Patents to Products: Innovation, Product Creation, and Firm Growth

David Argente Salomé Baslandze Douglas Hanley Sara Moreira

Penn State EIEF & CEPR Pittsburgh Northwestern

7-8 November, 2019

CEPR Macroeconomics and Growth Programme Meeting

Product Innovation

- Product innovation is a key mechanism through which innovation translates into economic growth.
- Lack of systematic data on product introduction.
- Patents – the most widely-used proxy for innovation.

Product Innovation [This Paper]

- Product innovation is a key mechanism through which innovation translates into economic growth.

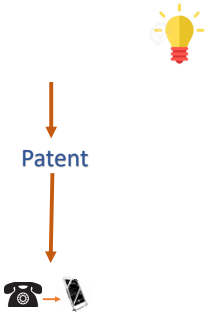
- Lack of systematic data on product introduction.
  Large-scale firm & product dataset covering consumer goods.

- Patents – the most widely-used proxy for innovation.
  [Q1] How do patents relate to the actual product innovation on the market?
  [Q2] How does product innovation and patenting vary by firm's market leadership?

Product Innovation and Patents

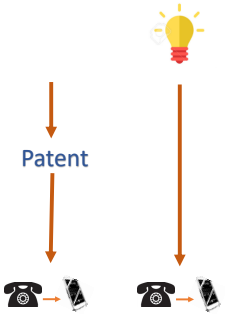
[Q1] How do patents relate to the actual product innovation on the market?

Product Innovation and Patents



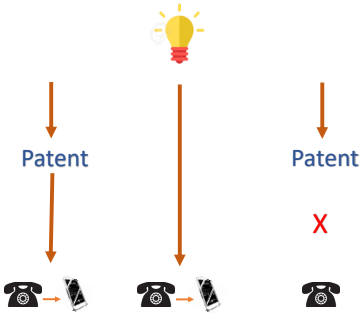
[Q1] How do patents relate to the actual product innovation on the market?

Product Innovation and Patents



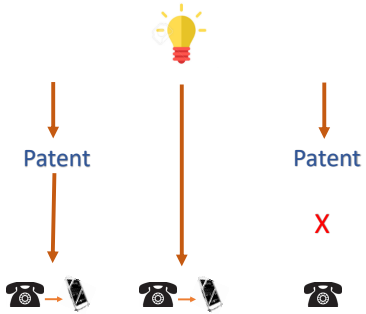
[Q1] How do patents relate to the actual product innovation on the market?

Product Innovation and Patents



[Q1] How do patents relate to the actual product innovation on the market?

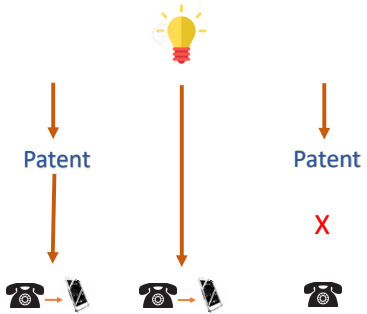
Product Innovation and Patents



[Q1] How do patents relate to the actual product innovation on the market?

- Build new dataset linking patents and products.
- Explore the relationship between patents and product introduction.

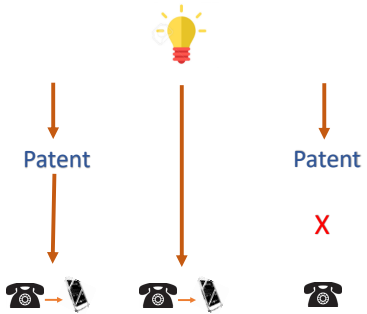
Product Innovation and Patents: Firm heterogeneity



[Q2] How does product innovation and patenting vary by firm's market leadership?

- *Empirically*: relationship between products and patents across the firm size distribution.

Product Innovation and Patents: Firm heterogeneity



[Q2] How does product innovation and patenting vary by firm's market leadership?

- *Empirically*: relationship between products and patents across the firm size distribution.

[Q2] Why? Patents signal productive value (innovation on the market), but also ... patents are a protective tool to shield from competition.

- *Theoretically*: role of patents in deterring innovation by the followers.

Outline

I. Data and Matching Algorithms

II. Patents-to-Products Relationship

III. The Role of Firm Heterogeneity

IV. Conceptual Framework and Patent Value

Data and matching algorithms

Product Data

- RMS Nielsen, 2006-2015
- CPG: groceries, drugs, general merchandise
- Product: 12-digit UPC
- Sales, prices, entry/exit of UPCs
- Text description, attributes
- GS1 - firm names

Data and matching algorithms

Product Data

- RMS Nielsen, 2006-2015
- CPG: groceries, drugs, general merchandise
- Product: 12-digit UPC
- Sales, prices, entry/exit of UPCs
- Text description, attributes
- GS1 - firm names

We classify products into distinct product categories:

- Products – barcodes/UPC codes
- Product category – a set of similar products (ex: lamps, detergents, shaving razors).

Data: Firm and Product Data

Product Data

- RMS Nielsen, 2006-2015
- CPG: groceries, drugs, general merchandise
- Product: 12-digit UPC
- Sales, prices, entry/exit of UPCs
- Text description, attributes
- GS1 - firm names

We construct for firm j in product category c in year t:

- Product introduction $N_{jt}^{c} = \sum_{i=1}^{T_{jt}^{c}} \mathbb{1}[\text{product } i \text{ is new}]$
- Novelty-adjusted product introduction $\tilde{N}_{jt}^{c} = \sum_{i=1}^{T_{jt}^{c}} \omega_i \times \mathbb{1}[\text{product } i \text{ is new}]$ where $\omega_i \in [0, 1]$ captures degree of novelty relative to existing products by using product attributes and hedonic price regressions.

Data: Patent Data

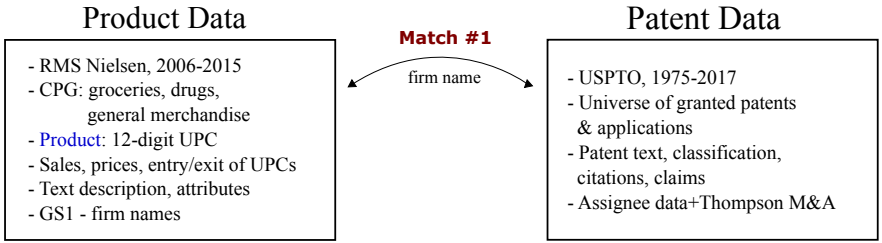
Product Data

- RMS Nielsen, 2006-2015
- CPG: groceries, drugs, general merchandise
- Product: 12-digit UPC
- Sales, prices, entry/exit of UPCs
- Text description, attributes
- GS1 - firm names

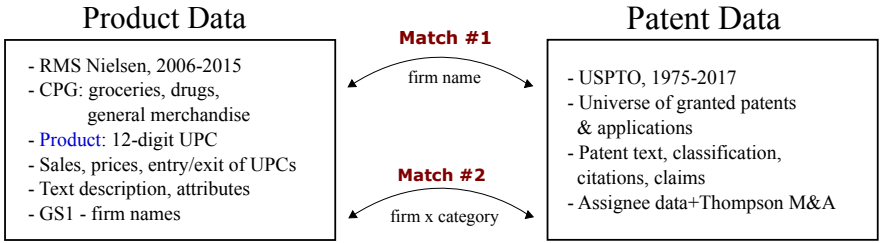
Patent Data

- USPTO, 1975-2017
- Universe of granted patents & applications
- Patent text, classification, citations, claims
- Assignee data+Thompson M&A

Data: Matching Algorithms



Data: Matching Algorithms



- We construct a patent-product link by developing an algorithm that allow us to classifying patents into product categories.
- *Text analysis* using document classification techniques (Manning et al., 2008).

Data: Matching Algorithms

Step 1: Collect *representative documents* details

- Patents: title (x5), abstract (x1), patent classification description (x3), title cited patents (x1)
- Product Categories: title (x10), entire text (x1), and first 10% text (x10) of Wikipedia article(s)

Step 2: Built *document vectors* details

- Use both 1-grams and 2-grams as tokens, and apply lemmatizer
- Exclude words that appear in $> 80\%$ of documents ("the", "and").
- Weight by total-frequency-inverse-document-frequency (Aizawa, 2003)

Step 3: Built *similarity score* between patent and product categories details

- Use inner product of normalized vectors (cosine similarity) to obtain similarity metric
- Define a *patent-product category match* – max-similarity product category (in top 5)

Validations

MATCH #1. EXAMPLE

P&G *Example*

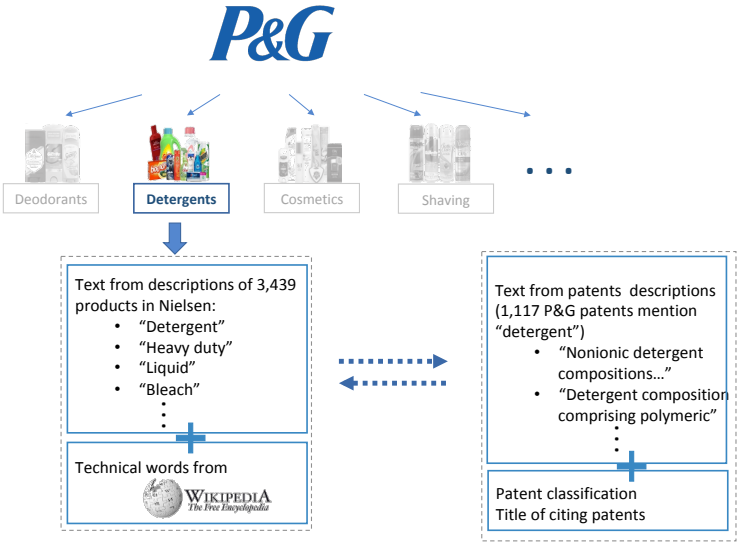
(2006 – 2015)

