New Products

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[PRELIMINARY AND INCOMPLETE]

Abstract

Measuring the welfare impact of new product introductions is a major, long-standing problem in economics. In this study, we make progress on this challenge by leveraging the informational efficiency of equity markets and a scalable hedonic consumer demand model. We use stock market reactions to new product announcements over a twenty-year period (2002-2021) to estimate the future profits they generate for their inventor firms. We then use a GHL oligopoly model to measure the change in competitors' profits as well as consumer welfare induced by these new products, ultimately obtaining their aggregate welfare contribution in dollars. Our analysis reveals that new products introduced annually by U.S. publicly-traded corporations alone produce substantial welfare gains, averaging 0.15-0.20% of US yearly GDP. Producer surplus accounts for roughly 60% of these gains. This estimate is significantly larger than the corresponding figure for existing products. We show that this is due to the fact that new product creation is highly concentrated among firms that have a high degree of market power.

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1 Introduction

Throughout human history, the composition of economic activity has undergone steady, yet dramatic transformation. The continuous invention and introduction of superior products and services, regularly displacing existing ones, have been fundamental drivers of the sustained improvements in living standards that societies have experienced. Schumpeter (1943) famously referred to this process as "creative destruction".

While it is easy to imagine how new product introductions must be contributing significantly (and at all times) to the growth of consumer welfare, measuring this contribution has long been an elusive goal for economists. This gap in understanding stems from multiple challenges. First, the welfare effect of new products is not captured by real GDP growth, which (by definition) only changes in production volume of existing varieties. Second, quantifying the welfare impact of new products involves significant conceptual and measurement obstacles.

When a new product is invented, it induces a multiplicity of welfare changes for different categories of economic agents: 1) it generates monopolistic profits for its inventor; 2) it generates negative profit spillovers to producers of substitute goods (which lose business to the new product) 3) it generates consumer surplus for customers who purchase those goods; 4) it generates positive spillovers for sellers of existing goods that are strategic complements for the newly-introduced ones. In order to measure the welfare contribution of new products, we must measure all of these effects (the change in total surplus is the sum of all these effects). The magnitude of all these effects in turn depends on the degree of substitution between novel and existing varieties. In other words, to measure the value of new products, we must understand how they interact in the product market (and in the consumer's utility) with existing varieties.

This is well understood in the field of empirical industrial organization (IO). Demand estimation techniques allow IO economists to recover, from observed price, quantity sold, and product characteristics data, the welfare contribution of new products (Petrin, 2002; Nevo, 2003). The main limitation of this approach is that it is only feasible for very few industries where this rich data is available. In other words, it is not scalable for most of the economy. Quantifying the value of new product introductions at scale remains an open research question.

In this paper, we make progress on this question: we develop a methodological framework that allows us to estimate the welfare impact of new product introductions for a very large set of firms, namely the universe of publicly-traded firms. We accomplish this with a three-step approach.

The first step consists of constructing a dataset of new product introductions, and estimating the contribution of those new products on the profit of the firm that introduced them. To do so, we construct a measure of new products, as follows. We obtain the dates of new product announcements from two different sources. The first is S&P CapitalIQ's Key Developments database. As an alternative data source, we use Dow Jones' Factiva database that involve firms traded on U.S. stock exchanges, and that Factiva has filed under New Products/Services category. Using a convolutional neural network trained on a human-generated dataset, we refine this set of article to a much smaller one that captures with high likelihood new product announcements. We then estimate abnormal returns on the mentioned firm's stock on the day of the media articles, and consider only those firms with a positive stock price reactions. This ensures that our procedure captures new product releases that are important enough to move firms' stock prices.

The second step in valuing the welfare contribution of new products is to rely on financial markets to identify important innovation. The stock price impact of a media article in a short time-window surrounding its publication reflects the market's estimation of all current and future profits from the new product mentioned in that article. In an efficient stock market, this is the correct estimate of the value of the product to the firm's shareholders. To the extent that expected profits for the innovating firm reflects the aggregate willingness-to-pay for that good or service by consumers, this value of the product to the firm, in turn, reflects the value created by that particular innovation. Such approach is similar to Kogan, Papanikolaou, Seru and Stoffman (2017), who value patents using stock market reactions to patent grants. The market-based measure of value is not only flexible – in that the same approach can be used to value any type of good, service, or activity – it also helps avoid issues associated with researchers trying to measure value of new business models, say, a ChatGPT 4.0 or a Meta virtual reality headset.

The third consists in computing the product market spillovers of new product introductions, including the impact on consumer surplus. In order to accomplish that, we need a demand system that can cover all U.S. publicly-traded firms. We use the GHL oligopoly model of Pellegrino (forth.), which is ideally suited to this purpose. The model allows us to estimate the impact of the product introduction not only on the firm itself, but also on its competitors and on consumers.

Using this approach we find that new products generate substantial welfare gains, averaging 0.15-0.20% of GDP annually. We find that most of the welfare gain from new products accrues to the innovating firms, rather than to the consumer. Further investigation reveals that the key reason behind such a pattern is that new products are introduced disproportionately by firms with substantial market power, who then extract most of the surplus from this process in the form of increased profits.

Looking at the cross-section, we find that product innovation generates significant spillovers to producers of substitute goods as well as strategic complements. Our methodology allows us to quantify these spillovers for each individual firm pair. We find significant heterogeity in the sign and size of these spillovers across firms.

We also find interesting cyclical patterns. The welfare contribution of new products declined significantly during the 2008-2009 financial crisis, possibly as a consequence of the fact that tight financial conditions limited firms' ability to invest in product innovation. The size of the product market spillovers, on the other hand, spiked around the COVID pandemic, reflecting the fact that product innovation was concentrated among an unusual set of firms, which likely were active in more competive markets.

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).

Relative to other measures of new products using product sales data from retailers (e.g., early work by Eddy and Saunders (1980), Wittink et al. (1982), or more recently Pukthuanthong and Wang (2021)), the advantages that this measure brings in are as follows. For one, our approach covers all industries in a uniform and systematic way. 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; it also prevents us from studying aggregate innovation in the economy.

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. (2021) 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. Eddy and Saunders (1980) was the first to study the impact of new product introductions on monthly stock returns using a sample of 66 firms, followed by Wittink et al. (1982) on computer and office machines business. Pakes (1985) also 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. Different from these papers, we do not aim to assess the market value of the average new product announcement; instead, we seek to sieve out valuable new products, and use them to measure firm innovation success.[1] 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. 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 modeled as an expansion of the *product* space, but typically proxied using patents or citations when testing model predictions in the data.

2 Methodology: New Product Announcements

2.1 CapitalIQ Key Developments

Our first source of new product announcements comes from S&P Capital IQ's Key Developments database. This database tracks significant corporate events, including new product introductions, across publicly traded companies. We specifically focus on event type 41 (Product-Related Announcements), which captures various forms of product-related news including product launches, unveilings, and major enhancements.

To ensure we capture genuine new product introductions rather than routine corporate announcements, we apply several filters to the raw data. First, we restrict our attention to headlines containing specific action words that signal new product introductions: "unveil", "reveal", "launch", "introduce", "release", "present", "issue", "upgrade", "enhance", "improve", "extend", or "new." We explicitly exclude announcements related to natural resource exploration (containing words such as "drill", "explore", or "excavate") to avoid confounding new product introductions with operational updates in extractive industries.

A crucial step in our methodology is to isolate the effect of new product announcements from other corporate events that might affect stock prices. To this end, we remove announcements that coincide with major corporate events in a three-day window centered on the announcement date. We exclude announcements that occur within one day of earnings announcements (identified using Compustat's earnings announcement dates), merger and acquisition announcements (sourced from SDC Platinum), and dividend declarations or

[1] There are also other methodological differences: (i) Our use of all media mentions and not just company announcements is less susceptible to information leakage-induced mismeasurement; (ii) Our use of machine learning techniques allow us to distil true new products from 660,958 news articles on 16,278 distinct public firms across industries over a 25-year period, something that was not technologically possible when many of these earlier papers were written. This is probably the reason why most of these papers focused on specific industries.

