New Products*

Abhiroop Mukherjee **Tomas Thornquist** **Alminas Žaldokas**

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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

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*Mukherjee and Žaldokas: Hong Kong University of Science and Technology; Thornquist: Shell Street Labs. Emails: amukherjee@ust.hk; tomas@thornquist.me; alminas@ust.hk. We thank Benas Žurauskas for excellent research assistance.

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.

Measuring innovation outcomes for a wide array of firms can not only help uncover the dynamics of the technological process, but also help understand how it relates to changes in the competitive environment across different industries, employment and capital shares, and commonly accepted measures of productivity.

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 1989-2010. 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. 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. 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, state, 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 find that about 36-39% 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 8%. Second, the probability of a firm staying in the top quintile of product innovators in two consecutive years is 50%. 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 2010.[2] 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 most new products come from industries that do not have a large share in aggregate employment. Moreover, 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.

[2] We are currently updating our sample up to 2015.

At the industry level, however, we uncover evidence linking product innovations to a general decline in both future wages and wage inequality. Innovative industries therefore seem to be more equal inside, but employ less people and pay them lower wages on average. 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. (2019) develop a new measure of innovation using textual analysis of analyst reports on large firms, which can measure 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. Austin (1993) uses an event-study approach to value biotech innovations. 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 disadvantages of our measure. First, we do not capture any 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. 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 are not captured by our measure. We leave it for future research to explore these avenues.

2 New Product Measure

In this section we describe the construction of new product measure 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-2010 May. We started with 325,366 articles. We then exclude 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, and 302,408. 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. We end up with 265,657 articles involving 11,841 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.[3] 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%.

In our final step, we extracted information on which firms are mentioned in each article. Next, 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). Finally, we kept only those announcements where the announcing firm had a positive cumulative abnormal return in the two days following the announcement (i.e., CAR(0,1)). 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.

We have applied a simpler version of the measure – not based on a machine-learning approach – in an earlier paper (Mukherjee et al., 2017) where we show that corporate taxes affect innovation activities, including new product introductions.[4]

[3]The students agreed on 76% of cases whether the news constitute a new product announcement, suggesting a relatively high rate of consitency. 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.

[4]The measures used in that paper are readily downloadable for public use at http://alminas.com/.

3 Stylized Facts: Patterns in Product Innovation

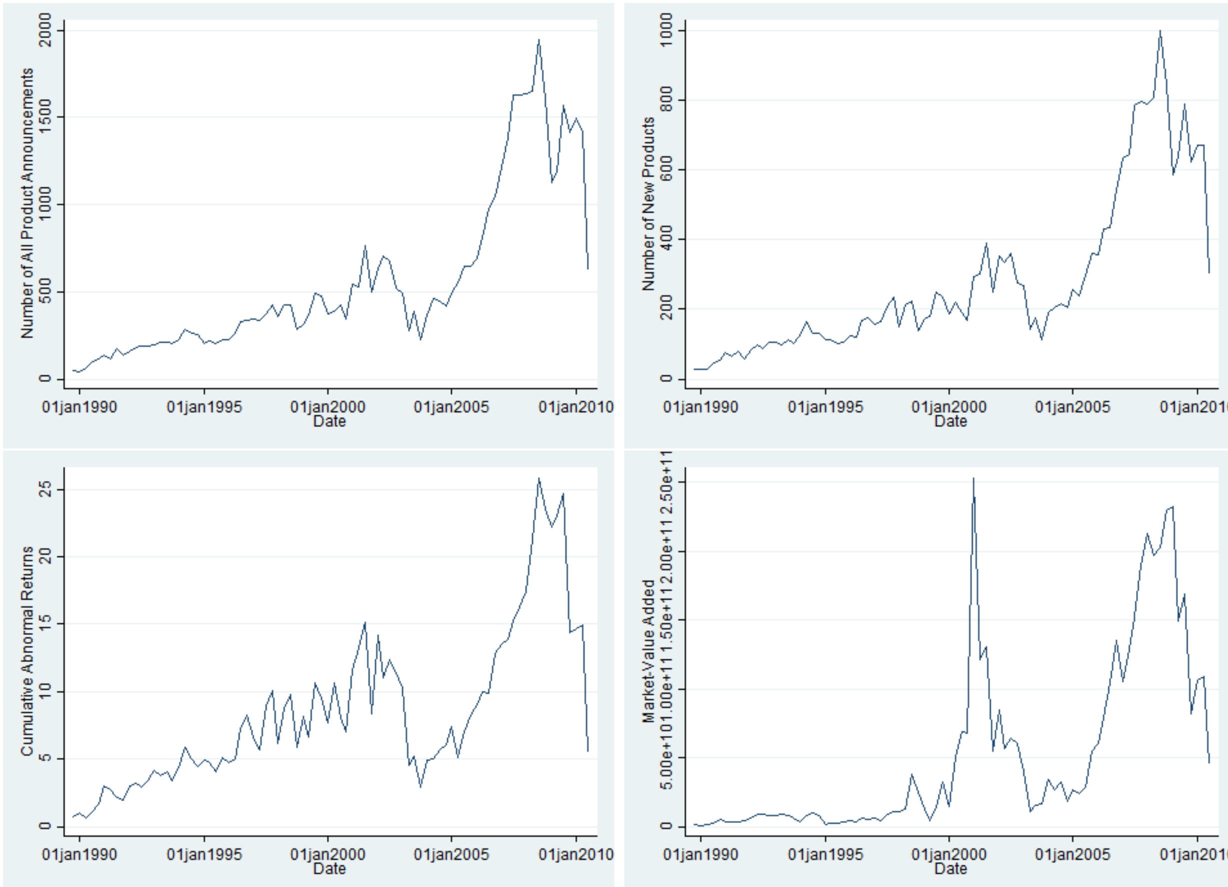
3.1 General Trends and Top Innovating Industries

