Domestic Knowledge Spillovers and Strategic Trade Policy (Preliminary Draft)

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Abstract

I show that whether domestic knowledge spillovers are domestic or international in scope is an important determinant of administered protection in the United States. Using data from U.S. patents, I construct, for each industry, a measure of the proportion of cites of patents in that industry that are made by a U.S. inventor. I use this as a measure of how domestic in scope knowledge spillovers are in each industry. I find that, within the U.S. between 1980 and 2005, whether knowledge flows are domestic or international in scope is an important determinant of the USITC's material injury decision in antidumping investigations. The ITC is more likely to rule affirmative if the petitioner is from an industry where knowledge spillovers tend to be domestic in scope.

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1 Introduction and Background

Research focusing on the determinants of a country's choice of strategic trade policies have recognized the importance of learning-by-doing and knowledge creation. When an industry features knowledge spillovers, protecting producers in the industry may also benefit producers in other industries.

What is often overlooked in this argument is the implicit assumption that these knowledge spillovers must be domestic in scope. That is, if much of the knowledge that is created from support and protection immediately flows outside of the country, then the knowledge creation helps foreign competitors just as much as domestic producers.

This is a point that has recently been made explicit by Busch (1999). He has suggested that not only is it important whether an industry exhibits learning-by-doing and knowledge spillovers, but also whether the spillovers are domestic or international in scope. A government may consider protecting an industry if protection causes increased innovation and learning. However, if the firms that benefit from knowledge spillovers are primarily foreign, then much of the benefits of protection flow outside of the country, while the domestic government and consumers bear the full cost of protection. When knowledge spillovers are not domestic in scope, then foreign firms benefit from domestic protection as much, or more, than domestic firms. In this case, the incentive for countries to support and protect a domestic industry to facilitate knowledge creation is low. Instead, each country has an incentive to free-ride on the other countries' knowledge creation.

Busch (1999) provides three case studies from the U.S. to support his argument: civil aircrafts, semiconductors, and high definition televisions. Busch argues that there are a number of reasons why the U.S. civil aircraft industry has received support and protection from the government. Part of the explanation for this is that the industry is large and geographically concentrated. What is also important is that the "returns to technology tend not to escape national borders" (Busch, 1999, 45). Because the production process is so complex, product or process innovations made in the U.S. are generally not applicable or helpful to the civil aircraft industry in Europe.

Busch then contrasts the civil aircraft industry with the semi-conductor industry. Both industries are approximately the same size and both are geographically concentrated. But why do semiconductors receive far less support and protection? The explanation, according to Busch, is that knowledge spillovers in the semiconductor industry tend to be international in scope. Any knowledge created in the U.S. almost immediately flows to Japanese semiconductor producers. Busch also considers the high definition television industry, and provides the same argument for why this industry has seen little government support.

In this paper, I take these arguments to the data and test whether the scope of knowledge spillovers is an important determinant of the extent to which a government protects a domestic industry. I restrict my analysis to antidumping decisions in the United States between 1980 and 2005. Whether the government (or more precisely the committees involved in the decision making process) rule in favor or against the domestic petitioners may, in part, be influenced by the strategic social benefit society gains from protecting the industry. This benefit, as Busch argues, will be determined, in part, by whether any knowledge gains from protection stay within the country or flow outside of the country. Therefore, whether knowledge spillovers are domestic or foreign in scope may affect the decisions made in antidumping investigations. This is the relationship that I test in the data.

To quantify how domestic in scope knowledge spillovers are, I rely on U.S. patent citation data and construct a measure of the extent to which knowledge created in the U.S. tends to stay within the U.S. rather than flow outside of the country.

I find that the final antidumping duty imposed is higher in industries where domestic knowledge spillovers are primarily domestic in scope. This is true even when one controls for numerous industry characteristics including differences in political influence. The results are driven by the ITC's material injury decision. The ITC is more likely to rule affirmative when the petitioning industry has knowledge spillovers that are domestic in scope. I do not find evidence that conditional on a final duty being imposed, the level of the final duty is affected by the scope of knowledge spillovers.

In the next section, I more thoroughly motivate the measures that I use and describe in detail their construction and their data sources. In Section 3 and 4, I report the estimating equations and the core empirical results. Section 5 concludes.

2 Data Description

2.1 Administered Trade Protection

As a measure of trade protection and the extent to which a government is willing to stand-up and fight for an industry, I rely on antidumping data from the *Global Antidumping Database* (see Bown, 2006). I consider antidumping cases filed by the United States between 1980 and 2005.

In my analysis I consider three independent variables. The first is the final antidumping duty. If the DOC determines that dumping did not occur or the ITC does not find material injury, then the final duty is zero. In these cases no final antidumping duty is imposed. I omit from the sample cases that are withdrawn by the petitioner. This measure summarizes a number of decisions that are made by the DOC and ITC throughout the full investigation process. If in the end a (high) antidumping duty is imposed then this may indicate that those involved in the investigation process were willing to stand-up for the industry in question.