MATCH #2. EXAMPLE

Match 2
firm name x category

MATCH #2. EXAMPLE

Match 2
Firm x category x year



Consumer Goods Sector: Size and Representativeness

- Product
  - Data covers non-durable and semi-durable consumer products, corresponding to about 14% U.S. consumption of goods and 4.4% U.S. total consumption
  - There are a total of 35K distinct firms manufacturing consumer products
  - Dataset covers about about 40% total U.S. consumer goods sales, and covers close to the universe of firms and product introduction in the sector

- Patents
  - 9.4% of firms with consumer products have at least a patent between 2006-2015, which compares with 6% manufacturing between 2001-2012 (Hall et al.2012).
  - There is a total of 5 million patents in the period 2001-2015, and about 15% of those have as assignees firms with consumer products (6% is we required to be matched to consumer products) Detailed table
  - Examples:
    Firms: *P&G* (16,211), *Kimberly Clark* (5,500), *Kraft* (964), *L'Oreal* (6,030), *Abbott Labs* (3,941); *Samsung* (39,395), *Toshiba Battery* (8,962), *Whirlpool* (2,495), *Basf* (907), *Nike* (4,584).

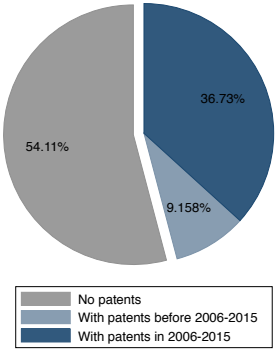
    Patents: Kiinde pump | Asthma inhaler | P&G, TidePod | Danone, obesity disorders | Beyond Meat, Plant-based

Empirical Facts

- FACT 1: A large amount of product innovation comes from firms that do not patent.

Product innovation by patenting status

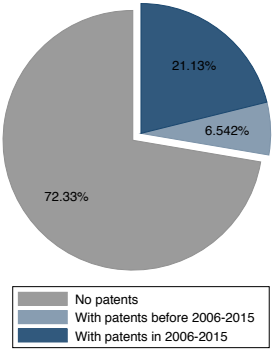
- **54%** of product introduction comes from never-patenting firms.



Heterogeneity by categories | Novelty-adjusted | Match 2

Product innovation by patenting status

- **72%** of product introduction comes from never-patenting firms $\times$ product category.



Heterogeneity by categories | Novelty-adjusted | Match 2

Empirical Facts

- FACT 1: A large amount of product innovation comes from firms that do not patent.
- FACT 2: Patenting is positively associated with product innovation (quantity and quality).

Product introduction and patenting: intensive margin

	Product Introduction Log N			Novelty-Adj. Product Introd. Log $\tilde{N}$		
Patents(t-1)	0.0412***			0.0188***		
	(0.010)			(0.006)		
Patents granted(t-1)		0.0467***			0.0214***	
		(0.011)			(0.007)	
Patents non-granted(t-1)			0.0204			0.0012
			(0.014)			(0.010)
Observations	412,004	412,004	412,004	412,004	412,004	412,004
R-squared	0.691	0.691	0.691	0.558	0.558	0.558
Time-Category	Y	Y	Y	Y	Y	Y
Firm-Category	Y	Y	Y	Y	Y	Y

Lag dependent | Extensive | Figures | Citations | Product/Process

Product introduction and patenting: intensive margin

	Product Introduction Log N			Novelty-Adj. Product Introd. Log $\tilde{N}$		
Patents(t-1)	0.0412***			0.0188***		
	(0.010)			(0.006)		
Patents granted(t-1)		0.0467***			0.0214***	
		(0.011)			(0.007)	
Patents non-granted(t-1)			0.0204			0.0012
			(0.014)			(0.010)
Observations	412,004	412,004	412,004	412,004	412,004	412,004
R-squared	0.691	0.691	0.691	0.558	0.558	0.558
Time-Category	Y	Y	Y	Y	Y	Y
Firm-Category	Y	Y	Y	Y	Y	Y

Lag dependent | Extensive | Figures | Citations | Product/Process

Product introduction and patenting: intensive margin

	Product Introduction Log N			Novelty-Adj. Product Introd. Log $\tilde{N}$		
Patents(t-1)	0.0412***			0.0188***		
	(0.010)			(0.006)		
Patents granted(t-1)		0.0467***			0.0214***	
		(0.011)			(0.007)	
Patents non-granted(t-1)			0.0204			0.0012
			(0.014)			(0.010)
Observations	412,004	412,004	412,004	412,004	412,004	412,004
R-squared	0.691	0.691	0.691	0.558	0.558	0.558
Time-Category	Y	Y	Y	Y	Y	Y
Firm-Category	Y	Y	Y	Y	Y	Y

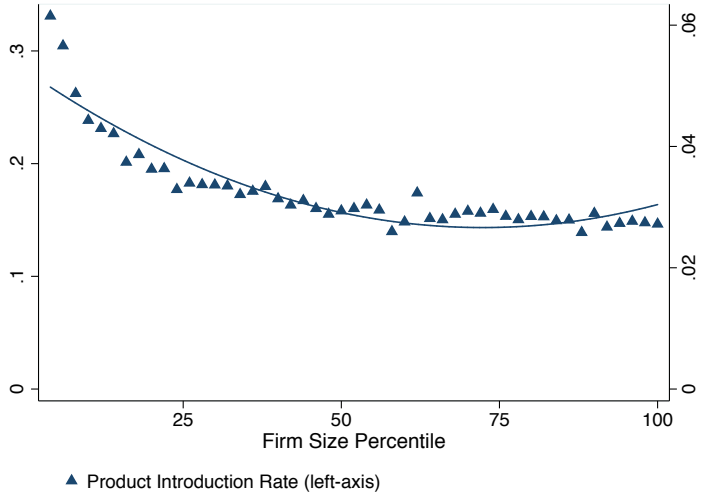
Lag dependent | Extensive | Figures | Citations | Product/Process

Empirical Facts

- FACT 1: A large amount of product innovation comes from firms that do not patent.
- FACT 2: Patenting is positively associated with product innovation (quantity and quality).
- FACT 3: Larger firms have lower product innovation rate (quantity and quality), but higher ratios of patents per new product.

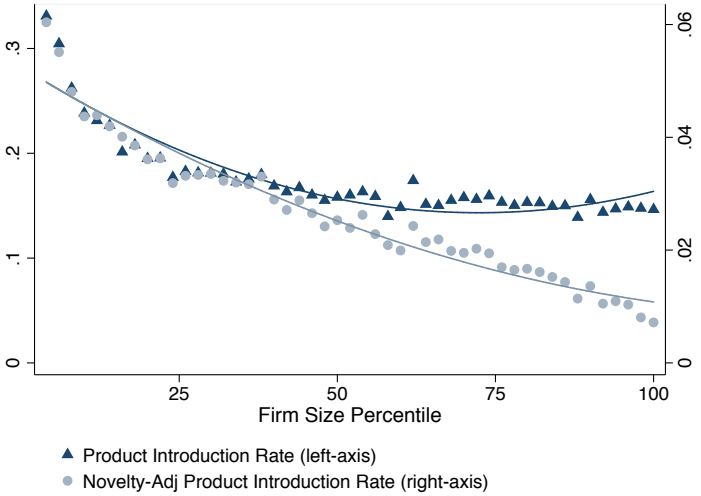
Larger firms do relatively less product innovation

- Product innovation rate declines with firm size...



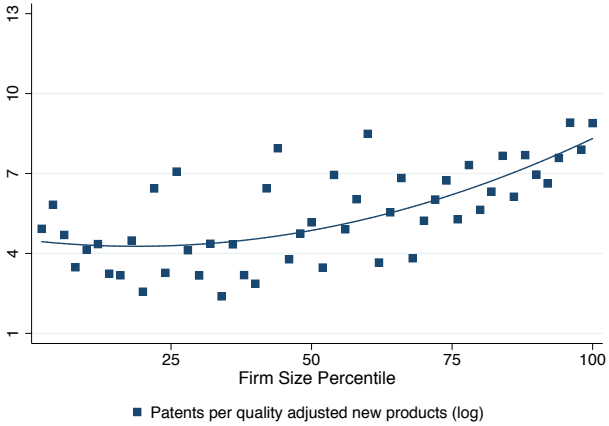
Larger firms do relatively less product innovation

- Product innovation rate declines with firm size...



... BUT RELATIVELY MORE PATENTING

- ... but patent-per-product ratio increases.



Empirical Facts

- FACT 1: A large amount of product innovation comes from firms that do not patent.
- FACT 2: Patenting is positively associated with product innovation (quantity and quality).
- FACT 3: Larger firms have lower product innovation rate (quantity and quality), but higher ratios of patents per new product.
- FACT 4: Patents of larger firms are associated with declines in competitors' product introduction.

Evidence on deterrence

Competitors react to the leaders' patenting...

New products (Log N)	...of Followers		...of Leaders	
Log Patent(t-1), Leader	-0.070***	-0.058***	-0.019	-0.016
	(0.019)	(0.019)	(0.056)	(0.056)
Log N(t-1), Leader	0.012**	0.007	0.216***	0.185***
	(0.005)	(0.005)	(0.071)	(0.072)
Observations	3,194	3,194	3,188	3,188
R-squared	0.927	0.928	0.878	0.879
Category	Y	Y	Y	Y
Time	Y	Y	Y	Y
Control	N	Y	N	Y

Evidence on deterrence

... but not to the followers'.