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 46,986 announcements over 1989-2010 hovers around zero. After we condition on these returns being positive, we are left with 23,485 announcements with the mean two-day return of 3% and an average market value added of $190m US dollars for each new product. This assures us that we are not capturing inconsequential innovations. Figure 4 depicts aggregate trends in these four values over time.

In Panel B, we aggregate these values at the firm level for each year and this results in 15,024 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 1.56 products in that year, with the maximum being 66. The mean total two-day abnormal return for these 1.56 products is 4.8% and the market-value added is $290m 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.

In our further analysis we use these two measures: number of new products and cumulative abnormal returns. When we study their summary statistics at the whole firm sample, including the years or firms where new products are not introduced, in Panel C, we see that the average is 0.146, i.e., every seventh public firm in the economy introduces a new product in a particular year. In total, our dataset includes 3,644 distinct firms that have launched at least one new product by our measure. Out of these 3,644 firms, 1,406 have never filed patents during our sample period of 1989-2010, and 896 firms have not reported positive R&D expenditures. This shows that patent- or R&D-based metrics might measure innovation with some noise, even for large public firms in the US.

Figure 1: Aggregate Trends of New Products

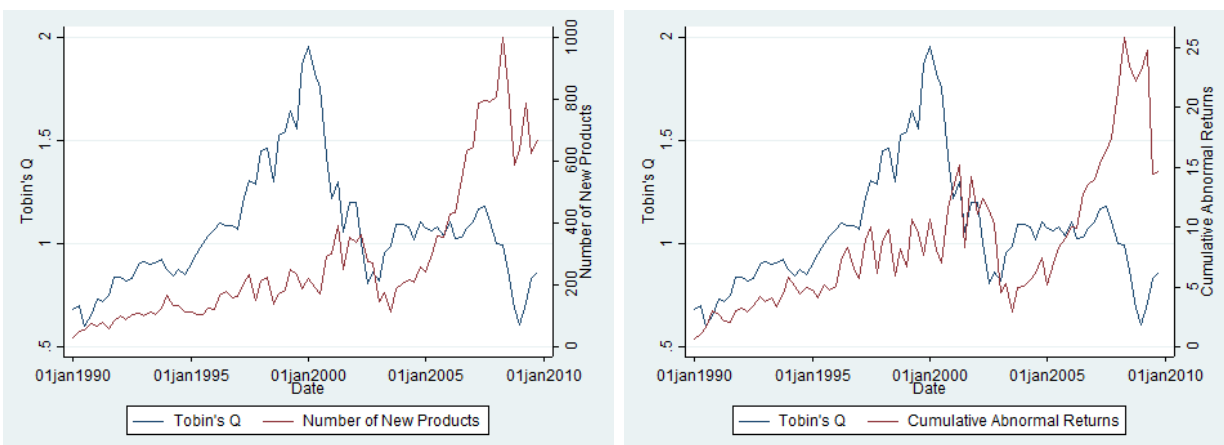


Notes: This figure represents new product announcements in the US for each quarter for years 1989-2010. New products are measured as the number of new product announcements, not conditional on the two-day abnormal returns being positive (top left panel), the number of new product announcements conditional 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).

