The Impact of Patent Protection on Outsourcing Decisions by U.S. Manufacturing Firms

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1. Introduction

Over the past 20 years, many countries have strengthened their patent laws as they have implemented their WTO intellectual property (IP) obligations. The effect has been especially significant in middle-income countries, which often had weak IP protection before joining the WTO. This benefits American firms, many of which lobbied for the establishment of enforceable intellectual property rights within the WTO framework.

This worldwide strengthening of IP protection is almost universally accepted as positive for American workers, and both businesses and labor unions seek to further strengthen IP rights abroad. David Hirschmann, President of the U.S. Chamber of Commerce Global Intellectual Property Center, has testified that "sound IP policies and enforcement of IP rights abroad are essential to advancing U.S. economic recovery, driving America's competitiveness and export growth, and creating high-quality, high-paying American jobs" (Hirschmann, 2013). AFL-CIO President Richard Trumpka has said that “if China protected intellectual property as the U.S. does, there would be approximately 923,000 new U.S. jobs” (Trumpka, 2012).

However, it may be that American workers who produce goods embodying intellectual property were better protected when the level of IP protection offered in the U.S. was higher than the level of IP protection in countries with lower production costs. This is especially true for physical products based on technology protected by patents. The rationale is straightforward – firms that rely on patent protection may have been more inclined to produce domestically when producing overseas was more likely to result in IP theft and competition from infringing goods. As patent protection improved in countries with lower production costs, it may have become more feasible for U.S. firms to outsource.

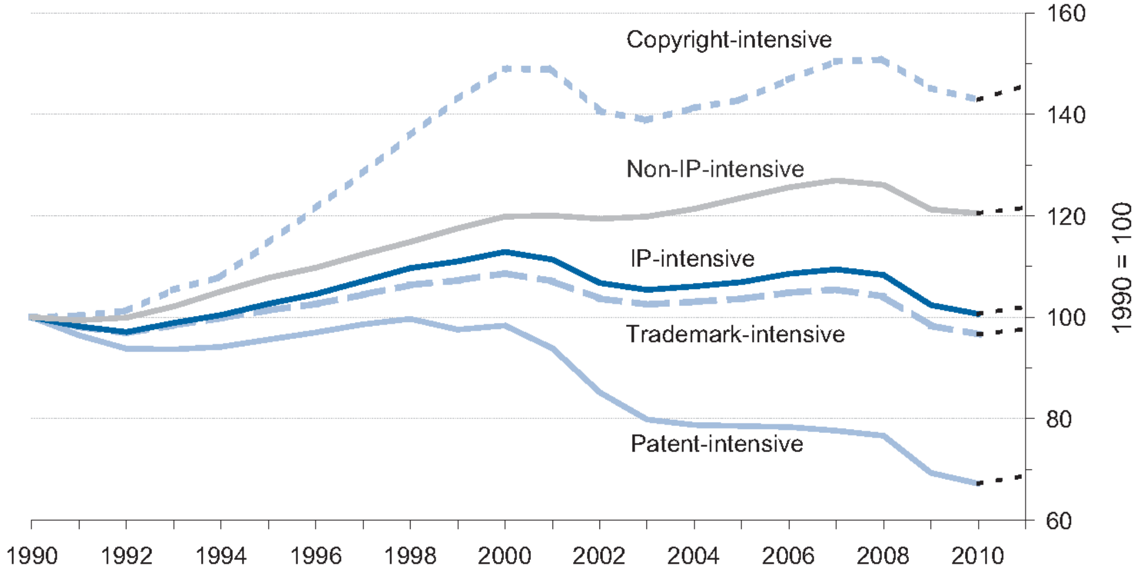
In fact, the post-WTO strengthening of global intellectual property protection has coincided with the expansion of international supply chains. More U.S. firms purchase inputs from foreign suppliers (or produce their inputs in overseas subsidiaries) now than they did in the early 1990s. For the purpose of this paper, both of these activities will be considered "outsourcing" because the American firm is importing inputs which otherwise would be produced domestically.[1] Some outsourced input markets may be unaffected by the strength of patent protection - i.e. commodities such as cloth. However, others may rely on patents to protect production technologies transferred to a foreign subsidiary or licensed to a trusted licensee, such as communications hardware.

The U.S. Department of Commerce has identified a set of such industries which are more reliant on patent protection than others, which it refers to as “patent-intensive industries” (U.S. Dept. of Commerce, 2012). Employment in these industries has been falling, even as overall employment has risen. Figure 1, reproduced from this report, shows that employment in patent-intensive industries fell approximately 25% between 1990 and 2012, while employment rose in firms less reliant upon intellectual property rights.

The current paper does not aim to assert that changing patent laws were the sole driver of employment declines in certain industries. It is acknowledged that many forces other than changing patent laws have driven increases in international supply chains, including lower transportation costs, lower tariffs, and greater mobility of international financial flows. Furthermore, patent-intensive industries tend to be concentrated in the manufacturing

[1] Definitions of outsourcing and offshoring technically differ depending on the ownership of the entity producing inputs overseas. Ownership of such entities is outside the scope of this paper, so the term “outsourcing” is used to cover both activities.

Fig. 1: Employment in IP-intensive and Non-IP-Intensive Industries



Source: U.S. Department of Commerce. *Intellectual Property in the U.S. Economy: Industries in Focus*. March, 2012.

industries, where employment has declined greatly due to both import competition and technological change. This paper merely proposes that rising intellectual property protection is an additional factor that ought to be considered as a possible determinant of a firm's decision whether, and where, to outsource.

In the pages below, I test the hypothesis that U.S. firms between 1997 and 2010 were more likely to offshore production of patent-intensive intermediate goods to countries with stronger patent laws. Section 2 reviews previous literature. Section 3 describes a theoretical model of the relationship between imports of intermediate goods and intellectual property protection, which is based on Feenstra and Hanson's model of trade in inputs. Sections 4 and 5 present my data and econometric results, and Section 6 concludes.