New products (Log N)	...of Followers		...of Leaders	
Log Patent(t-1), Followers	-0.070***	-0.058***	-0.019	-0.016
	(0.019)	(0.019)	(0.056)	(0.056)
Log N(t-1), Followers	0.012**	0.007	0.216***	0.185***
	(0.005)	(0.005)	(0.071)	(0.072)
Observations	3,194	3,194	3,188	3,188
R-squared	0.927	0.928	0.878	0.879
Category	Y	Y	Y	Y
Time	Y	Y	Y	Y
Control	N	Y	N	Y

Conceptual Framework. Summary

- A simple illustrative framework that builds on the quality-ladder model setup. The goal is to rationalize the previous empirical patterns.

Conceptual Framework. Summary

- A simple illustrative framework that builds on the quality-ladder model setup. The goal is to rationalize the previous empirical patterns.
- Firm operates in the product space and patent space.

Conceptual Framework. Summary

- A simple illustrative framework that builds on the quality-ladder model setup. The goal is to rationalize the previous empirical patterns.
- Firm operates in the product space and patent space.
- Firm decides on (costly) activities:
  - *Product commercialization* $\rightarrow$ higher-quality products on the market $V^1(q) > V^0(q)$;
  - *Patenting* $\rightarrow$ reduce creative destruction $\tilde{p} < p$.

Conceptual Framework. Summary

- A simple illustrative framework that builds on the quality-ladder model setup. The goal is to rationalize the previous empirical patterns.
- Firm operates in the product space and patent space.
- Firm decides on (costly) activities:
  - *Product commercialization* $\rightarrow$ higher-quality products on the market $V^1(q) > V^0(q)$;
  - *Patenting* $\rightarrow$ reduce creative destruction $\tilde{p} < p$.
- Implications:
  - Market leaders have lower incentives for product innovation (similar to the Arrow's replacement effect).

$$\Delta^{Product} = V^1(q) - V^0(q) \qquad \downarrow q$$

  - Market leaders have higher incentives to engage in patenting – protect higher value.

$$\Delta^{Patent} = V^1(q)\Big[\frac{1}{r+\tilde{p}} - \frac{1}{r+p}\Big] \qquad \uparrow q$$

Conceptual framework: Model Implications

Implication 1: Many firms (below threshold $q*$) do product innovation without patenting.

Implication 2: On average, patenting and product innovation are positively correlated.

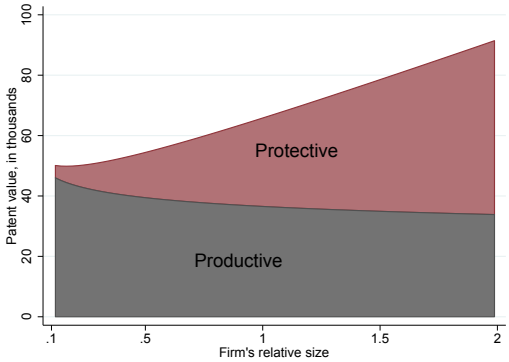
Implication 3: Larger firms do relatively less product upgrades, but more patenting.

Implication 4: Patents deter future entry by competitors;
Corollary: larger firms deter entry more.

Implication 5: The revenue premium from patents comes both from product upgrades and protection. The latter is stronger for larger firms.

Conceptual framework: private value of innovation

- Framework and richness of data allow us to compute value of patented innovation



- Productive ($\Delta^{Product}$) incremental value from higher-quality prod., holding creative destruction fixed.
- Protective (Δ^{Patent}) incremental value from lower creative destruction, holding product quality fixed.

Conclusion

- New *dataset* linking patents to products.
- Relationship between *patenting* and *product introduction*.
- Importance of *firm heterogeneity*: market leaders vs followers.
- *Value of patented innovation* and decomposition: productive vs protective.

Appendix

Product

- Products defined at the finest level of disaggregation: *12-digit UPC, barcode*.
  - Changes in any attribute of a good (e.g. forms, sizes, package, formula) result in changes in barcode.
  - Overall, 66% of new products enter the market with a new combination of observable attributes (as covered by RMS).
  - Hence, allow us to identify any product innovation, small or large.
- More than 100 billion unique observations at the week $\times$ store $\times$ level.
- During the sample, total sales are worth approx \$2 trillion.
- 40,000 stores covering 53% of sales in grocery stores, 55% in drug stores, 32% in mass merchandisers, 2% in convenience stores, and 1% in liquor stores.

Back

Newness index I

- Represent product i in product module m as a vector of characteristics $V_i^m = [v_{i1}^m, v_{i2}^m, .., v_{iK^m}^m]$.
- K^m – the number of attributes (e.g. color, formula) we observe in product module m, v_{ik}^m is characteristic (e.g. blue, red).
- Ω_t^m – set of product characteristics for each product ever sold in module m by time t.
- Then the *newness index* of a product i in product module m, launched at time t is defined as follows:

$$\text{Newness}_{i(t)}^{(m)} = \sum_{k=1}^{K^m} \omega_k^m \mathbb{1}[v_{ik}^m \notin \Omega_t^m],$$

where ω_k^m represents the module-specific weight given to new characteristics within attribute k.

Back

Newness index II

- Quantify importance of each attribute by estimating ω_k^m using hedonic methods.
- A linear characteristics model using the time-dummy method.
- Pooling data across products and periods, estimate non-negative LS, $\forall$ module:

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

where i denotes the product, j is the characteristic, and t is the time period (years). a_i^j – dummy for a given characteristic.

- π^j – the shadow price for each characteristics.
- ω_k^m is the average contribution of the characteristic within each attribute to the price normalized so that $\sum_{k=1}^{K^m} \omega_k^m = 1$.

Back

Newness index III. Pain Remedies - Headache

- Brand (310 distinct): Tylenol, Excedrin, Advil, Aleve
- Flavor (35 distinct): regular, orange, grape, cherry
- Container (17 distinct): pack, bottle, box, case, tube
- Style (3 distinct): children, regular, ACM
- Form (47 distinct): caplet, capsule, tablet, gelcap, powder
- Generic (2 distinct): yes or no
- Formula (25 distinct): regular, extra strength, rapid release, extended release
- Type (74 distinct): aspirin, aspirin caffeine, ibuprofen, naproxen
- Consumer (30 distinct): trauma, migraine, menstrual, arthritis
- Size (89 distinct): caplet (100, 250, 500), tablet (24, 30, 36)

Back

Newness index: Alternatives

- Alternative measures:
  1. Equal weights for each attribute.
  2. Revenue-based weights for each attribute.
  3. Weighting by inverse of distinct characteristics within an attribute.
  4. Account for new combination of characteristics across attributes.

Back

Newness index: External validation

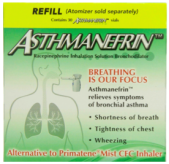
- Revenue growth higher for products with higher newness.
- Lifecycle of products is longer.

Newness Measure: Correlation with Firm Outcomes

	(1) Growth rate (DH)	(2) Growth rate (New)	(3) Duration 4q	(4) Duration 16q
Newness(t)	0.1476***	0.2773***	0.1172***	0.1118***
	(0.019)	(0.005)	(0.007)	(0.012)
Log N(t)	0.1946***	0.0224***	0.0274***	0.0190***
	(0.004)	(0.001)	(0.002)	(0.003)
Observations	93,290	112,218	97,692	54,148
R-squared	0.383	0.597	0.477	0.569
Time-Category	Y	Y	Y	Y
Firm-Category	Y	Y	Y	Y

Back

HIGH NEWNESS: EXAMPLES



Asthmanefrin Inhalation Solution Bronchodilator Asthma Refill Vials

Novelty = 0.75

Kiinde Direct-Pump Adapters for Kiinde Twist Pouch Breast Milk Storage Pouches

Novelty = 0.66

JAWS Hardwood Floor Cleaner Bottle with 2 Refill Pods

Novelty = 0.71

Fire & Flavor Evolution Salt Foot Soak Therapy

Novelty = 0.66

Back

Low newness: Examples

Swiffer Wetjet Hardwood Floor Mopping and Cleaning Solution Refills

Lavender Vanilla
Novelty = 0.14

Sweet Citrus
Novelty = 0.14

Back

Defining product categories

- *Product category*: a set of similar products.
  - Nielsen classifies UPCs into 1,070 low-level modules.
  - Manually expand module descriptors with Wikipedia articles.
  - Map text documents to a vector space. Document vector
  - Using *k-means clustering*, classify similar modules into same cluster. k-means
  - Baseline: 400 clusters.
  - Alternatives: groups, HDBSCAN
  - Examples: "Detergents – light duty" + "Detergents – heavy duty".

Back

K-MEANS CLUSTERING

- Each module's text document $\rightarrow$ *word frequency vector*. Document vector
- Aggregate module vectors into clusters using *k-means clustering*.
- Specify the desired number of clusters k beforehand.
- Procedure yields partitioning that minimizes the within-cluster vector variance.
- Letting x be a given module vector and set S_i be cluster i, we choose our cluster sets S_i so as to minimize

$$\sum_{i=1}^{k} \sum_{x \in S_i} ||x - \mu_i||^2$$

where $\mu_i = \frac{1}{|S_i|} \sum_{x \in S_i} x$.

