Industrial Designs and Firm Performance: Evidence from Publicly Traded Canadian Companies, 1990-2014

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Industrial designs (IDs) are a specialized form of intellectual property (IP) that protect unique designs. This paper estimates the effect on firm revenue and profitability of holding IDs. Using a new data set linking Canadian ID holdings with Canadian publicly traded firms over the years 1990-2014, the authors use three methods to identify a positive economic impact on firm revenue per employee and net income per employee from holding IDs. With a nearest-neighbour matching approach, we find a 19% total premium in revenue per employee for Canadian firms holding at least one industrial design, compared to those with none. To determine the marginal effect of each additional ID held, we use a fixed effects regression and find that a 1% increase in the stock of IDs increases revenue per employee by 0.1%, after controlling for patenting. We also consider the design orientation of a Canadian firm separately from the number of IDs, and find that being a firm that has held industrial designs gives a 12% total premium in revenue per employee and an 18% total premium in net income per employee in addition to the marginal effect of each ID currently held.

Keywords: intellectual property; industrial designs; firm performance; Canadian firms; Canada; nearest-neighbour matching

Subject classification codes: N/A

Introduction

The modern economy is, increasingly, a design economy. Modern firms differentiate their products not simply on functionality, but on distinct designs – subtle changes that affect presentation and functionality, but do not represent distinct inventions. Designs are a vital intangible asset, and yet in Canada and in many other countries, they cannot be protected by the three most common types of intellectual property right (IPR): a patent is only available for inventions; a copyright would not allow for mass reproduction; and a trademark will not prevent competitors from copying the essence of the product. However, there is a type of intellectual property right which allows for the protection of designs: industrial designs (called design patents in some other jurisdictions). Industrial designs (IDs) are a useful mechanism for firms to protect their designs, and lead to a temporary monopoly on that design.

One of the central questions in the field of intellectual property is the economic impact on firms from holding intellectual property rights, and in particular, the impacts of different types of IPRs. Many of the most recent high-profile disputes over IP, notably the Apple vs. Samsung lawsuit regarding features of smartphones, are commonly described in the press as "patent litigation", but these are actually lawsuits about industrial designs (which are called "design patents" in the US). Economists are interested in the effect of holding IDs on firm activity, because we want to know if any additional value is generated by the ID protection itself, or by the type of design-focused activity that leads firms to hold IDs. This has ramifications both for how firms should be operating, and for public policy about the ease of access to IDs and the scope of their included legal protections. However, owing to the much greater public focus on patents, there is relatively little information available on the economic impact of IDs.[1]

Observing an ID registration indicates several things: the firm's possession of a product line that has sufficient design distinctiveness to warrant intellectual property protection; the design work and innovation that went into the product; corresponding employee and

[1] The registrations of industrial designs tend to follow macroeconomic trends just like other IP variables. In particular, there is a correlation between ID registrations and GDP, and between foreign applications and imports.

management orientations; and the legal protection of the ID registration itself. Disentangling some of these effects is one goal of this paper. Industrial design registrations (as opposed to applications) are an excellent measure of a firm's total exposure to design-related intellectual property because IDs have very short application processing times. Unlike patents, which can have application processes lasting 5 to 10 years, ID applications in Canada are typically processed in six months to a year. (IP Canada Report 2017). Furthermore, in the large majority of cases, applications are granted and become registrations, so firm-level data on applications and registrations are closely related. Registrations have an initial 5 year period and can be renewed, so the use of ID registrations allows us to better capture design exposure over time.

This paper estimates the effect on firm revenue and profitability of holding IDs. Industrial designs held by Canadian publicly traded firms over the period 1990-2014 are examined, and the effect of holding IDs is separated from the 'design orientation' of a firm (i.e. whether a firm is the type of firm that ever holds IDs). With a nearest-neighbour matching approach, we find a 19% total premium in revenue per employee for Canadian firms holding at least one industrial design, compared to those with none. To determine the marginal effect of each additional ID held, we use a fixed effects regression and find that a 1% increase in the stock of IDs increases revenue per employee by 0.1%, after controlling for patenting.

This paper contributes to the economics and management literature by showing three different estimating methods, one of which allows for the separation of design orientation effects from the marginal effect of additional industrial designs, and the consistency of the results among these methods. This paper makes further contributions by looking at a unique Canadian data set, by considering firms from all sectors, and by studying IDs over a longer (25-year) period than other studies. We first use a nearest-neighbour matching algorithm to illuminate the impact of holding IDs, then use regression analysis to consider the effect of the stock of IDs. This is also the first paper to estimate the effects of IDs on Canadian firms. The results suggest that both IDs and a design orientation increase firm revenue and profitability.

This paper builds on two major strands in the economics and management literature: studies on the impact of IDs, and work on the impact of IP rights on firm performance. Bascavusoglu-Moreau and Tether (2011), writing for the UK Intellectual Property Office, analyze the impact of IDs held by firms in the United Kingdom. They focus on a number of particular design-intensive sectors. Using the nearest-neighbour matching procedure described by Abadie et al. (2004), they pair each ID-using firm with a no-ID firm, and examine the performance of the treatment and control groups in five year cohorts. They do not include any control for patenting in their matching procedure, which is an additional robustness check included in this paper. They find a 17% premium in revenue per employee for firms with an ID registration in the UK. The authors note that this difference cannot be definitively attributed to the ID, but merely that IDs are associated with a higher level of performance. This distinction between showing causation or correlation recurs in the literature. Toivanen et al. (2002) describe a theoretical model that shows that firm valuations are based on both tangible and intangible assets, such as IDs.