We next 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 in the last period. Also, traditional labor-intensive industries, such as fast-moving-consumer-goods industries (FMCG), that figured among major innovators in the early 1990s, have since dropped out of the list, being replaced mostly by technology-related sectors.

Looking at the aggregate trends, one 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 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.[5] 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.

Figure 2: Tobin's Q and New Products

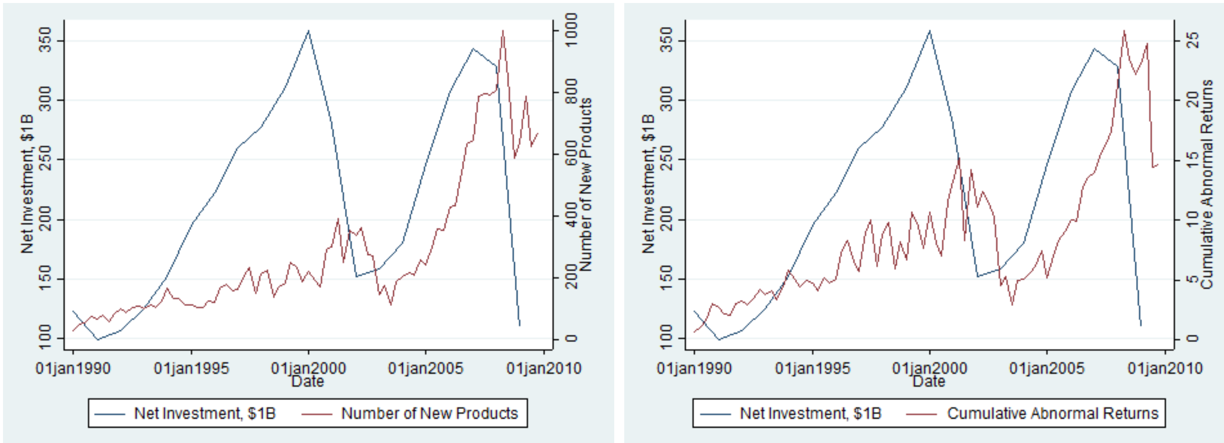


Notes: This figure represents new product announcements in the US for each quarter and Tobin's Q for years 1989-2010. New products are measured as the number of new product announcements in the left panel and the cumulative abnormal return in the right panel, Tobin's Q is extracted from from FRED database 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.

Next, we compare new product trends to net investment trends. In Figure 3, we see that while in the 2000s net investment leads new product introductions, such a relationship does not seem to be present in the earlier period.

[5]One reason why we do not rely on the dollar market value added measure is that (as can be seen in the bottom right panel of Figure 4) this measure has the largest spike around the dotcom boom period, given that it is dependent on the level of the innovating firm's stock price.

Figure 3: Aggregate Investment and New Products



Notes: This figure represents new product announcements in the US for each quarter and Tobin's Q for years 1989-2010. 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 Gross fixed capital formation minus consumption of fixed capital in $1m (series NCBGFCA027N minus NCBCFCA027N).

