, we derive a few facts on the correlation of new products with productivity at the economy, industry, and firm level. Fifth, we look at implications for the labor market.

Looking at either firm- or industry-level, we find that our measure is positively associated with other, more traditional measures of innovation, such as R&D expenses, patents, and their citations. We find that the correlation between new products and patents or R&D is the highest when these traditional measures are lagged by two or three years. This is consistent with the time it takes to productize the research conducted.

We then explore the persistence in product innovation. Like other measures of innovation, new product launches are also highly persistent. First, we look at variance decomposition and we find that about 38-43% of the variability of new products at the firm-level are explained by firm fixed effects alone, while industry trends (industry x year fixed effects) explain an additional 7%. Second, the probability of a firm in the top quintile of product innovators in some year staying in the same quintile next year is 52%. This is consistent with the rise of superstar firms in the economy – if highly innovative firms keep coming up with more and more profitable new products, in a way unmatched by other, less innovative, firms, it is perhaps not surprising to observe the former group of firms to grow larger and larger in the economy overall. Indeed, when we study firm characteristics, we find that firm size and its profitability are the key variables that correlate positively with new product introductions, even after accounting for firm fixed effects.

Next, we examine the relationship between product market competition and our measure of innovation. We find that more new product launches occur typically in more competitive industries. This is, again, consistent with the notion that continuous innovation is one strategy that firms adopt in the face of increasing product market pressure (see e.g., Hart (1983)). Moreover, we find that there is some clustering in product introductions, that is, new products typically get launched by multiple industry rivals at the same time.

We then turn to examining the association between product launches and productivity. Our new products measure is positively correlated with traditional productivity measures, consistent with theoretical models such as Klette and Kortum (2004). This motivates us to examine if our measure can help shed light on popular explanations of the slowdown in productivity growth in the last decade.

At least three explanations behind such a slowdown have featured prominently in the media.[1] First, the slowdown could be related to a real secular decline in productivity-enhancing innovative ideas. As important innovations from the past decade, e.g., micro-processing technology, reach maturity, their contribution to growth might be tapering off, leading to the slowdown. Our measure can directly speak to such hypotheses concerning such a general slowdown in ideas, which should be reflected in fewer or less valuable product launches. Second, the productivity slowdown could occur because the changing nature of

[1] See, e.g., `https://nyti.ms/1TgrJVD`

the economy has increased noise in the existing productivity measures. Our measure can contribute by capturing innovations in sectors that traditional measures might overlook. Third, the slowdown might reflect a time of transition, when the economy in aggregate is making investments that will take time to show their positive effects. Again, our new product measure might help, as it is explicitly designed to capture inventions in a forward-looking way.

We find that product innovation shows no signs of a secular decline, unlike aggregate productivity. So our evidence does not support the first explanation above – the US economy seems to be creating new products valued by the economy at the same pace as before if not faster, at least until 2015. Our evidence then seems more consistent with the slowdown being related to existing measures of productivity somehow missing out on new products that have been launched in the recent few years. One possible reason behind this could be the changing nature of new products that society finds valuable today. While traditional, e.g., TFP-based, productivity measures might be able to capture the growth of, say, automobiles or television sets, they may not be appropriate when it comes to measuring services provided by Facebook or Tripadvisor. If these companies are publicly listed, however, the stock market might be able to value their products and services. Still, there is no easy way to use our measure to directly shed light on the mis-measurement explanations above.

We conclude by considering the effects of product innovations on the labor market. The high pace of innovation in recent times, and its concentration among a few firms, has been accompanied by concerns about equitable sharing in the new economy. We focus our attention on the distribution of innovation with regard to labor-intensity. We find that new products exhibit negative correlation with the number of employees, the number of production employees, or their hours worked. The monetary rewards from product innovation, then, are unlikely to accrue to labor.

We also examine employment in industries following product launches, and find that new product launches are negatively correlated with future employment. Overall, our labor results suggest that product innovations in today's economy are occurring mostly in capital-intensive sectors; moreover, a lot of these innovations themselves are labor-saving in nature. This is consistent with concerns regarding the replacement of human labor in the path to growth paved by technology (see, e.g., Karabarbounis and Neiman (2013), or Elsby et al. (2013)).

Our paper contributes to an extensive literature on the measurement of innovation. Studying innovation as a process has its origins in Adam Smith's *Wealth of Nations*. The specific focus on US companies that have come up with important innovations has its origins in the 1960s (see, e.g., Scherer (1965) or Scherer (1983)). Many papers have studied the determinants of innovation in both the economics and finance strands of literature, using various measures of scientific value, the most popular ones being the number of patents and forward citations of firms' patents (see, e.g., Griliches (1998) for a survey of their use in various papers in economics).

One common critique of the use of patent-based measures as a proxy for innovation is that firms have a choice whether to patent their innovation or to keep it secret and rely on informal protection of their intellectual property (see Hall et al. (2014) for a survey on this trade-off). Similarly, firms face a choice whether to report their R&D separately or group it together with other operating expenses. As documented by Koh and Reeb (2015), many firms report missing R&D expenses even though they clearly invest in innovation, as evidenced by their subsequent patent filings.

A few other novel ways of measuring innovation have also been considered, for example, in Shea (1998), who uses direct measures of innovation to construct new measures of technology shocks. Alexopoulos (2011) also presents new measures of technical change based on books published in the field of technology. More recently, Bellstam et al. (2020) develop a new measure of innovation using textual analysis of analyst reports on large firms, which can capture innovation by firms with and without patenting and R&D.

The main difference between our paper and these studies lies in our focus on measuring product innovations directly, and in accounting for the economic value of such innovations by linking their announcement to stock market returns.

Our paper is certainly not the first one to link equity market valuations to innovation. Pakes (1985) provides an early contribution examining the relation between patents and the stock market rate of return. Chaney et al. (1991) study new product introductions over 1975-1984 and find an average stock price reaction of 0.75% over a 3-day window. Austin (1993) uses an event-study approach to value biotech innovations, while Sood and Tellis (2009) study five industries in electrical products. Chen et al. (2005) show a negative stock price effect on rivals. The relation between scientific measures of innovation and their economic value has also been explored more broadly by Hall et al. (2005) and Nicholas (2008), who document that firms with highly cited patents have higher stock market valuations. Harhoff et al. (1999) and Moser et al. (2011) show that the scientific value of innovation is positively related to its economic value. Abrams et al. (2013) use a novel dataset of licensing fee-based patent values, and show that the relation between values and citations is non-monotonic. Closer to our paper, Kogan et al. (2017) create a novel measure of economic importance of innovations based on stock market reactions to patents. Our paper contributes to this literature broadly, but differs from it in its focus on the value of *product* innovations, the final stage of innovation that directly reaches the consumer. This difference is also important in the light of many theoretical models of innovation and growth, where innovation is modelled as an expansion of the *product* space, but typically proxied using patents or citations when testing model predictions in the data.

Finally, it is important to caveat a few limitations of our measure. First, we do not capture products or services launched by private firms, for whom we do not have stock price data. This is a major disadvantage because innovation by private firms can also be very substantial, especially since more recent years have witnessed firms waiting longer before listing publicly amid a growth in the supply of private capital. While it is possible to extend the logic of our measure to counting new products launched by these private firms, it will be difficult to come up with a measure to derive their value to the economy in the absence of stock price data. Second, we only capture the private returns to innovation, i.e., any possible spillovers to other firms or the benefits of technological change that are passed on to consumers and not internalized by producers (Nordhaus, 2004) are not captured by our measure. Third, one might be concerned that we rely on the assumption of efficient capital markets and assume that on average stock price reaction reflects the rational expectation of the firm's future cash flows from innovation. In most of the tests we rely on the cross-sectional differences in stock price reactions, which mitigates the concern of such a systematic bias. We leave it for future research to explore these avenues.

2 New Products

In this section we describe how we track new product introductions in more detail.

We first extracted all media articles from the Dow Jones Factiva database that involve firms traded on US stock exchanges (NYSE, NASDAQ, AMEX). We focused on articles that Factiva has filed under New Products/Services category over 1989 July-2015 May. We started with 660,958 articles. We then only keep the announcements where the listed firm appears within the title or the first 50 words of an article, so that we can be sure that the product refers to that firm. That left us with 326,398 articles involving 16,278 distinct firms.

In order to classify these articles into those that truly are first mentions of new products versus those that are not (for example, references to earlier product launches in analyst reports justifying high firm earnings), we employed a convolutional neural network (machine-learning) approach. We sourced the labeled training data from undergraduate students, employing a custom-built visual interface in the form of an app on their mobile phones.

In total, 31 students were asked to classify 2,000 articles each in a binary fashion indicating whether each article presented to them discusses a major new product introduction. The students were asked not to consider cases such as a minor update of an existing product (especially, software), or a repeated presentation of the product at a trade show. Furthermore, they were asked to judge these articles from the perspective of that year, that is, to avoid any look-ahead bias. We randomly assigned each article to two separate students. Keeping only the articles where both students agreed on their classifications we ended up with a final training set containing 15,160 labeled articles out of which 3,762 were judged to be truly about new product or service mentions.[2] The remaining articles in the sample were classified using Google's pre-trained Word2Vec word embeddings. The final k-fold out-of-sample results give us a precision (ratio of true positives) of 93% and a recall (ratio of positive articles found) of 86%, thus giving an F1 score of 89%. That included 79,444 distinct announcements.

In our next critical step, we estimated abnormal returns on the mentioned firm's stock on the day of the release of the article (where expected returns were calculated based on the market model) in order to assign market value of the patent. This approach is similar to the one taken by Kogan et al. (2017) to value patents. Linking announcements to their stock market value ensures that we have a market-based measure of product value, which is both forward-looking in nature (given that the stock market's reaction to an announcement accounts for all future profits or losses from it), and avoids issues associated with the researcher figuring out what type of product actually adds value – be it an app or an appliance.

Finally, we excluded days if the firm in the article announced earnings or an M&A transaction on that day (including one day before and one day after for both events) as these major events might confound our estimates.