Figure 1: Examples

New Product

NVIDIA unveils GoForce 5500 handheld GPU

210 words
14 February 2006
Telecomworldwire
TLCW
English
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The NVIDIA GoForce 5500 handheld graphics processing unit (GPU) has been unveiled by NVIDIA Corporation (**Nasdaq**:NVDA), a programmable graphics processor technologies company.

According to NVIDIA the GoForce 5500 is the industry's first handheld GPU to enable true, fluid digital TV, rapid multi-shot photography, high-fidelity surround sound and console-class 3D graphics.

NVIDIA said its GoForce 5500 offers ultra-low power consumption and is the first handheld GPU to playback H.264, WMV9 and MPEG-4 video up to D1 resolution at 30f/s. It is compatible with the main mobile TV standards such as DVB-H, ISDB-T and DMB networks and NVIDIA claims it enables play of console-class 3D games such as Quake III Arena at unrivalled speeds on a handheld device.

The GoForce 5500 offers crossfade and multistream technologies to stop music cut-out and breaks between songs and enables sharp digital photography with support for up to 10 megapixel resolution and rapid multi-shot capabilities.

NVIDIA said that phones based on the NVIDIA GoForce 5500 handheld GPU are expected to be available before this year's holiday season, from the main handset manufacturers.

Not a New Product

Kosan Biosciences to Present at the Leerink Swann Solid Tumors Roundtable Conference

346 words
7 May 2008
04:00
PR Newswire (U.S.)
PRN
English
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HAYWARD, Calif., May 6 /PRNewswire-FirstCall/ -- Kosan Biosciences Incorporated (**Nasdaq**: KOSN) announced today that Jane Green, Kosan's Vice President, Corporate Communications, will present at the Leerink Swann Solid Tumors Roundtable Conference in New York at the Grand Hyatt Hotel on Friday, May 9, 2008 at 11:10 a.m. EDT. A live webcast of the presentation can be accessed through http://www.wsw.com/webcast/leerink15/kosn/.

Interested parties may also access a live webcast of the presentation by visiting the "Events Calendar" page under the "Investors/Press" tab on Kosan's website at http://www.kosan.com. A recorded replay of the presentations will be available for two weeks.

Figure Notes: The top panel provides an example of new product as classified by our algorithm and the bottom panel provides an example of the news article in our original data that was not classified as a new product.

stock splits (obtained from Capital IQ's corporate actions database). This cleaning procedure helps ensure that our measure captures the market's reaction to new product introductions rather than other coincident corporate events that might affect stock prices.

2.2 Factiva Articles, Filtered by Convolutional Neural Networks

As a secondary source of new product announcements, we analyze news articles from the Dow Jones Factiva database. This dataset complements our primary source (Capital IQ) and allows us to validate our findings using an alternative classification of product announcements. In this section, we describe in detail how we process and classify articles from this secondary data source.

We first extracted all media articles from the Dow Jones Factiva database that involve firms traded on U.S. 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, covering the period 1989-2015.

This database of new product announcements from Factiva complements the Capital IQ-based sample. Using both sources allows us to cross-validate our findings and provides a more comprehensive picture of product innovation across publicly traded U.S. firms.

2.3 Estimating the Profit Impact of New Products

In our next critical step, we leverage the efficient market hypothesis to obtain a forward-looking measure of the private value of new products for every firm/year. We estimate abnormal returns on the mentioned firm's stock surrounding the day of the article's release. Specifically, we calculate cumulative abnormal returns on the day of the product announcement. Expected returns are calculated based on the Fama-French 3-factor model. 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.

Figure 2: Product Announcement - Event Study

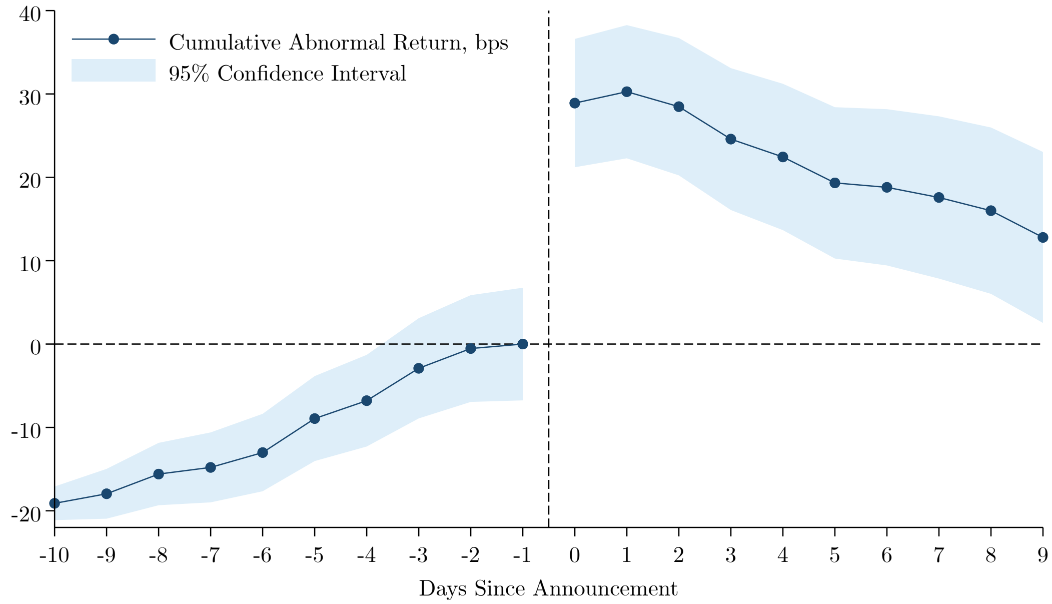


Figure Notes: This figure shows cumulative abnormal returns (CARs) around new product announcements, estimated using the Fama-French three-factor model. The solid line represents the average CAR, while the dashed lines represent the 95% confidence intervals. The event window spans from 10 days before to 9 days after the announcement ($t = 0$), with CAR normalized to zero at $t = -1$. CARs are expressed in basis points (one basis point equals 0.01%). The sample includes all new product announcements from both Capital IQ and Factiva that were identified by our methodology and that did not coincide with other major corporate events (earnings announcements, M&A, or dividend/split announcements) in a three-day window around the announcement.

This method is similar to the one taken by Kogan et al. (2017) (KPSS) to value patents, and it allows us to capture the market's immediate reaction to the new product announcement, which should reflect the expected present value of future profits generated by the new product. It is important to note that while our approach is inspired by KPSS, there are a few key differences. We focus on new products, which are the final outputs of innovation that directly reach consumers. This allows us to capture innovation that might not be patentable or types of innovation that firms might choose not to patent for strategic reasons.

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.

Figure 2 presents the event study analysis of cumulative abnormal returns (CARs) around new product announcements. The analysis is based on the Fama-French three-factor model and examines a window of 20 trading days, centered on the announcement date (from $t = -10$ to $t = +9$). We normalize the CAR to zero at $t = -1$ to focus on the announcement effect.

The results reveal a sharp and economically significant market reaction to new product announcements. On the announcement day ($t = 0$), we observe an immediate jump in CARs of approximately 29 basis points. This positive reaction continues into the following day (t=1), reaching a peak of about 30 basis points. The magnitude of this two-day response suggests that new product announcements convey substantial information about firms' future prospects.

The positive market response persists in the post-announcement period, though it gradually declines. By ten days after the announcement (t+9), CARs remain positive at around 13 basis points, indicating that the market's initial reaction is not reversed in the short term. The 95% confidence intervals (shown by the dashed lines) indicate that the positive CARs are statistically significant during the announcement window and remain so throughout most of the post-announcement period.