2. Literature Review

This hypothesis is related to a large literature that examines how foreign direct investment (FDI) and technology transfer are related to intellectual property laws.

Mansfield (1994) studied firm-level FDI decisions, noting that host county patent strength was important to firms in some industries, but not others. In some industries (i.e., metals) "competitors frequently cannot make effective use of a firm’s technology without many expensive and complex complimentary inputs." In other industries, (i.e., chemicals) "local firms can imitate an innovator’s new products relatively easily." Mansfield also found that the strength of IP protection influenced the *types* of investment made by U.S. companies. Firms might invest in countries with weak patent protection by setting up distribution or late-stage assembly facilities, but they were less likely to conduct advanced manufacturing or R&D in such countries. Nelson (2007) built upon the notion that firms act differently in foreign countries with different levels of patent protection. He found that firms avoid investing in countries where protection is lowest, establish their own operations in host countries where patent protection was somewhat stronger, and use licensing in countries where it is strongest.

Papers by Saggi (1994) and Ethier and Markuson (1996) explicitly model risk of intellectual property theft into firm decisions regarding home production, foreign direct investment, or licensing technology to foreign producers. Both papers begin with the consideration of a firm with a new, innovative product. The product gives the firm an advantage over competitors selling similar goods, yet the advantage is tied to its ability to stop competitors from copying the product. The most direct way for a firm to do business overseas is to produce in its home country and export overseas. However, this may be made more expensive by trade barriers, and the firm may face other transport costs and risks. If trade barriers or transactions costs are high, then a firm may choose to either open a subsidiary office in the other country, or license the new technology to a producer there and collect royalties. Licensing is often the least expensive option, yet it leaves the innovator firm the most exposed to the risk of copying by potential competitors (including its licensee) in the other country. Therefore, licensing is preferable, but it relies upon the ability of the innovator firm to block copying by others, whether through contracts (Ethier and Markuson, 1996) or intellectual property rights (Saggi, 1994).

Subsequent papers have considered ways in which the level of risk faced by various firms may vary. Bilir (2011) finds that firms manufacturing products with longer lifecycles place more weight on intellectual property when deciding where to establish operations overseas. If products become obsolete quickly (i.e. - smartphones) intellectual property protection is less important.

Awokuse and Gu (2013) examine how patents effect trade flows and FDI to countries with varying levels of imitative ability, measured by human development metrics such as the number of R&D researchers, patent applications, and education completion rates. They find that 1) exports are likely to fall to countries with weak imitative abilities after IPRs strengthened, consistent with theories that IPRs increase monopoly powers enjoyed by firms; 2) there is no significant change to exports in countries with stronger imitative abilities; and 3) stronger IPR increases FDI in all cases. Ivus, Park and Saggi (2015) consider the complexity of imitation of *industries* rather than the imitative abilities of *nations*. The incentives to produce at home, directly invest abroad, or license production to an overseas manufacturer is affected by this industry-level complexity as well as by patent rights. The optimal production option differs by industry.

To my knowledge there has been only one published paper to date that specifically examine the relationship between IP and outsourcing. Canals and Şener (2014) examine the relationship between patent rights in foreign countries and the degree to which U.S.-based multinational firms outsource from them. Their independent variable is an estimate of outsourced inputs as a share of total inputs. They authors test separately for "broad" outsourcing (the use of intermediaries from any industry overseas) and intra-industry outsourcing and test separately for “high tech” and “low-tech” industries. Canals and Şener find that high tech industries increase offshoring from countries that have strengthened IPR protection, and that effect is strong for intra-industry offshoring but weak for broad offshoring.

The present paper differs from these two by focusing on the patent-intensity of the *intermediate goods* imported into the U.S. rather than on the patent-intensity of the *firms or industries* engaged in outsourcing. As described in the next section, it adopts the Feenstra and Hanson (1997) model of production as a combination of internationally tradable intermediate goods, adding the element that some intermediate goods are more reliant upon patent protection than others. It is predicted that firms will outsource production of the more patent-intensive inputs to countries with stronger patent laws, where they would face lower risk of IP theft.

3. Theoretical Model

My theoretical model is based on the theory of production as “trade in inputs” introduced by Feenstra and Hanson (1997). In this model, one considers a continuum of inputs (z) which are produced by processes that use factors differently, and which can each be produced domestically or overseas. Feenstra and Hanson focus on inputs produced by processes that use skilled labor more or less intensely, but my adaptation considers inputs that rely more or less on intellectual property protection. Inputs (z_i) are arranged along a continuum so that the least IP-intensive inputs are those furthest to the left, and IP-intensity increases as one moves rightward. It should be stressed that the order of inputs along the continuum is not necessarily related to the order in which inputs are assembled to build a final product.

In this model, the location of production of an input depends on the ratio of the cost of producing it domestically to the cost of importing it. Feenstra and Hanson use a cost ratio based on labor costs. My adaptation uses an expected cost function that incorporates patent protection. I start with the notion that theft of a firm's intellectual property can be considered an expected "cost" of doing business, along with labor, capital, etc. A firm will choose to source inputs from the lowest cost supplier, including this expected cost from IP theft.

When an American firm produces an input domestically the probability of IP theft is very low, so it has a very small effect on the overall expected costs of production. When a firm outsources technologically-sensitive production to a country with weak patent protection, the risk is high. If the value of that technology weighted by the probability of theft is high enough, it will be economically unwise to produce there.