[2] The students agreed on 76% of cases whether the news constitute a new product announcement, suggesting a relatively high rate of consistency. We have also monitored the time the students have spent on average on the tasks, and we do not find statistically significant correlation between average time spent and the eventual agreement with the peer.

3 Stylized Facts: Patterns in Product Innovation

3.1 General Trends

We first present general trends in new product introductions. Table 1 presents summary statistics. We start with an event-level analysis in Panel A. First, we present the cumulative abnormal returns over two-day window (0,1) after the announcement. We see that the mean return for these 79,444 announcements over 1989-2015 hovers around zero. After we condition on these returns being positive, we are left with 40,099 announcements with the mean two-day return of 3.1% and an average market value added of $187m US dollars for each new product. This assures us that we are not capturing inconsequential innovations.

In Table 1, Panel B, we aggregate these values at the firm level for each year and this results in 24,123 firm-year observations with new products, conditional on the positive two-day abnormal return. That also means that firms that have new products in a particular year have on average 1.8 products in that year, with the maximum being 58. The mean total two-day abnormal return for these 1.8 products is 5.1% and the market-value added is $310m US dollars per firm per year. This shows that our measures are likely to capture innovation that is of substantial value to the innovating firm.

Figure 1 depicts aggregate trends in these four values over time. Across all graphs we see an increase over time, leading until 2001 and then a drop until 2003. We see the further run up stretching until 2008 and then a gradual levelling off.

Notably, across these four graphs we see some differences in how we incorporate the information on stock price reaction to screen out the important new product announcements. In the top left panel, we do not condition on the two-day abnormal returns being positive, thus we do not take into account how the stock market perceives the outcomes. In this way, we also capture the cases when the stock market did not consider the announcement as a major innovation. When we condition on the two-day abnormal returns being positive and report the trends in top right panel, we see that the the number of identified cases falls to half.

That said, the overall aggregate trends remain similar over time, suggesting that we are not simply capturing secular market misvaluation differences. Further, in the bottom left panel, instead of counting new products, we aggregate cumulative abnormal returns, conditional on them being positive, and we see steeper reactions before dotcom boom period and pre-2009. Finally, in the bottom right panel, instead of aggregating percentage returns, we plot the aggregated dollar market-value added conditional on the two-day abnormal returns being positive. We see the largest spike around the dotcom boom period, possibly because this measure is highly dependent on the level of the innovating firm's stock price.

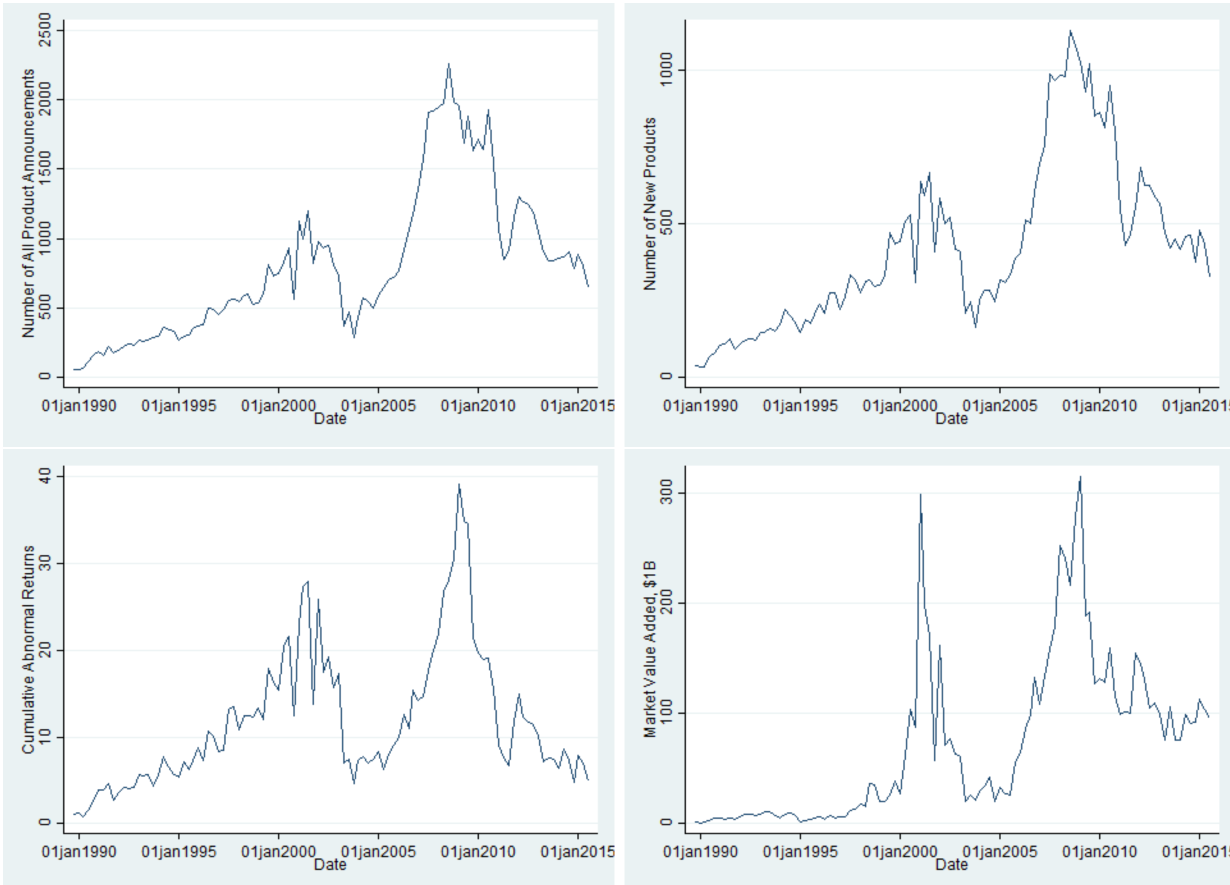
Given that the second and the third measures balance this trade-off, taking stock market reaction into account while mitigating the influence of misvaluation, we focus on them in our further analysis. We start by examining a few summary statistics of these two measures in the full sample (including the years or firms where new products are not introduced) in Table 1. Panel A shows that a typical new product announcement is associated with a 30 basis point announcement-day return. Panel B shows that conditional on having a new product, the average firm introduces 1.82 products per year. Panel C, we see that the average number of new products per firm-year is 0.234, suggesting that on average one firm in six introduces a new product in a typical year. In total, our dataset includes 5,224 distinct firms that have launched at least one new product by our measure.

While with our stock price reaction screening we mitigate the concern that the trends that we observe might be related to changes in the media coverage of firms over time, in all our regression specifications we will also control for time fixed effects where we will assume that any coverage changes are not systematic across firms and industries.[3]

Looking at the aggregate trends, a related concern could be that we are capturing general market overvaluations, especially in the periods where firms were releasing products that eventually had low social value, e.g., the dotcom boom period. In Figure 2, we overlay the

[3]Another alternative would be to scale the number of new product announcements by the extent of media coverage about the firm. However, this method would assume that the ratio of new product coverage to total media coverage is constant across firms, which is unlikely to be the case.

Figure 1: Aggregate Trends of New Products

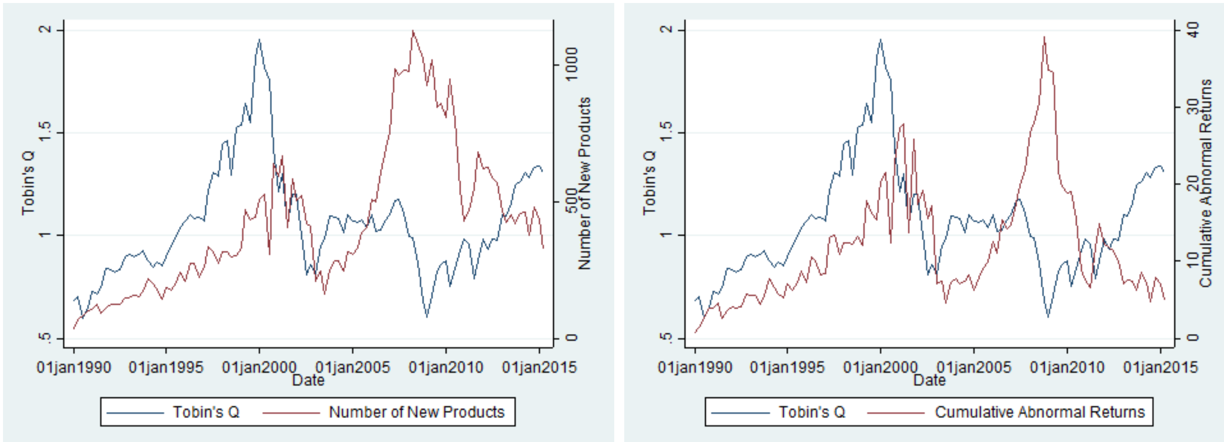


Notes: This figure represents new product announcements in the US for each quarter for years 1989-2015. New products are measured as the number of new product announcements, not conditional on the two-day abnormal returns being positive (top left panel), the number of new product announcements conditional on the two-day abnormal returns being positive (top right panel), cumulative abnormal returns, conditional on them being positive (bottom left panel), and dollar market-value added conditional on the two-day abnormal returns being positive (bottom right panel).

number of new product introductions in our sample and the aggregate Tobin's Q, which captures the market value over the replacement value of the economy's assets. We see little overlap in two graphs, possibly because Tobin's Q is more sensitive to stock market valuation cycles than our return-based measure. Aggregate Tobin's Q is lower today than in the late 1990s, although the launch of new products does not follow this pattern, leading to the low correlation we observe.