Looking at the pre-announcement period ($t-10$ to $t-1$), we observe a slight downward trend in CARs, from about -19 basis points ten days before the announcement to our normalization point of zero at $t=-1$. This pattern could suggest some anticipation effects or reflect broader market dynamics leading up to new product announcements.

2.4 From Market Capitalization to Profits

The event study analysis yields an estimate of the change in a firm's market capitalization as it introduces a new product. However, what we need for our measurement exercise is a measure of yearly profits that are generated by the corresponding product. While the two are naturally connected by the fact that a firm's market value is the discounted present value of all its future profits, to infer the latter from the first we need to make an assumption.

We make the conservative assumption that all new product introductions induce a parallel shift in the term structure of future dollar profits. Under this assumption, the contribution of new product z to next period profits (v_z) can be estimated as:

$$v_z \;=\; r_{it(z)}\,\delta_z\,\mathcal{M}_{it(z)-1} \tag{2.1}$$

where δ_z is the percent increase in the market capitalization of company i induced by product introduction z, $\mathcal{M}_{it(z)-1}$ is the previous period market capitalization, and $r_{it(z)}$ is a measure of the discount rate implied by the firm's market capitalization.

Now, it may be tempting to use the measured abnormal return - which we call $\mathcal{A}_{it(z)}$ - to proxy for δ_z. However, the abnormal return $\mathcal{A}_{it(z)}$ is bound to contain, along with information about the market value change induced by the introduction of product z, a significant amount of measurement error $\varepsilon_{it(z)}$. The standard and natural assumption (as suggested by KPSS) is that this error is additive:

$$\mathcal{A}_{it(z)} \;=\; \delta_z + \varepsilon_{it(z)} \tag{2.2}$$

One undesirable consequence of measurement error is that, if we were to use $\mathcal{A}_{it(z)}$ as a proxy for δ_z, we would infer that the profit impact of many new products is negative. By accounting for the presence of this measurement error, we can obtain a superior estimate of the economic contribution of the new products. Following KPSS, we assume that the signal follows a half-normal distribution with variance parameter τ_δ^2

$$\delta_z \sim \mathcal{N}^+\left(\tau_\delta^2\right) \qquad \varepsilon_{it} \sim \mathcal{N}\left(0, \tau_\varepsilon^2\right) \tag{2.3}$$

defining ρ to be the signal-to-noise ratio

$$\rho \;=\; \frac{\tau_\delta^2}{\tau_\delta^2 + \tau_\varepsilon^2} \tag{2.4}$$

we obtain the mean estimate of δ_z, conditional on the observed abnormal return $\mathcal{A}_{it(z)}$:

$$\mathbb{E}\left(\delta_z \middle| \mathcal{A}_{it(z)}\right) \;=\; \rho\,\mathcal{A}_{it(z)} + \sqrt{\rho}\cdot\tau_\varepsilon\cdot\frac{\varphi\left(-\sqrt{\rho}\cdot\delta_z\cdot\tau_\varepsilon^{-1}\right)}{1-\Phi\left(-\sqrt{\rho}\cdot\delta_z\cdot\tau_\varepsilon^{-1}\right)} \tag{2.5}$$

by plugging this expectation inside equation (2.1) we obtain our (non-negative) estimate of v_z.

Using this data, we create two measures of new product introductions at the firm-year level. Our first measure is a count of the number of new products launched by a firm in a given year. This is defined as the number of distinct times we uncover, using the approach described above, news media mentions of new products associated with the firm that lead to positive abnormal returns in the stock market. The positive abnormal return condition ensures that we are capturing products that are important enough for the firm mentioned in our articles to have a meaningful impact on its value (and consequently rules out cases where the article mentions new products introduced by rivals, or related firms; these are unlikely to affect a firm's return in the same manner).

For our second measure, instead of counting new products, we aggregate cumulative abnormal returns (conditional on them being positive, as before) coming from all new product news for a given firm in a given year. Note that the annual horizon of aggregation is to capture the fact that many consecutive news articles within a time span might refer to the same new product launch by a firm, with each articles revealing a bit more information on the product (and hence, each article being accompanied by positive stock price reactions). Aggregating over a longer time span, such as two years instead of one to capture even slower diffusion of information about new products in the stock market does not change our results materially.

Note also that our positive abnormal return screen can mitigate the concern that the trends that we observe might be related to changes in the media coverage of firms over time. Still, in all our regression specifications we also use time fixed effects to account for such possibilities (assuming that any media coverage changes are not systematically different across sectors over time).[3]

We aggregate over an annual horizon to capture the fact that multiple news articles within a time span might refer to the same new product launch, with each article revealing more information. To translate these abnormal returns into dollar values, we multiply the cumulative abnormal return by the firm's market capitalization. This gives us an estimate of the market value added for each new product announcement.

3 Demand Model, Spillovers and Welfare

3.1 Generalized Hedonic-Linear (GHL) Demand

The next step in our methodology is to estimate, starting from the measured profit contributions of new products, the corresponding product market spillovers and welfare contributions. In order to accomplish that, we need a demand system and a model of product market competition that can encompass all US publicly-traded firms. The standard and natural tool in this case is the Generalized Hedonic-Linear (GHL) Oligopoly model of Pellegrino (forth.), which we review briefly below.

There are n firms in the economy, indexed by $i \in \{1, 2, ..., n\}$, that produce differentiated products and compete oligopolistically. Each firm produces only one product, i.e., firm i only produces product i. The demand these firms face is hedonic, meaning that consumers evaluate each product as a bundle of characteristics.

There are two types of characteristics: m common characteristics indexed by $k \in \{1, 2, ..., m\}$ and n idiosyncratic characteristics indexed by $i \in \{1, 2, ..., n\}$. We assume that each unit of product i provides: 1) one unit of the corresponding idiosyncratic characteristic i; 2) a unit-length vector of $\mathbf{a}_i \in \mathbb{R}^n$ of common characteristics, formally:

$$\mathbf{a}_{it} = \begin{bmatrix} a_{1it} & a_{2it} & \dots & a_{nit} \end{bmatrix}' \tag{3.1}$$

[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.

$$\text{such that} \qquad \sum_{k=1}^{m} a_{kit}^2 = 1 \quad \forall\, i \in \{1,2,...,n\} \tag{3.2}$$

With regard to the n idiosyncratic characteristics, we assume that each unit of good i provides exactly one unit of its corresponding idiosyncratic characteristic i. Hence, we can just use q_i to denote the units of idiosyncratic characteristic i consumed by representative consumer.

We assume that the representative consumer's utility function $\mathcal{U}$ is linear quadratic in both common characteristics x_j and idiosyncratic characteristics vector q_i, and linear (decreasing) in the labor supply, L:

$$\mathcal{U}\left(\mathbf{x}_t, \mathbf{q}_t, L_t\right) \quad \stackrel{\text{def}}{=} \quad b_{it} q_{it} - \frac{\alpha}{2} \cdot \sum_{k=1}^{m} x_{kt}^2 - \frac{1-\alpha}{2} \sum_{i=1}^{n} q_{it}^2 + L_t \tag{3.3}$$

where b_i is the intercept demand shifter for product i and α is the weight placed by the consumer on the common characteristics. The representative consumer earns income from labor and the profits of all firms, and chooses an optimal consumption bundle $\mathbf{q}_t$ subject to a budget constraint. Firm i faces a marginal cost of production equal to c_i and chooses output q_i to maximize profits. Pellegrino (forth.) shows that the following linear demand system solves the consumer problem:

$$\mathbf{p}_t \;=\; \mathbf{b}_t - \left(\mathbf{I} + \mathbf{\Sigma}\right) \mathbf{q}_t \tag{3.4}$$

where $\mathbf{p}_t$, $\mathbf{q}_t$ and $\mathbf{b}_t$ are vectors of prices, quantities, and demand intercepts (respectively). $\mathbf{I}$ is the identity matrix, and

$$\mathbf{\Sigma}_t \quad \stackrel{\text{def}}{=} \quad \frac{\partial \mathbf{p}_t}{\partial \mathbf{q}_t} \quad = \quad \alpha \left(\mathbf{A}_t' \mathbf{A}_t - \mathbf{I}\right) \tag{3.5}$$

as explained in Pellegrino (forth.) the (i,j) entry of matrix $\mathbf{A}_t'\mathbf{A}_t$, equal to $\mathbf{a}_{it}'\mathbf{a}_{jt}$, is called the "cosine similarity" between firm i and firm j, and is a measure of product substitution. The Cournot-Nash equilibrium vector of profits $\boldsymbol{\pi}_t$ is given by:

$$\sqrt{\boldsymbol{\pi}_t} \quad = \quad \mathbf{\Omega}_t \left(\mathbf{b}_t - \mathbf{c}_t\right) \tag{3.6}$$

$$\text{where} \qquad \mathbf{\Omega}_t \quad \stackrel{\text{def}}{=} \quad \left(2\mathbf{I} + \mathbf{\Sigma}_t\right)^{-1} \tag{3.7}$$