The expected cost of domestic production of an input *z* can be written:

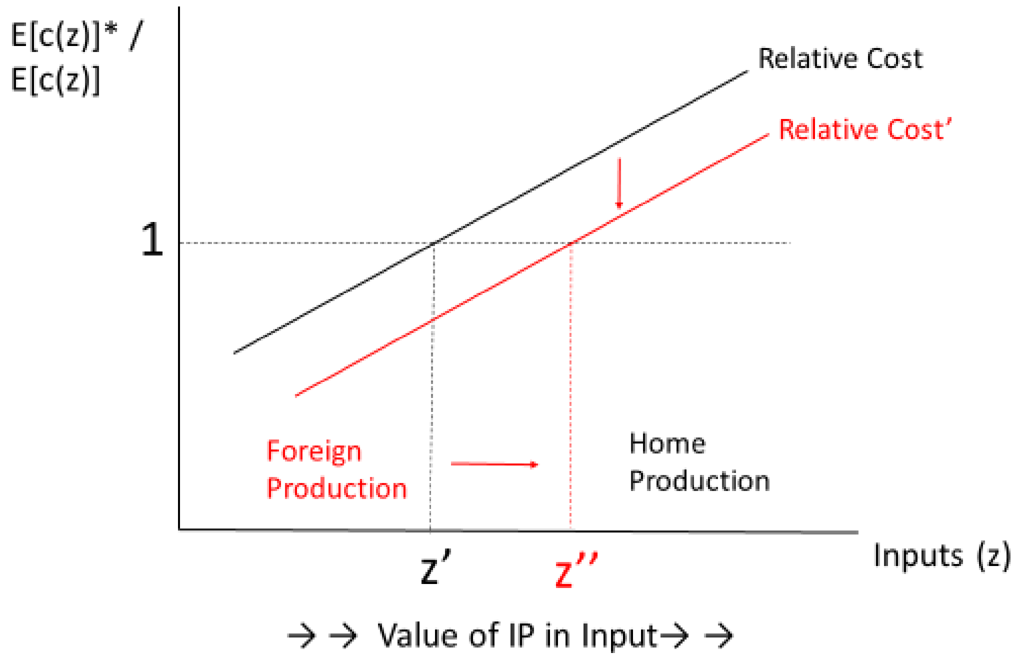
$$E[c(z)] = \beta\mathbf{X} + \Pr(THEFT_z)*V(IP_z) + \varepsilon$$

where **X** is a vector of the familiar cost determinants such as wages and the cost of capital; $\Pr(THEFT_z)$ is the probability of theft of intellectual property embodied in input z, and $V(IP_z)$ is the value of the intellectual property embodied in the input. The expected cost of foreign production is determined the same way, and denoted $E[c(z)]^*$.

Figure 2 illustrates the two-country model. "Home" is a country characterized by relatively high labor and capital costs, but low risk of IP theft due to strong patent protection. "Foreign" is characterized by lower labor and capital costs, but a higher risk of IP theft due to weaker patent protection. The vertical axis is the ratio of the expected cost of foreign-produced inputs to the expected cost of domestically-produced inputs and the horizontal axis is the continuum of inputs in the order of increasing IP-intensity. Given exogenously determined levels of patent protection in each country, there is a point (z') along the horizontal axis at which the estimated costs of production in Home and Foreign are equal, so the producer is indifferent to the location of production of an input. To the right of this point, production occurs at Home because the probability-weighted cost of IP theft raises the cost of production in Foreign above the cost of production at Home. To the left of this point, production occurs in Foreign because the value of the IP embodied in the input is small, so the probability-weighted cost of IP theft is not high enough to counteract Foreign's lower costs for other factors (i.e., wages).

If Foreign strengthens patent protection, this lowers the probability of IP theft, which lowers the relative expected cost of production at any point along the horizontal axis. This is represented in Figure 2 as the downward shift from Relative Cost to Relative Cost′, which shifts the critical point rightward from z′ to z″. The portion of the continuum representing inputs produced in Foreign grows, and the portion representing home production shrinks. With lower expected costs of production in Foreign, it has become optimal to produce more inputs – which will have more intensive embodiments of intellectual property – in Foreign. Thus, outsourcing increases.

Fig. 2: Relative Cost of Foreign v. Domestic Production of Inputs



The amalgamated location "overseas," of course, consists of numerous countries that produce inputs for American firms' global supply chains. Each provide different levels of intellectual property protection. To to test the theory, I must show that the amount of intermediate goods from patent-intensive industries that the United States imports from a given country is related to the level of patent protection it provides, while controlling for other determinants of sourcing decisions.