Next, we compare new product trends to net investment trends. In Figure 3, we see that

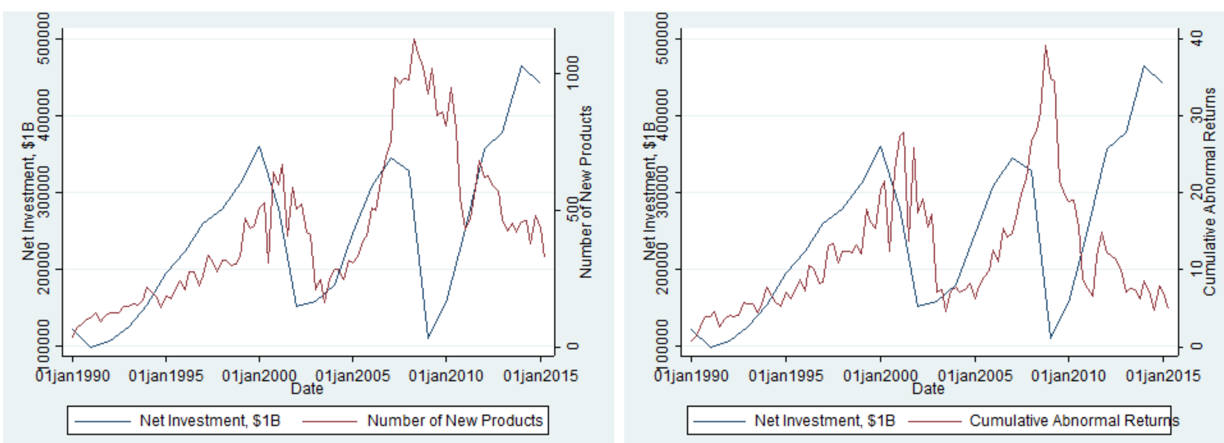
Figure 2: Tobin's Q and New Products



Notes: This figure represents new product announcements in the US for each quarter and Tobin's Q for years 1989-2015. New products are measured as the number of new product announcements in the left panel and the cumulative abnormal return in the right panel, Tobin's Q is extracted from from FRED database and constructed as (Ve + (L FA) − Inventories) / PkK, where Ve is the market value of equity, L are the liabilities, FA are nancial assets, PkK is the replacement cost of capital.

while in the 2000s net investment leads new product introductions, such a relationship does not seem to be present in the earlier period.

Figure 3: Aggregate Investment and New Products



Notes: This figure represents new product announcements in the US for each quarter and aggregate investment for years 1989-2015. New products are measured as the number of new product announcements in the left panel and the cumulative abnormal return in the right panel, aggregate investment is extracted from from FRED database and constructed as Gross fixed capital formation minus consumption of fixed capital in $1m (series NCBGFCA027N minus NCBCFCA027N).

Finally, we look at how new products are distributed across different US states, and in particular we examine how the geography of innovation has been changing in the US over the last 25 years. Figure 4 shows separate heat maps of firm headquarters that launched new products in 1989-1995, 1996-2000, 2001-2005, 2006-2010, and 2011-2015. As we can see from the figure, California has become increasingly important for innovative firms over time, perhaps as a reflection of the importance of technology in aggregate innovations over this period.

3.2 Industry Dynamics and Top Innovating Industries

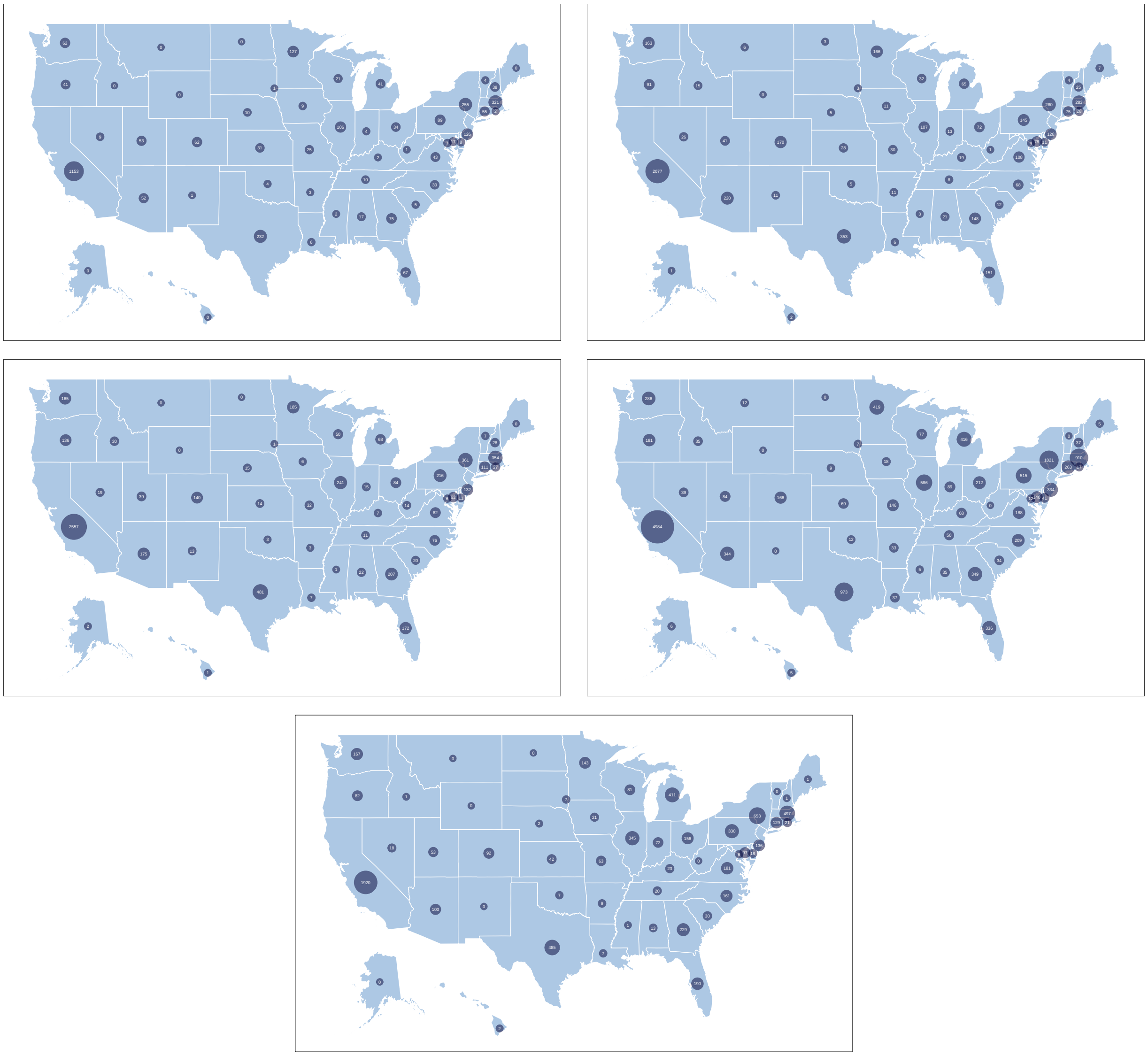
We next report the trends across a few major GICS (Global Industry Classification Standard) sectors: Health Care (GICS sector 35), Information Technology and Communication Services (GICS sector 45 and 50), Financials (GICS sector 40), and the rest grouped together. We report the trends for these four separate groups in Figure 5.

We also report top SIC 4-digit industries with major products in Table 2. We do so separately for each five-year window, starting in 1989. While electronic computing equipment and services-computer programming seem to be major innovating industries in all periods, many industries have changed. Notably, motor vehicles were one of the top innovating industries in the early period, then dropped from the top list, and came back again recently. Also, traditional labor-intensive industries, such as fast-moving-consumer-goods (FMCG) industries, that figured among major innovators in the early 1990s, have since dropped out of the list, being replaced mostly by technology-related sectors.

3.3 Other Innovation Measures

We now examine how our new products measure correlates with the other innovation measures. We consider innovation input such as R&D investments and intermediate output such as patents and the count of forward citations of these patents in other patent filings. Patent citations are commonly perceived as capturing the quality of the innovation, since higher