$\mathbf{b}$ and $\mathbf{c}$ are, respectively, the demand and supply function intercepts. Hence, $(b_i - c_i)$ is the marginal surplus of the very first unit produced by firm i. The equilibrium Consumer Surplus is given by:

$$S_t \;=\; \frac{1}{2} \cdot \left(\mathbf{b}_t - \mathbf{c}_t\right)' \mathbf{\Lambda}_t \left(\mathbf{b}_t - \mathbf{c}_t\right) \tag{3.8}$$

where

$$\mathbf{\Lambda}_t \;\stackrel{\text{def}}{=}\; \mathbf{\Omega}_t \;\left(\mathbf{I} + \mathbf{\Sigma}_t\right)\; \mathbf{\Omega}_t \tag{3.9}$$

3.2 Measuring Product Market Spillovers

We now introduce a time subscript t and consider how product introductions can change equilibrium profits and consumer surplus. We assume (without loss of generality) that product introductions do not affect the marginal cost of production c_{jt}.[4] Then (by total differentiation) the change in profit from $t-1$ to t can be written as:

$$\pi_{jt} \;\approx\; 2\sqrt{\pi_{jt}} \left(\sum_{j=1}^{n} \omega_{ijt}\, \Delta b_{jt} \;+\; \sum_{j=1}^{n} b_{jt}\, \Delta\omega_{ijt} \right) \tag{3.10}$$

[4]A 1 dollar change in b_{jt} has the same effect on firm j's profits as a 1 dollar decrease in c_{jt}. This difference is not material for our measurement exercise.

where Δ indicates the 1-period difference. The first term in parentheses reflects the parallel shifts in residual demand generated by the the introduction of new products. The second reflects the effect of changes in the degree of similarity between products.

We next make an important assumption that the second term in parentheses is small:

$$\sum_{j=1}^{n} b_{jt} \, \Delta \, \omega_{ijt} \;\approx\; 0 \tag{3.11}$$

This assumption requires that the cosine similarity $\mathbf{A}'\mathbf{A}$ is approximately constant over the time interval considered for the measurement (one year) and/or that its increments are broadly uncorrelated with $\mathbf{b}$. What this assumption means, intuitively, is that we can model new product introductions, over short time periods, as vertical innovations – which affect the demand intercept $\mathbf{b}$ but not $\mathbf{A}'\mathbf{A}$. In other words, over small (one-year) time horizons, new products tend to be upgraded versions of existing products.

Under this assumption, the expression for the change in profit of firm j simplifies to:

$$v_z \;\approx\; 2\sqrt{\pi_{it(z)}} \sum_{j=1}^{n} \omega_{ijt(z)} \, \Delta b_{jt(z)} \tag{3.12}$$

Although (by assumption) new product introductions will be reflected in changes in $\mathbf{b}$, and we do recover changes both ω_{ij} and Δb_{jt} by taking the model to the data, it would be imprudent to attribute all the time variation in $\mathbf{b}$ to new product introductions. It is important that we allow $\mathbf{b}$ to be influenced by other factors such as random shocks, which could originate for instance by changes in consumer taste.

Let us index new products introduced by firm i with the generic subscript z. Let also $\mathcal{Z}_{it}$ be the set of new products introduced by firm i, between $t-1$ and t. We model changes in b_i over time, as the sum of the effect of the introduction of new products (β_{zt}) and of a random shock ξ_{jt} which captures all other economic forces affecting willingness to pay b_{jt} (the underlying process is irrelevant for our measurement):

$$\Delta b_{jt} \;=\; \sum_{z \in \mathcal{Z}_{it}} \beta_{zt} + \xi_{jt} \tag{3.13}$$

where $\hat{b}_{zt}$ is the contribution of new product z, introduced at time t. We can then define v_{iz} the effect of introduction of product z on firm j as:

$$v_{jz} \quad \stackrel{\text{def}}{=} \quad \frac{\partial \pi_{jt}}{\partial b_{jt}} \cdot \beta_{zt} \quad = \quad 2\sqrt{\pi_{jt}} \cdot \omega_{jjt} \cdot \beta_{zt} \tag{3.14}$$

v_{jz} is what we actually estimate using stock returns in the previous step of our procedure. Specifically, our analysis of abnormal return results in a dataset of estimates of profit impacts (v_{jz}) for all covered products.

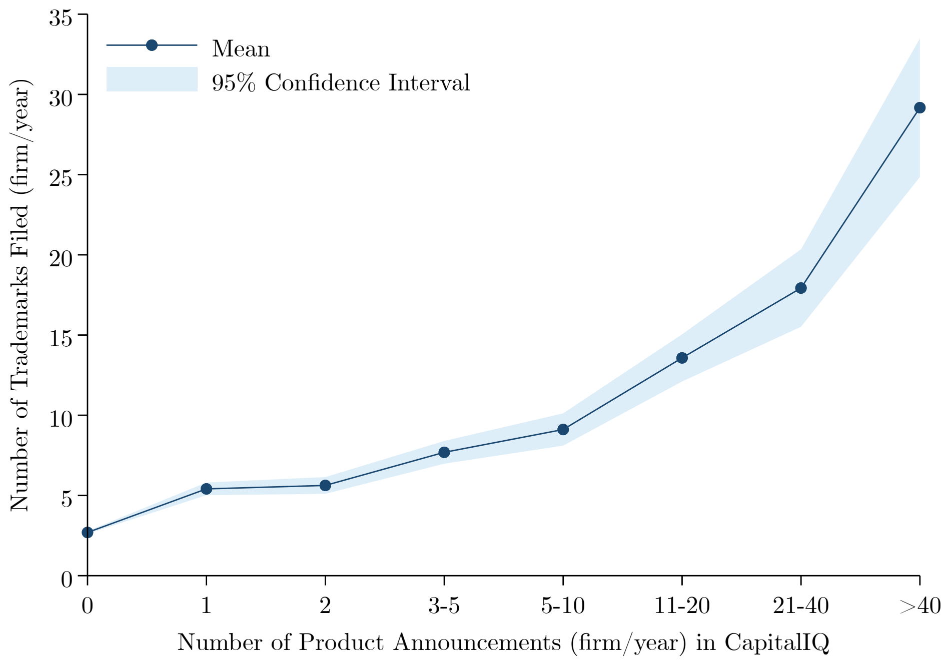
More generally, we can define v_{iz}, the effect of the introduction of z on a generic company i (not necessarily equal to j, who introduced the product):

$$v_{iz} \quad \stackrel{\text{def}}{=} \quad \frac{\partial \pi_{it}}{\partial b_{jt}} \cdot \beta_{zt} \quad = \quad 2\sqrt{\pi_{it}} \cdot \omega_{ijt} \cdot \beta_{zt} \tag{3.15}$$

