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An empirical investigation of patent and trademark ownership propensity and intensity in the U.S. food and drink industry

RESEARCH ARTICLE

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Abstract

We use patent and trademark ownership data to study product, process, and marketing innovation by 157 manufacturers in the U.S. public food and drink industry. For the 2000-2014 period, most patented innovations relate to processes for manufacturing and designs for marketing, whereas patented innovations in food and drink products or compositions are relatively few. Meanwhile, intellectual property in general is more often protected by trademark ownership. Empirically, we specify a panel logistic model and a panel negative binomial model to study the relationship of firm characteristics to the propensity and intensity of patent and trademark ownership, respectively. In each model, firm size exhibits a significant and positive relationship to the propensity and intensity of patented innovations in products, processes, and marketing. Past innovation, past income, and firm age also have a positive relationship to patent and trademark ownership in most models, whereas leverage is only estimated to negatively relate to the propensity and intensity of trademark ownership. We use our main findings and conclusions to inform research, management, and policy implications.

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JEL code: L66, O34, Q13

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1. Introduction

While the food and drink industry is traditionally not characterized by relatively intense research and development (R&D) (Allred and Park, 2007; Galizzi and Venturini, 1996), recent developments in the overall agri-food industry have forced or motivated food and drink manufacturers to increasingly engage in product, process, and marketing innovation for economic value creation (Johnson *et al.*, 2009). At the forefront is product differentiation as consumers in the developed world are increasingly critical and fragmented, which implies consumer satisfaction is in part dependent on the improvement of old products and the introduction of new products (Avermaete *et al.*, 2004; Grunert, 2005). A related development is the heavy emphasis on food safety and quality, which is manifested by the proliferation of public and private standards and regulations for producers and manufacturers (Aung and Chang, 2014). Furthermore, the increasing degree of consolidation and concentration in the food retail sector implies food and drink manufacturers face stiffer competition for scarce marketing opportunities (Adjemian *et al.*, 2016).

We place primary emphasis on intellectual property, which provides the legal and economic framework to connect innovation to value creation (O'Donnell *et al.*, 2008). To be specific, innovation is the commercial manifestation of *ex ante* investment in R&D, which implies value generation in tangible and intangible assets and resources, intellectual property in particular. If left unprotected, other individuals and organizations can appropriate the economic value. In fact, analogous to asset ownership in general, *ex ante* investment in R&D and innovation is irrational if *ex post* rent protection is suboptimal. In the food and drink industry, intellectual property is in practice often protected by means of patents, trademarks, trade secrets, and copyrights (O'Donnell *et al.*, 2008). While there is good reason to assume food and drink manufacturers use trade secrets,[1] we limit our study to patents and trademarks as its ownership is a matter of public record. As explained by O'Donnell *et al.* (2008) and Hall *et al.* (2014), a patent grants a limited monopoly to exclude other individuals and organizations from making, using, or selling an invention for 20 years. By comparison, a trademark is the exclusive right to use words, names, symbols, or any combination thereof to identify and distinguish a good from other goods (Hall *et al.*, 2014). Patents and trademarks offer different protections, and trademark ownership is often pursued in case of unpatented innovations (Flikkema *et al.*, 2015), which implies consideration of both patents and trademarks may provide a richer conceptualization of innovation by food and drink manufacturers than either patents or trademarks alone. Although we do not claim patent and trademark data capture or indicate the full extent of innovation in the food and drink industry, the recent literature has used patent and trademark data extensively as standard measures of innovation (Flikkema *et al.*, 2015; Hall *et al.*, 2014; Moser, 2013; Schautschick and Greenhalgh, 2016).

While we use patent and trademark data to infer innovation, it is important to adopt a multi-dimensional conceptualization of both 'soft' and 'hard' innovation in the food and drink industry, as demonstrated in the recent literature (Baregheh *et al.*, 2012; Capitanio *et al.*, 2010; Ciliberti *et al.*, 2016; Gehlhar *et al.*, 2009; Minarelli *et al.*, 2015; Triguero *et al.*, 2013; Vancauteren, 2016). Therefore, we study product, process, and marketing innovation, where '[a] product innovation is the introduction of a good or service that is new or significantly improved with respect to its characteristics or intended uses', '[a] process innovation is the implementation of a new or significantly improved production or delivery method', and '[a] marketing innovation is the implementation of a new marketing method involving significant changes in product design or packaging, product placement, product promotion or pricing' (Organization for Economic Co-operation and Development, 2005).

In the U.S food and drink industry, understanding of patent and trademark ownership and its determinants is limited. In general, applied research on innovation in the U.S. food and drink industry is not extensive. Recent empirical literature on food and drink innovation for the most part emphasizes small European enterprises and uses survey data. Because of differences in social, economic, and political environments, it is uncertain

[1] In perhaps the only study of its kind, Cohen *et al.* (2000) determined food manufacturers find trade secrets to be more effective as compared to patents in terms of appropriating rent from product and process innovations.

if findings and conclusions from such studies are generalizable to the U.S. food and drink industry, which implies a considerable gap in the literature. We therefore formulate the following research question: what is the relationship of firm characteristics to product, process, and marketing innovation propensity and intensity?[2] Specifically, we emphasize firm size, firm age, past income, past innovation, and leverage as the firm characteristics of interest. We approach the research question by means of panel analysis on 157 U.S. public food and drink manufacturers for the 2000-2014 period.

The article proceeds as follows. Section 2 provides the background of our study, and Section 3 contains a brief overview of relevant literature. In Section 4 we discuss our methodology, including the data, the summary statistics, the empirical model specifications, and the model variables. We present and discuss the results of our empirical analysis in Section 5. Section 6 contains the summary and conclusions, including a discussion of implications for academics, practitioners, and policy makers.