The Office for the Harmonization of the Internal Market (OHIM, now called the European Union Intellectual Property Office), published a report in 2015 which also considers the economic impact of IP rights including ID (Wajsman et al. 2015). The study examined a sample of over 130,000 EU firms, and included data on patents, trademarks, and industrial designs. They use a panel data approach. By including the three different types of IPR that are registered, the study is able to test the impact of different IP rights combinations on firm performance. They also examine both the impact of simply having some IP rights (as measured by a dummy variable), and the impact of higher stocks of IP rights. They find the following premia in revenue/employee: 15% for designs alone, 15% for patents and designs, 39% for trademarks and designs, and 16% for all three. They also find that a 10% increase in the stock of national designs leads to a 0.7% increase in revenue per employee.

Most papers and studies conclude that there is a positive effect on firm performance associated with IPRs. Munari and Santoni (2010) examine interactions among different types of IPRs in small and medium sized enterprises (SMEs) in Northern Italy and find that firms with patents and either designs or trademarks have a higher level of return on assets and return on sales. Other work on Finnish manufacturing firms (Lindstrom and Pajarinen 2006) and Danish firms (National Agency for Enterprise and Housing 2003) has found positive economic impacts of IDs on firm performance.[2] There is also extensive literature on determining the impact of holding patents on firm performance. There are some limitations to these approaches. In particular, papers in this field do not typically consider the possibility of firms licensing IP rights that they do not own. We follow that approach here.

For example, Bloom and Van Reenen (2001) examine 200 major British firms since 1968, and find that patents (as measured by patent stocks or citation-weighted patent stocks) have a statistically significant effect on firm revenue. They use a simple Cobb-Douglas model of the firm that is adapted in this paper. Ernst (2001) considers time-series cross-sectional data to determine the impact of patent applications on firm

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[2] See literature review by Munari, 2012, for the EU Observatory, section 6.4.

performance. He finds a positive impact on firm sales of holding patents, with a lag time of 2 or 3 years. All of these approaches find a positive impact of holding patents on firm performance. Further work suggesting positive revenue or profit impacts from IPRs would include Bosworth and Rogers (2001) as well as Buddelmeyer et al (2009). Both Gemser and Leendersb (2001) and Hertenstein et al (2005) find these impacts for industrial designs. Mol and Masurel (2012) further discuss how the literature often focuses on patents, and neglects industrial designs and copyrights. Baldwin et al. (2000) study the effect of patents on Canadian manufacturing firms, and find that the use of IPRs other than patents and trade secrets (this would include IDs) have a positive and significant effect on innovation, but they don't specifically examine the effects on revenue or net income.

Appropriability regimes, including such factors as the strength of intellectual property rights, will affect the appropriation strategies of the firm. Appropriability can be thought of as "the capacity of the firm to retain the added value it creates for its own benefit" (Kay 1995). Registering an ID will increase the capacity of the firm to profit from the design by blocking competition by other firms, which should increase both revenue and markups. Holding the ID gives the firm the legal right to block others from using it, but it also represents a signal that the underlying design is worth protecting. There may be positive second order effects that occur as a result of the design being held, such as increased capacity to engage in certain types of marketing strategies. When the option of registering an industrial design is present in an appropriability regime, this option will likely facilitate more unique designs and more research on designs by firms, because they know they can more easily recover the costs of doing so. Thus, the presence of additional patents and of additional registered industrial designs should both increase revenue and net income of a firm. By limiting ourselves to

Canadian firms, we have a constant appropriability regime rather than comparing across firms in different jurisdictions.

Thoma and Bizer (2013) discuss how smaller firms use a different mix of appropriation strategies, relying on secrecy, complexity of design, and lead time of development more than the use of formal intellectual property rights. Firms of any size have multiple options to protect the profitability of inventions or designs. However, protecting a design may differ from protecting an invention in terms of the need for an IPR because of the higher difficulty of other techniques – secrecy, lead time, complexity of design – in providing advantages for designs rather than for inventions. Design is visible and acts as a product differentiator, and designs are more easily copied and less easily concealed, so formal legal protection may be more necessary for designs than for inventions.

Cohen et al. (2000) discuss motives for patenting other than the prevention of copying – blocking competitors from patenting, forcing negotiations, or avoiding lawsuits – and how they may be more prevalent in industries with complex products. These motives are less applicable in the case of IDs. However, some types of designs involving more complex features (such as the Apple vs. Samsung litigation settled in 2012), may have similarities to the strategic context of patenting activity. Registered IDs can prevent competitors from copying a design and may even discourage them from competing directly at all.

In sum, the presence of an IPR captures a higher markup from blocking competition and potentially higher volume of units sold, but is also a signal of the strength of the product. In general, it is difficult to differentiate between the market power effects of additional IPRs and the other effects on profitability. Despite this, it is possible to partially disentangle the effect of the designs from the selection effect of "being the type of firm that holds designs", as we explore with our design orientation regression.