Then, combining equations (3.14) and (3.15) we can finally write the spillover to firm j in terms of the private rent v_{jz} and other observables ($\boldsymbol{\pi}$ and $\boldsymbol{\Omega}$):

$$v_{iz} \quad = \quad \sqrt{\frac{\pi_{it}}{\pi_{jt}}} \cdot \frac{\omega_{ijt}}{\omega_{jjt}} \cdot v_{jz} \tag{3.16}$$

FIGURE 3: VALIDATION USING TADEMARKS AND RAVENPACK PRODUCTS



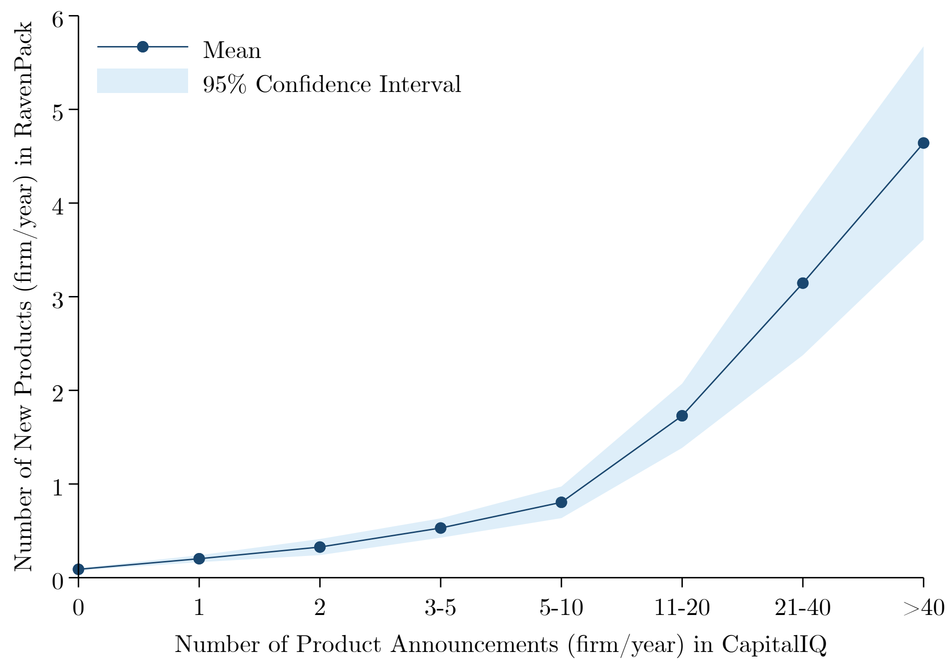


FIGURE NOTES: The figures above shows the relationship between product announcements in Capital IQ and trademarks (upper figure) and product announcements in Capital IQ and product introductions identified from RavenPack dats (lower figure) over 2002-2019. The horizontal axis shows bins for the number of product announcements per firm-year in Capital IQ. The vertical axis shows the average number of new products identified by RavenPack for firms in each Capital IQ announcement bin. A product is considered new in RavenPack when it is first associated with a company in news coverage. The blue dots represent means while the light blue bands show 95% confidence intervals.

Finally, we consider the effect on consumer surplus S_t, which we indicate with the capital letter V:

$$V_z \quad \stackrel{\text{def}}{=} \quad \frac{\sum_{i=1}^{n} (b_{it} - c_{it}) \lambda_{ijt}}{2\sqrt{\pi_{jt}} \cdot \omega_{jjt}} \cdot v_{jz} \tag{3.17}$$

The sum of all these effects (own profits, competitors' profits as well as consumer surplus) is the change in total surplus resulting from a new product introduction. If we then aggregate across all new products introduced in a given year we obtain a measure of the dollar change in welfare from year to year due to the introduction of new products.

3.3 Data and Implementation

There are two crucial inputs required to estimate GHL demand. The first is revenue and cost data for publicly-traded companies from Compustat. Based on this data Pellegrino (forth.) shows how to recover the prices $\mathbf{p}$, the quantities $\mathbf{q}$, and the marginal costs $\mathbf{c}$.

The second crucial input is the dataset of Hoberg and Phillips (2016): it provides a time-varying empirical estimate of $\mathbf{A}_t'\mathbf{A}_t$, and is constructed from textual descriptions of products contained in the mandatory annual 10-K filings of the public corporations. Armed with this estimate, we can recover the matrices $\mathbf{\Sigma}_t$, $\mathbf{\Omega}_t$, $\mathbf{\Lambda}_t$ as well as the vector of demand intercepts $\mathbf{b}$ (see Pellegrino for full details).

4 Validation and Relation to Other Measures of Innovation

4.1 Validation using RavenPack and Trademark Filings

Unlike patents or R&D expenditures, there are no comprehensive, well-established databases tracking the dynamics of product introductions across companies over time. This creates a validation challenge: how can we ensure that our new dataset of product announcements from Capital IQ accurately captures meaningful product innovation?

We first look at the data on trademarks that that are filed with US Patent and Trademark Office (USPTO) when a firm launches a new product line or service.[5] The upper figure in Figure 3 presents a validation exercise, in which we plot the average number of trademarks filed by firms with different frequencies of Capital IQ product announcements, over the period 2002-2019. The relationship between the two measures is strongly monotonic: firms with more product announcements in Capital IQ tend to have more trademarks.

As our second and a more direct way to validate our measures, we construct an independent product-firm panel using RavenPack Analytics, a dataset of news articles from over 19,000 sources. RavenPack employs natural language processing algorithms to tag news articles with various entity identifiers, including "company" and "product" tags. A key advantage of using RavenPack for validation is that its product tags provide independent verification of whether something is truly a product – if something appears in RavenPack with a product tag, we can be highly confident it is indeed a product. However, RavenPack has two important limitations. First, it identifies a product as "new" in the year when it is first tagged together with a company in a news article, which may occur well after the actual product announcement. Second, RavenPack's coverage is incomplete – many genuine products are never tagged in its system. While these limitations explain why RavenPack identifies far fewer products than Capital IQ (16,732 versus 97,096 over our sample period), RavenPack's independent verification of product status makes it valuable for validating our main dataset.

Similarly to trademarks, the bottom figure in Figure 3 plots the average number of product introductions identified by RavenPack for firms with different frequencies of Capital IQ product announcements, over the

[5] We thank the authors of Hsu et al. (2021b,a)for sharing this data.

Table 1: New Product Introductions vs. Patenting

		Receives a Patent: No	Receives a Patent: Yes	Total
Announces New Products	No	3,681 (39.0%)	722 (7.7%)	4,403 (46.7%)
	Yes	2,182 (23.1%)	2,848 (30.2%)	5,030 (53.3%)
Total		5,863 (62.2%)	3,570 (37.9%)	9,433 (100.0%)

Table Notes: This table presents the joint distribution of patenting activity and new product announcements for U.S. publicly-traded firms over the period 2002-2021. The sample consists of 9,433 unique firms. "Announces New Products" is a dummy variable equal to one if a firm has at least one new product announcement in the CapitalIQ database. "Receives a Patent" is a dummy variable equal to one if a firm was granted at least one patent during the sample period, based on the USPTO patent data assembled by Kogan, Papanikolaou, Seru and Stoffman (2017). Numbers in parentheses show the percentage of firms in each cell relative to the total sample.

period 2002-2019. The relationship between the two measures is strongly monotonic: firms with more product announcements in Capital IQ tend to have more new products identified by RavenPack. For instance, firms with no announcements in Capital IQ average close to zero new products in RavenPack, while firms with more than forty announcements per year in Capital IQ average about 5 new products annually according to RavenPack.

This strong correlation between two independently constructed measures provides additional validation for our Capital IQ-based sample of new product announcements. The fact that RavenPack identifies fewer products than Capital IQ announces is expected given RavenPack's limitations in timing and coverage. However, the strong relationship between the two measures, combined with RavenPack's reliable product identification, suggests that Capital IQ is indeed capturing genuine product introductions.