Figure 4: Geographic Distribution Over Time

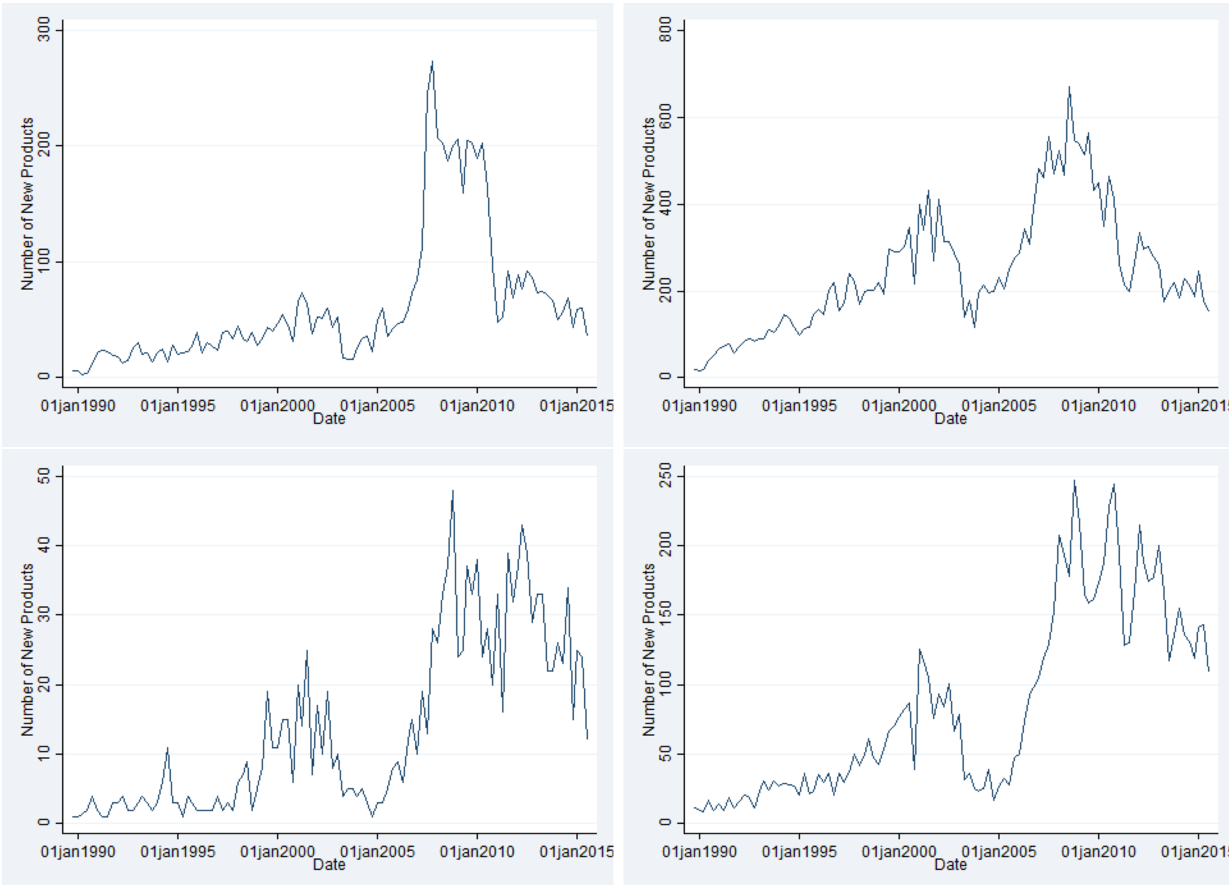


Notes: This figure represents the total number of new product announcements in different US states in years 1989-1995 (top left panel); 1996-2000 (top right panel); 2001-2005 (middle left panel); 2006-2010 (middle right panel); and 2011-2015 (bottom panel).

impact patents are likely to be cited more.

In Table 3, we consider industry aggregates constructed using these measures at the SIC 4-digit level. We examine the contemporaneous correlation of the number of new products (Panel A) and cumulative abnormal returns (Panel B) with R&D and patents. Columns (1), (3), and (5) only consider year fixed effects while columns (2), (4), and (6) also control for

Figure 5: Differences Across Sectors



Notes: This figure represents new product announcements in the US across different economic sectors for each quarter for years 1989-2015. New products are measured as the number of new product announcements conditional on the two-day abnormal returns being positive. Top left panel corresponds to Healthcare, top right panel corresponds to Information Technology and Communication Services, bottom left panel corresponds to Financials, and bottom right panel corresponds to Other Sectors.

industry fixed effects. We see that when industry fixed effects are not accounted for, new product measures correlate positively with the other innovation variables. This suggests that industries differ in their innovative capacity.

However, when industry fixed effects are controlled for, only the number of patents is contemporaneously positively related with new products, which is likely driven by the trend that the industries which are introducing new products are also investing into the follow up innovation at the same time. On the other hand, there is no robust correlation between new product introductions and either the R&D or patent citations at the industry level. In fact, if anything, in the years with high new product introductions, firms file patents with fewer forward citations. One explanation consistent with this observation is that new product launches indicate maturity of the innovation process.[4]

Next, we directly explore the life cycle of innovation at the industry level. The typical cycle is likely to consist of the following steps: Firms invest into R&D and following the successful investment, they file patents that eventually lead to the new products. Seeing the success of the introduction of new products, firms follow up with the successive R&D but patents lag by a few years when this R&D materializes. Our measure of the final new products allows us to shed light on such a life-cycle of innovation directly. In Table 4, we examine this hypothesis and we indeed see a lag between patents and new product introductions, and even a longer lag from R&D to new products.

We now extend this analysis to the firm level. We estimate a panel regression with firm and year fixed effects and report results in Table 5 for both the number of new products and cumulative abnormal returns. Consistent with Balasubramanian and Sivadasan (2011) who link patent stock to the product information in Census data, we find that at the firm level patents are related to new product introductions. Contrary to the evidence from the industry level specifications in Table 3, at the firm level, after we control for firm fixed effects, we also see a positive relationship between citations and new products as well as R&D and new products, suggesting substantial within industry heterogeneity of the innovation process that links R&D, patents, and new products.

3.4 Firm Determinants

In this subsection we focus on firm-level determinants of the new product introductions. We first examine how persistent new product innovations are. We approach this in two ways.

First, we look at variance decomposition and study how much of the annual variation in new products can be explained by various fixed effects. We look at three sets of fixed effects:

[4] All results in this table are also robust when controlling for the industry asset size.

SIC4 industry fixed effects; SIC4 industry trends captured by the industry x year fixed effects; and firm fixed effects. In the former and the latter cases, we also keep the year fixed effects to account for the economy-level variations. We present results in Table 6. In columns (1)-(3) of Panel A, we present the results for the number of products while in columns (4)-(6) we present the results for the cumulative abnormal returns. We see that industry and time fixed effects explain 12.7-16.9% variation in annual firm-level new products, and this improves to 21.5-25.9% if we consider industry trends. On the other hand, firm and year fixed effects explain 37.9%-43.3% of variation by themselves, suggesting that annual industry trends are not as important in explaining variation as time-invariant firm characteristics are.[5]

We repeat the same exercise for R&D and patents in Panel B to benchmark our findings for new products. We find that these three, i.e., time-invariant industry characteristics, time-varying industry-trends, and time-invariant firm characteristics explain nearly twice as much of the variation for patents and R&D, as for new products. For example, firm and year fixed effects alone explain 93.3% of variation in R&D and 84.3% for patents. This suggests that while firm-level investments in the innovation process are quite persistent over time, determining which firms are successful in converting this investment into new products is much less persistent over time.

Second, we confirm this trend by looking at the transition matrix. The probability that a firm ranked in the top quintile according to our new products measure across all firms in one year is also ranked in the top quintile in the following year is 52.1%. The respective figures for patents and R&D are 81.56% and 93.33%. This is consistent with our evidence in Table 6.

Our next step is to study which firm characteristics are correlated with new product introductions. We do it in Table 7 separately for the number of new products (Panel A) and cumulative abnormal returns (Panel B). We include firm fixed effects and year fixed effects, and study firm size (captured by firm sales), profitability (captured by gross margin), phys-

[5]When both firm and industry-year fixed effects are considered, R^2 rises to 45-50%.

ical capital factor (captured by property, plants, and equipment), innovative capital factor (captured by intangible assets), and labor factor (captured by the number of employees). For the number of new products, we see that when these firm characteristics are considered separately, all of these characteristics are positively related to new products, suggesting that larger and more profitable firms drive innovation output.[6] When all these variables are considered together, we see that product innovations seem to be more present at larger and more profitable firms *that use fixed assets less*. The correlation with the number of employees is not statistically significant while the relationship with property, plants and equipment is negative, suggesting a weak contemporaneous link to the traditional inputs of production function at the firm level. We observe similar findings for our second measure of new product introductions.[7]

3.5 New Products with No Patents and R&D

We further note that out of 5,224 firms for which we observe new product introductions, 1,978 have never filed patents during our sample period of 1989-2015 (based on the firm appearing either in Bena et al. (2017), or in Kogan et al. (2017) match), and 1,471 firms have not reported positive R&D expenditures. 981 firms (or 18.7%) with new product records have neither R&D expenditures, nor patents. This shows that patent- or R&D-based metrics might measure innovation with some noise, even for large public firms in the US.

When we compare these 981 firms that have new product introductions but do not have patents or record R&D expenditures to the rest of the firms that have new products, we do not see consistent differences in terms of observable characteristics. However, when we study patents and R&D separately (these univariate tests available on request), we see statistically significant differences in terms of size. Among firms with new product introductions, smaller firms are more likely not to have patents but larger firms are more likely not to report R&D.

[6] These results are also consistent with Balasubramanian and Sivadasan (2011) who find that patent stock is associated with firm size, scope, and skill and capital intensity.

[7] In separate tests we also see positive correlations with the firm age, measured as the time since the IPO, suggesting that mature firms are innovating more than younger IPO firms.

We also see some sectoral differences. Across sectors, we see that firms with new products in Information Technologies and Health Care have patents or report R&D, while firms in Industrials, Consumer Discretionary, and Financials Sectors are likely not to have patents and report R&D but still produce new products by our measures.

4 Stylized Facts: Industry and Economic Conditions

4.1 Competitive Environment

In this subsection we study whether there is any association between industry structure and the development of new products.

The relationship between innovation outcomes and industry concentration has been a subject of contentious debate in the literature. On the one hand, Hart (1983) has argued for a positive relationship between product market competition and technological investment, based on the premise that competition induces more managerial effort. Meanwhile, the literature as early as Schumpeter (1943) but also later contributions, including various models of endogenous growth (e.g., Romer (1990); Aghion and Howitt (1992)), have predicted that more intense product market competition discourages innovation by reducing resulting rents. Aghion et al. (2005) have combined the two sets of insights and suggested an inverse-U relationship where competition discourages laggard firms from innovating but encourages neck-and-neck firms to invest into research and development.