Methodology

A Cobb-Douglas production function is a straightforward way of conceptualizing firm performance, as seen in many papers, including Bloom and Van Reenen (2001). We use the following notation: Q is revenue, A is a parameter measuring firm-year productivity, K is the firm capital stock as measured by assets, and N is the number of employees. Let ID be the stock of industrial designs and P be the stock of patents. We can think of IP rights entering multiplicatively as a factor of production, rather than affecting the separate productivity parameter. Productivity (A) is understood as the effect of three components: firm-specific fixed effects, a time effect, and a random error. We would have IP rights entering in the Cobb-Douglas form the same way as K or N, and define productivity as $A_{it} = \exp(\eta_i + \tau_t + e_{it})$. Then

$$Q = AK^{\alpha}N^{\beta}ID^{\gamma}P^{\delta}$$

We anticipate that additional industrial designs represent both additional innovations and the legal protections for those innovations, so that revenue will be higher for any given levels of capital, labour, and innate firm productivity. This is consistent with standard conceptions of the representative firm in the IP literature, such as Budish et al. (2016). Having industrial designs may also be indicative of a 'design orientation' which would be associated with more specific product differentiation and branding, and thus lead to higher markups and higher revenue. The knowledge stock variables thus capture the economic impacts on revenue of these three effects: innovation (as in Baldwin 2000), legal protection, and differentiation/branding.

By separating the effects of these different variables, we can better analyze the tradeoffs faced by both firms and policymakers. If the innovation orientation and the marginal effects of legal protection can be disentangled and one effect size is larger, it may have substantial ramifications for firm strategy.

Firm revenue per employee is our main variable of interest. Revenue per employee can be used as a measure of firm productivity, due to its relatively straightforward comparability across jurisdictions. This interpretation is plausible, but we should note that additional revenue from higher appropriability due to an IPR is not the same as labour productivity gains due to more productive workers. Because the regression is estimated with logarithms, this gives the same result as regressing with revenue as the independent variable, with the coefficient on employees affected by 1. Net income tends to be affected substantially by variations in tax and accounting rules. Despite this issue, net income is also considered. The central research question is to determine if there is a statistically significant effect on firm performance associated with Canadian firms having registered or renewed industrial designs in Canada. The Canadian Intellectual Property Office (CIPO) provided ID data that was then integrated with existing sources of financial data on Canadian firms. The primary methodology involves using records of domestic Canadian registrations and renewals of IDs to determine the total ID stock of Canadian firms in each year.

We obtained financial data on 723 Canadian publicly traded companies, which was paired with data on industrial designs from CIPO. After combining and matching data sets, and eliminating observations with insufficient data, we were left with 580 firms, of which 63 had at least one industrial design in the years 1990-2014. This gives 6245 observations of firm/year pairs, of which 494 are observations where the firm holds at least one ID, and 531 are observations from firms that hold IDs in other years but not in that year. Data was adjusted for inflation and the time trend was removed. Details on the procedures for obtaining and sorting the data, and on generated variables, are provided in the Appendix below.

Nearest-Neighbour Matching Method

The properties of firms with at least one industrial design (the ‘treatment group’) were substantially different from the rest of the sample. There are substantial differences in the propensity to hold IDs and in the other variables among different sectors, so we calculated the averages for ID and non-ID observations in each sector (manufacturing; oil refining; non-oil resource; finance, insurance, and real estate (FIRE); and other) and took the ratio of those averages. The oil-refining, non-oil resource, and FIRE sectors include a significant number of observations of non-ID holding companies with many assets and few employees, which dramatically increases the averages of revenue per employee and assets per employee in those sectors.

Using a paired t-test that compares the variable for each ID firm with the average of that firm’s sector, we see that there are statistically significant differences in revenue per employee and assets per employee.

Table 1 Here

We conclude that a simple comparison of averages is inappropriate due to the differences in sample composition. We also perform a two-sample Kolmogorov-Smirnov test for equality of distribution functions for revenue per employee, assets per employee, net income per employee, and number of employees among the ID and no-ID observations. These tests all reject the null hypothesis of equal distributions, significant at the 1% level.

As a result, we use a nearest-neighbour matching algorithm to pair each ID-holding observation with a similar non-ID observation from the same fiscal year. A matching methodology is particularly useful because it can control for a large set of covariates without specifying a particular functional form. In the two regressions presented later in the paper, we do specify such a form, but we recognize that the relationships among the variables may be more complex or non-linear.

For each firm in the data set, we want to find a comparison with similar properties. We use nearest-neighbour matching as defined in Abadie and Imbens (2002). This matching method matches each observation to one that received the opposite treatment, rather than simply matching the treated observations.

The following variables are used to match to the nearest neighbour: revenue, number of employees, assets, the patent index, and the four sector dummies. The Abadie and Imbens (2002) matching estimator is used and implemented in Stata. Mahalanobis distance for all of the variables is used to find the nearest neighbour, defined as the observation with the opposite treatment with the smallest Mahalanobis distance from the observation to be matched. Each observation is given a match with the opposite treatment. Replacement is allowed, as the number of firms that hold IDs is much smaller than those that do not. Because there is replacement, some firms may be the nearest neighbour for multiple observations of the opposite treatment group.