2. Background

Following the OECD (2005), we interpret innovation as the discovery of a new or the improvement of an existing and useful product, process, or marketing method. Economically, there exist different perspectives of innovation. For example, innovation is the catalyst in the entrepreneurial theory of the firm, where Schumpeter (1942) described innovation as creative destruction. According to Schumpeter (1942), constant disequilibrium is the natural state of the overall economy as bold, creative individuals and organizations make constant innovations in products and processes. As first movers, these innovators have temporary power in input supply or output demand markets and can thus appropriate profit. Kirzner (1997), however, placed emphasis on the reaction to the creative destruction. Through alertness, individuals and organizations react to profit possibilities in the spot market. To appropriate profit, the entrepreneur may make innovations in products and processes (Kirzner, 1997, 2009). In doing so, the primary effect of innovation is market equilibration. While different in conceptualization, the practical interpretations of innovation by Schumpeter and Kirzner are not too dissimilar as value generation and profit appropriation are the main processes (Bostaph, 2013).

However, these theories do not consider explicitly the legal or economic implications of knowledge or intellectual property and its protection. To start, Arrow (1962) argued the acquisition of technological knowledge may explain variability in per capita income across countries. By extension, it is possible knowledge may inform heterogeneity in firm competitiveness. Posner and Landes (2003) defined intellectual property as an idea, invention, discovery, or any human product of potential value separable from a unique physical embodiment. Without protection of such intellectual property, the inventor or innovator is susceptible to *ex post* rent appropriation by other individuals and organizations. In fact, *ex post* rent protection must be guaranteed in order to secure *ex ante* investment (Posner and Landes, 2003), which corresponds to the main theme of property rights theory. In practice, intellectual property is protected by patents, trademarks, trade secrets, copyrights, and *sui generis* rights (O'Donnell *et al.*, 2008). Although the legal definition and execution varies, each mechanism is an indicator of intellectual property and economic value protection. Therefore, as noted by Flikkema *et al.* (2015), Hall *et al.* (2014), Moser (2013), Nagaoka *et al.* (2010), and Schautschick and Greenhalgh (2016), increasingly more studies use patent and trademark ownership data to inform innovation.

3. Literature review

Generally, studies of patent data in relation to the food and drink industry use two types of approaches: (1) within-country firm comparisons, and (2) cross-country firm comparisons. Examples of the former approach are Gopinath and Vasavada (1999), Martinez and Briz (2000), and the Government of Australia (2014), who studied such topics as market structure, sales performance, and innovation type in relation to patent ownership.

[2] As we explain in the data section, propensity is a binary measurement of innovation (1 if patent or trademark ownership is non-zero, 0 otherwise) and intensity is a continuous measurement of innovation (total owned patents or trademarks).

Examples of the second approach are Alfranca *et al.* (2003), Allred and Park (2007), Martinez and Rama (2012), and Van Galen *et al.* (2013), who emphasized R&D expenditure and new product introductions.

While patent ownership is the common denominator in the cited studies, there is much diversity in the samples and methodologies, which is characteristic of the general literature on innovation in the food and drink industry. For example, innovation is studied in terms of core competences (Traill and Meulenberg, 2002), the causal impact of retailer concentration (Weiss and Wittkopp, 2005) and vertical integration (Karantininis *et al.*, 2010), innovation probability determinants (Capitanio *et al.*, 2010), local and regional networking (Gellynck and Kuhne, 2010; Gellynck *et al.*, 2007), product and process innovation complementarity (Triguero *et al.*, 2013), market liberalization (Ghazalian and Fakih, in press), and external knowledge acquisition (Ciliberti *et al.*, 2016).

Meanwhile, our study is most relatable to Avermaete *et al.* (2004), who analyzed the causal impact of firm size on innovation, as well as Bhaskaran (2006) and Giovannetti *et al.* (2011), who studied the different characteristics of food and drink innovators and non-innovators, and Baregheh *et al.* (2012) and Minarelli *et al.* (2015), who emphasized the difference in food product, process, and marketing innovation. As stated in the introduction, our objective is to combine the three themes by studying the relationship of firm characteristics to product, process, and marketing innovation by U.S. food and drink manufacturers.

4. Methodology

4.1 Demographic and financial data

First, we collected secondary data for food and drink manufacturers listed on U.S. stock exchanges during the 2000-2014 period.[3] We extracted the full population of public food and drink manufacturers from Compustat[4], which yielded a total of 180 firms. We deleted 23 firms for various reasons: (1) the firm is listed on the Canadian stock exchange; (2) the firm is not primarily active in the U.S.; (3) the firm is not primarily active in the food and drink industry; (4) the firm has under $1 million in revenue; and (5) missing information.[5] The 110 observations with less than $1 million in revenue are deleted because of the large disproportionate impact on the sample. These observations are primarily of firms in the development stage with low revenue, negative income, substantial debt, low equity, and no patent or trademark ownership. As startups are not our primary interest, the exclusion of these observations likely contributes to better empirical estimation. Altogether, the final sample is comprised of 157 firms and 1,355 firm-year observations. As illustrated in Table 1A (Panel A), the geographical distribution of firm headquarters is rather even, although most (54 of the 157) are in California, Illinois, and New York. In terms of sectoral distribution, we use the standard industrial classification (SIC) system in which each firm is classified based on the business activity which generates the most revenue. As such, food and drink manufacturers may have activities in multiple categories, which implies caution is necessary when interpreting the data. As reported in Table 1B (Panel B), drink manufacturers form approximately 27% of the sample, whereas there are relatively few fats and oils manufacturers and bakery manufacturers.

Table 2A (Panel A) reports the basic summary statistics for the demographic and financial data. The age of the mean firm is approximately 59 years, which reflects the year of incorporation to the present.[6] As companies with revenue of $1 million or less have been deleted, there are few companies below the age of

[3] The following three-digit SIC codes are included: 20 (food manufacturing), 201 (food manufacturing – meat products), 202 (food manufacturing – dairy), 203 (food manufacturing – fruits and vegetables), 204 (food manufacturing – grain), 205 (food manufacturing – bakery), 206 (food manufacturing – confectionery), 207 (food manufacturing – fats and oils), 208 (food manufacturing – beverages), and 209 (food manufacturing – miscellaneous).
[4] https://wrds-web.wharton.upenn.edu/wrds.
[5] Although the food and drink industry is assumed to be well-integrated, in particular the American-Canadian market, non-U.S. observations are deleted in order to facilitate robust as well as parsimonious analysis. Otherwise, inclusion of such observations raises the chance variability in performance is explained by cross-country differences in income, population, and other macro-economic indicators.
[6] The date or year of the initial public offering (IPO) is not used to calculate firm age because few companies start on the public market. Using the year of incorporation allows consideration of resource and knowledge acquisition prior to the IPO.