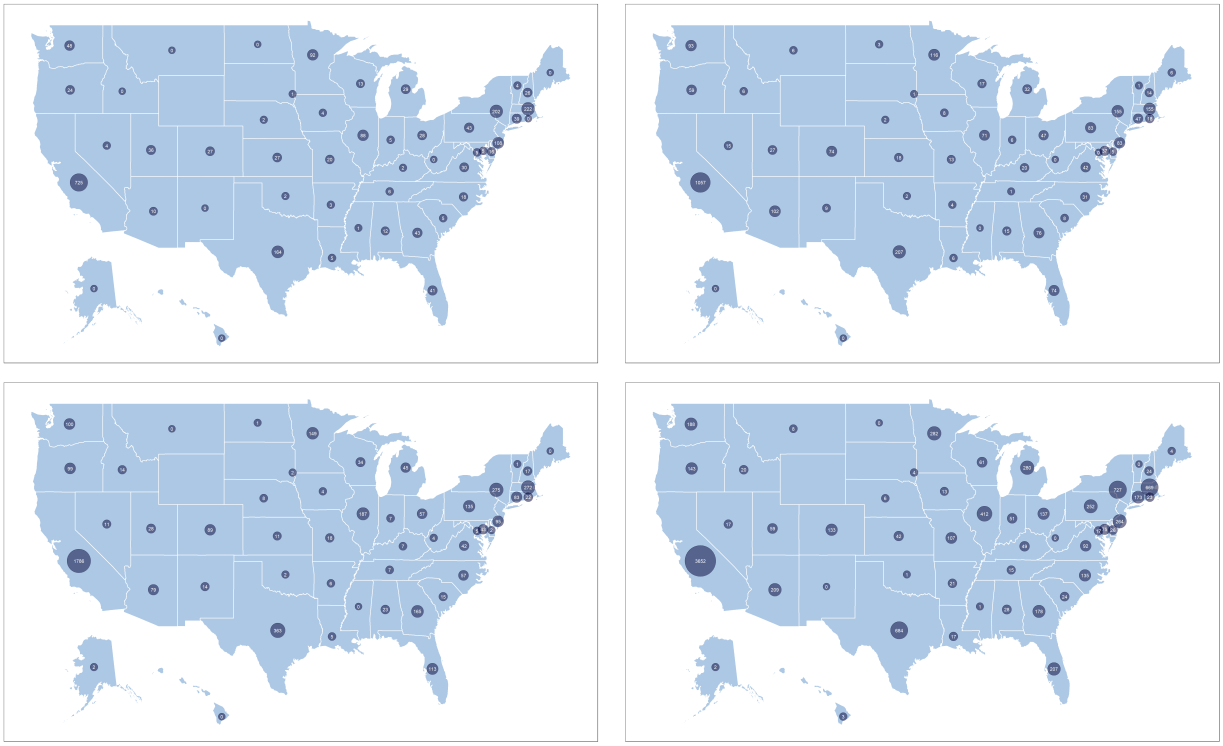
Finally, we look at how new products are distributed across different US states, and in particular we examine how the geography of innovation has been changing in the US over the last 20 years. Figure 4 shows separate heat maps of firm headquarters that launched new products in 1989-1995, 1996-2000, 2001-2005, and 2006-2010. 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 Other Innovation Measures

We first 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 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

Figure 4: Geographic Distribution Over Time



Notes: This figure represents the total number of new product announcements in different US states in years 1989-1994 (top left panel); 1995-1999 (top right panel); 2000-2004 (bottom left panel); and 2005-2009 (bottom right panel).

(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 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 R&D is 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 number of patents or their 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.

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. Similar to the industry-level analysis, at the firm-level we see that new products are positively correlated with R&D but not with patents or forward citations. In fact, the correlation with the citations is negative. A part of the firm's investments may be related to intellectual property related to the new product itself (such as continuing innovations related to iTunes after the launch of the iPod). Alternatively, they could reflect follow up innovations as the firm receives feedback on the new product from consumers, or relaxed financial constraints as the firm receives additional cash flows from the product. However, it is likely that the effect first shows up in R&D and it might take longer for it to be reflected in patents or citations.

3.3 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 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: 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 11-13.2% variation in annual firm-level new products, and this improves to 19.8-22.9% if we consider industry trends. On the other hand, firm and year fixed effects explain 36.2%-39.3% of variation by themselves, suggesting that annual industry trends are not as important in explaining variation as are time-invariant firm characteristics.[6]

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 93.6% of variation in R&D and 80.4% 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 49.59%. The respective figures for patents and R&D are 77.07% and 92.93%. 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), physical capital factor (captured by property, plants, and equipment), innovative capital factor

[6]When both firm and industry-year fixed effects are considered, R^2 rises to 44.3%-47.6%.