4.2 New Product Introductions vs. Patents and R&D

A natural question is how our database of new product announcements relates to patent data, which has been extensively used in prior literature to measure innovation. In particular, Kogan, Papanikolaou, Seru and Stoffman (2017) develop an influential approach to measuring innovation by combining patent grants with stock market reactions. Like our methodology, KPSS leverage financial markets to estimate the private value of innovation. However, while patents capture the creation of new technologies, our measure focuses on the introduction of new products - the final stage of the innovation process where firms actually bring novel offerings to market. To understand how these two measures relate to each other, we examine their joint distribution.

Table 1 presents the joint distribution of patenting activity and new product introductions at the firm level over the period 2002-2021. The results reveal a striking pattern: while patenting and new product introductions are positively correlated (correlation coefficient of 41.4%), there is substantial divergence between these two measures of innovation.

Perhaps the most notable finding is that 23.1% of firms in our sample introduce new products without receiving any patents during this period. This substantial group of non-patenting innovators highlights a key

Table 2: Correlation with other Measures of Innovation

Panel A: R&D

	All Sectors (1)	Industrials (2)	Consumer (3)	Healthcare (4)	Financials (5)	ITC (6)	Others (7)
R&D	0.163***	0.084***	0.073*	0.257***	0.134**	0.163***	0.039*
	(0.013)	(0.029)	(0.039)	(0.019)	(0.068)	(0.026)	(0.023)
Firm F.E.	Y	Y	Y	Y	Y	Y	Y
Year F.E.	Y	Y	Y	Y	Y	Y	Y
R^2	0.588	0.508	0.493	0.454	0.608	0.681	0.437
N	67,741	7,798	11,840	18,386	1,983	19,737	7,978

Panel B: Patents

	All Sectors (1)	Industrials (2)	Consumer (3)	Healthcare (4)	Financials (5)	ITC (6)	Others (7)
Patents	0.012**	0.017	0.023	0.036***	0.073***	0.018**	0.006
	(0.005)	(0.012)	(0.015)	(0.012)	(0.026)	(0.009)	(0.012)
Firm F.E.	Y	Y	Y	Y	Y	Y	Y
Year F.E.	Y	Y	Y	Y	Y	Y	Y
R^2	0.611	0.528	0.471	0.464	0.573	0.668	0.361
N	129,931	14,727	18,715	17,763	21,496	24,038	21,290

Figure Notes: The table is constructed from regressions estimated in a panel setting at a firm level. In all specifications, the outcome is the number of new products over the period 2002-2021. Panel A presents results where we correlate new product measure with R&D expenditures as reported in Compustat. Panel B presents results where we correlate new product measure with the number of new eventually-granted patents that the firm has filed in the year as reported in Kogan, Papanikolaou, Seru and Stoffman (2017). We split the observations by GICS sectors: Column (1) pools all sectors, Column (2) reports Industrials (GICS=20), Column (3) reports Consumer (GICS=25&30), Column (4) reports Healthcare (GICS=35), Column (5) reports Financials (GICS=40), Column (6) reports Information Technology and Communication Services (GICS=45&50), and Column (7) reports Other Sectors. Standard errors are clustered at the firm level.

limitation of using patents alone to measure innovation: many firms engage in product innovation without seeking patent protection for their innovations. This could reflect various factors, including strategic decisions to protect intellectual property through secrecy rather than patents, innovations that are not patentable (such as new business models or service innovations), or incremental improvements that build on existing technologies.

At the same time, 7.7% of firms receive patents but do not announce any new products. These firms might be engaging in more basic research or developing technologies that they license to others rather than commercializing directly. The largest group in our sample (39.0%) consists of firms that neither patent nor introduce new products during this period.

Notably, 30.2% of firms both receive patents and introduce new products, indicating that these two innovation metrics often complement each other. However, the fact that over half of the innovating firms in our sample (23.1% out of 53.3%) would be missed by looking at patents alone underscores the importance of our new product-based measure in capturing a more complete picture of corporate innovation activity.

These findings suggest that patent counts, while informative, may significantly underestimate innovation activity by missing firms that innovate through channels that do not require or warrant patent protection. Our new product announcement measure thus provides important complementary information about innovation activity, particularly in sectors where patenting may be less relevant or strategic secrecy more valuable.

4.3 Correlation with Other Measures of Innovation

We now examine how our new products measure correlates with the other constructs of innovation. We consider innovation inputs such as R&D investments and intermediate outputs such as patents. We gather R&D expenditure data from Compustat and patent data from USPTO with a firm-level match provided by Kogan et al. (2017).

In Table 2 we estimate such contemporaneous correlations between our annual new new product measure and R&D as well as patents in a firm-level panel regression with firm and year fixed effects. Panel A reports the correlations for R&D and Panel B reports the correlations for patents. Looking at the columns (1) across both panels, we find that both R&D and patents are correlated with new product introductions. The latter is consistent with the evidence in Balasubramanian and Sivadasan (2011) who link patent stock to the product information in Census data.

We further look at how these contemporaneous correlations vary by industry sector. In Table 2, Panel A, columns (2)-(7), we see that for R&D a contemporaneous correlation holds for all sectors. In Panel B, we look at patents and we see contemporaneous correlation for Financials, Healthcare and, Information Technologies, suggesting that for these sectors traditional measures of innovation could be capturing product innovation trends quite well, but this might not hold universally across all sectors.

5 Results

5.1 Welfare Contribution of New Products

Figure 4 presents our estimates of the aggregate welfare contribution of new products introduced by publicly-traded U.S. firms from 2002 to 2021. The welfare effects are decomposed into producer surplus (profits) and consumer surplus, and are presented both in absolute terms (billions of U.S. dollars) and as a percentage of U.S. GDP. Welfare estimates are calculated using our three-step methodology: first identifying valuable new products through media coverage and stock market reactions, then estimating their profit impact through event studies, and finally computing welfare effects using the GHL demand system. Both producer and consumer surplus are expressed in current prices.

Our analysis reveals that new product introductions generate substantial welfare gains, with total benefits ranging from 0.10% to 0.24% of GDP over the sample period. The welfare contribution peaked in 2007, when new products generated approximately $21.6 billion in profits and $13.6 billion in consumer surplus, totaling about 0.24% of GDP. Throughout our sample period, the distribution of welfare gains remains relatively stable, with producer surplus consistently accounting for roughly 60% of the total benefits, while consumer surplus comprises the remaining 40%.

The temporal pattern of welfare contribution exhibits significant cyclicality and sensitivity to macroeconomic conditions. This is particularly evident during the 2008-2009 financial crisis, when we observe a sharp decline in both components of welfare. Producer surplus fell from $19.8 billion in 2008 to $15.3 billion in 2009, with consumer surplus following a similar pattern, dropping from $12.6 billion to $9.8 billion. The market subsequently recovered, but the post-2015 period shows generally lower levels of welfare contribution compared to the pre-2015 era.