We proceed with two slightly different matching methods. Firstly, we compel an exact match on the fiscal year. This method ensures that no company is matched with itself in a different fiscal year. It was not possible to compel an exact match on the sector dummies and on the fiscal year simultaneously due to a lack of available matches in some years, but the sector dummies were included in the matching criteria, generating a preference for but not a requirement for in-sector matching.[3] The estimator, when used on this data set, returns exactly one match for each observation.

The second method compels an exact match with an observation from a firm in the same sector, but because an exact matching in the fiscal year is not compelled, this method allows the possibility of a firm being matched with an observation from itself in a different year.

We then use each of the matching variables in the bias adjustment (see Abadie 2011). This is necessary because the nearest-neighbour matching (NNM) estimator converges slowly when matching on more than one continuous covariate. The sector dummies were also included in the bias adjustment.

The graphs below show the changes in outcome for the matching procedure. These graphs show the changes in kernel density for having industrial designs in that year as the treatment variable, and are from the matching procedure that matches on the year rather than the sector (see the data appendix). When “having ever held ID” is used as the treatment variable, or when exact matches are done on the sector, the results are similar.

Figures 1, 2, 3, 4 here

The firms selected are from a variety of sectors and represent a broad base of both larger and smaller Canadian listed firms. Not all firms were present in the data set in all

[3] The use of NNM requires the conditional independence assumption – the belief that conditional on the observed characteristics, selection bias disappears. This may not be true, but the degree of selection bias may be reduced sufficiently for these results to be relevant.

years, and not all firms that have an ID in one year have one in every year. Accordingly, some firms may be in both the treatment group in certain years, and in the control or matching group in other years.

As well, we are only considering domestic registrations of IDs and not considering international ID registrations by Canadian firms. Thus, matched firm pairs may contain different exposure to international ID registrations not captured by the matching procedure. In particular, there may be some firms with no domestic registrations, which do in fact have ID registrations in other countries. To the extent that this is possible, it will likely bias the estimated treatment effect downwards towards zero, as a treatment group with no ID registrations either internationally or domestically would likely have lower average firm revenue and profitability.

We consider four different matching comparisons. Two examine the premium in revenue per employee, and the other two consider the premium in net income per employee. The net income data is unavailable for many of the observations, and so in these tests some observations are dropped from the sample. The average treatment effect on the treated is used, which means that we find the effect of having an ID on those firms that actually had one, as opposed to what the effect would have been on all firms. We also separately consider the impact of firms ever having IDs, rather than having them in a particular year. Results are found for the average treatment effect on the treated, as we are interested in the effect of those firms that actually held IDs. This is the average difference of the treatment and control potential outcomes in the treated population. The standard error is given in percentage points, not as a percentage of the estimated effect.

Regression Method

To analyze the individual effects of each factor, we perform an OLS regression. We take logs on both sides of the model equation presented above, and we rearrange to conceptualize the model in terms of revenue and assets per employee.

$$Q = \exp(\eta_i + \tau_t + e_{it})\, K^{\alpha} N^{\beta} ID^{\gamma} P^{\delta}$$

$$\log Q_{it} = \alpha \log K_{it} + \beta \log N_{it} \ + \gamma\ log\ ID_{it}\ +\ \delta\ log\ P_{it} + \eta_i + \tau_t + e_{it}$$

$$\log(Q_{it}/N_{it}) = \alpha \log(K_{it}/N_{it}) + (\beta - 1 + \alpha) \log N_{it} + \gamma\ log\ ID_{it}\ +\ \delta\ log\ P_{it} + \eta_i + \tau_t + e_{it}$$

We also conjecture an identical model for firm income, with net income replacing revenue as the Q variable. The economic interpretation of this specification is similar, as we expect that industrial designs assist with some combination of product innovation, legal protection, and product differentiation, thereby contributing to higher profits at any given level of capital, labour, and firm characteristics.

Past work on the impact of patents on firm performance, notably Ernst (2001), have used lagged patent counts as an explanatory variable. Because IDs have an approval process that lasts less than a year, this paper uses grants (registrations) of IDs rather than applications, and considers only the current stock of granted IDs, without the use of lagged counts.

Fixed effects were used, as a Hausman test suggests that random effects do not adequately capture firm-specific factors. Multicollinearity among the firm variables was tested using variance inflation factors, and the only problems were those associated with using net income and revenue at the same time. Accordingly, net income regressions do not include revenue as a regressor. Ernst (2001) points out that “it cannot be assumed for the set of data … that all variables explaining the sales of a firm are captured by the estimating model and that these unobservable variables are independent of the other regressors.” Accordingly, we follow Ernst in applying a Hausman test and concluding that a fixed effects model is necessary. (See also Hsiao 1985).

To adjust for the possibility of heteroscedasticity, we used standard errors adjusted for the possibility of intragroup correlation. A Wooldridge test (Drukker 2003) suggests the possibility of AR(1) errors when we are not using group and year fixed effects. The cluster adjustment for intragroup correlation may not return a consistent estimator if there is serial correlation in the errors, so we cannot simultaneously make a cluster adjustment and an AR(1) adjustment. Accordingly, we use both group and year fixed effects, and also cluster standard errors at the firm level.