Table 1. Distribution of U.S. public food and drink manufacturers by region and by sector.

	State	Census region	Total	% of total
Panel A: distribution by region	California	West	23	18.70
	Illinois	Midwest	18	14.63
	New York	Northeast	13	10.57
	Missouri	Midwest	11	8.94
	Colorado	West	10	8.13
	New Jersey	Northeast	9	7.32
	Other		73	46.50
	Total		157	100.00

	SIC[1]	Description	Total	% of total
Panel B: distribution by sector	20	Food Manufacturing	8	5.10
	201	Food Manufacturing – Meat Products	16	10.19
	202	Food Manufacturing – Dairy	13	8.28
	203	Food Manufacturing – Fruits and Vegetables	21	13.38
	204	Food Manufacturing – Grain	15	9.55
	205	Food Manufacturing – Bakery	8	5.10
	206	Food Manufacturing – Confectionery	12	7.64
	207	Food Manufacturing – Fats and Oils	4	2.55
	208	Food Manufacturing – Beverages	42	26.75
	209	Food Manufacturing – Miscellaneous	18	11.46
		Total	157	100.00

[1] SIC = standard industrial classification.

Table 2. Demographic, financial, patent and trademark ownership data statistics.

	Variable	Mean	Median	Std. dev.
Panel A: summary statistics of demographic and financial data	Firm age	58.95	48.00	45.13
	Employees	13,561.04	1,870.00	31,297.95
	Total assets (million)	4,736.05	485.07	11,178.71
	Total liabilities (million)	2,973.59	178.85	7,027.81
	Total equity (million)	1,734.31	201.01	4,392.59
	Total revenue (million)	4,788.44	569.20	10,583.05
	Net income (million)	314.01	15.03	980.75

	Variable	Mean	Median	Std. dev.
Panel B: summary statistics of patent and trademark ownership data	Product innovations	0.55	0.00	2.49
	Process innovations	1.02	0.00	4.04
	Marketing innovations	1.05	0.00	4.95
	Total owned patents	2.29	0.00	8.76
	Patenter (>0 patents)	0.20	0.00	0.40
	Total owned trademarks	6.06	1.00	11.77
	Trademarker (>0 trademarks)	0.58	1.00	0.49

ten. Also, some companies in the panel are the products of mergers or acquisitions, which implies the mean firm age is in fact underestimated. Based on the means, medians, and standard deviations for the balance sheet and income statement data, there is great heterogeneity in the sample. While the median firm has $490 million in total assets and $571 million in total sales, both figures rise to $4.8 billion for the mean firm. As such, the sample is characterized by large influential observations in the right tail, which we address in the empirical model by means of log transformation of most variables in order to obtain normal distributions.

4.2 Patent and trademark data

Second, our patent and trademark data source is the U.S. Patent and Trademark Office (USPTO), which maintains an online database of all patents and trademarks, both granted and rejected as well as pending.[7,8] We categorize each patent as either product, process, or marketing innovation. Correspondingly, we filed a patent as product innovation if its main claim relates to food products or food compositions. We inferred process innovation by the terms 'method', 'system', or 'process', and marketing innovation by the terms 'design' or 'package'. We make no similar distinction for trademarks, in part because the quality of the data is not high enough to allow definitive categorization. The innovation is assumed to take place in the year the patent or trademark is filed, not granted, as there is no good reason to assume the invention is not used during the application process.

Table 2B (Panel B) presents the summary statistics for the full panel and the full period. Based on patent ownership data, public food and drink manufacturers for the most part engaged in process and marketing innovation. However, the mean is not the most informative number as manufacturers with no patent ownership impose a downward bias. Of the 157 firms in the sample, only 37 (24%) patented one or more innovations during the 2000-2014 period. For the sub-sample of 37 firms, the mean number of patented innovations per year increases to approximately 6.41, which in turn is affected by seven large outliers. Specifically, Kraft Foods (786), Coca-Cola Company (480), PepsiCo (404), General Mills (342), Archer Daniels Midland (225), ConAgra (148), Wrigley (134), and Kellogg (72) together accounted for 84% (2,591 of 3,088 patents) of all patented innovations in the public food and drink industry. As such, we can conclude ownership of patented innovations is highly concentrated. Also, on average, the total number of patented product innovations per firm-year is 0.55, while the corresponding averages for patented process and marketing innovations are 1.02 and 1.05, respectively. Consequently, the data suggest food and drink manufacturers do not necessarily depend on patenting product innovations for value creation, protection, or appropriation, which is indicative of price-based as opposed to quality-based competition (Vaona and Pianta, 2008).

In comparison to patent ownership, trademark ownership is more common for the protection of intellectual property (6.04 trademarks per firm-year), which corresponds to the general observation by Hall *et al.* (2014) regarding the relative use and importance of patents, trademarks, trade secrets, and copyrights. As such, while often neglected or dismissed in the empirical literature (Schautschick and Greenhalgh, 2016), the raw data suggest it is necessary to consider trademark ownership as an alternative or supplemental method of formal intellectual property protection in the food and drink industry.

In terms of propensity, trademark ownership is observed in 58% of the firm-year observations, yet 45 of the 157 firms (29%) did not register a single trademark during the 2000-2014 period. There are once again large outliers, although trademark ownership is less concentrated as compared to patent ownership. Hershey (595), Kraft Foods (575), Pepsico (536), General Mills (533), ConAgra (528), Coca-Cola (524), Kellogg (486), and Anheuser-Busch (408) owned 51% of all registered trademarks.