(captured by intangible assets), and labor factor (captured by the number of employees). For both of the new product measures, we see that when these firm characteristics are considered separately, all variables that are correlated with firm scale (sales; property, plants, and equipment (PPE); intangible assets; and employees) are positively related to new products, suggesting that larger and more profitable firms drive innovation output. When all these variables are considered together, size-related variables continue to dominate, but we find an interesting exception: product innovations seem to be happening at larger firms *that employ less people*. We come back to this issue in Section 3.6.

3.4 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.[7] In this paper, we contribute to this debate by documenting stylized facts – we do not claim any causality in

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

the following analysis, just as in the rest of this paper.

We first 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 SIC4 industry, and perform panel analysis at the industry level, controlling for industry and year fixed effects. Indeed, if we look at Table 8, Columns (3) and (4), we see that contemporaneous HHI does not have a statistically significant relationship with patents and R&D. On the other hand, as reported in Columns (1) and (2), our new product measures are negatively correlated with the concentration indices, suggesting that more new product introduction occurs in less concentrated industries.

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 4-digit 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.[8] 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. This result holds even after controlling for number of firms in the industry. Our evidence shows that the distribution of sales maps into the distribution of product innovations at the industry level.

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

3.5 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, their contribution to growth is tapering off while new inventions have less potential to improve growth.[9] 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. 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.

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

[9] As Peter Thiel famously put it, "We wanted flying cars, instead we got 140 characters".

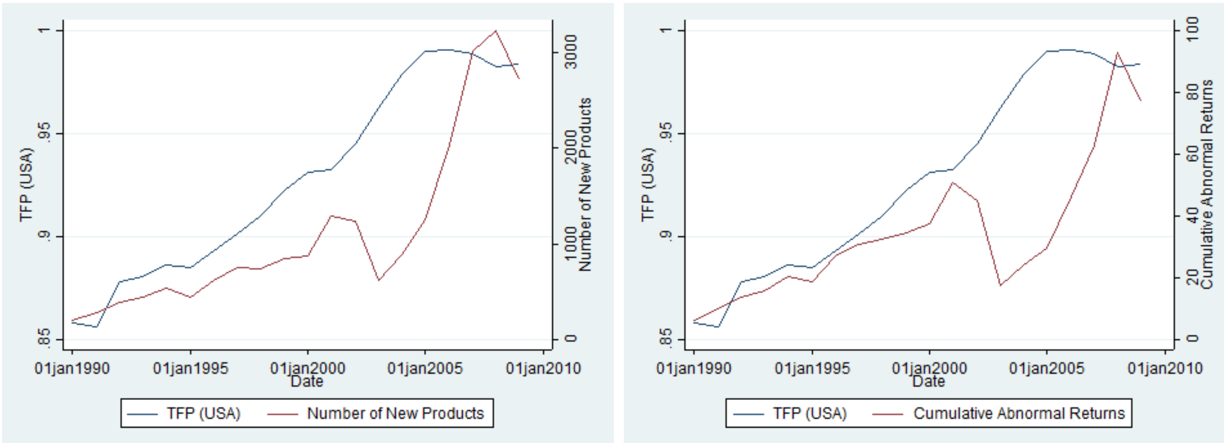
sample, while in Columns (2) and (4), we do that separately for each broad SIC2 industry as different industries might have different loadings on the factors. As with the industry analysis we again find a positive correlation between these productivity measures and new product introductions.

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 5, both show an increase in the first period but then new product introductions continue rising while aggregate productivity tappers off.

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, calculates 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 is tapering off. If this trend continues, it might indicate that the slowdown of ideas takes some time to show up in new products. We are currently expanding our sample to examine the period from 2010-2015, and these results can help us provide more evidence on the slowdown of innovations explanation.

Figure 5: Aggregate Productivity and New Products



Notes: This figure presents new product announcements in the US and aggregate productivity for each quarter during the years 1989-2010. 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.

3.6 Labor Market

Our next 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. Does this have implications for employment and wages at a broader industry level?

In this subsection, we examine employment and wages 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. Coupled with the earlier results on capital, this suggests that product innovations in today's economy are occurring mostly in capital-intensive sectors.