4. Data

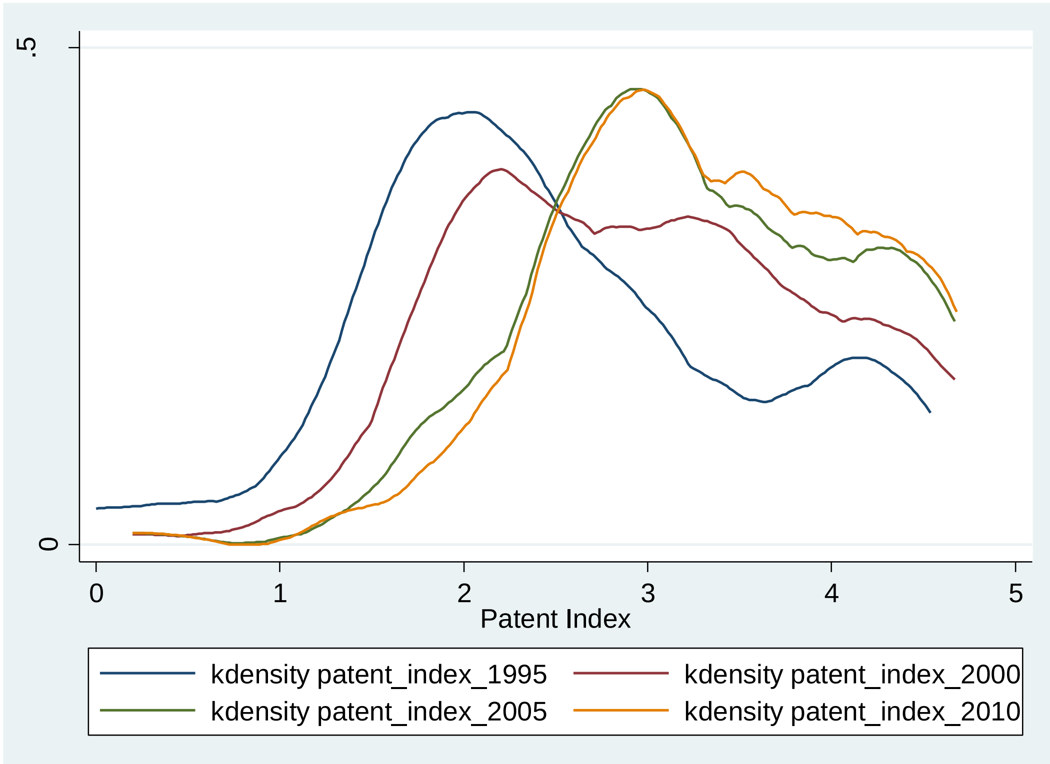
My independent variable of interest is the strength of patent protection, as measured by the Ginarte-Park Patent Index.

The index is based on 20 'factors' of patent protection, which are grouped into five 'components' – what types of subject matter are patentable; whether a country is a member of certain treaties with obligations to enact robust IP rights; the duration of protection provided by a patent; available enforcement mechanisms; and restrictions on patent rights (Ginarte and Park, 1997).[2] It is a well-known metric that is frequently used as a tool for cross-country comparisons of the strength of patent protection. For instance, the International Trade Commission recently used it in its analysis of the potential economic effect of the Trans Pacific Partnership (Signoret and Bloodgood, 2016).

The index scores countries on a scale that runs from zero to five, though the highest actual score is 4.68. It contains data on the patent strength in 122 countries at five year intervals from 1960 to 2010. However, the data for my dependent variable does not go back this far, so I only utilize the index scores from 1995-2010. Over this period, the average index score has risen and the distribution has become tighter: the mean increased from 2.53 to 3.35 and the standard deviation decreased from 1.07 to 0.86. Figure 3 shows the kernel density plot for the patent index score for 1995, 2000, 2005 and 2010, illustrating these trends. It is clear that most of the change occurred between 1995 and 2005 – during which time developing countries were required by the WTO to bring their law into compliance with TRIPS.

[2] The paper cited provides the best explanation of the factors that make up the index. The index has been updated since its publication, and data up to 2010 is available on Prof. Park's faculty webpage.

Fig. 3: Kernel Density of Ginarte-Park Patent Index, 1995-2010



The raw scores described in this paragraph and presented in Figure 3 are standardized in my regressions in order to assist interpretation. The standardized index is labelled *patent* in the section that follows.

My dependent variable is the estimated value of imported patent-intensive commodities that are used as intermediate goods (inputs) from various trading partners. Patent intensive commodities are those produced by industries identified by the Department of Commerce report as "patent-intensive" industries (U.S. Dept. of Commerce, 2012).[3] The classification is based on

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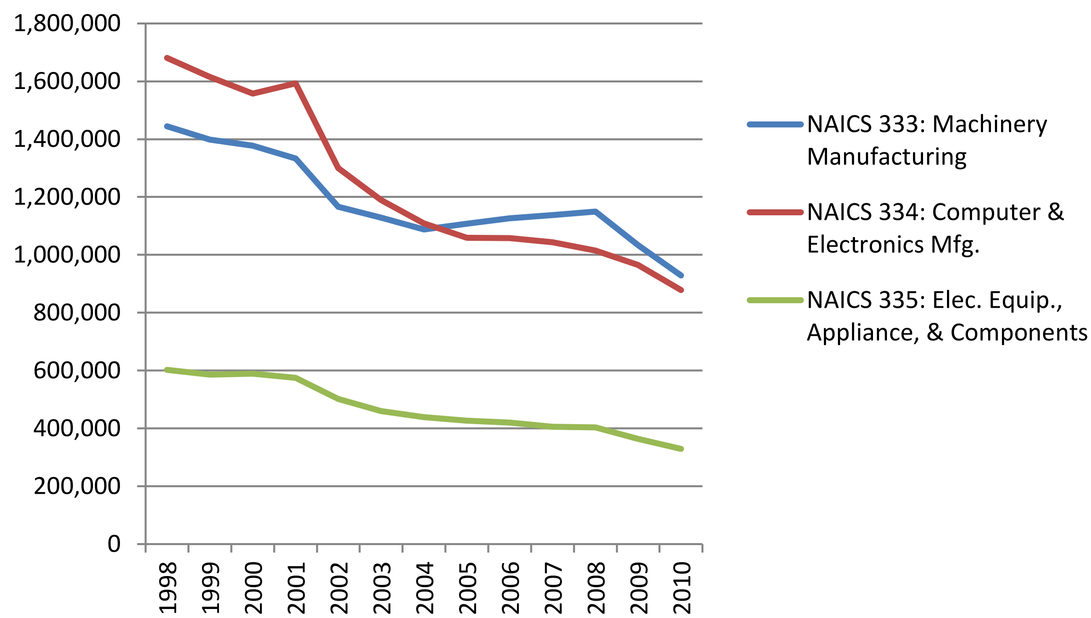
[3] This report was recently updated, but the original report measures patent intensity based on patents-per-worker in a time period that is more closely aligned with time period from which my data is taken. For this reason, I use the industry classifications reported in the original report.

the number of patents granted to firms within the industry relative to the number of people employed by that industry; an industry with above median patents-per-worker is classified as patent intensive. Due to data availability issues described below, I am focusing on imports from three particular patent-intensive industries defined at the three-digit NAICS level: “Machinery manufacturing” (333), “Computer and electronic products manufacturing” (334), and “Electrical equipment, appliances, and components manufacturing” (335). Workers in these three industries experienced job losses ranging from 36% to 48% between 1998 and 2010, as illustrated in Figure 4.