Back

Data: Match Validation

1. Extensive manual checks of many patent-to-product classifications.

2. External validation. Case studies with virtual patent markings.
   - *P&G*. Show
   - *Clorox*, *Kimberly Clark* to come soon...

3. Understanding non-matches:
   - CPG-only firms vs non-CPG only firms. Show
   - Product vs process patents. Show

4. Verifying the similarity-based category choice:
   - Actual vs placebo similarity of patents classified into the same product categories. Show
   - Similarity distribution comparison with different ranks. Show

Back

Representative documents

- Construct *representative documents* on patent and product sides.
- *Patents:*
  - Text of patent application (or publication).
  - Title, abstract, patent claims, U.S. and International Patent Classification text.
  - Concatenate all of the available text.
- *Product categories:*
  - Set of module titles that belong to the category.
  - Set of *Wikipedia* articles manually assigned to product modules within a category.
  - Repeat the first 10% of each Wikipedia entry 10 times.
  - Vectorize each Wiki entry, then average these vectors together (preserving ℓ^2-norm).

Document vector

- Use 1-grams and 2-grams (phrases) as tokens.
- Exclude words that appear in $> 80\%$ of documents ("the", "and").
- Run each document through a lemmatizer.
- Convert each document to word (token) vectors with counts.
- Corpus of documents represented by a sparse matrix c_{ij} of counts, $i \in \{1, \ldots, N\}$ is the document and $j \in \{1, \ldots, K\}$ the word.
- Use total-frequency-inverse-document-frequency (tf-idf) (using document frequencies from the patent data)

$$w_j = \log\left(\frac{N+1}{d_j+1}\right) + 1 \quad \text{where} \quad d_j = |\{i \in \mathcal{N} | c_{ij} > 0\}|$$

Back

Similarity metric & patent-product match

- We are left with a weighted, ℓ^2-normalized token frequency vector for each document, both on the patent and product side defined as

$$f_{ij} = \frac{w_j c_{ij}}{\sqrt{\sum_{j'} (w_j c_{ij'})^2}}$$

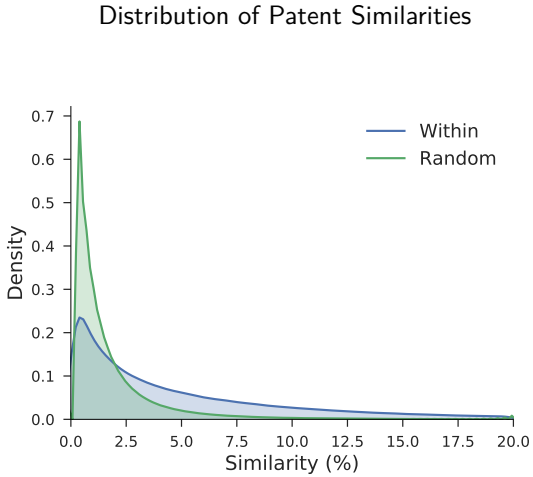
- Multiplying any two such vectors together yields a *similarity metric* between two documents.
- Range $[0, 1]$ (e.g. 0 means no word overlap).
- *Patent-product category match* from the similarity matrix:

$$l^*(k) = argmax_{l \in \Delta}\ s_{kl} = \sum_{j \in \mathcal{M}} f_{kj} f_{lj},$$

k corresponds to patents, l to product categories, and Δ denotes the set of firm's active product categories (in any year).

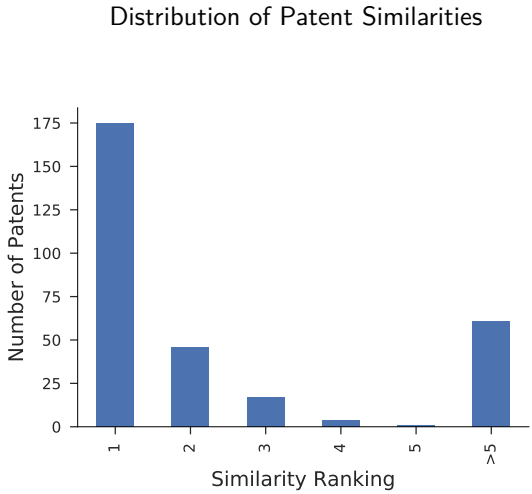
Back

Actual vs placebo similarity of patents classified into same product categories.



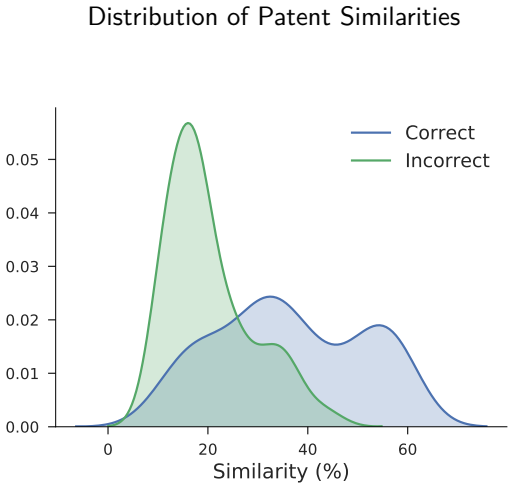
Back

P&G CASE STUDY WITH EXTERNAL INFORMATION ON PATENT MARKINGS I



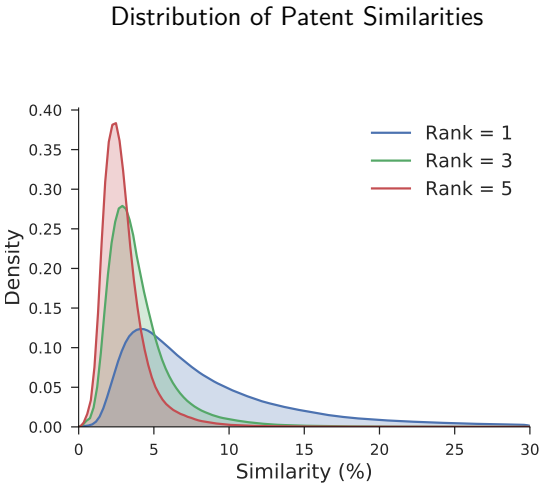
Back

P&G CASE STUDY WITH EXTERNAL INFORMATION ON PATENT MARKINGS II



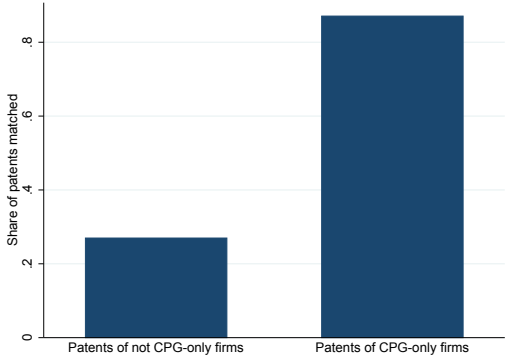
Back

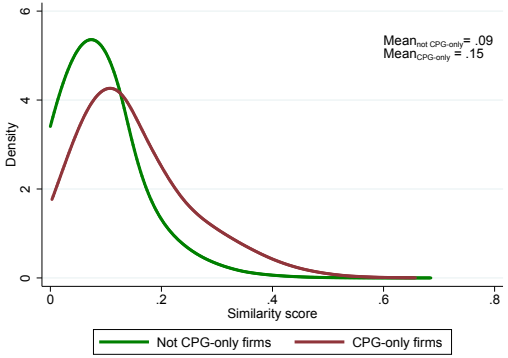
SIMILARITY DISTRIBUTION COMPARISON WITH DIFFERENT RANKS



Back

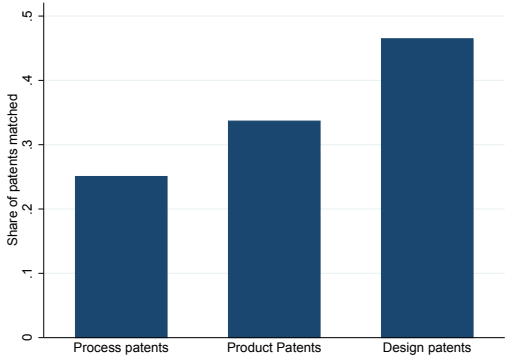
CPG-ONLY FIRMS

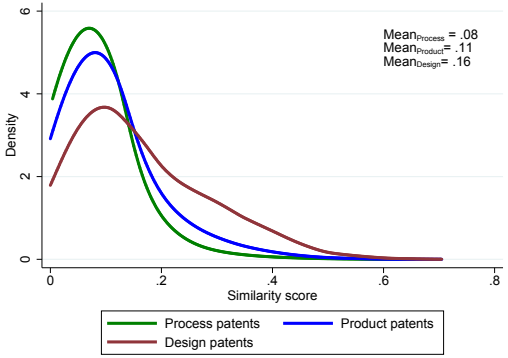




Back

Product-related patents





Back

Patenting by largest CPG firms

Patents of Largest Firms in CPG

Company Name	Patents, '90-'15	Company Name	Patents, '90-'15
Procter & Gamble	16211	Dr. Pepper/Seven Up	53
Kraft Heinz Foods	964	L'Oreal	6030
General Mills	700	The Clorox Company	734
Frito-Lay Company	318	Mars	650
Nestle	215	Sara Lee Foods	195
Coca-Cola	844	Church & Dwight Co	467
Pepsi-Cola	699	Reckitt Benckiser,	1069
Philip Morris	1045	Pinnacle Foods	3
Kimberly-Clark	5500	The Quaker Oats	148
The Kellogg Company	213	Colgate Palmolive S.A.	3159
Anheuser-Busch	101	The Minute Maid Company	0
Unilever	1700	Abbott Laboratories Inc	3941
The J.M. Smucker Co	68	E & J Gallo Winery	26
The Hershey	73	Pepperidge Farm	7
Nabisco	72	Glaxosmithkline Cons. Health.	468
Conagra Brands	145	Molson Coors Brewing Co	0
Campbell Soup	70	Johnson & Johnson	1160
		Bimbo Bakeries USA	3
Total (top 35 firms)	*47051*		
Average (top 35 firms)	*1344.31*		

Back

A PATENT BY DANONE S.A.