Temporal variation in patent and trademark ownership propensity and intensity is reported in Table 3. As illustrated, there is relatively great volatility in the intensity of patent ownership. Meanwhile, the mean number of issued trademarks peaked in 2006 and then decreased by approximately 50% in 2014. In both

[7] We only record issued patents. Although the underlying information may contain economic value, a rejected patent application implies USPTO did not consider the proposed invention a true invention. If so, the applicant is unable to protect the associated income stream by patenting. Subsequently, the applicant may use secrecy instead.

[8] The U.S. has a two-tiered system of trademark registration: state and federal. As discussed by O'Donnell *et al*. (2008), federal trademark registration has both legal and economic advantages as compared to state trademark registration. As competition in the food and drink industry is not limited to local or regional (state) environments, the public manufacturers in our sample likely do not rely much on state-registered trademarks. Hence, in our study we only record federal trademarks as registered by USPTO.

Table 3. Summary statistics of patent and trademark ownership data by year.

Year	n	Innovation propensity		Innovation intensity	
		1 or more patents	1 or more trademarks	Total patents	Total trademarks
2000	107	0.15	0.51	1.58	4.55
2001	99	0.16	0.53	2.12	5.62
2002	94	0.23	0.66	2.26	6.00
2003	92	0.20	0.59	2.30	6.84
2004	90	0.20	0.63	1.93	6.66
2005	95	0.17	0.64	3.12	7.37
2006	89	0.19	0.63	2.43	8.24
2007	87	0.21	0.67	2.56	7.34
2008	87	0.18	0.59	3.01	6.39
2009	85	0.22	0.55	2.26	6.56
2010	85	0.27	0.65	2.87	6.85
2011	85	0.22	0.53	2.45	5.31
2012	90	0.24	0.53	2.08	5.13
2013	88	0.22	0.51	2.18	4.41
2014	82	0.20	0.51	1.29	3.70

cases, the application-issue and the application-registration lag are possible explanations for the downturn at the end.[9] Table 3 also reports the evolution in patent and trademark ownership propensity.

As illustrated in Table 4, sectoral heterogeneity must also be addressed. Per the summary statistics, bakery manufacturers do not patent innovations, and patented innovations in new products or compositions are relatively few for meat and fruits and vegetables manufacturers in particular. Grain manufacturers engage in each type of innovation, while fats and oils manufacturers only emphasize product and process innovation.

Presenting the results for the mean group comparison tests, Table 5 gives a first impression of what separates owners and non-owners of patents and trademarks in terms of firm characteristics. Because of the panel

[9] In terms of the macro-environment, a more complex explanation is offered by Damanpour (2010), who suggested the overall decrease in competition has limited motivation to innovation, as well as Archibugi *et al.* (2013), who observed a negative impact of the most recent economic crisis on innovation input and output.

Table 4. Summary statistics of patent and trademark ownership data by sector.

SIC[1]	n	Innovation propensity		Innovation intensity	
		1 or more patents	1 or more trademarks	Total patents	Total trademarks
200	81	0.41	0.75	11.58	15.46
201	144	0.22	0.58	0.58	3.91
202	95	0.09	0.63	0.52	4.55
203	181	0.18	0.62	0.61	3.01
204	105	0.49	0.75	4.80	12.46
205	67	0.00	0.46	0.00	3.03
206	122	0.20	0.51	1.34	7.89
207	50	0.30	0.64	4.50	3.34
208	356	0.14	0.51	2.58	6.72
209	154	0.19	0.55	0.73	2.47

[1] SIC = standard industrial classification.

Table 5. Mean group comparisons of firm characteristics for innovators and non-innovators.

Firm characteristic	Patent ownership			Trademark ownership		
	Yes (n=275)	No (n=1,080)	*t*-test	Yes (n=788)	No (n=567)	*t*-test
Firm age	93.05	50.27	<0.0001	64.82	50.79	<0.0001
Employees	39,053.13	6,955.41	<0.0001	19,105.72	5,855.20	<0.0001
Total assets (million)	15,288.90	2,048.98	<0.0001	6,776.94	1,899.68	<0.0001
Total sales (million)	15,833.43	1,976.06	<0.0001	6,863.72	1,904.28	<0.0001
Net income (million)	1,211.36	85.52	<0.0001	489.78	69.72	<0.0001
Debt ratio	0.62	0.69	0.9141	0.54	0.88	0.9996

analysis, some firms are both owners and non-owners during the 2000-2014 period, which complicates the analysis. Nonetheless, it is obvious there exist significant differences in the firm characteristics of public food and drink manufacturers in relation to patent and trademark ownership. Whether indicated by patent or trademark ownership, manufacturers which patent or trademark innovations are relatively older and larger in terms of employees, assets, sales, and profit. The difference in leverage (debt ratio) is not characterized by statistical significance.

4.3 Variables

Our outcome variables are patent and trademark ownership propensity and intensity, which are binary and continuous indicators, respectively (Table 6). We include the following firm characteristics: (1) past innovation; (2) firm age, which proxies knowledge accumulation; (3) total employees, which proxies both firm size and human capital; (4) past income, which proxies R&D capacity; and (5) leverage, which proxies short- and long-term perspectives.[10] Excepting leverage, we hypothesize a positive relationship of each firm characteristic to the propensity and intensity of patent and trademark ownership. We address heterogeneity in the external environment by including binary variables for the years, regions, and sectors.

4.4 Panel logistic model: innovation propensity

When comparing owners and non-owners of patents and trademarks, the outcome variable is obviously binary in nature. The panel binary choice model is given by

$$pr(y_{it} = 1 | x_{it}, c_i) = f(\beta' x_{it} + c_i) \tag{1}$$

where y is the binary indicator of patent or trademark ownership for firm i in year t, x is the vector of predictors, c is the firm-specific intercept, β is the vector of parameters to be estimated, and f denotes the functional form of the model. In practice, the choice is often between the logit model and probit model, which respectively impose a logistic and a normal distribution on the data. Theoretically, it is difficult to justify the choice of one distribution or another (Greene, 2011). Here, preference is given to the logit model to facilitate comparison to other studies on innovation in the food and drink industry with similar approaches.