Next we study the employee wage distribution in relation to product launches. Drawing data from the BLS Occupational Employment Statistics (OES) Survey, we look at the interquartile hourly wage dispersion, the wage dispersion between top and bottom deciles, and the median wage. In the Table 16, based on the panel regressions at the SIC4 industry level, we see a negative correlation of our new products measure with wage dispersion and the median wage. This shows that, first, new product launches happen mostly in industries that have less inequality between workers in terms of wages, Second, our evidence also suggests that most product innovations happen in industries where employees have lower wages. Coupled with our evidence on employment, and on the capital intensity of firms, this is consistent with the view that labor, on average, is not seeing large gains from new product introductions (Karabarbounis and Neiman (2013)). Of course, we do not suggest that this evidence is causal, nor do we claim that top innovators within the industry do not benefit. At the moment, we do not have the data to examine these issues.

3.7 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 17. 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 while the introduction of new products is not correlated with future HHI, it is negatively correlated with the recent HHI. This suggests that more new products are launched in more competitive industries, consistent with our evidence on the contemporaneous relation between new products and concentration. However, new product launches are not systematically related to changes in future industry concentration.

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 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). 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 (6)), 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, but product introductions are typically followed by lower levels of employment in the industry.

4 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 do not present any causal evidence. Further research on both modifying our methodology to improve upon our short-comings, 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	0.002	0.039	-0.147	0.227	46986
Cumulative Positive Abnormal Returns	0.030	0.031	0.000	0.227	23485
Market-Value Added	1.9e+08	7.0e+08	214.757	3.2e+10	23442

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

	Mean	Std. Dev.	Minimum	Maximum	Count
Number of New Products	1.563	2.825	0.000	66	15024
Cumulative Abnormal Returns	0.048	0.080	0.000	1.336	15024
Market-Value Added	2.9e+08	2.3e+09	0.000	9.9e+10	15024

Panel C. Firm/year-level, All Observations

	Mean	Std. Dev.	Minimum	Maximum	Count
Number of New Products	0.146	0.992	0.000	66.000	149959
Cumulative Abnormal Returns	0.004	0.029	0.000	1.336	149959

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)	(2)
	1989-1995	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
	Number of New Products	
	(3)	(4)
	2001-2005	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

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	0.192***	0.011				
	(0.020)	(0.013)				
R&D			0.151***	0.036*		
			(0.018)	(0.019)		
Citations					0.136***	-0.038***
					(0.015)	(0.009)
Industry f.e.	N	Y	N	Y	N	Y
Year f.e.	Y	Y	Y	Y	Y	Y
R^2	0.176	0.538	0.152	0.538	0.153	0.540
N	13820	13820	13820	13820	13820	13820

Panel B

	Cumulative Abnormal Returns					
	(1)	(2)	(3)	(4)	(5)	(6)
Patents	0.233***	0.014				
	(0.024)	(0.017)				
R&D			0.183***	0.045**		
			(0.021)	(0.023)		
Citations					0.167***	-0.040***
					(0.018)	(0.011)
Industry f.e.	N	Y	N	Y	N	Y
Year f.e.	Y	Y	Y	Y	Y	Y
R^2	0.163	0.517	0.140	0.518	0.143	0.518
N	13820	13820	13820	13820	13820	13820

Notes: The table is constructed from regressions estimated in a panel setting at a SIC4 industry level over 1989-2010. 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 Kogan 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 Kogan 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$_{t-1}$	-0.020		-0.016	
	(0.018)		(0.022)	
R&D$_{t-2}$	0.026		0.022	
	(0.018)		(0.023)	
R&D$_{t-3}$	-0.006		-0.013	
	(0.018)		(0.023)	
R&D$_{t-4}$	0.070***		0.083***	
	(0.020)		(0.026)	
Patents$_{t-1}$		-0.021		-0.029*
		(0.013)		(0.016)
Patents$_{t-2}$		0.025**		0.034**
		(0.012)		(0.016)
Patents$_{t-3}$		0.038***		0.040**
		(0.013)		(0.016)
Patents$_{t-4}$		0.031**		0.031*
		(0.014)		(0.017)
Industry f.e.	Y	Y	Y	Y
Year f.e.	Y	Y	Y	Y
R^2	0.565	0.565	0.539	0.539
N	11056	11056	11056	11056

Notes: The table is constructed from regressions estimated in a panel setting at a 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. 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 Kogan 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	0.089***			0.016***		
	(0.006)			(0.001)		
Patents		0.000			-0.000	
		(0.004)			(0.001)	
Citations			-0.022***			-0.004***
			(0.003)			(0.001)
Firm f.e.	Y	Y	Y	Y	Y	Y
Year f.e.	Y	Y	Y	Y	Y	Y
R^2	0.345	0.339	0.340	0.302	0.297	0.298
N	148593	148596	148596	148593	148596	148596