Functional peptides for obesity disorders

Abstract

The present invention concerns certain peptides obtainable by hydrolysis from soy glycinin by the action of supernatant cultures of strains belonging to the genera *Lactobacillus* or *Streptococcus*. These peptides, extracts containing them and food products containing them are useful for the treatment and/or prevention of obesity and oxidative stress.

Images (2)

Classifications

C07K14/415 Peptides having more than 20 amino acids; Gastrins; Somatostatins; Melanotropins; Derivatives thereof from plants

View 10 more classifications

US9802990B2
United States

Download PDF | Find Prior Art | Similar

Inventor: Agusti Montserrat Carreras, Cristina Alvarez Fernandez, Montserrat Andreu Corominas, Daniel RAMÓN VIDAL, Esther Bataller Leiva, Patricia Martorell Guerola, Salvador GENOVÉS MARTÍNEZ

Current Assignee : Danone SA

Worldwide applications

2013 · ES EP RU WO CA *MX* CN US JP

Application US14/768,823 events

2013-02-19 • Application filed by Danone SA

2013-02-19 • Priority to PCT/EP2013/053233

2016-01-07 • Publication of US20160002303A1

2017-07-18 • Assigned to DANONE, S.A.

2017-10-31 • Application granted

2017-10-31 • Publication of US9802990B2

Back

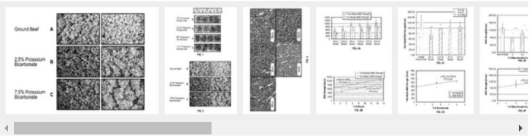
A PATENT BY BEYOND MEAT INC.

Plant based meat structured protein products

Abstract

Provided are food products having structures, textures, and other properties similar to those of animal meat. Also provided are processes for producing such food products. The processes comprise producing the food products under alkaline conditions.

Images (15)



Classifications

A23J3/04 Animal proteins

View 8 more classifications

US20150296834A1
United States

Download PDF | Find Prior Art | Similar

Inventor: Timothy Geistlinger

Current Assignee : Savage River Inc dba Beyond Meat , Savage River Inc dba Beyond Meat Inc

Worldwide applications

2015 · ~~US~~ ~~AU~~ EP CA CN JP WO

Application US14/687,803 events

2014-04-17 • Priority to US201461981119P

2015-04-15 • Application filed by Savage River Inc dba Beyond Meat, Savage River Inc dba Beyond Meat Inc

2015-04-15 • Priority to US14/687,803

2015-04-15 • Assigned to SAVAGE RIVER, INC. dba BEYOND MEAT

2015-10-22 • Publication of US20150296834A1

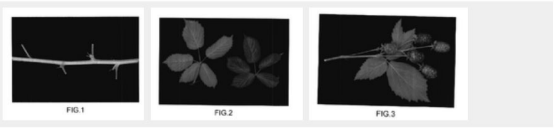
Back

Blackberry plant named ‘Driscoll Thornless Sleeping Beauty’

Abstract

The present invention relates to a new and distinct cultivar of blackberry plant named ‘Driscoll Thornless Sleeping Beauty.’ The new cultivar is distinguished from other blackberry cultivars by its early season crop, large fruit size and thornless canes. ‘Driscoll Thornless Sleeping Beauty’ produces fruit with improved quality and shipping characteristics. The new cultivar is distinguished from its parent by having thornless canes.

Images (3)



Classifications

A01H6/7499 Rubus, e.g. blackberries or raspberries

View 1 more classifications

USPP17983P2
United States

Download PDF | Find Prior Art | Similar

Inventor: Reynaldo Cabrera Avalos

Current Assignee : Driscolls Inc

Worldwide applications

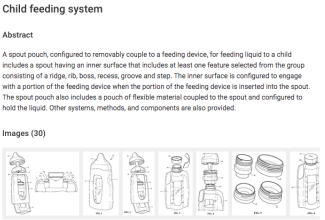
2004 · US

Application US10/969,663 events

- **2004-10-20** • Application filed by Driscolls Inc
- **2004-10-20** • Priority to US10/969,663
- 2004-10-20 • Assigned to DRISCOLL STRAWBERRY ASSOCIATES, INC.
- **2007-09-04** • Application granted
- **2007-09-04** • Publication of USPP17983P2

Back

A patent and product by Kiinde



Child feeding system

Abstract

A spout pouch, configured to removably couple to a feeding device, for feeding liquid to a child includes a spout having an inner surface that includes at least one feature selected from the group consisting of a ridge, rib, boss, recess, groove and step. The inner surface is configured to engage with a portion of the feeding device when the portion of the feeding device is inserted into the spout. The spout pouch also includes a pouch of flexible material coupled to the spout and configured to hold the liquid. Other systems, methods, and components are also provided.

Images (30)

Classifications

A61J9/005 Non-rigid or collapsible feeding-bottles

View 6 more classifications

US9713576B2

United States

Download PDF · Find Prior Art · Similar

Inventor: John M. McBean, Kailas N. Narendran

Current Assignee : KIINDE LLC

Worldwide applications

2014 · US · 2016 · US · 2017 · US

Application US14/510,567 events

2012-10-11 • Priority to US201261712527P

2014-10-09 • Application filed by John M. McBean, Kailas N. Narendran

2015-01-22 • Publication of US20150024085A1

2017-07-25 • Application granted

2017-07-25 • Publication of US9713576B2

2019-07-09 • Application status is Active

2033-03-30 • Anticipated expiration

Show all events

Info: Patent citations (29), Non-patent citations (4), Cited by (11), Legal events, Similar documents, Priority and Related Applications

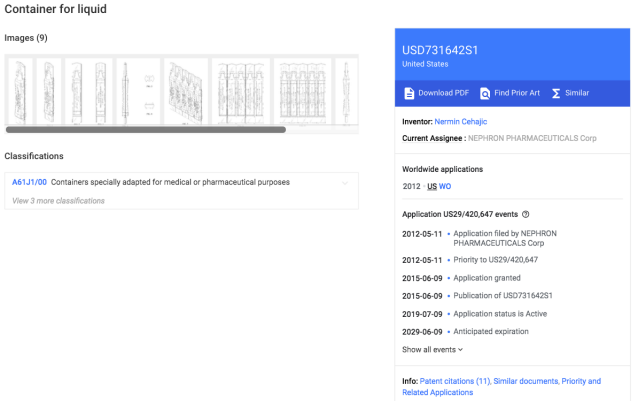
External links: USPTO, USPTO Assignment, Espacenet, Global Dossier, Discuss

Kiinde Direct-Pump Adapters for Kiinde Twist Pouch Breast Milk Storage Pouches

- Patent application - 2013q1.
- Product introduction: 2014q1.

Back

A patent and a product by Nephron Pharma

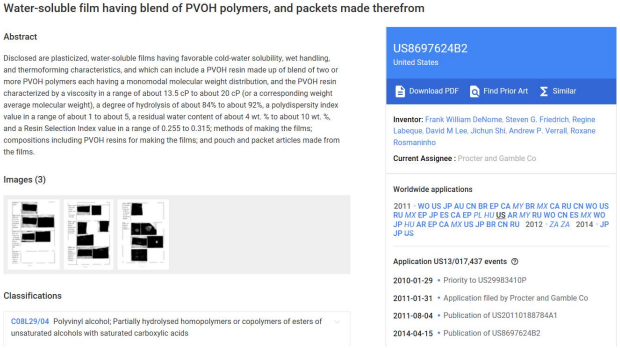


Asthmanefrin Inhalation Solution
Bronchodilator Asthma Refill Vials

- Patent application: 2012q2.
- Product introduction: 2012q4.

Back

A PATENT AND A PRODUCT BY P&G



Water-soluble film having blend of PVOH polymers, and packets made therefrom

Abstract

Disclosed are plasticized, water-soluble films having favorable cold-water solubility, wet handling, and thermoforming characteristics, and which can include a PVOH resin made up of blend of two or more PVOH polymers each having a monomodal molecular weight distribution, and the PVOH resin characterized by a viscosity in a range of about 13.5 cP to about 20 cP (or a corresponding weight average molecular weight), a degree of hydrolysis of about 84% to about 92%, a polydispersity index value in a range of about 1 to about 5, a residual water content of about 4 wt. % to about 10 wt. %, and a Resin Selection Index value in a range of 0.255 to 0.315; methods of making the films; compositions including PVOH resins for making the films; and pouch and packet articles made from the films.