Total ID stock and its log are both non-stationary and have a unit root in every panel according to a Fisher-type panel Dickey-Fuller test. However, use of first differences is problematic because holding industrial designs likely has a longer-term effect that is not captured in one year’s change in revenue. Tests for cointegration such as the Westerlund test (Persyn 2008) are also problematic because we have panel data with gaps in 220 of the firm time series.

Many of the publicly traded companies in the data set are non-oil resource companies, typically small mining companies. These were coded with a separate dummy variable from the major oil refiners. Only 11 observations of resource companies with IDs were present, out of 1684 observations of such firms. Some oil-refining companies had IDs and had much larger revenue per employee numbers, so separate dummies were created for oil-refining companies and non-refining resource companies. As a robustness check, these firms were excluded from the regression, which gave similar results for all specifications.[4] When using net income, 58 unusual observations with net income exceeding revenue are excluded.

We are also interested in the impact of the ‘design orientation’ of a firm. In other words, is it the presence of the IDs themselves that boosts firm performance, or is it a propensity to engage in the sorts of activities with which IDs are associated? To shed light on this question, we run a regression with firm-specific dummy variables describing the sector and whether or not the firms holds at least one industrial design at some point in the period 1990-2014. This dummy variable is meant to capture whether the firm has a ‘design orientation’. A regression was run on the full data set with a cluster adjustment to the standard errors. However, the use of firm-specific dummy variables means that a fixed effect adjustment is not possible, which may reduce the accuracy of this specification.

As a control for patents, which are the most important type of non-ID IPR, we construct an index of patenting activity. Our patent data comes from Clarivate’s Derwent Innovation database and includes all patents available for each firm. The index we construct adds together patent applications and grants from all jurisdictions from which data is available, including Canadian domestic patents, WIPO patents, European patents, American patents, and patents from over 14 other jurisdictions. Unlike IDs, patents have an application process lasting 5 to 10 years, so it is important to include applications as well as grants. It also includes utility models in jurisdictions where those

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[4] The excluded firms had much lower than average revenue, number of employees, assets, and stocks of IPRs. The Canadian mining sector is characterized by low-growth public firms, most of which are in the business of pure resource extraction and do not develop products for which industrial designs are suitable (see Bradley and Sharpe 2009).

exist, such as Germany and Japan. In countries such as the US where designs are a subset of patents, those are included. We note that this is not a measure of patent families, and so it includes multiple patents for the same invention if the firm has made those applications in multiple jurisdictions. More granular detail is not available due to the structure of the query system and the requirement of matching to firms. As well, this is administrative data, primarily constructed with a focus on top applications, so the data may lack consistency for smaller firms. For the patent data, we only have patents in the name of the parent company or names that are similar to the name of the patent company – each firm chooses the name that is on the patent, and different firms have different naming policies. The patent data is thus much noisier than the hand-matched ID data. Since IDs are our main variable of interest, this noisy patent data is still preferable to the absence of any control.

One limitation of this approach is that we do not have research and development (R&D) expenditure as a controlling variable. This is not present in the current data. Thus, we cannot separate the effort of a firm from its results. Perhaps the R&D is producing both the IPRs and the revenue, but the IPRs themselves are not producing the revenue. However, the use of firm fixed effects may partially address this. Since firm age is increasing at a pace of 1 per year, age will be collinear with combined firm and year fixed effects, so we do not need to separately control for it.

As a robustness check, we also use a depreciating patent index rather than the simple total, which gives similar results. Following Bloom and van Reenen (2001) and Griliches (1990), we construct the depreciating stock by assuming 30% annual depreciation in the prior year's level of patents, and then adding the number of new patents each year. The patent data starts in 1961, so by using this method the 1990-2014 data points should provide an accurate picture of the patent stock. Industrial designs have a much shorter lifespan – just 5 years – and our data also includes renewals for an additional 5 years. Accordingly, we just use the total stock of IDs held rather than depreciating the stock.

There exists the possibility of multicollinearity between the ID and patent variables, especially when looking at total stocks rather than logs of stocks. Among all firms, the correlation between the total stock of IDs and the total stock of patents is 0.90, in large part because many firms hold zero of each type. We see some evidence of this in the table, where using either IDs or patents on their own is significant but using both at the same time may not be. Thus, a log specification that limits itself to firm-years with at least one of each may be preferable.

We believe in a multiplicative model, with an elasticity rather than a semi-elasticity. We clearly find that both IDs and patents have an additional marginal effect. Thus, we are finding the marginal effect of an increase in IDs in firms that have at least one ID and at least one patent.

Results

For the nearest-neighbour matching method, the results are seen in Table 2. We include the patent index as one of the matching criteria. When compelling an exact match on the fiscal year, we find a 19.5% premium in revenue per employee and a 23.5% premium in net income per employee associated with the treatment group holding industrial designs, significant at the 1% level. There are also higher revenue and net income when the treatment is having ever held an ID. Results when compelling an exact sector match are higher and statistically significant at the 1% level for three of the four premia. As well, note that this NNM method implicitly treats all firms without an ID as if they enjoyed no benefits from an ID. This may not be the case, as firms that had an ID in the past may enjoy some residual benefit.

Table 2 Here

The results of estimating the regression model are in Table 3. Year dummies are included in the regression but are omitted from these tables. In this table and others below, we follow the standard convention that one asterisk is significance at the 10% level, two asterisks is the 5% level, and three is the 1% level.