By the end of our sample period in 2021, new products generated approximately $13.5 billion in profits

Figure 4: Aggregate Welfare Contribution of New Products (2001-2021)

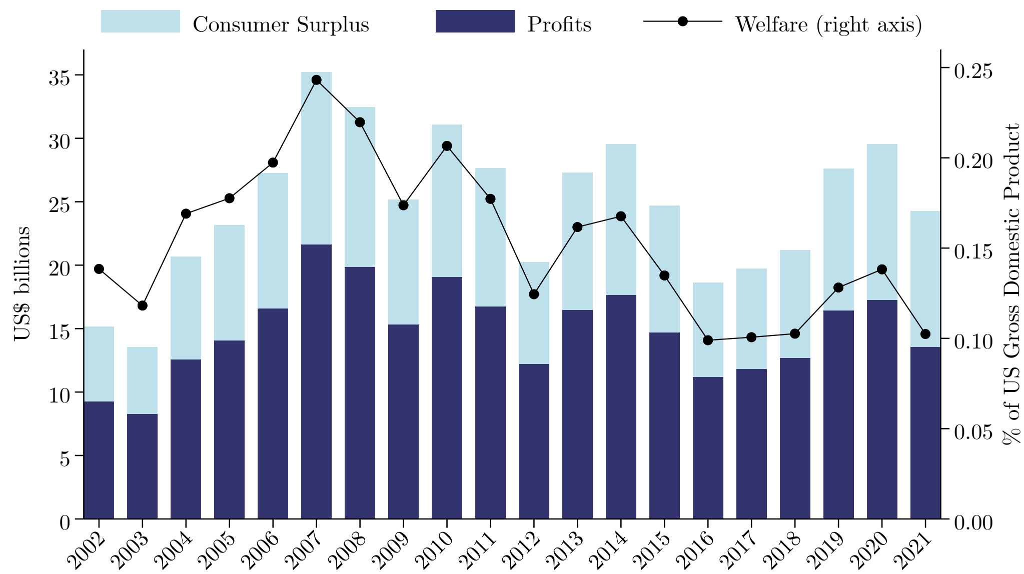


Figure Notes: This figure shows the aggregate welfare contribution of new product introductions by publicly-traded U.S. firms from 2002 to 2021. The stacked bars represent the composition of welfare gains, decomposed into producer surplus (profits, shown in dark blue) and consumer surplus (shown in light blue), measured in billions of U.S. dollars on the left axis. The black line, scaled on the right axis, shows the total welfare contribution as a percentage of U.S. GDP.

and \$10.7 billion in consumer surplus, amounting to about 0.10% of GDP. This represents a notable decline from the peaks observed in the mid-2000s, suggesting potential changes in the innovation landscape or in the ability of firms to capture value from their new product introductions. These findings quantify the substantial economic impact of new product introductions and highlight the importance of innovation for both producer and consumer welfare.

5.2 Spillovers and Heterogeneity

Figure 5 decomposes the aggregate welfare effects into four distinct components: consumer surplus, complementary profits (positive spillovers to other firms), substitution effects (negative spillovers to competitors), and own profits of innovating firms. This decomposition reveals the complex interplay between value creation and value capture in product markets.

Our analysis shows that the direct profits captured by innovating firms form the largest component of welfare gains, averaging around \$18-20 billion annually during our sample period. However, these gains are partially offset by negative spillovers to competitors through substitution effects, which typically amount to \$5-7 billion per year. This substitution effect reflects the business-stealing aspect of new product introductions, where innovative firms capture market share from their competitors.

Interestingly, we also find substantial positive spillovers to complementary firms, averaging \$2-3 billion annually throughout most of the sample period. These complementary effects arise when new products enhance the value of related products or services offered by other firms. The magnitude of these positive spillovers is particularly noteworthy in the later years of our sample, with a marked increase during 2020-2021 to around \$7 billion annually, possibly reflecting the growing importance of product ecosystem effects in the modern economy.

Figure 5: Aggregate Welfare Decomposition (2001-2022)

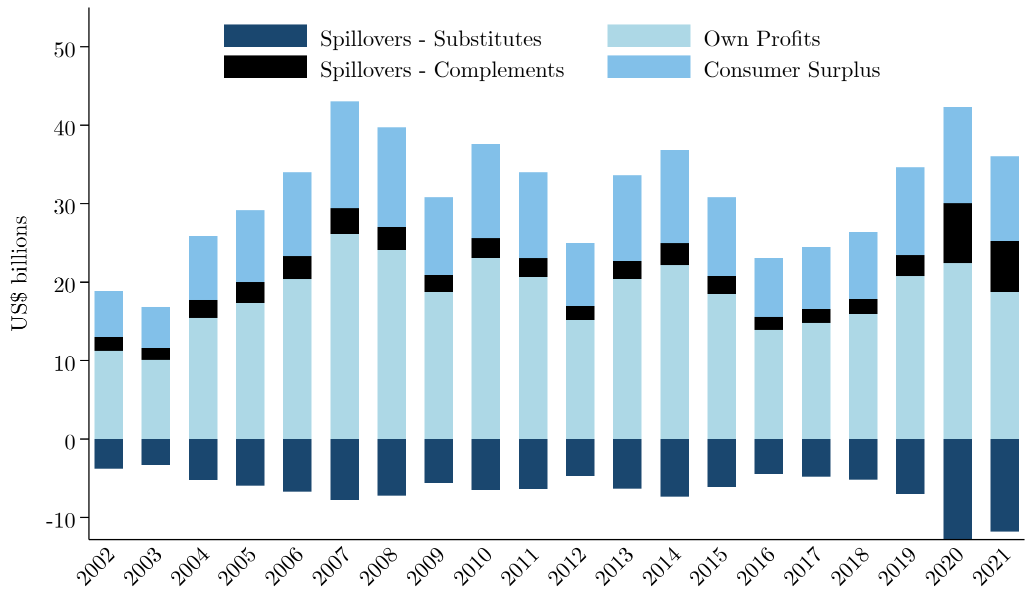


Figure Notes: this figure decomposes the aggregate welfare contribution of new product introductions by U.S. publicly-traded firms into four components over the period 2002-2021. The stacked bars show: (1) consumer surplus (mid blue), representing the direct benefit to consumers; (2) complementary profits (black), capturing positive spillover effects on firms producing complementary products; (3) substitution effects (dark blue), measuring negative spillovers on competing firms; and (4) own profits (light blue), representing direct profits accruing to innovating firms. All values are expressed in billions of current U.S. dollars.

Consumer surplus remains a significant and stable component of total welfare, typically ranging between \$8-12 billion annually. This relatively stable share of consumer surplus suggests that firms have maintained consistent pricing power over their new products throughout our sample period, despite changes in market structure and competitive dynamics.

Figure 6 presents the distribution of product market spillovers across firms in 2021, measured in cents per dollar of innovating firms' own profits. The histogram reveals substantial heterogeneity in how new product introductions affect other market participants. The distribution is roughly bell-shaped but slightly asymmetric, with a longer left tail, indicating that negative spillovers can be more extreme than positive ones.

The majority of spillover effects cluster around zero, with the highest frequency of observations falling in the range of -10 to +10 cents per dollar of innovating firm profits. However, the distribution extends significantly in both directions, ranging from approximately -120 to +70 cents per dollar. This wide range suggests that while most new products have relatively modest effects on other firms, some innovations can generate substantial positive or negative externalities.

5.3 New Products Introductions and Market Power

An important question that emerges from our welfare analysis is why the consumer surplus generated by new product introductions appears relatively small compared to producer surplus, with a ratio of roughly 40:60. This is particularly striking when compared to the much larger consumer surplus share generated by existing products in steady state, which prior research has shown to be around 80% of total surplus. What

Figure 6: Heterogeneity of Spillovers to Competitors and Consumer (2021)