The underlying relationship for the outcome variable is defined as

$$y_{it}^* = \beta' x_{it} + c_i + \varepsilon_{it} \tag{2}$$

where each symbol is as before, y* is the latent variable, and ε is the stochastic term. While y* is unobserved, observed variation in patent and trademark ownership is related to the latent variable in the following manner:

[10] With total employees, we use a personnel-based indicator of firm size, which may not function as the ideal proxy in the differentiation of innovators and non-innovators (Damanpour, 2010). Although we exclude a financial-based indicator of firm size (total assets) to avoid multicollinearity, we believe total employees is an adequate proxy of firm size for our sample.

Table 6. Overview of model variables.

Variable	Description	Source
Innovation propensity		
Patent ownership	1 if total issued patents in year t is one or more; 0 otherwise	USPTO
Trademark ownership	1 if total issued trademarks in year t is one or more; 0 otherwise	USPTO
Product innovation	1 if total patented product innovations in year t is one or more; 0 otherwise	USPTO
Process innovation	1 if total patented process innovations in year t is one or more; 0 otherwise	USPTO
Marketing innovation	1 if total patented marketing innovations in year t is one or more, 0 otherwise	USPTO
Innovation intensity		
Total patents	Number of issued patents in year t	USPTO
Total trademarks	Number of issued trademarks in year t	USPTO
Total product innovations	Number of patented product innovations in year t	USPTO
Total process innovations	Number of patented process innovations in year t	USPTO
Total marketing innovations	Number of patented marketing innovations in year t	USPTO
Firm characteristics		
Ln age	Natural logarithm of year t – year of incorporation	Compustat
Debt ratio	Total liabilities/total assets	Compustat
Ln size	Natural logarithm of total employees recorded in year t	Compustat
Lagged income (billion $)	Total income recorded in year t-1	Compustat
Macro-level characteristics		
Year	Fiscal year relating to 10-k filing, t=1, 2,..., 14	Compustat
Sector	[1]SIC200; SIC201; SIC202; SIC203; SIC204; SIC205; SIC206; SIC207; SIC208; SIC209	Compustat
Region	New England; Middle Atlantic; East North Central; North Central; South Atlantic; East South Central; West South Central; Mountain; Pacific	U.S. Census Bureau

[1] SIC = standard industrial classification.

$$y_{it} = \begin{cases} 1 & if\ y_{it}{}^* > 0 \\ 0 & if\ y_{it}{}^* \leq 0 \end{cases} \tag{3}$$

In choosing random over fixed effects for our panel logistic model, we considered three advantages of random effects: (1) the ability to compare between companies; (2) the ability to generalize findings and conclusions; and (3) the ability to include time-invariant predictors (Bell and Jones, 2015; Greene, 2011). Thus, empirically, the panel random effects logistic model is defined as

$$pr(y_{it} = 1|x_{it}, c_i) = \varphi_i x_{it} + c_i + \pi + \vartheta_i + \tau_i + \mu_{it} + \varepsilon_{it} \tag{4}$$

where each symbol is as before, π indicates the year, ϑ indicates the region, λ indicates the sector, φ is the vector of unknown parameters to be estimated via maximum likelihood, μ is the between-entity stochastic term, and ε is the within-entity stochastic term. As motivated in our introduction, φ is of primary interest to our study. We estimate Equation 4 for patent ownership and trademark ownership in general as well as each type of patented innovation (product, process, and marketing) by means of the xtlogit command in STATA (StataCorp, College Station, TX, USA).

4.5 Panel negative binomial model: innovation intensity

The question is not only if public food and drink manufacturers use patents and trademarks to protect intellectual property, but also how much or how often. The Poisson regression model is considered to be the most appropriate for the analysis of discrete data with many zeros and small values (Greene, 2011). However, overdispersion is apparent in our data, which motivates a negative binomial model to relax the assumption of equal conditional mean and variance functions (Greene, 2011).[11] As described by Hilbe (2011), the negative binomial model is specified as

$$pr\left(Y_{ij} = y_{ij} \middle| x_{ij}\right) = \frac{e^{-\lambda_{ij}u_{ij}}\left(\lambda_{ij}u_{ij}\right)^{y_{ij}}}{y_{ij}!}, y_{ij} = 0, 1, 2, \ldots \tag{5}$$

Here, the conditional mean λ is linked to an exponential function of a vector of predictors and its parameter estimates,

$$E\left[y_{ij}|x_{ij}\right] = var\left[y_{ij}|x_{ij}\right] = \lambda_{ij} = exp(\beta' x_{ij}) \tag{6}$$

Because of our panel approach, Equation 6 is further specified as

$$\tilde{\lambda}_{it} = exp(\beta' x_{it} + \varepsilon_i) \tag{7}$$

which is equivalent as

$$\tilde{\lambda}_{it} = \lambda_{it}\mu_i \tag{8}$$

where μ represents the firm-specific intercept. Empirically, Equation 7 and 8 translate into

$$\tilde{\lambda}_{it} = \varphi_{it}x_{it} + c_i + \pi + \vartheta_i + \tau_i + \mu_{it} + \varepsilon_{it} \tag{9}$$

where each symbol is as before. Again serving as our main variables of interest, the included firm characteristics are the same as in Equation 4, which implies we expect patent and trademark ownership intensity to relate to the same firm characteristics as patent and trademark ownership propensity. Equation 9 is estimated separately for the total number of patented and trademarked innovations as well as for the total number of patented product, process, and marketing innovations by means of the xtpoisson command in STATA.

5. Results and discussion

5.1 Patent and trademark ownership propensity

First, we report the panel logistic model results for innovation propensity in terms of patent and trademark ownership (Table 7). Then, we report results for the three different types of patented innovation (Table 8). While presented separately, we discuss the results simultaneously. In Table 7, we report the raw coefficients, which indicates the estimated relationship of a one-unit increase in the given variable to the log odds of innovation propensity, as well as the odds ratios, which are the exponentiated values of the coefficients. In Table 8 we only report the odds ratios to conserve space.

Past innovation is found to be of statistical significance in each model, except for patented innovation in food and drink products. Specifically, past innovation is estimated to multiply the odds of patent ownership propensity by a factor of 7.07. Thus, for the most part, patented innovation in the previous year increases

[11] Indeed, the estimated alpha parameter for the general Poisson model is characterized by statistical significance, which implies negative binomial is the appropriate model.