Fig. 4: Total U.S. Employment in NAICS 333, 334, 335



Source: U.S. Census Bureau, Statistics of U.S. Businesses

To estimate the value of inputs from these industries, I combine Bureau of Economic Analysis (BEA) data on uses of imports of various commodities with International Trade Commission (ITC) data on overall imports from each trading partner. The estimation relies on an assumption called the “proportionality assumption” that has been used by in previous papers studying supply chains, such as Feenstra and Hanson (1997), Johnson and Noguera (2012), Canals and Şener (2014) and Gawande et. al. (2014). The proportionality assumption assumes that "within each sector imports from each source country are split between final and intermediate in proportion to the overall split of imports between final and intermediate use." (Johnson and Noguera, 2012).

BEA import matrices report how imports of commodities are used. Commodities are identified at the three-digit NAICS level, and data is available from 1997 to the present.

I use the data on the proportion of each commodity used as intermediate inputs and the total imports of each commodity to find the percentage of imports of each commodity that are used as inputs in production processes for four time periods – 1997, 2000, 2005, and 2010. This is multiplied by ITC data on total imports from each country for each time period to derive the *estimated value of imported patent-intensive commodities that are used as intermediate goods (inputs) from each trading partner*.

The proportionality assumption has been criticized by some as being unrealistic – it is likely that the ratio of imported intermediate goods to imported final-use goods imported varies by country (Timmer et. al., 2015). To address this problem, the economists working with the European Commission have created the Word Input Output Database (WIOD),[4] which reports different annual import-to-use ratios for each sector-and-country-of-origin pair. However, WIOD identifies commodities at very broad levels: either the two-digit ISIC level or combinations of two-digit ISIC groups. Not only is this classification system different than that used by the

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[4] WIOD is available at http://www.wiod.org

Department of Commerce to identify patent-intensive industries, it is also too broad to match to the Department of Commerce's classifications.[5]

The Department of Commerce identifies patent-intensive industries using more disaggregated NAICS classifications. Some industries are identified at the 3 digit level, others are identified at the 4-, 5- or 6- digit level. As stated above, the BEA import matrices provide use-of-imports at the three digit NAICS level over many time periods. Since the Department of Commerce, BEA, and ITC all identify industries using 3-digit NAICS codes, I am able to match data sources without resorting to imperfect concordance tables that aim to match overlapping-yet-different classification systems. I would prefer disaggregation to at least the four digit level, but I think that a three-digit NAICS is an improvement over the two digit ISIC aggregation reported by WIOD. For the purpose of this paper, the estimates based on BEA and ITC data are therefore the best available.

Between 1997 and 2010 there were large increases in the estimated imports of intermediate goods in two of the sectors – a 111% increase in from machinery (NAICS 333) and an 88% increase from electronics (NAICS 335). In the computer and electronic products sector (NAICS 334), an initial rise in imports of intermediate goods was followed by a drop and leveling off, so the overall change over the past 18 years has been an only 4% increase. The dependent variable data is skewed, but it logs normal; Table 1 shows the summary statistics. With the zero values dropped, my logged dependent variable includes 1278 data points between the three industries.

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[5] The decision to use BEA data instead was based on the data available from different sources in October. In November, WIOD released a new version that includes more industry groups than the 2013 release, but it is still based on two digit ISIC codes, and matching issues remain.

Table 1: Summary statistics for logged dependent variable

Industry	Obs.	Mean	St. Dev.
Machinery (333)	429	7.81	4.27
Computer and electronic products (334)	456	8.13	4.46
Electrical equipment, appliances, and components (335)	393	7.83	4.08

Note that the patent index's first time period is 1995 and the estimated imported intermediate goods data's first time period is 1997. The match is approximate, so after I report the results of regressions on my basic model with the full dataset I repeat them using observations from only three time periods for which the data on imports and patent strength come from the exact same year. The earliest time period is included in the test of the basic model because I believe it to be qualitatively important – 1997 was the beginning of the time period during which WTO members had to implement stronger intellectual property laws.

My first control variables are the logged average wages and capital rents for each country/year, taken from the dataset compiled by Karabarbounis and Neiman for their paper on the "Global Decline of the Labor Share." (Karabarbounis and Neiman, 2014). These controls correspond to the theoretical model's consideration of the cost of labor and capital.

The authors combine data from national offices and UN agencies to produce a dataset with wage data on 73 countries and rent data on 75 countries for some-or-all of my time periods. This level of coverage is much more broad than that available from other data sources, including the International Labor Organization, the U.S. Department of Labor and the OECD. However, the Karabarbounis and Neiman dataset still covers fewer country-year pairs than all of my other data sources. This results in a substantially smaller dataset, and the country-year pairs omitted from the smaller dataset of tend to be smaller, poorer countries. Table 2 shows how the inclusion of the wage and rent change the mean of the dependent and other independent variables.

Table 2: Mean variables, full sample versus subsample with corresponding wage and rents data

Variable	Full Sample (n=1223)	Subsample (n = 672)
Imports of Intermediate goods	5.15 e+8	8.11 e+8
Patent index	3.15	3.62
Institutional quality index	0.57	0.65
GDP	3.03 e+11	4.54 e+11

Karabarbounis and Neiman's wage and rent variables will nonetheless be included in my basic econometric models presented in the next section, because they are needed to test the theory that both production costs and intellectual property protection affect sourcing decisions for US firms' IP-intensive inputs. They are skewed, but they log normal, and their logged values are reported as *wage* and *rent* in the following section. Due the substantial degree to which these variables affect the overall sample I will also test my hypothesis using variations of my models without these variables.