Table 3 Here

When we take the logs of both IDs and patents we encounter a common problem: one cannot take the log of zero. Thus, when using logs we must omit all firms with none of that type of IPR. In the last column, we use the depreciating stock rather than the total stock as a robustness check, and still find significant and similar coefficients.

We find that a 1% increase in the ID stock has a positive impact on revenue per employee of about 0.1%, significant at the 5% level. This includes our patent index as a control. A 1% increase in the patent index increases revenue per employee by 0.13%, significant at the 1% level. Because we are using log values, this includes only firm-years with at least one ID and at least one patent observed. For columns (2) through (5) we fail to reject the hypothesis that the coefficient on IDs and on patents are equal. Values of other coefficients in the table may also be of interest.

The size of the sample is somewhat smaller than other studies. For the specification where all firms have at least one patent and one ID, there are 40 firms with a total of 306 observations, as few firm-year observations have at least one ID. Bosworth and Rogers (2001) have 60 firms, and Bloom and van Reenen (2001) have 211 patenting firms with 2,219 observations.

Table 4 Here

Net income data is only available for about 70% of the firm-years in our sample, so there are 238 firm-year observations with net income, patents, and IDs. We find no statistically significant marginal effects on profitability using a log-log specification. Accordingly, we can expand the number of observations by using the total stock of IDs rather than the log of that stock, seen in the last column of table 4. We still take the log of the patent stock. While this is less consistent with a Cobb-Douglas conception of the firm, it suggests that each additional ID held increase net income per employee by 1.1%. (The same specification for revenue finds that each additional ID held increases revenue per employee by 0.38%).

Lastly, Table 5 shows the results of the design orientation regression. This suggests that being a design-oriented firm is associated with having 12% higher revenue per employee and 18% higher net income per employee, significant at the 10% and 5% levels respectively, while the marginal effect of each ID held is lower. Note that because we have a firm-level dummy we cannot use firm fixed effects, so instead we use sector fixed effects. As above, these regressions also control for the total number of patents held using the patent index.

Table 5 Here

Discussion

The nearest-neighbour matching shows substantial premia in holding IDs, consistent with the literature. The regression design also shows marginal effects of additional IDs on both revenue and net income, which are large and statistically significant at better than the 1% level. This is highly suggestive of a substantial role for industrial designs in increasing the capacity of firms to increase revenue and net income from product lines.

The design orientation regression suggests that IDs, unlike patents in highly dynamic industries such as software, are typically not “complementary” in the sense discussed by Bessen and Maskin (2009) – in other words, industrial designs are not facilitative of distinct research lines, so the firms pursuing and holding them benefit from less competition.

Any analysis of IPRs must consider the possible impacts of other forms of intellectual property. Trademarks are generally held by almost all publicly traded Canadian companies. As such, trademark data is not considered in this study. Copyrights do not need to be registered to be protected, so any data would be inconclusive.

Conclusion

These findings suggest that industrial designs are associated with increased firm revenue per employee and net income per employee, which helps confirm a theory of the firm in which IP is a separate factor of production. The presence of designs, and a design orientation, are associated with both higher revenue and higher net income. Since the effect on net income is estimated to be larger than the effect on revenue in both of these estimated specifications, this suggests that the presence of designs is associated with higher profit margins. The finding of marginal effects suggests that there is a benefit associated with additional protection of intellectual property, not simply being a design-oriented firm. All of this reinforces the theoretical idea that intellectual property is a complement with capital and labour in firm production.

For firms, the promotion and protection of IDs specifically and IP generally is a strategic choice. IDs are often an overlooked form of IP, but this work suggests they should be seriously considered as part of a portfolio of IP choices.

There are other possible explanations for the higher revenue per employee and net income per employee associated with having industrial designs. One is the propensity to use intellectual property in general. If patents, as indicated by the literature, are also associated with a higher degree of firm performance, and if firms that use IDs are more aware of and more comfortable with barriers to use of IP, such as lawyers or a management team that is comfortable with the use of IP, then we may simply be measuring that effect. Another possibility is that firms that use IDs are simply better managed, more forward thinking or proactive, or have a higher degree of long-term focus, and those effects are simply being captured.

Future research could include two additional types of firm level data not present in this paper: R&D spending and marketing spending. Both of these would better control for key covariates and illuminate firm performance and behaviour.

The study of IP always involves complex questions of endogeneity and causality. This paper attempts to examine these questions and disentangle some the effects surrounding industrial designs in Canada. Our finding that the presence of IDs is associated with higher levels of firm performance, in both revenue per employee and net income per employee, suggests that IDs are a useful tool for firms to use and for future academic study.

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Appendix: Detail on Data and Variables

To determine the impact of industrial designs on firm performance, both financial variables and ID variables are required. Those two types of variables need to be matched, to correspond to the same firm and year.

Dr. Michael King, professor at the Ivey Business School, provided annual financial data on 723 publicly traded Canadian companies from the years 1990-2014. The data was retrieved from Compustat, a privately run financial database service. Variables include revenue, assets, number of employees, and the sector for each firm as tracked by the North American Industry Classification System (NAICS) code, as well as some additional control variables related to market conditions. Net income is simply profit, as defined in Compustat. Net income was only reported in some of the firm years, so all others are dropped from the sample when net income is being considered. For all these financial variables the impact of interest is the relative impact of having IDs compared to firm-years without IDs, so elasticities (which measure responsive to change) are considered. Accordingly, all of these variables then had their natural log taken. Some financial data was reported in US dollars, and annual exchange rate data from the St. Louis Federal Reserve's FRED (Federal Reserve Economic Data) was used to convert it. All financial data was adjusted for inflation using the Canadian GDP deflator from Statistics Canada.