Table 7. Panel logistic model results for patent and trademark ownership (innovation propensity).[1]

Variable	**Model 1 – patent ownership**		**Model 2 – trademark ownership**	
	Coefficient	**Odds ratio**	**Coefficient**	**Odds ratio**
Intercept	-12.508*** (2.775)	0.000 (0.000)	-3.324* (1.723)	0.036 (0.062)
Past innovation (y_{t-1})	1.956*** (0.444)	7.070 (3.138)	0.905*** (0.297)	2.473 (0.734)
ln firm age	0.862** (0.381)	2.369 (0.902)	0.103 (0.318)	1.109 (0.353)
ln total employees	0.526*** (0.177)	1.692 (0.299)	0.649*** (0.128)	1.914 (0.245)
Past income (t-1)	0.678* (0.363)	1.971 (0.716)	0.331 (0.209)	1.393 (0.292)
Debt ratio	-0.098 (0.523)	0.907 (0.474)	-1.275** (0.632)	0.279 (0.177)
Region binary variables	Yes		Yes	
Sector binary variables	Yes		Yes	
Year binary variables	Yes		Yes	
n	1,198		1,198	
n (groups)	136		136	
Wald X^2	121.16		92.35	
Prob>X^2	0.0000		0.0000	
McKelvey & Zavoina's R^2	0.83		0.54	

[1] *, **, and *** indicate significant differences at 0.05, 0.01 and 0.001%, respectively.

Table 8. Panel logistic model results for product, process, and marketing innovation propensity.[1]

Variable	**Model 3 – product innovation Odds ratio**	**Model 4 – process innovation Odds ratio**	**Model 3 – marketing innovation Odds ratio**
Intercept	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)
Past innovation (y_{t-1})	1.577 (0.866)	3.802*** (1.855)	5.921** (4.254)
ln firm age	5.549*** (2.982)	2.667** (1.103)	2.786** (1.186)
ln total employees	1.379 (0.308)	2.062*** (0.540)	1.711*** (0.317)
Past income (t-1)	2.297*** (0.605)	2.457* (1.177)	2.444** (0.900)
Debt ratio	0.685 (1.010)	1.111 (0.140)	0.730 (0.542)
Region binary variables	Yes	Yes	Yes
Sector binary variables	Yes	Yes	Yes
Year binary variables	Yes	Yes	Yes
n	1,198	1,198	1,198
n (groups)	136	136	136
Wald X^2	55.74	85.34	113.55
Prob>X^2	0.0144	0.0000	0.0000
McKelvey & Zavoina's R^2	0.91	0.85	0.95

[1] *, **, and *** indicate significant differences at 0.05, 0.01 and 0.001%, respectively.

the probability of patented innovation in the following year, which may imply innovation and the protection and appropriation of its value is path dependent (Antonelli *et al.*, 2013). In terms of innovation persistence, Triguero *et al.* (2013) reached the same conclusion for 671 food manufacturers in Spain. Like Triguero *et al.* (2013), we also observe a stronger lagged effect for process innovation as compared to product innovation, although the magnitude associated with marketing innovation is even higher. As such, all else equal, prior innovations in food and drink products or compositions are the least likely to spur similar innovations in the future. Another explanation for innovation persistence in general is an intra-firm knowledge spillover effect from year to year, which corresponds to the knowledge stock interpretation. Such an effect is related to the recent interest in patent citation data, which informs the quality of the patent and therefore the quality of the innovation (Bernstein, 2015; Nagaoka *et al.*, 2010; Odasso *et al.*, 2015). In general, a high number of forward citations is interpreted as high-quality innovation, which in theory is more likely to facilitate innovation persistence.

Firm age has a significant and positive relationship to the propensity to patent each type of innovation, which corresponds to general observations by Cefis and Marsili (2006). As such, the probability of patent ownership is increasing in age, which may imply innovation and protection and appropriation of its value is a long-term process associated with organizational learning (Jimenez-Jimenez and Sanz-Valle, 2011).[12] With a 5.549 increase in the odds ratio, the largest magnitude of firm age is observed in relation to the propensity of patented innovations in products or compositions. However, firm age is not characterized by statistical significance in terms of the propensity to own trademarks, suggesting both young and old firms use trademarks for intellectual property protection.

With total employees as its proxy, statistical significance is also observed in terms of firm size in relation to the propensity to patent process and marketing innovations. Our result is comparable to Vancauteren (2016), who measured a positive impact of employee size on the patent portfolios of Dutch food manufacturers for the 2000-2008 period. Alternatively, we can interpret total employees as human capital stock, which is necessary for product and process innovation (Berchicci, 2013). As such, a 1% increase in human capital increases the probability of process and marketing innovation by factors of 2.062 and 1.711, respectively. Also, at an odds ratio of 1.914, food and drink manufacturers are approximately twice as likely to register trademarks as size increases by 1%.

Past income, which is the one-year lagged observation of net income, is observed to have a positive relationship to each type of patented innovation. The propensity to patent innovation of any type is thus correlated with equity availability, which is interpreted as an important barrier to innovation and the protection and appropriation of its value. As argued by D'Este *et al.* (2012), cost is the primary concern when firms consider innovation. However, the coefficient corresponds to a \$1 billion increase in net income, suggesting the positive relationship to patent ownership propensity is most noticeable toward the far end of the spectrum in terms of size.[13] Meanwhile, the hypothesized negative relationship of leverage to innovation is not characterized by statistical significance, except for the propensity to register trademarks. Capital structure is thus determined to only be of partial importance to the protection of intellectual property in the food and drink industry.

Although we included vectors of binary variables for the years, the regions, the sectors, the parameter estimates are not reported in the interest of space.[14] Overall, statistical significance is observed for many but not all binary variables, which implies patented innovation in the food and drink industry is heterogeneous across time, space, and industry. Specifically, patented innovation propensity is observed to be relatively low for the year 2014, which is likely attributable to the application-issue lag. Otherwise, there is not much consistency in the statistical significance of the control variables.