Images (3)

Classifications

C08L29/04 Polyvinyl alcohol; Partially hydrolysed homopolymers or copolymers of esters of unsaturated alcohols with saturated carboxylic acids

US8697624B2

United States

Download PDF | Find Prior Art | Similar

Inventor: Frank William DeNome, Steven G. Friedrich, Regine Labeque, David M Lee, Jichun Shi, Andrew P. Verrall, Roxane Rosmarinho

Current Assignee : Procter and Gamble Co

Worldwide applications

2011 · WO US JP AU CN BR EP CA MY BR MX CA RU CN WO US RU MX EP JP ES CA EP PL HU US AR MY RU WO CN ES MX WO JP HU AR EP CA MX US JP BR CN RU · 2012 · ZA ZA · 2014 · JP JP US

Application US13/017,437 events

2010-01-29 • Priority to US29983410P

2011-01-31 • Application filed by Procter and Gamble Co

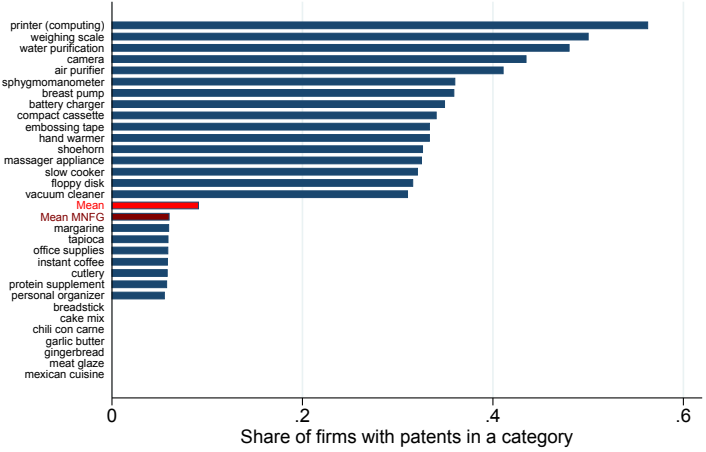
2011-08-04 • Publication of US20110188784A1

2014-04-15 • Publication of US8697624B2

- Patent application: 2011.
- Product introduction: 2012.

Back

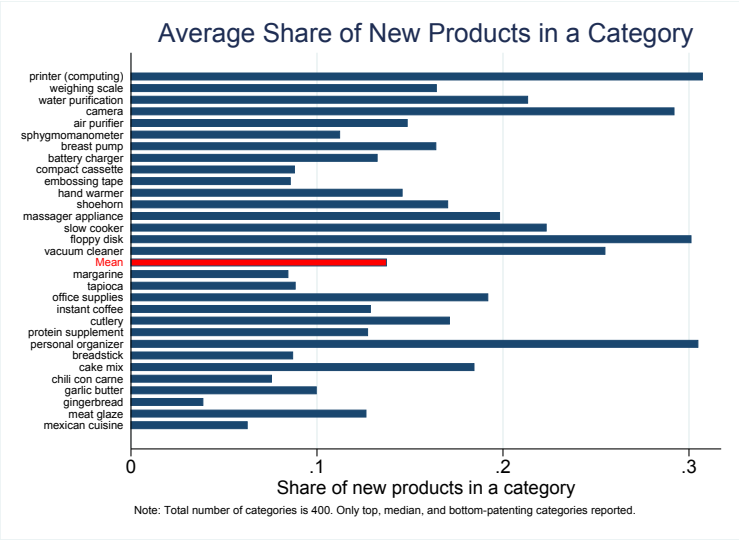
RICH HETEROGENEITY



Note: Total number of categories is 400. Only top, median, and bottom-patenting categories reported.

Back

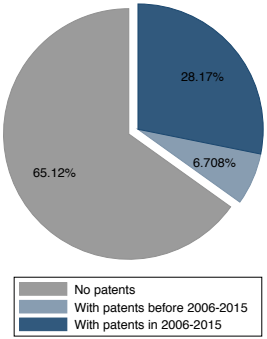
RICH HETEROGENEITY



Back

Product innovation by patenting status

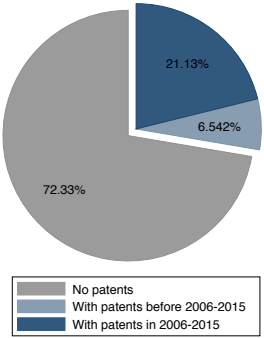
- **65%** of novelty-adjusted product introduction comes from never-patenting firms.

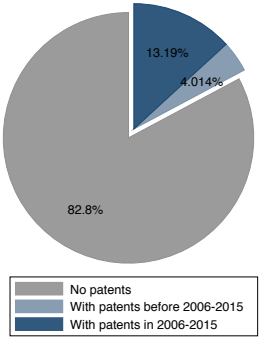


Back

PRODUCT INNOVATION BY PATENTING STATUS: MATCH 2

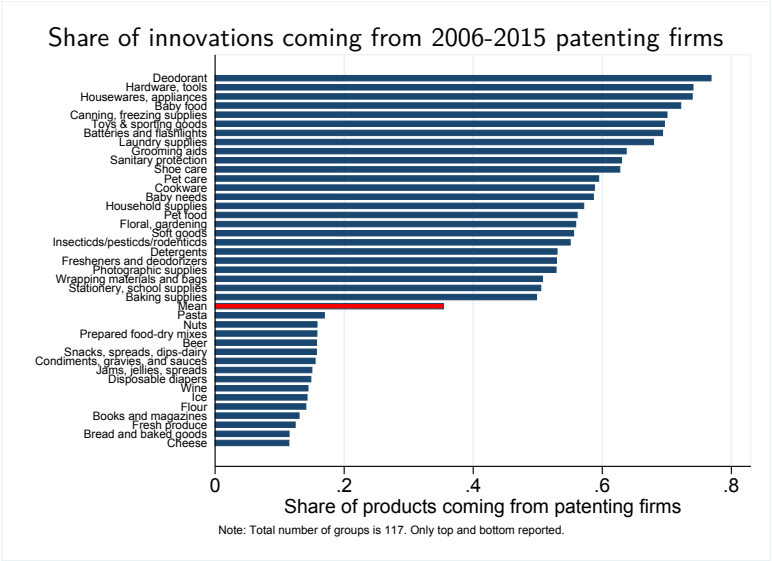
- **72%** (82%) of product introduction (novelty-adjusted) comes from never-patenting firms $\times$ category.





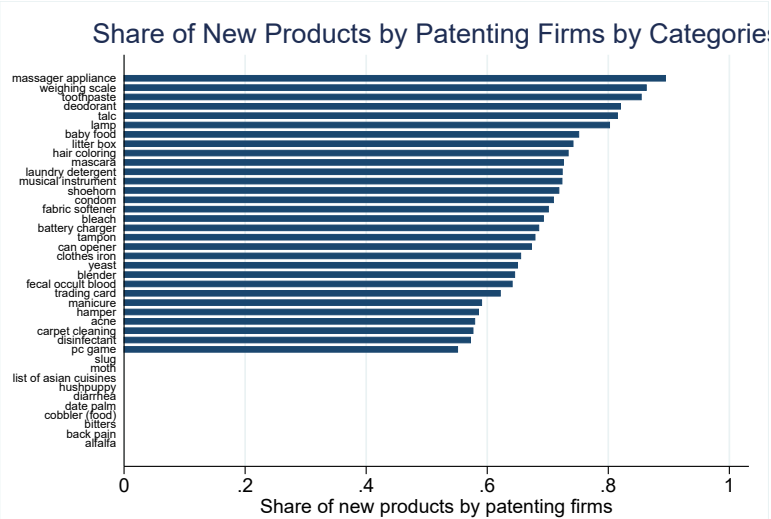
Back

Patenting intensity by product groups: match 1



Back

PATENTING INTENSITY BY PRODUCT GROUPS: MATCH 2



Back

Comparison of CPG and non-CPG patents

1990-2015	Match1	Match2	All
Total applications	1,000,707	280,860	6,058,569
Granted patents (%)	80	80	79
Product patents (%)	65	71	68
Utility patents (%)	72	67	72
Cites mean	7	6.7	6.9
Cites median	2	2	2
Time to grant (med)	2	2	2
Licensing (%)	.59	1.7	.7
Litigation (%)	6.1	7.9	4.4

Back

Summary Statistics by Patenting Status

	(1) No Patents	(2) Patents before '06	(3) Patents in '06-'15
Rev. all products	3708.75	12275.72	27598.79
Rev. new products	243.27	988.62	1670.12
Rev. new products, post entry period	386.62	2064.76	3955.06
Num. products	16.11	35.09	74.09
Num. new products	2.60	6.73	12.91
Product entry rate	0.19	0.17	0.22
Num. product categories	2.36	3.11	4.11
Share new products lasting more than 4 qtrs.	0.74	0.70	0.75
Share new products lasting more than 16 qtrs.	0.44	0.40	0.42
Average newness new products	0.13	0.09	0.10
Newness-weighted num. new products	0.57	0.70	1.07
Num. patent applications	0.00	0.00	6.14
Num. granted patent applications	0.00	0.00	4.47
Num. citations-weighted patent applications	0.00	0.00	8.87
Stock patent applications until year t	0.00	10.88	125.93
Stock granted patent applications until year t	0.00	10.59	115.39
Num. of diff. technology classes (IPC3) on patents	.	.	5.56
NumFirms	29373	1879	3284
Observations	188118	15285	29030