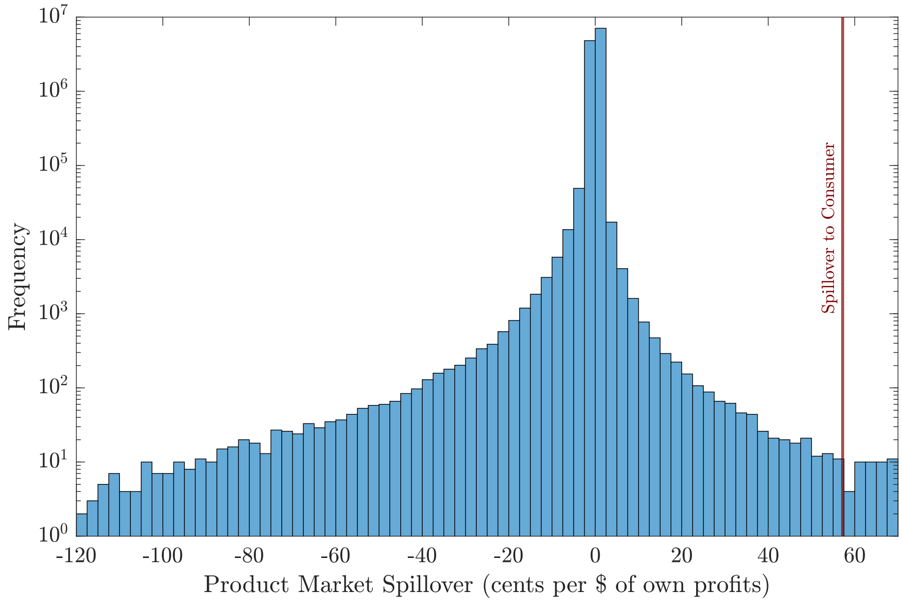


Figure Notes: this figure shows the distribution of product market spillovers generated by new product introductions in 2021, measured in cents per dollar of the innovating firm's own profits, while the vertical axis shows the frequency on a logarithmic scale. Spillovers are estimated using our GHL demand system and capture how each new product introduction affects the profits of other firms in the market. The red vertical line indicates the average spillover to consumer welfare for reference. The distribution is based on all new product introductions by publicly-traded U.S. firms in 2021 that generated significant stock market reactions.

explains this discrepancy?

The answer lies in understanding where in the product market network new product creation occurs. To measure firms' market power, we employ the measure of product market centrality (χ_i) developed by Pellegrino (forth.) – a metric that captures a firm's competitive position in the network of product market rivalries. Firms with low centrality face less competition from substitutes and thus behave more like monopolists, while highly central firms face intense competition and behave more competitively. Figure 7 provides key insight into this question by showing the distribution of product market centrality across firms, both unweighted and weighted by the number of new product announcements.

The contrast between these two distributions is striking. The unweighted distribution (light blue area) shows that most firms in the economy have relatively high centrality ($\chi_i > 0.7$), indicating they operate in competitive product markets. However, when we weight firms by their new product announcements (dark line), we observe a marked shift in the distribution toward lower centrality values, with significantly more mass in the range of $\chi_i = 0.2 - 0.6$. This indicates that firms with greater market power – those facing relatively little competition from substitute products – are more active in introducing new products.

This pattern helps explain why new products generate relatively low consumer surplus compared to producer surplus. Firms with low centrality can behave more like monopolists when pricing their innovations, allowing them to capture a larger share of the surplus created. The fact that these less central firms are more active in introducing new products naturally leads to a lower share of surplus accruing to consumers. In contrast, the higher consumer surplus share for existing products reflects that most firms in the steady state operate in more competitive markets where their ability to extract surplus is more limited.

Figure 7: Distribution of Product Market Centrality

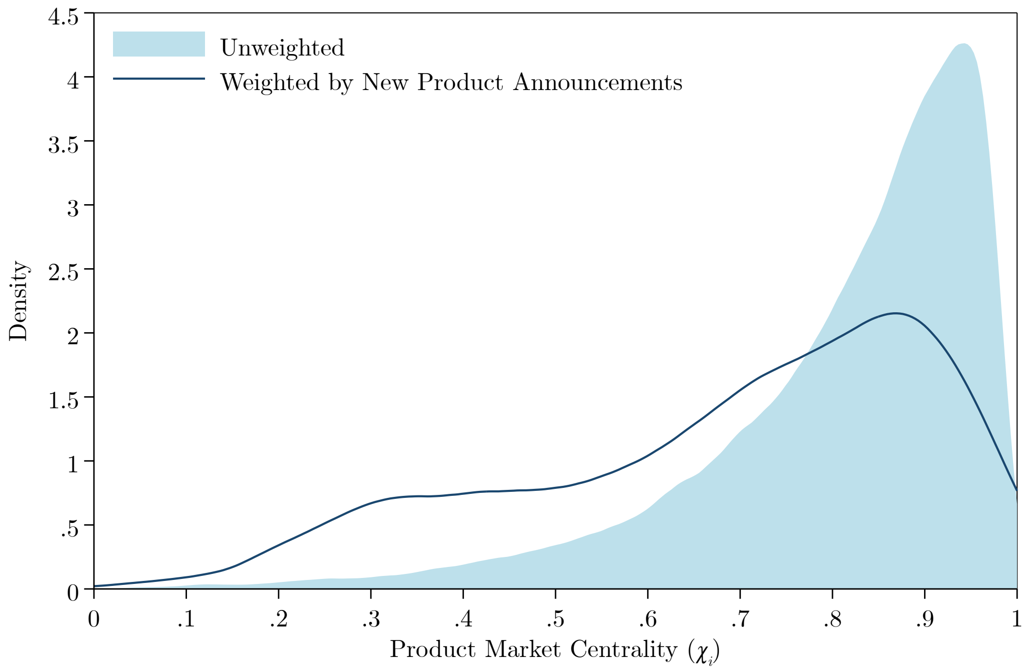


Figure Notes: This figure shows two distributions of product market centrality (χ_i) for U.S. publicly-traded firms in 2021. Product market centrality measures a firm's competitiveness based on its position in the network of product market rivalries, ranging from 0 (monopolist-like behavior) to 1 (perfect competition). The light blue area shows the unweighted distribution across all firms, while the dark line shows the distribution weighted by the number of new product announcements per firm.

6 Conclusions

This paper introduces a novel methodology to measure the welfare contribution of new product introductions at scale. Our approach combines two key innovations: first, we develop a systematic way to identify valuable new products by analyzing media coverage and stock market reactions across the universe of publicly traded U.S. firms; second, we use a scalable demand system to translate these market reactions into welfare estimates, accounting for both direct effects and market spillovers.

Our analysis yields several important findings. First, we document that new products generate substantial welfare gains, averaging around 0.15-0.20% of GDP annually during our sample period. These gains are split between producer surplus (roughly 60%) and consumer surplus (roughly 40%), suggesting that firms are able to capture a significant portion of the value they create through innovation. This relatively low share of consumer surplus, compared to what is typically observed for existing products, reflects a crucial feature of the innovation landscape: new product creation is disproportionately concentrated among firms with low product market centrality – those facing limited competition from substitutes and thus able to exercise significant market power.

Second, our decomposition of welfare effects reveals complex patterns of value creation and redistribution in product markets. While innovating firms capture substantial profits from their new products, we find significant negative spillovers to their competitors, reflecting the "creative destruction" aspect of innovation. We also document substantial positive spillovers to firms producing complementary products, particularly in recent years, highlighting the growing importance of product ecosystem effects in the modern economy.

We find considerable heterogeneity in how new products affect different market participants. While most product introductions have modest spillover effects on other firms, some innovations generate large positive or negative externalities, with effects ranging from -120% to +70% of the innovating firm's own profits. This heterogeneity underscores the importance of accounting for market spillovers when assessing the welfare implications of innovation.

Third, we note that, unlike for existing varieties, the majority of the welfare gains accrue to the producers in the form of monopoly profits. We show that this is likely a consequence of the fact that product innovation tends to be carried out by firms with signifant market power.

Finally, we show that the welfare contribution of new products appears to be tied to macroeconomic environment. We observe a notable decline during the 2008-2009 recession (when financial conditions were tight), coupled with a large spike in the size of the product market spillovers during the COVID pandemic, when product innovation was concentrated more than usual in competitive sectors.

Our findings have important implications for both research and policy. For researchers, we provide a new framework for studying product innovation that can be applied consistently across industries and over time. For policymakers, our results highlight the substantial welfare gains from product innovation while also drawing attention to its redistributive effects. Particularly noteworthy is our finding that the innovation process is dominated by firms with significant market power, resulting in a relatively small share of surplus accruing to consumers. The decline in welfare contribution we observe in recent years raises important questions about potential barriers to innovation and the changing nature of competition in product markets.

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