5.2 Patent and trademark ownership intensity

We now proceed to the panel negative binomial model results in relation to the intensity of patent and trademark ownership (Table 9 and 10). Similar to the panel logistic model results, we report the raw coefficients as well as the incidence rate ratios, which are the exponentiated values of the coefficients and indicate the estimated impact of one-unit increases in the given variable on the expected count in terms of percentages (Hilbe, 2011).[15] Table 10 only contains the incidence rate ratios in order to conserve space.[16]

[12] Squared age, which is often included in empirical specifications to test if the causal impact of age is nonlinear, proved to be nonsignificant in our model and is therefore excluded in the table.
[13] Net income of the mean firm in our sample is \$314 million, and \$1 billion or more in revenue is only observed in 97 of the 1,355 observations (7%).
[14] Full results are available upon request.
[15] The interpretation of the incidence rate ratio is intuitive. The threshold is 1, which indicates no relationship between the predictor and the outcome variable. An estimate of below 1 indicates a negative relationship, and an estimate of above 1 indicates a positive relationship.
[16] Full results are available upon request.

Table 9. Panel negative binomial model results for patent and trademark ownership intensity.[1]

	Model 6 – patent ownership intensity		Model 7 – trademark ownership intensity	
Variable[2]	**Coefficient**	**I.R.R.**[3]	**Coefficient**	**I.R.R.**
Intercept	-5.226*** (1.399)	0.005*** (0.008)	-0.879* (0.515)	0.415* (0.214)
Past innovation (y_{t-1})	0.010*** (0.003)	1.010*** (0.003)	0.011*** (0.002)	1.011*** (0.002)
ln firm age	0.194*(0.110)	1.214* (0.133)	0.042 (0.075)	1.043 (0.078)
ln total employees	0.405*** (0.090)	1.499*** (0.135)	0.282*** (0.042)	1.326*** (0.056)
Past income (t-1)	0.019 (0.053)	1.019 (0.054)	-0.032 (0.041)	0.969 (0.040)
Debt ratio	-0.747* (0.451)	0.474* (0.214)	-0.643*** (0.213)	0.526*** (0.112)
Region binary variables	Yes		Yes	
Sector binary variables	Yes		Yes	
Year binary variables	Yes		Yes	
N	1,198		1,198	
N (groups)	136		136	
Wald X^2	157.64		244.16	
Prob>X^2	0.0000		0.0000	
AIC	1,928.045		4,726.001	
BIC	2,121.404		4,919.361	

[1] * and *** indicate significant differences at 0.05 and 0.001%, respectively.

[2] AIC = Akaike information criterion; BIC = Bayesian information criterion.

[3] I.R.R. = incidence rate ratio.

Table 10. Panel negative binomial model results for product, process, and marketing innovation intensity.[1]

Variable[2]	**Model 8 – product innovation I.R.R.**[3]	**Model 9 – process innovation I.R.R.**	**Model 10 – marketing innovation I.R.R.**
Intercept	0.004*** (0.008)	0.000*** (0.000)	0.000*** (0.000)
Past innovation (y_{t-1})	1.027** (0.013)	1.021*** (0.008)	1.011** (0.005)
ln firm age	1.243* (0.160)	1.456*** (0.196)	1.213 (0.179)
ln total employees	1.488*** (0.203)	1.958*** (0.233)	1.983*** (0.251)
Past income (t-1)	1.151* (0.091)	1.057 (0.065)	0.908 (0.058)
Debt ratio	0.486 (0.305)	0.605 (0.337)	
Region binary variables	Yes	Yes	Yes
Sector binary variables	Yes	Yes	Yes
Year binary variables	Yes	Yes	Yes
N	1,198	1,198	1,198
N (groups)	136	136	136
Wald X^2	130.64	143.87	141.96
Prob>X^2	0.0000	0.0000	0.0000
AIC	933.8048	1,343.17	1,265.819
BIC	1,127.164	1,536.53	1,454.09

[1] *, **, and *** indicate significant differences at 0.05, 0.01 and 0.001%, respectively.

[2] AIC = Akaike information criterion; BIC = Bayesian information criterion.

[3] I.R.R. = incidence rate ratio.

In relation to past innovation, the magnitude of its estimated relationship to patent and trademark ownership intensity is low as compared to propensity. With total patented innovations in products as the outcome variable, each past patented innovation is only estimated to increase the probability of more product innovations in the following year by 2.7%, which may be indicative of a poor carryover effect. For process and marketing innovations, the positive relationship to past innovation is similarly low (incidence rate ratios of 1.021 and 1.011, respectively). While significant in each case, past innovation is therefore concluded to be of primary importance to the propensity but not the intensity of patent and trademark ownership.

All else equal, a 1% increase in firm age is associated with more patented innovations in products and processes (factors of 1.243 and 1.456, respectively). As age is concluded to be non-significant to trademark ownership in both propensity and intensity, the use of trademarks to protect intellectual property is similar among young and old firms, all else equal.

The relationship of firm size to the intensity of patent and trademark ownership is observed to be characterized by statistical significance in each model. Moreover, firm size is the most influential firm characteristic, as determined by the magnitude of the parameter estimates. For example, patent and trademark ownership is expected to increase by 49.9 and 32.6%, respectively, for a 1% increase in firm size. Firm size is thus important to the propensity and the intensity to protect innovations by means of patents and trademarks, which lends partial support to the Schumpeterian hypothesis of firm size, R&D expenditure, market structure, and innovation. Specifically, Schumpeter (1942) hypothesized the majority of innovation activity is generated by large firms with considerable power to drive creative destruction in the market. We do not have sufficient data to determine if the large manufacturers in our sample indeed have market power.

Similar to the propensity of patent and trademark ownership, firm capital structure is apparently of limited importance to intensity. Past income is only concluded to significantly relate to the total number of patented innovations in products, but the incidence rate ratio of 1.151 is almost negligible as income is measured in billions. As for leverage, its estimated relationship to each type of patented innovation is non-significant, yet its relationship to patent and trademark ownership intensity is strong, significant, and negative. Per the incidence rate ratio, a 1% increase in the debt ratio is associated with 52.6% fewer patented innovations. The relationship to total registered trademarks is comparable. All else equal, the mean food and drink manufacturer is expected to own 47.4% fewer trademarks for each 1% increase in the debt ratio.