Gravity model controls are added as well, utilizing GDP data from the World Bank and distance data from the Centre d'Etudes Prospectives et d'Informations Internationales GeoDist database (Mayer and Zignago, 2011). The selection of countries includes small, medium and large economies, and intercountry variation in the other variables is expected to be large. To illustrate, the mean GDP is equal to 2.79e+11 and the standard deviation is 6.92e+11. These variables are logged as well for use in regressions, and are reported in the next section as *gdp* and *distance*.

Finally, I use World Institutional Quality Index scores from Kuncic, Aljaz (2014) to control for the strength of institutions in each country and year. These index scores come from a meta-analysis of previous institutional studies, combining information on economic, political and legal institutions. Since it is another qualitative index, I standardize to assist interpretation, creating the variable *institution.* It is correlated with *patent*, (simple correlation coefficient= 0.72), so I present regression results in models with and without its inclusion.

5. Results

The basic model

In my basic model, *intermediate* is regressed against *patent* and the control variables for factor costs, gravity model determinants, and institutional strength, using OLS and controlling for time, industry and country fixed effects. Four variations of this model are reported in Table 3. Column (1) reports the results without *institution* and with fixed effects for time and industry, but not for country. The coefficient on *patent* is positive and statistically significant, as expected. A one standard deviation increase in a country's patent strength is associated with a 68% increase in U.S. imports of intermediate goods from that country. All of the controls are significant, and all except *wage* have the expected sign. A plausible explanation for the positive coefficient on *wage* is that patent-intensive industries require more highly skilled labor and therefore pay a wage premium, an effect that has been found in some previous studies of patent-intensive industries (Pham, 2010). In any case, the significance of *wage* is not robust to most changes to this basic model. The overall fit of the model is good; the R^2 is 0.70.

Column (2) reports the results with the addition of country-level fixed effects. This increases the overall fit of the model (R^2=0.94), but strips all of the control variables' statistical significance, indicating that most of the variance is between countries – likely due to the

Table 3: OLS Regressions with fixed effects.
Dependent variable = estimated imports of intermediate goods

VARIABLES	(1)	(2)	(3)	(4)
patent	0.677**	0.430**	0.458*	0.426**
	(0.275)	(0.174)	(0.245)	(0.173)
wage	0.264**	0.333	0.0622	0.334
	(0.116)	(0.368)	(0.176)	(0.372)
rent	-1.227***	0.334	-0.869**	0.326
	(0.373)	(0.590)	(0.405)	(0.598)
gdp	1.272***	0.341	1.335***	0.355
	(0.0699)	(0.420)	(0.0734)	(0.422)
distance	-0.773***	-0.730	-0.731***	-0.778
	(0.212)	(0.797)	(0.208)	(0.857)
institution			0.600**	-0.0482
			(0.270)	(0.394)
Constant	-17.94***	7.354	-18.44***	7.406
	(2.922)	(7.391)	(2.772)	(7.591)
Observations	672	672	669	669
R-squared	0.702	0.937	0.706	0.937
Time and industry F.E.	Yes	Yes	Yes	Yes
Country F.E.	No	Yes	No	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

diversity of countries in my sample. Furthermore, the regressors are country-level variables. The coefficient on *patent* retains its significance, but it falls to 0.43.

The index of institutional strength added is added, and the results are reported in Columns (3) and (4). As noted above, *institution* is correlated with *patent*, and its inclusion in the third specification of the model reduces the significance of *patent* to the 10% level. *Patent* does remain significant at the 5% level once country fixed effects are added. The coefficient on patent is similar in specifications three and four (0.46 and 0.43, respectively). All of the control variables except for *wage* retain their significance absent country fixed effects, and all become insignificant when country fixed effects are added. It is notable that the coefficient on *patent* in the specification controlling for institutional quality but without country fixed effects is similar to the coefficient in both models with country fixed effects. This may indicate that institutional index captures (or proxies for) much of what differs between countries.

To sum up the basic model, *patent* is has at least 10%, but usually 5% significance across the specifications. Columns (1) and (3) have been included to indicate that most of the controls behave as one would expect considering production costs, gravity factors, and institutional strength. Even without controlling for country effects, these regressors describe 70% of the variation in the data. Columns (2) and (4) add country fixed effects, and though they take away the significance of the country-level control variables, they improve the overall fit of the model. The coefficient on *patent* in both models with fixed effects indicates that an increase of one standard deviation in a country's score on the patent index is associated with a 43% increase in U.S. imports of intermediate goods from it.

Adjustments to the model

Dropping observations from 1997: As noted in the previous section, the BEA publishes annual U.S. import matrix data from 1997 forward, but the patent index is produced every five years on the 00s and 05s. Therefore, my full dataset includes one time period where I match 1995 patent data to 1997 data for all other variables. Obviously, this is suboptimal. The first time period is nevertheless included in the basic model because it is closest to 1996, when countries agreed to increase the strength of patent protection as a requirement of the WTO.