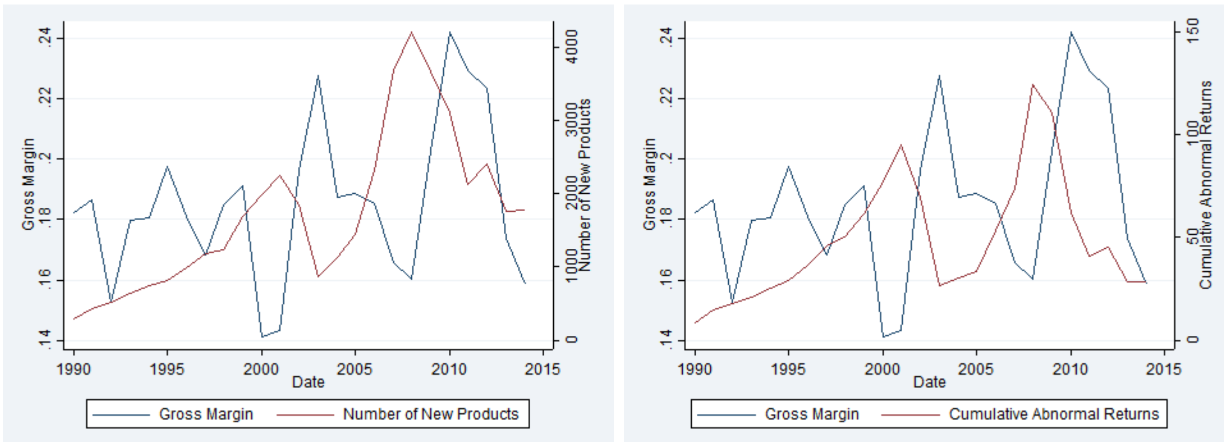
Empirical tests of these theories have also found conflicting results, mainly depending on the identification strategy used to establish the causal relationship, but also based on the measures of concentration and innovation used in different analyses.[8] In this paper, we contribute to this debate by documenting stylized facts – we do not claim any causality in the following analysis, just as in the rest of this paper.[9]

[8] See Gilbert (2006) for an extensive summary on the empirical findings.

[9] We also note our limitation that concentrated industries might not need to signal new product introductions with press releases as much as firms in the competitive industries, and this might affect the frequency

We first plot new product trends together with a proxy for markups – gross profit margins. In Figure 6, we see that new product introductions lead gross profit margin bumps, especially in the period after 2005.

Figure 6: Gross Profit Margins and New Products



Notes: This figure represents new product announcements in the US for each quarter and gross profit margins for years 1989-2015. New products are measured as the number of new product announcements in the left panel and the cumulative abnormal return in the right panel, Average gross profit margins are extracted from Compustat.

We next study the competitive environment within an industry and examine whether industry concentration is related to product innovation. We calculate a Herfindahl-Hirschman Index (HHI) based on the sales of publicly listed firms in each SIC3 industry, and perform panel analysis at the industry level, controlling for industry and year fixed effects, and industry size. Indeed, if we look at Table 8, columns (3)-(4), we see that contemporaneous HHI does not have a statistically significant relationship with patents, either captured with Bena et al. (2017) or Kogan et al. (2017) measures. Also, in columns (5)-(6), we see that contemporaneous HHI does not have R&D, either measured in log terms or scaled by industry sales. On the other hand, as reported in columns (1) and (2) of Table 8, our new product measures are negatively correlated with the concentration indices, suggesting that more new product introduction occurs in less concentrated industries.

of news mentions in the media.

Second, we perform the analysis at the firm level. We report results in Table 9. The literature has recognized that industry definitions based on SIC classifications might not be reflecting the degree of concentration in that industry since many firms compete in more narrow product markets. We then rely on the industry definitions based on the textual analysis of firm 10K product descriptions as provided by Hoberg-Phillips industry concentration database (Hoberg and Phillips (2016)). We use both the TNIC-3 HHI index and the total similarity score of the firm, where the latter reflects the scaled number of similar firms in the economy. For both of these measures we find consistent evidence that higher competition and more rival firms is positively related to new product introductions.

We further analyse the correlation of new product introductions within the industry. First, we study whether rival new product announcements is correlated with the firm's new product announcements. We define rivals in three ways. For the first two classifications, we rely on Hoberg-Phillips Text-based Network Industry Classification database, which provides pairwise similarity scores between firms according to their 10K product descriptions. In the first classification we consider all firms and calculate the weighted sum of rival new products where weights are the similarity scores as per Hoberg-Phillips database. In the second classification we take the unweighted sum of rival new product introductions but only consider rivals with similarity score of over 0.1, which is the top quartile similarity score as per Hoberg-Phillips database. Our third classification makes use of our own dataset. We define rivals based on their mentions in the news related to products in the same article in the Factiva dataset. For instance, this could be Samsung being mentioned in an article on the new product introduced by Apple. As these mentions are likely to be added by journalists, contrary to Hoberg-Phillips methodology this approach does not rely on the firm's own choice in mentioning certain product market rivals but not others. We use all news before we apply any filters and our machine learning algorithm and merge it with the stock market data. The similarity score is determined by the share of firm's news related to products that also mention a rival firm.[10] Similarly, to the first classification, rival new product announcements correspond to the weighted sum of rival new products where weights are equal to these similarity scores. Based on all three classifications, reported in Table 10, we find a strong correlation between firm's new product introductions and rival new product introductions in the same year. Overall, this evidence indicates a race to innovate in competitive industries.

We follow up this analysis by examining how concentration in the product market is associated with concentration in new product introductions at the industry level. For that purpose we take the number of new products of all firms in the SIC4 industry and calculate HHI index based on the number of new products that each firm introduces that year. As shown in Table 11, when we estimate such a measure and correlate it with the HHI based on firm sales, which is meant to capture industry concentration, we indeed find that more concentrated industries also have more concentrated products, i.e., fewer firms introduce them, and conversely there are more innovating firms in more competitive environments. This result holds even after controlling for number of firms in the industry and industry size. Our evidence shows that the distribution of sales maps into the distribution of product innovations at the industry level.

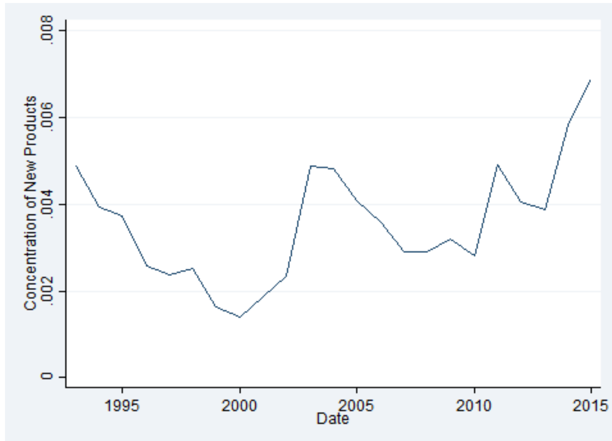
In fact, if we just plot the concentration of new product introductions in each year, in Figure 7, we see a downward trend until early 2000s, a rather flat level in mid-2000s, and an increase in concentration since 2010, suggesting only a recent appearance of superstar firms.

4.2 Productivity and Output

We now turn to linking the new product introductions to the productivity and output. Ongoing academic and policy discussion seems to suggest that productivity growth in the US, and in the rest of the world (see, e.g., Byrne et al. (2016) or Syverson (2017), is slowing. A growing perception is that this could be related to a secular decline. As productivity-enhancing innovations from the decade before, like computing technology, reach maturity,

[10] The correlation of our similarity score to that in Hoberg-Phillips database is 0.13.

Figure 7: Concentration of New Products



Notes: This figure represents the concentration of new product announcements in the US each year for years 1989-2015. Concentration index is calculated as the sum of the squared shares of new products that each firm has introduced in a year over the total number of new products in that year.

their contribution to growth is tapering off while new inventions have less potential to improve growth.[11] However, measuring inventions in a comprehensive way across industrial sectors is inherently challenging. While physical products in supermarkets might have product codes and each new drug needs to go through FDA approval, other industries might not have a systematic way to track these inventions. This limits our ability to understand what economic forces contribute to variation of inventions across industries. Our measure can then, perhaps, contribute to this discussion given that it does provide coverage across a broader cross-section of industries.

We first relate productivity measures in the literature to our new product measures at the SIC4 industry level. We use Total Factor Productivity (TFP) measures from NBER-CES Manufacturing Industry Database over 1989-2010.[12] As reported in Table 12, both 5-factor and 4-factor TFP correlate with the number of new products and cumulative abnormal returns contemporaneously, after controlling for industry and year fixed effects.[13]

Next, we move to a firm-level analysis. We use all firms in the Compustat database,

[11]As Peter Thiel famously put it, "We wanted flying cars, instead we got 140 characters".
[12]NBER-CES Manufacturing Industry Database stops at 2011.
[13]The results are also robust when controlling for the industry asset size.

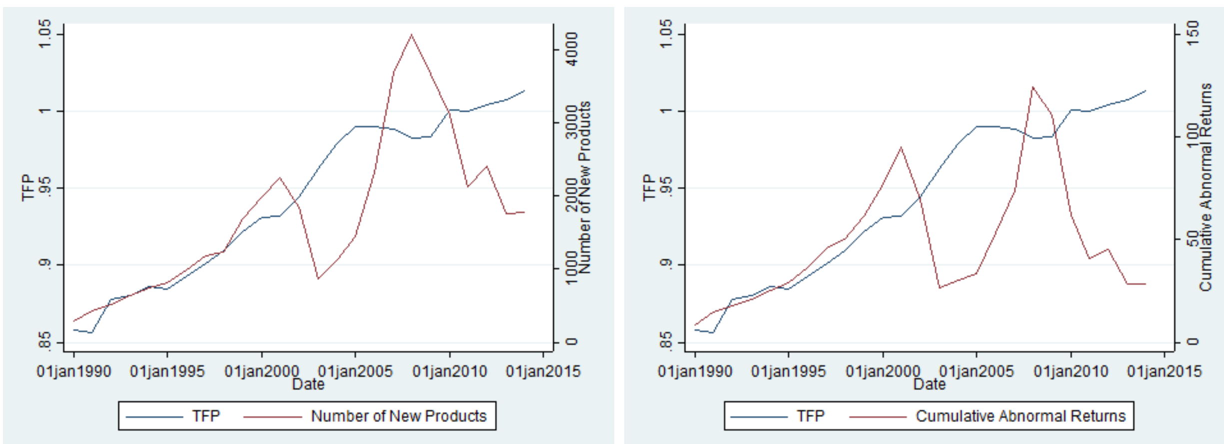
and perform an Olley-Pakes regression. We proxy output by log sales, the labor factor by the number of employees, and the capital factor by the book value of property, plants, and equipment. Further, we consider the labor factor as a free parameter and the capital factor as state parameter. We proxy for unobserved productivity by log investment which we estimate by the change in tangible and intangible assets, adjusted for depreciation. We consider that the firm exits if it no longer appears in the Compustat sample. In Columns (1) and (3) of Table 13, we estimate one Olley-Pakes regression (Olley and Pakes (1992)) for the overall sample, while in Columns (2) and (4), we do that separately for each broad SIC2 industry as different industries might have different loadings on the factors. As with the industry analysis we again find a positive correlation between these productivity measures and new product introductions.