Back

Product introduction and patenting: intensive margin. Lag dependent

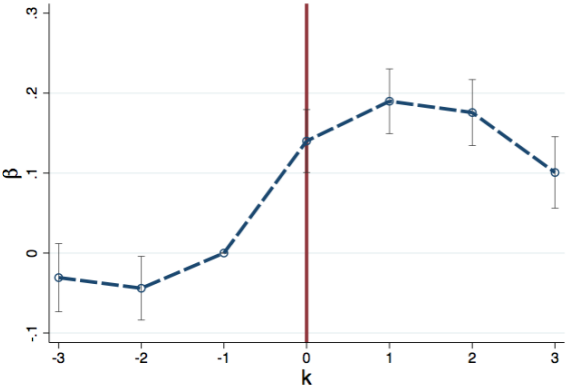
	New products (Log N)			Q_adjusted New products (Log q_N)		
Patents(t-1)	0.0241**			0.0109		
	(0.010)			(0.007)		
Patents granted(t-1)		0.0271**			0.0103	
		(0.011)			(0.007)	
Patents non-granted(t-1)			0.0173			0.0013
			(0.015)			(0.015)
Log N(t-1)	0.0325***	0.0325***	0.0325***	-0.0262***	-0.0262***	-0.0262***
	(0.003)	(0.003)	(0.011)	(0.003)	(0.003)	(0.003)
Observations	365,402	365,402	365,402	365,402	365,402	365,402
R-squared	0.702	0.702	0.702	0.575	0.575	0.575
Time-Category	Y	Y	Y	Y	Y	Y
Firm-Category	Y	Y	Y	Y	Y	Y

Back

Product introduction and patenting: extensive margin. Event study

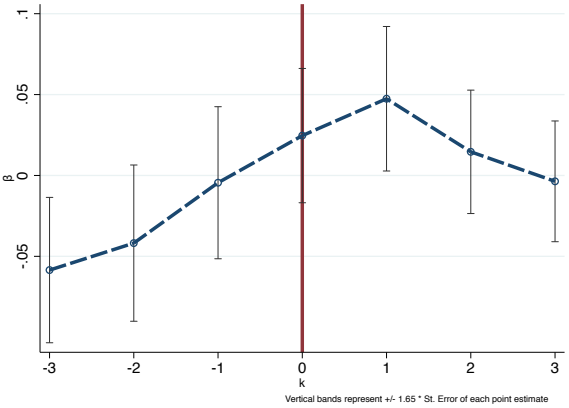
- Event study, where the event = application year of the first patent.
- j is firm, t is calendar year, s is event time.

$$\ln Y_{jts} = \sum_{k \neq -1} \beta_k \mathbb{1}\{k = s\} + \alpha_j + \gamma_t + u_{jts}$$



PRODUCT INTRODUCTION AND PATENTING: INTENSIVE MARGIN

$$\ln Y_{j,t+k} = \beta \ln \text{Patents}_{i,t} + \alpha_i + \gamma_{t+k} + u_{i.t+k} \text{ , } k = -5, ..., 0, ..., 5$$



Back

Product introduction and patenting: intensive margin. Citations & claims

	New products (Log N)			Q_adjusted New products (Log q_N)		
Patents(t-1)	0.0412***			0.0188***		
	(0.010)			(0.006)		
Patent cites(t-1)		0.026***			0.014***	
		(0.007)			(0.004)	
Patent claims(t-1)			0.0012***			0.006**
			(0.004)			(0.003)
Observations	412,004	412,004	411,889	412,004	412,004	411,889
R-squared	0.691	0.691	0.691	0.558	0.558	0.558
Time-Category	Y	Y	Y	Y	Y	Y
Firm-Category	Y	Y	Y	Y	Y	Y

Back

Product introduction and patenting: intensive margin.

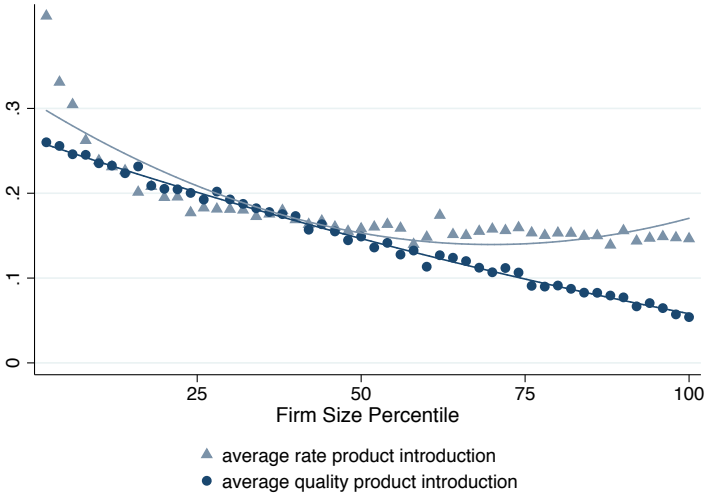
Product vs process patents

	New products (Log N)			Q_adjusted New products (Log q_N)		
Patents(t-1)	0.0412***			0.0188***		
	(0.010)			(0.006)		
Patents product(t-1)		0.0429***			0.0191***	
		(0.010)			(0.007)	
Patents process(t-1)			0.0124			-0.0003
			(0.018)			(0.013)
Observations	412,004	411,889	411,889	412,004	411,889	411,889
R-squared	0.691	0.691	0.691	0.558	0.558	0.558
Time-Category	Y	Y	Y	Y	Y	Y
Firm-Category	Y	Y	Y	Y	Y	Y

Back

Larger firms do relatively less product innovation

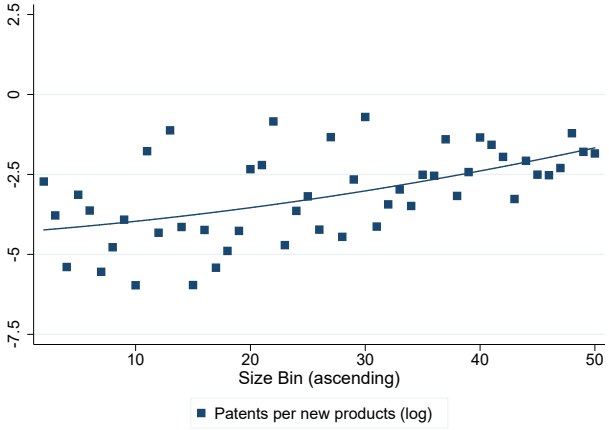
- Product innovation rate declines with firm size...



Back

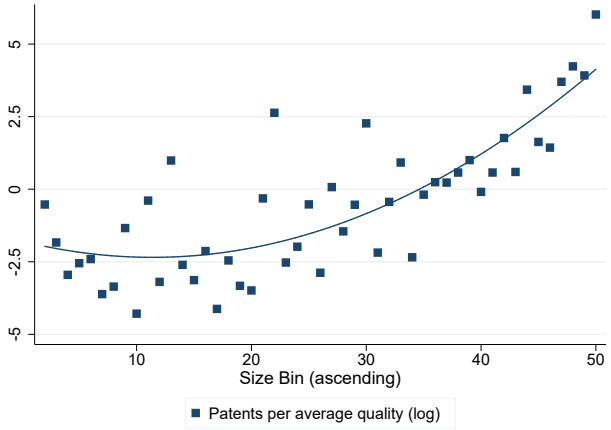
... BUT RELATIVELY MORE PATENTING

- ... but patent-per-product ratio increases.



... BUT RELATIVELY MORE PATENTING

- ... but patent-per-product ratio increases.



Patents-to-Products elasticity by firm size

	Product introduction rate			Quality product introduction		
Patent(t-1)	0.015***		0.012***	0.005***		0.006**
	(0.003)		(0.005)	(0.002)		(0.002)
Size(t-1)		-0.088***	-0.088***		-0.016***	-0.016***
		(0.001)	(0.001)		(0.001)	(0.001)
Patent(t-1) x Size(t-1)			-0.005*			-0.005***
			(0.003)			(0.002)
Observations	412,004	410,801	410,801	412,004	410,801	410,801
R-squared	0.357	0.375	0.375	0.330	0.334	0.334
Time-Category	Y	Y	Y	Y	Y	Y
Firm-Category	Y	Y	Y	Y	Y	Y
Time-Firm	N	N	N	N	N	N

Back

Patents-to-Products elasticity by firm size

	Product introduction rate			Quality product introduction		
Patent(t-1)	0.015***		0.012***	0.002		0.012**
	(0.003)		(0.005)	(0.003)		(0.006)
Size(t-1)		-0.088***	-0.088***		-0.031***	-0.030***
		(0.001)	(0.001)		(0.002)	(0.002)
Patent(t-1) x Size(t-1)			-0.005*			-0.008**
			(0.003)			(0.003)
Observations	412,004	410,801	410,801	93,912	93,290	93,290
R-squared	0.357	0.375	0.375	0.510	0.513	0.513
Time-Category	Y	Y	Y	Y	Y	Y
Firm-Category	Y	Y	Y	Y	Y	Y
Time-Firm	N	N	N	N	N	N

Back

Patents relate to future sales growth beyond their effect through product introduction

Log revenue			Small ($> p25$)	Large ($< p75$)	Leader
Patent(t-1)	0.059**	0.044*	-0.055	0.055**	0.230***
	(0.026)	(0.026)	(0.094)	(0.026)	(0.054)
New(t)		0.434***	0.440***	0.394***	1.876***
		(0.006)	(0.021)	(0.009)	(0.021)
Observations	361,176	361,176	70,648	97,369	25,428
R-squared	0.857	0.860	0.717	0.778	0.435
Time-Category	Y	Y	Y	Y	Y
Firm-Category	Y	Y	Y	Y	Y

Patents relate to future sales growth beyond their effect through product introduction

Log revenue			Small ($< p25$)	Large ($> p75$)	Leader
Patent(t-1)	0.059**	0.044*	-0.055	0.055**	0.230***
	(0.026)	(0.026)	(0.094)	(0.026)	(0.054)
New(t)		0.434***	0.440***	0.394***	1.876***
		(0.006)	(0.021)	(0.009)	(0.021)
Observations	361,176	361,176	70,648	97,369	25,428
R-squared	0.857	0.860	0.717	0.778	0.435
Time-Category	Y	Y	Y	Y	Y
Firm-Category	Y	Y	Y	Y	Y