In order to have a record of the results with all of the time periods properly matched, I repeat the four regressions with the first time period dropped. Results are reported in Table 4. The coefficient on *patent* is higher for this subsample, and it is significant across all specifications at the 5% level. The control variables retain their signs and significance from the

Table 4: OLS regression with fixed effects; Observations from year 1997 dropped
Dependent variable = estimated imports of intermediate goods

VARIABLES	(1)	(2)	(3)	(4)
patent	1.019**	0.741**	0.858**	0.742**
	(0.420)	(0.354)	(0.398)	(0.354)
wage	0.295**	0.264	0.190	0.263
	(0.140)	(0.399)	(0.189)	(0.414)
rent	-1.012***	0.781	-0.804**	0.783
	(0.366)	(0.804)	(0.408)	(0.826)
gdp	1.154***	0.280	1.194***	0.279
	(0.0878)	(0.460)	(0.0896)	(0.461)
distance	-0.707***	1.156	-0.687***	-4.947***
	(0.234)	(0.892)	(0.232)	(0.906)
institution			0.345	0.00565
			(0.287)	(0.568)
Constant	-17.02***	-4.959	-17.34***	41.69**
	(3.383)	(7.586)	(3.282)	(16.68)
Observations	524	524	521	521
R-squared	0.703	0.942	0.704	0.942
Time and industry F.E.	Yes	Yes	Yes	Yes
Country F.E.	No	Yes	No	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

basic model regressions, with the exception that *distance* is now significant in the model that controls for both country effects and institutions. The overall fit of the model as defined by the R^2 is nearly identical.

Dropping the wage and rent variables: Another consideration noted in the previous section is the fact that my dataset contains substantially fewer observations for wages and rents than it does for all of the other variables, so their inclusion effects both the size and the qualities of the dataset.

Therefore, I repeat the regressions with *wage* and *rent* dropped and report the results in Table 5. The size of the coefficient on *patent* is higher in the specifications without country fixed

Table 5: OLS regression with fixed effects; Wage and rent variables dropped
Dependent variable = estimated imports of intermediate goods

VARIABLES	(1)	(2)	(3)	(4)
patent	1.289***	0.358***	0.664***	0.357***
	(0.107)	(0.136)	(0.130)	(0.136)
gdp	1.343***	0.647***	1.335***	0.692***
	(0.0461)	(0.194)	(0.0470)	(0.204)
distance	-0.903***	-7.307***	-0.728***	-7.549***
	(0.149)	(0.538)	(0.148)	(0.656)
institution			0.835***	-0.158
			(0.103)	(0.229)
Constant	-16.47***	52.43***	-18.19***	53.32***
	(1.709)	(8.405)	(1.675)	(8.575)
Observations	1,223	1,223	1,220	1,220
R-squared	0.718	0.926	0.733	0.925
Time and industry F.E.	Yes	Yes	Yes	Yes
Country F.E.	No	Yes	No	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

effects, but lower in the specifications that do include fixed effects. This may reflect the inclusion of more countries with lower levels of patent protection in the sample. The significance of *patent, GDP, and distance* rises to the 1% level across all specifications, reflecting the larger sample size, and the R^2 values are similar to those in the basic model.

These two adjustments to the basic model serve as a robustness test for the basic model. The independent variable of interest, *patent*, remains positive and significant across all specifications. When country fixed effects are applied, the coefficient on *patent* ranges from 0.36 to 0.74.

Table 6: OLS regression with fixed effects; Each industry regressed separately
Dependent variable = estimated imports of intermediate goods

VARIABLES	(1) NAICS 333	(2) NAICS 334	(3) NAICS 335
patent	0.488**	0.404**	0.644***
	(0.197)	(0.179)	(0.176)
wage	-0.539	0.837**	0.892
	(0.343)	(0.337)	(0.615)
rent	-0.351	0.557	0.542
	(0.643)	(0.732)	(1.078)
gdp	0.824**	0.432	-0.538
	(0.398)	(0.384)	(0.613)
distance	-2.359***	0.0979	0.774
	(0.817)	(0.822)	(1.163)
institution	0.138	-0.0166	-0.138
	(0.408)	(0.373)	(0.484)
Constant	14.74**	-5.988	13.68
	(6.563)	(9.867)	(8.991)
Observations	224	227	218
R-squared	0.983	0.985	0.973
Time F.E.	Yes	Yes	Yes
Country F.E.	Yes	Yes	Yes

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Separate regressions using the basic model for each industry

Since previous research has shown that intellectual property affects industries differently, I test the fourth iteration of my basic model – the one with all of the control variables and fixed effects[6] – on my observations for each industry. The results, reported in Table 6, show that patent strength has the highest effect on imports of intermediate goods in the electrical equipment and appliance industry where the coefficient on patent is 0.64, and lowest for machinery

[6] This is the specification reported in Column 4 of Table 4.

manufacturing, where it is 0.40. Coefficients on *patent* are significant across all three regressions. Coefficients on the control variables are mostly insignificant, as has been the case in the other regression incorporating time and country fixed effects.

Overall, these results are consistent with previous findings of the importance of intellectual property protection to different industries. The results confirm that 1) patent protection affects the outsourcing decisions of firms importing intermediate goods from all three of the patent-intensive industries examined in this paper, yet 2) the level of importance varies from one industry to the next.

Panel regressions

The basic model and its adjustments above control for year, industry and country using simple fixed effects. They test how patent strength in various countries affects U.S. firms' sourcing decisions when they outsource production of intellectual property-intensive inputs, while controlling for these three important factors. However, they do not show how changes in countries' patent laws over time have affected the level of intermediate goods sourced from those countries, which requires a series of panel regressions.

I structure the dataset with industry-country pairs as panel variables, allowing me to test how trade in intermediate goods from each industry in each country have changed as their patent laws have changed. Fixed effect panel regressions based on the basic model and its adjustments are summarized in Table 7. Across specifications, the coefficient on *patent* is positive, relatively stable, and significant at the 1% level. All but one of the control variables are insignificant, as the country-level variation is picked up by the panel.