In the next step we relate our measure of new product introductions across a wide array of industries to the aggregate US productivity measures as reported by St Louis Fed FRED database. As we can see in Figure 8, both follow the same pattern in the first period but then new product introductions fall after 2000 when the correlation between the two trends turns out to be negative.

This suggests that the slowdown in aggregate productivity in the mid-2000s is not accompanied by a slowdown in new product introductions. If one thinks of explanations of the productivity slowdown related to a general slowdown in ideas, this slowdown in ideas at least does not seem to be reflected in a slowdown in new products. The evidence here seems to be more consistent with a measurement-based explanation (Brynjolfsson and McAfee (2014), Feldstein (2015)). Given that our measure of new products does not rely on valuing output using value of sales (and hence, prices), we might be capturing innovation related to products where prices are not a good reflection of utility derived by society. For example, in the technology sector firms take time to monetize their innovations, so current sales or profits might not be a good measure of the value they add. The stock market, however, internalizes the possibility of all future revenue streams the product might possibly yield for the firm, and reflects it in its valuation of the launch. A classic example of such forward-looking valuation, where – arguably – the stock market does a better job of reflecting utility values as compared to current profitability, is amazon.com.

That said, however, we see that towards the end of the sample period the rapid growth rate of product introductions dropped.

Figure 8: Aggregate Productivity and New Products



Notes: This figure presents new product announcements in the US and aggregate productivity for each quarter during the years 1989-2015. New products are measured as the number of new product announcements in the left panel and the cumulative abnormal return in the right panel, aggregate productivity is Total Factor Productivity at Constant National Prices for United States, extracted from St Louis Fed FRED database

Finally, we examine correlations between new products and a few other industry characteristics, in particular the industry's output and capital stock. We again rely on NBER-CES Manufacturing Industry Database and we extract information on the value of shipments and value added. As reported in Columns (1)-(4), Table 14, both of these measures are positively related to new products. Finally, in Columns (5)-(6) we show that new products are also correlated with one of the major factors in production – real capital stock.

4.3 Labor Market

Our final step is to consider the labor market implications of new product introductions. As we have seen in Table 7 that showed correlations of new products with various firm characteristics, new products are mostly introduced by firms that have higher sales but a lower number of employees.[14] Does this have implications for employment at a broader industry level?

In this subsection, we examine employment at the industry-level to shed light on this issue. We separately look at total employment, the number of production workers, and the number of production worker hours in Table 15. We find that new product introductions, measured either as the number of launches or as the cumulative abnormal returns from them, are negatively related to the employment intensity of the industry.[15] Coupled with the earlier results on capital, this suggests that product innovations in today's economy are occurring mostly in capital-intensive sectors.

4.4 Dynamic Associations

In this last subsection, we combine our previous discussion on concentration, productivity, and employment, and study their dynamic relationship with new product introductions. We set up our estimation at the SIC4 industry level and focus on leads and lags up to three-years. These results are reported in Table 16. We separately look at whether competition, employment, and productivity are correlated with the lagged new products, and then whether new products are correlated with these lagged industry characteristics. For brevity we report the results for the number of new products, but they are consistent if we consider cumulative abnormal returns from these products.

We start with the HHI. In Columns (1)-(2), we see that the introduction of new products is negatively correlated with future HHI, while it is not negatively correlated with the recent HHI. This suggests that new product launches are making industries more competitive.

In Columns (3)-(4), we see a similar trend with the productivity. More new products at the industry level are positively correlated with future productivity, but these correlations

[14] Kehrig and Vincent (2020) have recently documented that low labor share establishments benefit from high revenue labor productivity and also enjoy a product price premium relative to their peers.

[15] The results are robust when controlling for industry asset size.

are not statistically significant. Coupled with our results on significant correlations between new products and contemporaneous productivity, this suggests that productivity improves when new products are launched, but there are no further improvements in future years related to that particular product launch.

Finally, we focus on the dynamic relationship between new product and employment in Columns (5)-(6). We see that employment has a negative lagged relationship to past new product introduction, suggesting some labor displacement. While employment measured at the year of the product launch is lower in more innovative industries, we do not find any systematic relationship between lagged employment and products. Worryingly, however, employment decreases in the industries that recently introduced new products (Column (5)), and this relationship is robust.

Taken together, these trends suggest that less concentrated industries with higher levels of productivity are associated with higher new product introduction intensity, which is then followed by lower employment in the future, but product introductions are typically followed by lower levels of employment in the industry.

5 Conclusion

In this paper we introduce a new measure of the final stage in the innovation life-cycle – new product introductions. We construct our measures by applying machine learning techniques to news articles, and then examining stock price reactions for the innovating firm around the launch.

Our measures have two substantial advantages, and two main disadvantages. Among the advantages, first, we can cover product or service launches in any industry. Second, we rely on stock markets to value new products. This automatically ensures that our measure of value is not dependent on current prices (or sales) of the product, which may not accurately reflect the value derived by society from some of these inventions, especially in the dominant technology sector. If the market estimates that the product or service adds value and that value can be monetized later, price reactions to the product will account for this value, even if it has not been monetized yet. The main disadvantages of our measurement approach is that our methodology does not account for products introduced by private firms, nor can it account for spillovers on innovation at other firms fuelled by the product launch.

We present a series of stylized facts using our measures, but we do not claim any causal evidence. Further research on both modifying our methodology to improve upon our shortcomings, as well as on using the measure to examine causal relationships can perhaps add value to the literature beyond the scope of this paper.

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Tables

Table 1: Summary Statistics

Panel A. Event-level

	Mean	Std. Dev.	Minimum	Maximum	Count
Cumulative All Abnormal Returns	0.003	0.041	-0.139	0.197	79,444
Cumulative Positive Abnormal Returns	0.031	0.034	0.000	0.197	40,099
Market-Value Added ($bn)	0.187	0.678	0.000	30.768	40,014

Panel B. Firm/year-level, Conditional on Events

	Mean	Std. Dev.	Minimum	Maximum	Count
Number of New Products	1.820	3.193	0	58	24,123
Cumulative Abnormal Returns	0.051	0.089	0.000	1.785	24,123
Market-Value Added ($bn)	0.310	2.536	0.000	195.348	24,123

Panel C. Firm/year-level, All Observations

	Mean	Std. Dev.	Minimum	Maximum	Count
Number of New Products	0.234	1.314	0	58	177,443
Cumulative Abnormal Returns	0.007	0.037	0.000	1.785	177,443

Notes: This table reports summary statistics for the new product measures used in the analysis. Panel A presents summary statistics at each event (announcement) level; Panel B aggregates these announcements at the firm-year level for the cases when the two-day abnormal returns is positive but only considers firms that have introduced a new product in a that year; Panel C considers all publicly-listed firms in the sample.

Table 2: Top Industries

Number of New Products

	(1) 1989-1995	(2) 1996-2000
1	Electronic Computing Equipment	Services-Computer Programming
2	Pharmaceutical Preparations	Computer and Office Equipment
3	Telephone Communication	Electronic Computers
4	Services-Computer Programming	Communication Equipment
5	Photographic Equipment and Supplies	Electronic Components and Accessories
6	Motor Vehicles and Passenger Car Bodies	Radiotelephone Communications
7	Household Audio and Video Equipment	Telephone Communications
8	Soap and other detergents	Semiconductors and Related Devices
9	Perfumes, Cosmetics and Other Toilet Preparations	Computer Related SVCS, NEC
10	Computer and Office Equipment	Holding Offices

	(3) 2001-2005	(4) 2006-2010
1	Services-Computer Programming	Electronic Computers
2	Semiconductors and Related Devices	Pharmaceutical Preparations
3	Computer and Office Equipment	Services-Computer Programming
4	Telephone Communications	Telephone Communications
5	Electronic Computers	Semiconductors and Related Devices
6	Electric Lamps	National Commercial Banks
7	Radio, TV and Communications Equipment	Radio, TV and Communications Equipment
8	Electronic Components and Accessories	Motor Vehicles and Passenger Car Bodies
9	Electromedical and Electrotherapeutic Apparatus	Turbines and Turbine Generator Sets
10	Pharmaceutical Preparations	Information Retrieval Services

	(5) 2011-2015
1	Semiconductors and Related Devices
2	Motor Vehicles and Passenger Car Bodies
3	Services-Prepackaged Software
4	Pharmaceutical Preparations
5	Services-Business Services, NEC
6	Services-Computer Programming
7	Radio, TV and Communications Equipment
8	Electronic Computers
9	Surgical and Medical Instruments, and Apparatus
10	Air Transportation, Scheduled

Notes: This table reports the top SIC4 industries by the number of new product announcements for each five year period.