Patents relate to future sales growth beyond their effect through product introduction

Log revenue			Small ($< p25$)	Large ($> p75$)	Leader
Patent(t-1)	0.059**	0.044*	-0.055	0.055**	0.230***
	(0.026)	(0.026)	(0.094)	(0.026)	(0.054)
New(t)		0.434***	0.440***	0.394***	1.876***
		(0.006)	(0.021)	(0.009)	(0.021)
Observations	361,176	361,176	70,648	97,369	25,428
R-squared	0.857	0.860	0.717	0.778	0.435
Time-Category	Y	Y	Y	Y	Y
Firm-Category	Y	Y	Y	Y	Y

Patents relate to future sales growth beyond their effect through product introduction

Log revenue			Small ($< p25$)	Large ($> p75$)	Leader
Patent(t-1)	0.059**	0.044*	-0.055	0.055**	0.109***
	(0.026)	(0.026)	(0.094)	(0.026)	(0.033)
New(t)		0.434***	0.440***	0.394***	0.684***
		(0.006)	(0.021)	(0.009)	(0.031)
Observations	361,176	361,176	70,648	97,369	25,428
R-squared	0.857	0.860	0.717	0.778	0.435
Time	Y	Y	Y	Y	Y
Firm	Y	Y	Y	Y	Y

Back q_N

Patents relate to future sales growth beyond their effect through product introduction

Log revenue			Small ($< p25$)	Large ($< p75$)	Leader
Patent(t-1)	0.059**	0.053**	-0.068	0.061**	0.308***
	(0.026)	(0.026)	(0.095)	(0.027)	(0.049)
New q_adj(t)		0.385***	0.658***	0.299***	0.601***
		(0.012)	(0.061)	(0.013)	(0.039)
Observations	361,176	361,176	70,648	97,369	25,428
R-squared	0.857	0.857	0.715	0.769	0.280
Time-Category	Y	Y	Y	Y	Y
Firm-Category	Y	Y	Y	Y	Y

Back

Production Side

- Production of a sector (product category)

$$Y = \frac{1}{1-\beta}\left[\sum_{i=1}^{M} q_i^{\frac{\alpha}{1-\beta}} y_i\right]^{1-\beta}, \quad 0 < \alpha < \beta < 1$$

  where intermediates differ in quality q_i and price p_i.

- Production of intermediate producers

$$y_i = l_i$$

- Since MC same and qualities different, highest quality-producer wins and becomes a monopolist.

Monopolist's static maximization

- Profit maximization:

$$\begin{aligned} \pi &= \max_{l} \{py - wl\} \\ s.t. &\quad p = q^{\alpha} y^{-\beta} \text{ and } (\textbf{??}) \end{aligned}$$

- The resulting revenue and profit for the firm are

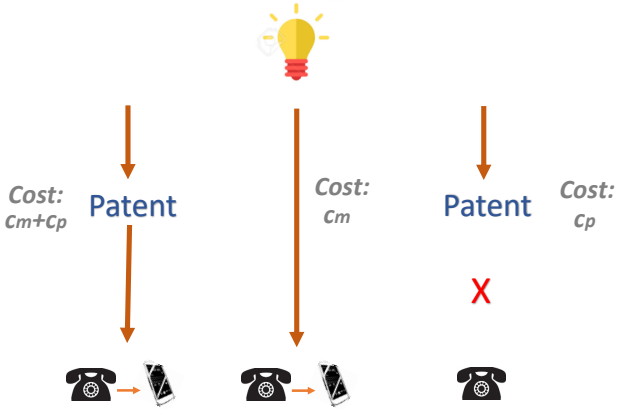
$$\textit{Revenue} = \left(\frac{1-\beta}{w}\right)^{\frac{1+\beta}{\beta}} q^{\gamma} \equiv \tilde{\pi} q^{\gamma}$$

$$\Pi = \left(\frac{1-\beta}{w}\right)^{\frac{1+\beta}{\beta}} \left(1 - \frac{w^2}{1-\beta}\right) q^{\gamma} \equiv \pi q^{\gamma}$$

where $\gamma \equiv \alpha/\beta < 1$

Choices. Incumbent with quality q

An incumbent with initial quality q and makes a product upgrade and a patenting choice:



Choices. Incumbent with quality q

- If product upgrade $\rightarrow$ increase profits
  - $q \uparrow q + \lambda$ in product space.

- If patent $\rightarrow$ increase protection
  - $\forall t$ entrant arrives at (exog) rate p with an innovation of size $\lambda^e \sim U(0,1)$.
    - If incumbent does not have a patent, it is replaced with probability p.
  - Patent creates ε wall of protection, such that:
    - for an entrant to replace

$$\underbrace{q + \lambda^e}_{\text{Entrant's quality height}} > \underbrace{q + \varepsilon}_{\text{Incumbent's patent height}}$$

Hence, the probability of creative destruction is $\tilde{p} = (1 - \varepsilon)p < p$.

Value Functions

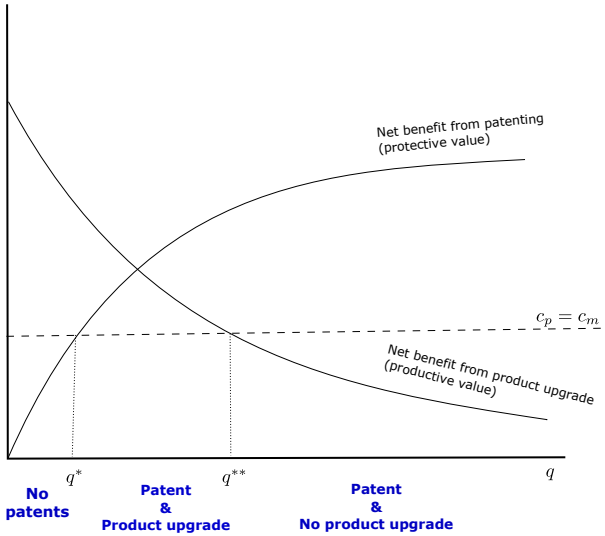
Firm values under different patent/product upgrade choices:

$$V(q) = \max\Big\{\ V^{11}(q) - c_m - c_p,\ V^{10}(q) - c_m,\ V^{01}(q) - c_p\ ,\ V^{00}(q)\ \Big\},$$

where

$$V^{11}(q) = \frac{\pi(q+\lambda)^\gamma}{r + p(1-\varepsilon)}, \quad V^{10}(q) = \frac{\pi(q+\lambda)^\gamma}{r+p},$$
$$V^{01}(q) = \frac{\pi q^\gamma}{r + p(1-\varepsilon)}, \quad V^{00}(q) = \frac{\pi q^\gamma}{r+p}.$$

Optimal Choices of Patenting and Product Upgrades



Value of a Patent

- Value of a patent – revenue premium of products protected by a patent:

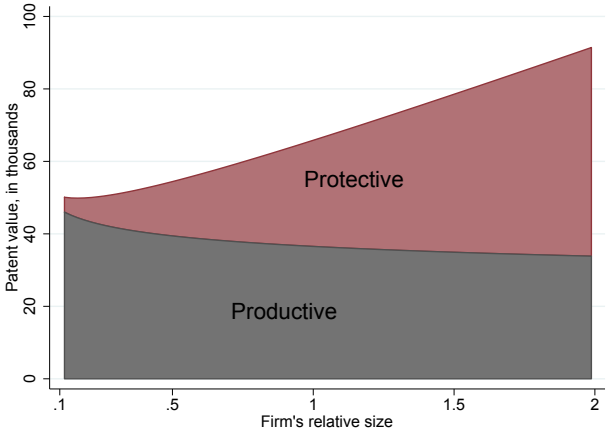
$$\begin{aligned} \textit{Patent Value} &= V^{11} - V^{00} \\ &= \underbrace{\frac{\pi(q+\lambda)^{\gamma}}{r+p(1-\varepsilon)} - \frac{\pi(q+\lambda)^{\gamma}}{r+p}}_{\textit{Protective}} + \underbrace{\frac{\pi(q+\lambda)^{\gamma}}{r+p} - \frac{\pi q^{\gamma}}{r+p}}_{\textit{Productive}} \end{aligned}$$

  - Productive: incremental value from higher-quality products, holding creative destruction fixed.
  - Protective: incremental value from lower creative destruction, holding product quality fixed.

- Calibrate $\pi, \lambda, \gamma, p, \varepsilon$ using size, patenting, sales growth relationships in the data.

Details

Parameters



- Dual role of patenting exploited by firms differently.
  - Productive: incremental value from higher-quality products, holding creative destruction fixed.
  - Protective: incremental value from lower creative destruction, holding product quality fixed.

Estimated average patent value for CPG firms

- π: Take markup $\mu = 1.21$ (Barkai, 2017) & $\Pi = \frac{\mu-1}{\mu} R$.
- p & ε from sales growth of firms that do not innovate and patent/not patent.
- Jointly estimate λ and γ using the model-implied relationship

$$\Delta \ln R_t = \gamma ln\left(1 + \lambda\left[\frac{R_{t-1}}{\overline{R_{t-1}}}\right]^{-\frac{1}{\gamma}}\right)$$

- Resulting parameters: $\lambda = 0.024, \gamma = 0.899, p = 0.098, \varepsilon = 0.031$.

Back