Table 7: Panel regression with fixed effects; Panel variable = Industry/country groups
Dependent variable = estimated imports of intermediate goods

VARIABLES	(1) Wage Rent Gravity	(2) Wage Rent Gravity Institution	(3) Subsample w/o 1997 Data	(4) Full Sample w/o Wages or Rents
Patent	0.620***	0.617***	0.672***	0.507***
	(0.109)	(0.110)	(0.206)	(0.0983)
wage	0.360	0.369	0.424	
	(0.283)	(0.294)	(0.295)	
rent	0.159	0.146	0.873	
	(0.485)	(0.478)	(0.671)	
gdp	0.0590	0.0667	-0.0595	0.387***
	(0.254)	(0.253)	(0.258)	(0.102)
institution		-0.0789	-0.141	-0.125
		(0.225)	(0.224)	(0.199)
Constant	4.844	4.606	7.328*	-1.579
	(4.227)	(4.201)	(4.334)	(2.516)
Observations	672	669	521	1,220
Within-Entity R-squared	0.212	0.212	0.141	0.142
# Industry/country groups	215	215	214	335

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Columns (1) and (2) describe the panel regressions of estimated imports of intermediate goods against *patent*, *wage*, *rent,* and *GDP*, with and without *institution*. The coefficient on *patent* in both equations is 0.62, and the within-entity R^2 indicates that the model describes about

a fifth of the variation of the dependent variable in each industry/country . Column (3) demonstrates that dropping the observations from 1997 (slightly) raises the coefficient on *patent*, while lowering the R^2 as one would expect due to the smaller sample size. Column (4) demonstrates that dropping the wage and rent variables – and therefore enlarging the sample –

Table 8: Panel regression with fixed effects; Panel variable = country;
Dependent variable = estimated imports of intermediate goods

VARIABLES	(1) NAICS 333	(2) NAICS 334	(3) NAICS 335
patent	0.725***	0.523***	0.675***
	(0.208)	(0.162)	(0.158)
wage	-0.714**	1.014**	0.791
	(0.332)	(0.403)	(0.637)
rent	-0.556	0.585	0.271
	(0.537)	(0.843)	(0.991)
gdp	1.197***	-0.712**	-0.319
	(0.293)	(0.338)	(0.514)
institution	0.254	0.000486	-0.451
	(0.326)	(0.340)	(0.468)
Constant	-14.92***	19.25***	10.41
	(4.911)	(5.628)	(8.214)
Observations	224	227	218
R-squared	0.436	0.136	0.186
# Industry/country groups	72	73	70

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

leads to a smaller coefficient on *patent*, but the R^2 remains lower than in Columns (1) and (2). Additionally, the coefficient on *gdp* becomes positive and significant.

Overall, the four panel regressions with all of the industries present in the same dataset demonstrate that, within a particular industry in a particular country over this time period, a one standard deviation in the patent index has generally been associated with a 50% to 67% increase in U.S. imports of intermediate goods.

To see how the effects differ by industry, I repeat the specification with all controls separately for each, and report the results in Table 8. The coefficient on *patent* ranges from 0.52 for computers and electronics to 0.73 for machinery manufacturing, and it is significant for each industry. The within-entity R^2 is 44% for machinery manufacturing, but less than 0.20 for the other two industries, so the model explains variation much better for imported inputs of machinery than computers or electrical equipment. Overall, the results in Table 8 indicate that changes in the level of patent protection over time have been important for firms in each of the industries, though to varying degrees. The coefficients on *wage* and *GDP* are significant for NAICS 333 and 334,but their algebraic signs are not consistent. American firms in these industries may have responded differently to changes in labor costs and country characteristics in their outsourcing decisions.

6. Conclusion/Discussion

I have tested the hypothesis that U.S. firms are more likely to outsource production of patent-intensive intermediate goods from countries with stronger patent laws. A series of regressions have demonstrated that this was indeed the case for three broad patent-intensive industries between 1997 and 2010, a time when both the strength of intellectual property rights and outsourcing were on the rise. Controlling for variables related to factor costs, gravity model determinants, and institutional quality, as well as time, industry, and country fixed effects, an increase of one standard deviation in a country's score on the Ginarte-Park Patent Index was associated with a 43% increase in U.S. imports of these intermediate goods from it. The degree to which patent protection affected these trade flows differed by industry, as is predicted by previous literature. As individual countries adjusted the level of patent protection they provided during this time, firms in those countries found themselves shipping more intermediate goods from these industries to the U.S.

These findings complement those of Canals and Şener, who found that high-tech firms were more likely to import inputs from countries where IP protection was stronger. By focusing not on the importing industry but on the imported input, the present paper demonstrates another way in which intellectual property and outsourcing are linked.

The relationship between intellectual property protection and outsourcing is an area that offers many opportunities for further study. The tests in this paper use *estimated imports of intermediate inputs* based on the proportionality assumption. This is an imperfect metric, but one that is consistent with the current literature on outsourcing. Future research in this area could benefit from more precise estimates, or possibly from firm-level data reflecting actual supply-chain transactions. Such studies could augment an often-cited body of white papers that tally up jobs in IP-intensive industries without describing the ways in which intellectual property effects employment (Pham 2010; Rogers and Szamosszegi, 2011; Commerce, 2012; Siwek, 2016).

Many factors have contributed to the decline of U.S. employment in manufacturing sectors, especially lower tariffs and technological advances. The establishment of higher intellectual property norms to the point where outsourcing became more attractive to U.S. firms ought to be considered as an additional factor influencing the decline.

Current U.S. trade policy includes the promotion of intellectual property rules stronger than the international norms required by the WTO. Through trade negotiations and less formal diplomacy, higher levels of protection are sought, especially in countries like China and India with large markets and large workforces. Relatively new industries, like digital communications and biotechnology are seeking greater protection for products that did not exist during the Uruguay Round of trade negotiations. Policymakers may want to consider the possible domestic employment effects of continued rising levels of IP protection overseas, and possible assistance to workers who may lose their jobs.

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