Table 3: Correlation with Innovation Proxies

Panel A

	Number of New Products					
	(1)	(2)	(3)	(4)	(5)	(6)
Patents	0.209***	0.092***				
	(0.020)	(0.020)				
R&D			0.164***	0.035		
			(0.017)	(0.021)		
Citations					0.146***	-0.029***
					(0.014)	(0.010)
Industry f.e.	N	Y	N	Y	N	Y
Year f.e.	Y	Y	Y	Y	Y	Y
R^2	0.182	0.536	0.162	0.534	0.158	0.534
N	20,925	20,925	20,925	20,925	20,925	20,925

Panel B

	Cumulative Abnormal Returns					
	(1)	(2)	(3)	(4)	(5)	(6)
Patents	0.242***	0.099***				
	(0.023)	(0.024)				
R&D			0.191***	0.040		
			(0.019)	(0.025)		
Citations					0.171***	-0.029**
					(0.017)	(0.012)
Industry f.e.	N	Y	N	Y	N	Y
Year f.e.	Y	Y	Y	Y	Y	Y
R^2	0.167	0.509	0.150	0.508	0.146	0.508
N	20,925	20,925	20,925	20,925	20,925	20,925

Notes: The table is constructed from regressions estimated in a panel setting at a SIC4 industry level over 1989-2015. Panel A presents results where the outcome variable is the number of new products and Panel B presents results where the outcome is cumulative abnormal returns for these products. In Columns (1)-(2) of both panels we correlate new product measures with the number of new eventually-granted patents that the firm has filed in the year as reported in the Bena et al. (2017) dataset. In Columns (3)-(4) we correlate new product measures with R&D expenditures as reported in Compustat. In Columns (5)-(6) of both panels we correlate new product measures with the number of forward citations received in the future by new eventually-granted patents that the firm has filed in the year as reported in Bena et al. (2017) dataset. Standard errors are clustered at the SIC4 industry level.

Table 4: Correlation with Lagged Innovation Proxies

	Number of New Products		Cumulative Abnormal Returns	
	(1)	(2)	(3)	(4)
R&D$_{t-1}$	-0.016		-0.018	
	(0.020)		(0.027)	
R&D$_{t-2}$	-0.006		-0.012	
	(0.019)		(0.026)	
R&D$_{t-3}$	0.011		0.022	
	(0.020)		(0.027)	
R&D$_{t-4}$	0.084***		0.092***	
	(0.021)		(0.026)	
Patents$_{t-1}$		0.011		0.008
		(0.016)		(0.021)
Patents$_{t-2}$		0.015		0.014
		(0.014)		(0.018)
Patents$_{t-3}$		0.042***		0.043**
		(0.014)		(0.017)
Patents$_{t-4}$		0.085***		0.090***
		(0.016)		(0.019)
Industry f.e.	Y	Y	Y	Y
Year f.e.	Y	Y	Y	Y
R^2	0.560	0.562	0.529	0.531
N	17,577	17,577	17,577	17,577

Notes: The table is constructed from regressions estimated in a panel setting at a SIC4 industry level over 1989-2015. Columns (1)-(2) present results where the outcome variable is the number of new products and Columns (3)-(4) present results where the outcome is cumulative abnormal returns for these products. In Columns (1) and (3) we correlate new product measures with four-year lags of R&D expenditures as reported in Compustat. In Columns (2) and (4) we correlate new product measures with the four-year lags of the number of new eventually-granted patents that the firm has filed in the year as reported in Bena et al. (2017) dataset. Standard errors are clustered at the SIC4 industry level.

Table 5: Correlation with Firm-Level Innovation Proxies

	Number of New Products			Cumulative Abnormal Returns		
	(1)	(2)	(3)	(4)	(5)	(6)
R&D	0.088***			0.015***		
	(0.006)			(0.001)		
Patents		0.049***			0.008***	
		(0.004)			(0.001)	
Citations			0.008***			0.002***
			(0.002)			(0.000)
Firm f.e.	Y	Y	Y	Y	Y	Y
Year f.e.	Y	Y	Y	Y	Y	Y
R^2	0.390	0.387	0.385	0.326	0.324	0.323
N	175,751	175,755	175,755	175,751	175,755	175,755

Notes: The table is constructed from regressions estimated in a panel setting at a firm level over 1989-2015. Columns (1)-(3) present results where the outcome variable is the number of new products and Columns (4)-(6) present results where the outcome is cumulative abnormal returns for these products. In Columns (1) and (4) we correlate new product measures with R&D expenditures as reported in Compustat. In Columns (2) and (5) we correlate new product measures with the number of new eventually-granted patents that the firm has filed in the year as reported in Bena et al. (2017) dataset. In Columns (5)-(6) we correlate new product measures with the number of forward citations received in the future by new eventually-granted patents that the firm has filed in the year as reported in Bena et al. (2017) dataset. Standard errors are clustered at the firm level.

Table 6: Fixed Effects

Panel A

	Number of New Products			Cumulative Abnormal Returns		
	(1)	(2)	(3)	(4)	(5)	(6)
Industry f.e.	Y	N	N	Y	N	N
Industry x Year f.e.	N	Y	N	N	Y	N
Firm f.e.	N	N	Y	N	N	Y
Year f.e.	Y	N	Y	Y	N	Y
R^2	0.161	0.259	0.433	0.127	0.215	0.379
N	153,993	153,993	177,443	153,993	153,993	177,443

Panel B

	R&D			Patents		
	(1)	(2)	(3)	(4)	(5)	(6)
Industry f.e.	Y	N	N	Y	N	N
Industry x Year f.e.	N	Y	N	N	Y	N
Firm f.e.	N	N	Y	N	N	Y
Year f.e.	Y	N	Y	Y	N	Y
R^2	0.561	0.607	0.933	0.282	0.342	0.843
N	153,989	153,989	177,439	153,993	153,993	177,443

Notes: The table is constructed from regressions estimated in a panel setting at a firm-year level over 1989-2015. Columns (1)-(3) of Panel A present results where the outcome variable is the number of new products, Columns (4)-(6) of Panel A present results where the outcome is cumulative abnormal returns for these products, Columns (1)-(3) of Panel B present results where the outcome variable is the R&D expenditures, Columns (4)-(6) of Panel B present results where the outcome variable is the number of new eventually-granted patents that the firm has filed in the year. All estimations regress the outcome variable on different fixed effects that are reported separately for each column. Standard errors are clustered at the firm level.

Table 7: Firm Characteristics

Panel A

	Number of New Products					
	(1)	(2)	(3)	(4)	(5)	(6)
Sales	0.000***					0.000***
	(0.000)					(0.000)
Gross Margin		0.010***				0.013***
		(0.002)				(0.003)
Property, Plant and Equipment			0.000**			-0.000***
			(0.000)			(0.000)
Intangible Assets				0.000***		0.000***
				(0.000)		(0.000)
Employees					0.002***	0.000
					(0.000)	(0.000)
Firm f.e.	Y	Y	Y	Y	Y	Y
Year f.e.	Y	Y	Y	Y	Y	Y
R^2	0.382	0.382	0.380	0.393	0.381	0.396
N	159,965	157,247	155,806	144,869	149,905	129,163

Panel B

	Cumulative Abnormal Returns					
	(1)	(2)	(3)	(4)	(5)	(6)
Sales	0.000***					0.000**
	(0.000)					(0.000)
Gross Margin		0.002***				0.003***
		(0.000)				(0.001)
Property, Plant and Equipment			0.000*			-0.000**
			(0.000)			(0.000)
Intangible Assets				0.000***		0.000**
				(0.000)		(0.000)
Employees					0.000	-0.000
					(0.000)	(0.000)
Firm f.e.	Y	Y	Y	Y	Y	Y
Year f.e.	Y	Y	Y	Y	Y	Y
R^2	0.321	0.321	0.319	0.334	0.320	0.336
N	159,965	157,247	155,806	144,869	149,905	129,163

Notes: The table is constructed from regressions estimated in a panel setting at a firm-year level over 1989-2015. Panel A presents results where the outcome variable is the number of new products and Panel B presents results where the outcome is cumulative abnormal returns for these products. We obtain firm-level characteristics from Compustat. In both panels we correlate new product measures with sales (Column (1)), gross margin (Column (2)), property, plants, and equipment (Column (3)), intangible assets (Column (4)), and number of employees (Column (5)). In Column (6), we include all these measures together. Standard errors are clustered at the firm level.

Table 8: Competitive Environment

	Number of New Products	Cumulative Abnormal Returns	Patents (Bena et al., 2017)	Patents (Kogan et al., 2017)	Log R&D	R&D/Sales
	(1)	(2)	(3)	(4)	(5)	(6)
HHI	-0.542***	-0.467**	-0.114	-0.352	-0.380	0.032
	(0.177)	(0.207)	(0.320)	(0.353)	(0.410)	(0.030)
Log Assets	0.077**	0.089**	0.531***	0.536***	0.550***	-0.010
	(0.037)	(0.041)	(0.072)	(0.073)	(0.088)	(0.007)
Industry f.e.	Y	Y	Y	Y	Y	Y
Year f.e.	Y	Y	Y	Y	Y	Y
R^2	0.653	0.609	0.833	0.867	0.887	0.091
N	6,163	6,163	6,163	6,163	6,163	6,162

Notes: The table is constructed from regressions estimated in a panel setting at a SIC3 industry level over 1989-2015. Columns (1) presents results where the outcome variable is the number of new products, Column (2) presents results where the outcome is cumulative abnormal returns for these products, Column (3) presents results where the outcome variable is the number of new eventually-granted patents that the firm has filed in the year as reported in Bena et al. (2017) dataset, Column (4) presents results where the outcome variable is the number of new eventually-granted patents that the firm has filed in the year as reported in Kogan et al. (2017) dataset, Column (5) presents results where the outcome variable is logged transformation R&D expenditures as reported in Compustat, and Column (6) presents results where the outcome variable is scaled R&D expenditures by industry sales. We estimate HHI based on the firm sales in each SIC3 industry as reported in Compustat. Standard errors are clustered at the SIC4 industry level.

Table 9: Firm-level Concentration

	Number of New Products		Cumulative Abnormal Returns	
	(1)	(2)	(3)	(4)
TNIC3-HHI	-0.103***		-0.014***	
	(0.021)		(0.004)	
TNIC3-Similarity		0.002***		0.000***
		(0.000)		(0.000)
Firm f.e.	Y	Y	Y	Y
Year f.e.	Y	Y	Y	Y
R^2	0.406	0.405	0.350	0.350
N	100,921	100,921	100,921	100,921

Notes: The table is constructed from regressions estimated in a panel setting at the firm level over 1996-2015. Columns (1)-(2) present results where the outcome variable is the number of new products and Columns (3)-(4) present results where the outcome is cumulative abnormal returns for these products. We take firm-level concentration measures from Hoberg-Phillips database. In Columns (1) and (3) we use the HHI based on TNIC-3 industry concentration. In Columns (2) and (5) we use the total similarity score based on TNIC-3 industry concentration. Standard errors are clustered at the firm level.