Notes: The table is constructed from regressions estimated in a panel setting at a firm 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. 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 Kogan 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 Kogan 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	0.132	0.229	0.393	0.110	0.198	0.362
N	129635	129635	149959	129635	129635	149959

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	0.554	0.594	0.936	0.277	0.329	0.804
N	129632	129632	149956	129635	129635	149959

Notes: The table is constructed from regressions estimated in a panel setting at a firm-year level over 1989-2010. 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		0.018***				0.021***
		(0.006)				(0.007)
Property, Plant and Equipment			0.000***			-0.000
			(0.000)			(0.000)
Intangible Assets				0.000***		0.000
				(0.000)		(0.000)
Employees					0.001	-0.002***
					(0.001)	(0.001)
Firm f.e.	Y	Y	Y	Y	Y	Y
Year f.e.	Y	Y	Y	Y	Y	Y
R^2	0.280	0.279	0.279	0.292	0.280	0.297
N	40665	40397	40407	35577	39524	34088

Panel B

	Cumulative Abnormal Returns					
	(1)	(2)	(3)	(4)	(5)	(6)
Sales	0.000**					0.000**
	(0.000)					(0.000)
Gross Margin		0.005***				0.005***
		(0.001)				(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	-0.001***
					(0.000)	(0.000)
Firm f.e.	Y	Y	Y	Y	Y	Y
Year f.e.	Y	Y	Y	Y	Y	Y
R^2	0.273	0.273	0.272	0.293	0.273	0.297
N	40665	40397	40407	35577	39524	34088

Notes: The table is constructed from regressions estimated in a panel setting at a firm-year level over 1989-2010. 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	R&D
	(1)	(2)	(3)	(4)
HHI	-0.005***	-0.006***	0.000	-0.002
	(0.000)	(0.001)	(0.001)	(0.002)
Industry f.e.	Y	Y	Y	Y
Year f.e.	Y	Y	Y	Y
R^2	0.583	0.551	0.857	0.875
N	6492	6492	6492	6492

Notes: The table is constructed from regressions estimated in a panel setting at a SIC4 industry level over 1989-2010. 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 Kogan et al. (2017) dataset, and Column (4) presents results where the outcome variable is R&D expenditures as reported in Compustat. 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 9: Firm-level Concentration

	Number of New Products		Cumulative Abnormal Returns	
	(1)	(2)	(3)	(4)
TNIC3-HHI	-0.068***		-0.010**	
	(0.020)		(0.004)	
TNIC3-Similarity		0.001***		0.000***
		(0.000)		(0.000)
Firm f.e.	Y	Y	Y	Y
Year f.e.	Y	Y	Y	Y
R^2	0.370	0.370	0.336	0.336
N	80166	80166	80166	80166

Notes: The table is constructed from regressions estimated in a panel setting at the firm level over 1996-2010. 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 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	0.126***	0.042***	0.205***	0.119***	0.040***	0.239***
	(0.007)	(0.005)	(0.011)	(0.009)	(0.005)	(0.019)
Firm f.e.	Y	Y	Y	Y	Y	Y
Year f.e.	Y	Y	Y	Y	Y	Y
R^2	0.349	0.341	0.354	0.312	0.301	0.315
N	148596	148596	148596	148596	148596	148596

Notes: The table is constructed from regressions estimated in a panel setting at a firm level over 1996-2010 in Columns (1)-(4) and 1989-2010 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	0.190***	0.149**
	(0.070)	(0.061)
Number of Firms		-0.008**
		(0.003)
Industry f.e.	Y	Y
Year f.e.	Y	Y
R^2	0.496	0.524
N	1707	1707

Notes: The table is constructed from the regressions estimated in a panel setting at a SIC4 industry level over 1989-2010. 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	0.083***		0.076***	
	(0.004)		(0.003)	
4-factor TFP Index		0.084***		0.076***
		(0.004)		(0.003)
Industry f.e.	Y	Y	Y	Y
Year f.e.	Y	Y	Y	Y
R^2	0.561	0.561	0.547	0.547
N	9084	9084	9084	9084