Missing financial and employee data was obtained from Canada's SEDAR (System for Electronic Document Analysis and Retrieval), which has prospectuses for Canadian firms. A number of firms did not have available financial data or employee data. These firms were removed from the sample. For gaps in the employee data, interpolation between existing years was used. Averages were used for gaps in the data of two years or less. Some years were dropped when this was not possible.

The totals of all Canadian domestic ID registrations since 1980 were obtained from CIPO's ID Branch. IDs can be renewed after 5 years, so CIPO also provided all Canadian domestic ID renewals since 1980. These lists include the name of the applicant, identifying information such as the address, and the number of registrations by that applicant in that year. The data about IDs relies on the firm names being listed. This study is limited to domestic registrations, which may ignore international subsidiaries of Canadian firms that hold Canadian IDs. As well, international design registrations by Canadian firms are not included.

The financial data set and the ID data set were then matched to produce a combined set of firm-years. Each data point includes the total ID stock of the firm in that year, along with all of the financial variables. This matching process was done manually because the listed applicant's name commonly differs from the firm name due to typos or the use of subsidiaries. The Inter-Corporate Ownership software, which lists subsidiaries of Canadian firms, was obtained from Statistics Canada. By searching the ID list for the names of firms and their subsidiaries, the current total of IDs held by firms in each year for which they had financial data was determined. Partially owned subsidiaries with a minority stake were excluded. In cases where firms had an industrial design right in a year outside of the year 1990-2014, that right was not included in this study, and the firm was coded for 0 in the dummy variable that measures whether a firm ever has industrial designs.

Due to the 5 year lifespan of each ID registration or renewal, each registration is counted in 5 different years. Of the 723 Canadian firms, 70 had IDs. Seven of those 70, and 136 non-ID firms, were dropped from the sample due to unavailability of financial or employee data, leaving a total of 580 firms. One firm did have an ID on file, but outside of the 1990-2014 date range, so it was also dropped rather than being considered as an ID or non-ID firm.

From the 63 firms with at least one ID and sufficient financial and employee data, we have about 500 observations from years with an ID and about 500 more from years without an ID. While it would have been beneficial to include data from non-publicly traded firms, particularly SMEs, there was no access to sufficient financial data on a large enough number of those firms at this time. When doing analysis on net income, the data set was cleaned by excluding a small number of observations where net income exceeded revenue. From this matched data, ID variables were generated: a dummy variable showing whether a firm has IDs in that year, the total stock of IDs in that year, and a dummy variable showing whether a firm ever had IDs.

De-trending of the revenue, asset, employee, and asset variables was done by regressing each variable on the year and a constant and retaining the residuals. All regressions and matching procedures were then done on these residuals. For the kernel density matching procedure, we are matching on revenue, assets, number of employees, and sector. Kernel density graphs were made in Stata. To make the graphs, we show only the matching on year, rather than on sector, but the procedure of matching on sector also produces substantial alignment in covariates.

Sector dummies were added for the following sectors: non-hi-technology manufacturing, oil refining, hi-tech firms (including technology manufacturing, software, and telecommunications), non-oil resource, and FIRE. Firms that are not in any of those sectors were used as the baseline. The creation of the sector dummies was motivated in part by observations about divergent revenue per employee numbers. Financial firms, certain real estate firms, and oil refining companies were particularly divergent. The industry of firms was determined by using the NAICS code given in the Compustat database. The manufacturing sector dummy was found by aggregating all manufacturing categories.

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Tables and Figures

Table 1: Pre-matching comparison of averages in treatment and control groups

Variable	Ratio of Treatment Group to Sector Average	P-Value
Revenue/Employee	0.729	0.000
Assets/Employee	0.482	0.000
Net Income/Employee	1.309	0.2997
Employees	2.530	0.000

Figures 1,2,3,4

Kernel Density of Log Revenue

Figure 1 Kernel Density of Log Revenue Pre-Match:

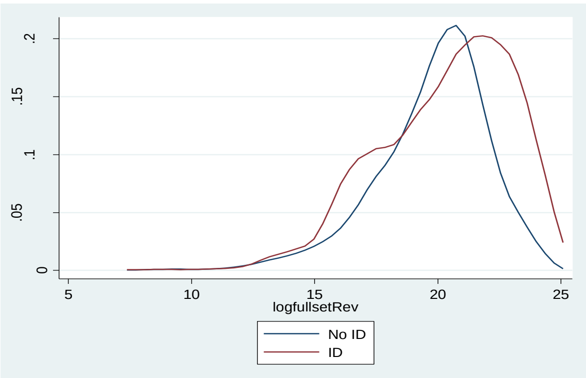

Figure 2 Kernel Density of Log Revenue Post-Match :