Table 10: Rival New Products

	Number of New Products			Cumulative Abnormal Returns		
	(1)	(2)	(3)	(4)	(5)	(6)
Rival NPA	0.117***	0.039***	0.221***	0.111***	0.040***	0.268***
	(0.006)	(0.004)	(0.011)	(0.007)	(0.004)	(0.019)
Firm f.e.	Y	Y	Y	Y	Y	Y
Year f.e.	Y	Y	Y	Y	Y	Y
R^2	0.392	0.387	0.405	0.336	0.327	0.342
N	175,755	175,755	149,262	175,755	175,755	149,262

Notes: The table is constructed from regressions estimated in a panel setting at a firm level over 1996-2015 in Columns (1)-(4) and 1989-2015 in Columns (5)-(6). Columns (1)-(3) present results where the outcome variable is the number of new products and Columns (4)-(6) present results where the outcome is cumulative abnormal returns for these products. In Columns (1), (2), (4), and (5) we correlate new product measures with the rival new product measures where rivals are determined based on Hoberg-Phillips Text-based Network Industry Classification database. In Columns (1) and (4) all rivals are considered and Rival NPA corresponds to the weighted sum of rival new products where weights are the similarity score as per Hoberg-Phillips database. In Columns (1) and (4) only rivals with similarity score of over 0.1 are considered and Rival NPA corresponds to the sum of these rival new products. In Columns (3) and (6) we correlate new product measures with the rival new product measures where rivals are determined based on their co-mentions in news related to products. The similarity score is determined by the share of firm's news related to products that also mention a rival firm. Rival NPA corresponds to the weighted sum of rival new products where weights are this similarity score. Standard errors are clustered at the firm level.

Table 11: Concentration of New Products

	Concentration of New Products	
	(1)	(2)
HHI	0.181**	0.170**
	(0.086)	(0.082)
Number of Firms		-0.004*
		(0.002)
Log Assets		0.021
		(0.014)
Industry f.e.	Y	Y
Year f.e.	Y	Y
R^2	0.151	0.159
N	3,668	3,668

Notes: The table is constructed from the regressions estimated in a panel setting at a SIC4 industry level over 1989-2015. Columns (1)-(2) present results where the outcome variable is the concentration index of the number of new products for each SIC4 industry, where the concentration index is calculated as the sum of the squared shares of new products that each firm has introduced in a year over the total number of new products that the firm's SIC4 industry introduced in that year. We estimate HHI based on the firm sales in each SIC4 industry as reported in Compustat. Standard errors are clustered at the SIC4 industry level.

Table 12: Industry-level TFP

	Number of New Products		Cumulative Abnormal Returns	
	(1)	(2)	(3)	(4)
5-factor TFP Index	0.082***		0.081***	
	(0.003)		(0.004)	
4-factor TFP Index		0.082***		0.081***
		(0.003)		(0.004)
Industry f.e.	Y	Y	Y	Y
Year f.e.	Y	Y	Y	Y
R^2	0.578	0.578	0.552	0.552
N	9,084	9,084	9,084	9,084

Notes: The table is constructed from regressions estimated in a panel setting at the SIC4 industry level over 1989-2010. Columns (1)-(2) present results where the outcome variable is the number of new products and Columns (3)-(4) present results where the outcome is cumulative abnormal returns for these products. We get the TFP measures from NBER-CES Manufacturing Industry Database. In Columns (1) and (3) we correlate new product measures with the 5-factor TFP index. In Columns (2) and (4) we correlate new product measures with the 4-factor TFP index. Standard errors are clustered at the SIC4 industry level.

Table 13: Firm-level TFP

	Number of New Products		Cumulative Abnormal Returns	
	(1)	(2)	(3)	(4)
Residual from Overall Oaley-Pakes	0.042***		0.010***	
	(0.016)		(0.003)	
Residual from Industry Oaley-Pakes		0.032**		0.008**
		(0.015)		(0.003)
Firm f.e.	Y	Y	Y	Y
Year f.e.	Y	Y	Y	Y
R^2	0.413	0.413	0.389	0.390
N	40,991	41,223	40,991	41,223

Notes: The table is constructed from regressions estimated in a panel setting at the firm level over 1989-2015. Columns (1)-(2) present results where the outcome variable is the number of new products and Columns (3)-(4) present results where the outcome is cumulative abnormal returns for these products. We proxy output by log sales, labor factor by the number of employees, and capital factor by the book value of property, plants, and equipment. Further, we consider labor factor as free parameter and capital factor as state parameter. We proxy for unobserved productivity by log investment which we estimate by the change in tangible and intangible assets, adjusted for depreciation. We consider that the firm exits if it no longer appears in the Compustat sample. In Columns (1) and (3) we use the residual from this estimation when it is performed on the all sample of Compustat firms. In Columns (2) and (5) we use the residual from this estimation when it is performed for each SIC2 industry separately. Standard errors are clustered at the firm level.

Table 14: Value Added

	Number of New Products			Cumulative Abnormal Returns		
	(1)	(2)	(3)	(4)	(5)	(6)
Value of Shipments	0.006*			0.005*		
	(0.003)			(0.003)		
Value Added		0.030***			0.030***	
		(0.010)			(0.011)	
Real Capital Stock			0.094***			0.100***
			(0.023)			(0.027)
Industry f.e.	Y	Y	Y	Y	Y	Y
Year f.e.	Y	Y	Y	Y	Y	Y
R^2	0.574	0.576	0.585	0.549	0.551	0.558
N	9,084	9,084	9,084	9,084	9,084	9,084

Notes: The table is constructed from regressions estimated in a panel setting at the SIC4 industry level over 1989-2010. Columns (1)-(3) present results where the outcome variable is the number of new products and Columns (4)-(6) present results where the outcome is cumulative abnormal returns for these products. We get the industry size data from NBER-CES Manufacturing Industry Database. In Columns (1) and (4) we correlate new product measures with the Total value of shipments in $1bn. In Columns (2) and (5) we correlate new product measures with the Total value added in $1bn. In Columns (3) and (6) we correlate new product measures with the Total real capital stock in $1bn. Standard errors are clustered at the SIC4 industry level.

Table 15: Employment

	Number of New Products			Cumulative Abnormal Returns		
	(1)	(2)	(3)	(4)	(5)	(6)
Total Employment	-0.006**			-0.006**		
	(0.002)			(0.003)		
Production Workers		-0.005**			-0.006**	
		(0.003)			(0.003)	
Production Worker Hours			-0.003**			-0.004***
			(0.001)			(0.001)
Industry f.e.	Y	Y	Y	Y	Y	Y
Year f.e.	Y	Y	Y	Y	Y	Y
R^2	0.574	0.573	0.573	0.550	0.549	0.549
N	9,084	9,084	9,084	9,084	9,084	9,084

Notes: The table is constructed from regressions estimated in a panel setting at the SIC4 industry level over 1989-2010. Columns (1)-(3) present results where the outcome variable is the number of new products and Columns (4)-(6) present results where the outcome is cumulative abnormal returns for these products. We get the employment data from NBER-CES Manufacturing Industry Database. In Columns (1) and (4) we correlate new product measures with the Total employment in 1000s. In Columns (2) and (5) we correlate new product measures with the Production workers in 1000s. In Columns (3) and (6) we correlate new product measures with the Production worker hours in 1m. Standard errors are clustered at the SIC4 industry level.

Table 16: Dynamics

	HHI	New Products	TFP	New Products	Employment	New Products
	(1)	(2)	(3)	(4)	(5)	(6)
New Products$_{t-1}$	-0.006***		0.110		-0.564**	
	(0.001)		(0.075)		(0.239)	
New Products$_{t-2}$	-0.004***		0.098		-0.744***	
	(0.001)		(0.070)		(0.234)	
New Products$_{t-3}$	-0.004**		0.119		-0.993***	
	(0.002)		(0.085)		(0.315)	
HHI		-0.380*				
		(0.225)				
HHI$_{t-1}$		-0.015				
		(0.239)				
HHI$_{t-2}$		-0.226				
		(0.234)				
HHI$_{t-3}$		-0.309				
		(0.224)				
5-factor TFP Index				0.099***		
				(0.017)		
TFP$_{t-1}$				0.019		
				(0.020)		
TFP$_{t-2}$				0.018		
				(0.037)		
TFP$_{t-3}$				-0.076***		
				(0.026)		
Employment						-0.007*
						(0.004)
Employment$_{t-1}$						-0.001
						(0.004)
Employment$_{t-2}$						0.007*
						(0.004)
Employment$_{t-3}$						-0.007
						(0.004)
Industry f.e.	Y	Y	Y	Y	Y	Y
Year f.e.	Y	Y	Y	Y	Y	Y
R^2	0.774	0.661	0.590	0.607	0.968	0.605
N	5,419	5,404	7,708	7,708	7,708	7,708

Notes: The table is constructed from regressions estimated in a panel setting at the SIC3 or SIC4 industry level over 1989-2015. In Columns (1)-(2) we focus on the relationship between the number of new products and HHI based on the firm sales in each SIC3 industry as reported in Compustat. In Column (1), we regress HHI on the lagged new products up to three year lags. In Column (2), we regress new products on the HHI lagged up to three year lags. In Columns (3)-(4) we focus on the relationship between the number of new products and 5-factor TFP index from NBER-CES Manufacturing Industry Database. In Column (3), we regress TFP on the lagged new products up to three year lags. In Column (4), we regress new products on the TFP lagged up to three year lags. In Columns (5)-(6) we focus on the relationship between the number of new products and the Total employment in 1000s from NBER-CES Manufacturing Industry Database. In Column (5), we regress the Total employment on the lagged new products up to three year lags. In Column (6), we regress new products on the Total employment lagged up to three year lags. Standard errors are clustered at the industry level.