6. Summary and conclusions

Recent developments in the agri-food industry have forced or motivated food and drink manufacturers to innovate in order to remain competitive. However, it is unclear to what extent recent research on innovation in the food and drink industry, often driven by survey data on European manufacturers, is generalizable to the United States. As such, we addressed the gap in the empirical literature by using patent and trademark ownership data to study product, process, and marketing innovation in the U.S. public food and drink industry. Considering data for the 2000-2014 period, patented innovations in the manufacturing and marketing of food and drink products are the most common. We thus concluded food and drink manufacturers do not often patent innovations in food and drink products or compositions, if they engage in much product innovation at all. We also concluded food and drink manufacturers rely more on trademark ownership, which is pursued to secure the exclusive right to use words, names, or symbols associated with product, process, and marketing innovations. The data also illustrated a dichotomy as only 20% of the 157 firms in our sample patented one or more innovations during the 2000-2014 period. Furthermore, large multinationals such as Coca-Cola, Kellogg, and Pepsi own the majority of patents and trademarks, whereas smaller organizations in general do not often own patents and trademarks to protect intellectual property. We thus observed a strong concentration of intellectual property as protected by patents and trademarks, which may or may not impact the future viability of small manufacturers in the food and drink industry.

Empirically, we specified a panel logistic model to study the propensity of patent and trademark ownership and a panel negative binomial model to study the intensity of patent and trademark ownership. Firm characteristics served as our main interest, and we used random effects to address heterogeneity across time, space, and industry. Per the panel logistic model and panel negative binomial model results, firm characteristics for the most part have a significant relationship to the propensity and intensity of patent and trademark ownership. Specifically, we observed a positive association to firm size as well as firm age, which is not too surprising as patent and trademark ownership is concentrated among established and large multinationals in the food and drink industry. Furthermore, variability in patent and trademark ownership propensity and intensity might be explained by lagged income and lagged innovation, which is suggestive of path dependence in R&D investment and innovation. Together, our findings raise a general perception of cost and time barriers to innovation and the protection and appropriation of its value for small manufacturers in the food and drink industry (D'Este *et al.*, 2012), which is an important consideration as 76 of the 157 firms in our sample reported an average size of 1000 or fewer employees. In all likelihood, innovation is considered to be a long-term process with significant cost and uncertain payoff, a combination only affordable to large established firms. The result is worrisome as patenting is considered to be beneficial, if not crucial, to the survival probability of small firms (e.g. Helmers and Rogers, 2011; Rosenbusch *et al.*, 2011).

There are several weaknesses and limitations to consider. First, patent ownership may not capture the full or the true extent of product innovation in the food and drink industry as intellectual property is also often protected by means of trade secrets (Cohen *et al.*, 2000; O'Donnell *et al.*, 2008), which concern any form of confidential information with actual or potential economic value.[17] Trade secret protection is traditionally pursued by means of state law (Png, 2017), but federal governance is likely to increase as U.S. Congress passed the Defend Trade Secrets Act in 2016. Obviously, trade secrets make objective observation of product and process innovation complicated as registration is nonexistent. Second, R&D expenditure often proxies innovation, but such data proved to be unreliable in our case as many firms acknowledge R&D activity yet do not explicitly report R&D expenditure, probably in the interest of secrecy. Therefore, the impact of R&D expenditure is perhaps captured in the parameter estimate of firm size, which is likely correlated with investment in long-term growth. Third, we do not have adequate data to differentiate between firm size and human capital. Ideally, total sales or total assets is used to proxy firm size and total employees is used to proxy human capital. However, total employees is correlated with both total sales and total assets, which forced us to use total employees to proxy firm size as well as human capital to avoid multicollinearity. As such, we cannot conclude with absolute certainty if the parameter estimates for total employees report the relationship of firm size or human capital to the propensity and intensity of patent and trademark ownership, although the model results with total assets in place of total employees are similar.

Our results and conclusions have several implications for managers as well as policymakers. First, considering the large impact of past innovation in terms of both propensity and intensity, managers of non-innovative food and drink manufacturers may first consider engaging in some type of research partnership or collaboration to jumpstart the process. Then, once some knowledge or intellectual property is generated, a spillover effect may facilitate independent R&D and innovation. Second, as the relationship of firm size to patent and trademark ownership is positive, managers of relatively small manufacturers may consider investing in human capital to secure specific knowledge. Since leverage is only associated negatively to trademark ownership, managers may consider debt acquisition if there is intention to make patented innovations in products or processes. Of course, capital structure decisions cannot be made in a vacuum, and any investment should be contingent on its future return. Third, policy may address the apparent concentration of patent ownership by increasing opportunities for intellectual property protection for relatively small food and drink manufacturers, thus improving *ex ante* incentives for specific investments in intangible assets and resources. The recent implementation of the Defend Trade Secrets Act, which is a piece of federal legislation to fight trade secret misappropriation, may constitute a step in the right direction. Fourth, policy may also lend financial or

[17] In terms of economic strategy, a trade secret can last forever, but the protected information is susceptible to reverse engineering (Hall *et al.,* 2014). However, academic discussion or exploration of the relative relevance of patents, trademarks, and trade secrets in the food and drink industry is, to our knowledge, nonexistent.

technical support to small food and drink manufacturers to spur innovation and thus competitiveness in the industry. One possibility is to provide tax benefits for R&D investment or subsidies for patent or trademark applications.

While we produced evidence of the relationship of firm characteristics to product, process, and marketing innovation in the food and drink industry, there exist many more open research questions to be answered. For example, what percentage of firm value is composed of patents, trademarks, and trade secrets? What is the causal relationship of patented innovation to firm performance? Is patent and trademark ownership propensity and intensity similar among non-public companies? When is patent ownership complementary with trademark ownership? We recommend future research to address such questions to further our collective understanding of innovation, particularly in the food and drink industry.

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