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 (5) we correlate new product measures with the Total value added in $1m. In Columns (3) 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 Olley-Pakes	0.053***		0.009***	
	(0.014)		(0.003)	
Residual from Industry Olley-Pakes		0.057***		0.010***
		(0.015)		(0.003)
Firm f.e.	Y	Y	Y	Y
Year f.e.	Y	Y	Y	Y
R^2	0.333	0.332	0.327	0.326
N	33587	33807	33587	33807

Notes: The table is constructed from regressions estimated in a panel setting at the firm 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 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	0.005**			0.005*		
	(0.002)			(0.003)		
Value Added		0.028***			0.026***	
		(0.008)			(0.010)	
Real Capital Stock			0.095***			0.096***
			(0.020)			(0.026)
Industry f.e.	Y	Y	Y	Y	Y	Y
Year f.e.	Y	Y	Y	Y	Y	Y
R^2	0.556	0.558	0.569	0.544	0.546	0.554
N	9084	9084	9084	9084	9084	9084

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	-0.007***			-0.007***		
	(0.002)			(0.003)		
Production Workers		-0.007**			-0.007**	
		(0.003)			(0.003)	
Production Worker Hours			-0.004***			-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	0.558	0.556	0.556	0.546	0.545	0.545
N	9084	9084	9084	9084	9084	9084

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: Wages

	Number of New Products			Cumulative Abnormal Returns		
	(1)	(2)	(3)	(4)	(5)	(6)
Interquartile Wage Dispersion	-1.105**			-0.238		
	(0.463)			(0.171)		
Interdecile Wage Dispersion		-0.510***			-0.120**	
		(0.174)			(0.061)	
Median Wage			-0.139***			-0.060***
			(0.046)			(0.021)
Industry f.e.	Y	Y	Y	Y	Y	Y
Year f.e.	Y	Y	Y	Y	Y	Y
R^2	0.493	0.494	0.504	0.476	0.477	0.495
N	4880	4820	4880	4880	4820	4880

Notes: The table is constructed from regressions estimated in a panel setting at the NAICS5 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 wage data from BLS Occupational Employment Statistics (OES) Survey. In Columns (1) and (4) we correlate new product measures with the Hourly 75th percentile wage / Hourly 25th percentile wage. In Columns (2) and (5) we correlate new product measures with the Hourly 90th percentile wage / Hourly 10th percentile wage. In Columns (5)-(6) we correlate new product measures with the Hourly median wage (or the 50th percentile). Standard errors are clustered at the NAICS5 industry level.

Table 17: Dynamics

	HHI	New Products	TFP	New Products	Employment	New Products
	(1)	(2)	(3)	(4)	(5)	(6)
New Products$_{t-1}$	0.105		0.125		-0.640**	
	(0.108)		(0.086)		(0.296)	
New Products$_{t-2}$	-0.135		0.110		-0.917***	
	(0.132)		(0.078)		(0.278)	
New Products$_{t-3}$	0.116		0.142		-1.275***	
	(0.121)		(0.101)		(0.369)	
HHI		-0.005***				
		(0.000)				
HHI$_{t-1}$		-0.005***				
		(0.000)				
HHI$_{t-2}$		-0.160				
		(0.135)				
HHI$_{t-3}$		0.005				
		(0.131)				
TFP				0.091***		
				(0.021)		
TFP$_{t-1}$				-0.010		
				(0.018)		
TFP$_{t-2}$				0.092***		
				(0.034)		
TFP$_{t-3}$				-0.106***		
				(0.028)		
Employment						-0.010**
						(0.005)
Employment$_{t-1}$						0.005
						(0.004)
Employment$_{t-2}$						-0.000
						(0.004)
Employment$_{t-3}$						-0.004
						(0.004)
Industry f.e.	Y	Y	Y	Y	Y	Y
Year f.e.	Y	Y	Y	Y	Y	Y
R^2	0.002	0.602	0.592	0.586	0.969	0.584
N	5513	5472	7708	7708	7708	7708

Notes: The table is constructed from regressions estimated in a panel setting at the SIC4 industry level over 1989-2010. In Columns (1)-(2) we focus on the relationship between the number of new products and HHI based on the firm sales in each SIC4 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 SIC4 industry level.