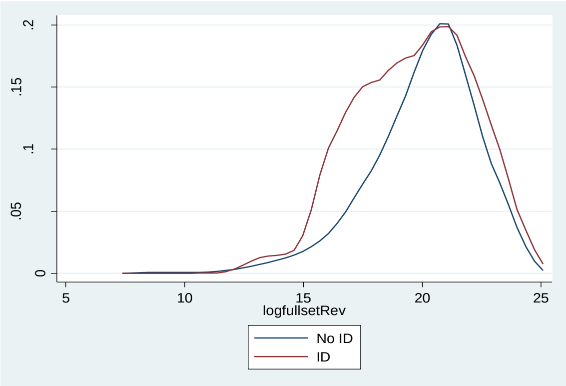

Figure 3 Kernel Density of Log of Employees Pre-Match:

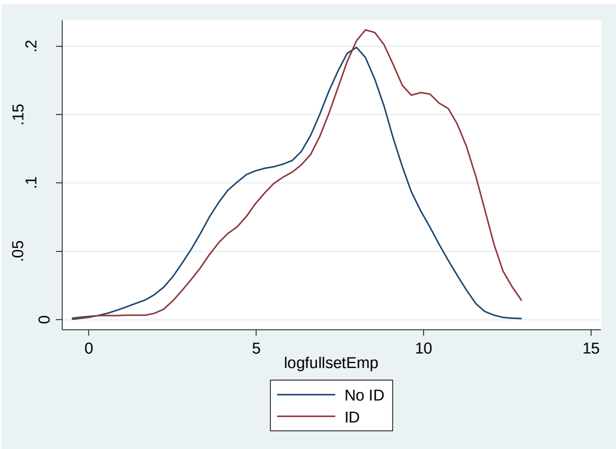

Figure 4 Kernel Density of Log of Employees Post-Match:

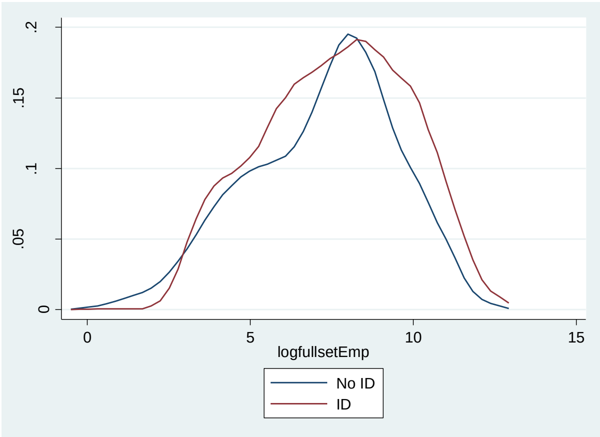

Table 2: Results of Nearest-Neighbour Matching

Performance Variable	**Treatment Variable**	**Exact Match Variable**	**Treatment Premium**	**Standard Error**	**p-value**
Revenue/Employee	Has ID That Year	Year	19.5%	4.1%	0.000
Net Income/Employee	Has ID That Year	Year	23.5%	8.6%	0.006
Revenue/Employee	Ever Has ID	Year	17.0%	3.5%	0.000
Net Income/Employee	Ever Has ID	Year	23.6%	5.8%	0.000
Revenue/Employee	Has ID That Year	Sector	-4.5%	5.9%	0.438

Net Income/Employee	Has ID That Year	Sector	30.5%	10.5%	0.004
Revenue/Employee	Ever Has ID	Sector	9.9%	3.5%	0.005
Net Income/Employee	Ever Has ID	Sector	38.9%	7.2%	0.000

Table 3: Effect on Revenue Per Employee

	IDs Only	**Patents Only**	**Both IDs and Patents**	**Depreciating Patent Stock Used**
Log(IDs)	0.121* (0.0702)		0.0968** (0.0376)	0.122** (0.0484)

Log(Patents)		0.0237 (0.0489)	0.132*** (0.0391)	0.0695** (0.0261)
Assets/ Employee	0.445*** (0.114)	0.551*** (0.0866)	0.288* (0.153)	0.323* (0.166)
Employees	0.108 (0.101)	0.0468 (0.0657)	0.113 (0.104)	0.118 (0.109)
Observations	489	1,622	306	312
Within R^2	0.344	0.167	0.368	0.345

Table 4: Effect on Net Income Per Employee

	IDs Only	**Patents Only**	**Both IDs and Patents**	**Depreciating Patent Stock Used**	**Using ID Stock, not Log**
Log(IDs) (or IDs in	-0.0323 (0.170)		-0.163 (0.179)	-0.138 (0.178)	0.0113***

Column 5)					
Log(Patents)		-0.024 (0.105)	0.0366 (0.158)	0.0631 (0.085)	-0.0587
Assets/ Employee	0.664* (0.363)	0.802*** (0.124)	1.48*** (0.297)	1.250*** (0.310)	0.786***
Employees	-0.482* (0.281)	-0.322*** (0.0883)	0.112 (0.221)	-0.0485 (0.240)	-0.348***
Observations	390	1,124	238	242	1,124
Within R^2	0.215	0.179	0.308	0.279	0.187

Table 5: Results of ‘Design Orientation’ Regressions, selected coefficients

	Revenue/Employee	Net Income/Employee
Firm Ever Has IDs	0.125*	0.178**
SE	0.0698	0.0888
ID Stock	0.00625	-0.00390

SE	0.00431	0.00933
R-squared	0.590	0.705