The second measure that I use isolates the ITC's decision of whether there is material injury or not, and uses this ruling as an indicator of the government's willingness to back an industry. This variable is an indicator variable that equals one if the ITC's injury ruling is affirmative and zero if the ruling is negative. I omit from the sample ITC decisions that are any other than a clear affirmative or negative ruling.

The final measure that I consider isolates the level of the final duty that is imposed. Here, I only consider the level of the final antidumping duty among the cases that received a positive final duty. That is, I omit from the analysis cases that were withdrawn or terminated, as well as cases for which the DOC or ITC's final or preliminary ruling were negative.

2.2 Knowledge Spillovers

Knowledge flows are by their nature inherently difficult to observe. However, a large influential literature has emerged arguing that patent citations leave a paper trail that can be used to track the flow of knowledge (Jaffe *et al.*, 1993). The validity of patent citations as a proxy for knowledge flows was assessed by Jaffe *et al.* (2000a,b). The authors compare patent citation data with information from interviews with inventors citing and being cited in the patents. The authors conclude that although patent citations are a proxy for knowledge flows that do contain measurement error, there is a strong significant relationship between patent citations and knowledge flows.

Because patents provide detailed information on the inventor, including the inventor's address, one knows the geographic location of the inventor of the cited patent and the inventor of the citing patent. Therefore, for each patent citation, one knows the origin and final location of the knowledge flow.

This logic has been used by a number of authors to estimate measures of how geographically local in scope knowledge flows are. A number of studies (e.g., Jaffe *et al.*, 1993; Branstetter, 2001; Thompson & Fox-Keane, 2005) find strong evidence of international localization effects; that is, that knowledge flows tend to stay within the country. The focus of this paper differs from these studies. I am interested not in how strong international localization effects are, but rather how this differs across industries.[1] Therefore, I construct measures of the scope of knowledge flows in *each* industry.

To construct my measure, I use citation information from patents granted by US Patent and Trademark Office (USPTO) between 1980 and 2002. The data are from Jaffe & Trajtenberg (2002). The patents are classified by over 400 4-digit technology categories and by over 120,000 patent 6-digit subcategories. This classification is called the International Patent Classification (IPC).

A concordance between the IPC system and the Canadian SIC industry classification is available from the Yale Technology Concordance (YTC). The concordance was conceived by Robert E. Evenson, Samuel Kortum, and Jonathan Putnam (see Kortum & Putnam, 1997). This concordance converts the IPC technology categories to the 4-digit cSIC industry classification based either on the invention's industry of manufacture (IOM) or its sector of use (SOU).[2] Using a concordance available from Statistics Canada (1997), I then match the 4-digit cSIC classification to the 6 digit NAICS classification, which is the classification used in the analysis.

In the end, I have information on patents and their citations for each NAICS 6-digit industry. Using the information on the country of each patent's first inventor, I am able to construct measures of how domestic in scope patent citations are in an industry. Let c_i^{US} denote the number of citations of patents in industry i that are made by U.S. inventors, and let c_i^{total} denote the number of citations of patents in industry i made by foreign and U.S. inventors. The first measure of knowledge flows is the proportion of total citations that are made by U.S. inventors:

$$K_i = c_i^{US}/c_i^{total}$$

The variable K_i is the fraction of citations of patents in an industry made

[1] Other studies have focused on knowledge flows in specific industries. For example, Irwin & Klenow (1994) look at the semi-conductor industry, and find knowledge spillovers are *not* domestic in scope. The fact that the authors' finding in this industry is different from what is found when looking at all industries suggests that there may be a great deal of heterogeneity across industries in the scope of knowledge flows.

[2] The concordance is based on more than 250,000 patents that were granted by the Canadian Intellectual Property Office (CIPO) between 1976 and 1993. Because these patents were each individually assigned IPCs, IOMs and SOUs by the CIPO, it was possible to construct the probability that a patent assigned to an IPC category would also be assigned to an cSIC category based either on its IOM or SOU.

by U.S. inventors. A value closer to one indicates that knowledge does not flow outside of the United States.

The second measure that I construct restricts the sample of patent citations to only include those that cite a patent that was originally made by a U.S. inventor. Let $\widetilde{c}_i^{US}$ denote the number of citations of patents (by U.S. inventors) in industry i that are made by U.S. inventors, and let $\widetilde{c}_i^{total}$ denote the total number of citations of patents (by U.S. inventors) made by U.S. and foreign inventors. The the second measure is calculated as follows.

$$\widetilde{K}_i = \widetilde{c}_i^{US} / \widetilde{c}_i^{total}$$

$\widetilde{K}_i$ measures the fraction of citations of U.S. inventor patents that are made by U.S. inventors.

2.3 Checking the Sensibility of the Scope of Knowledge Spillovers Measures

In this section, I examine how sensible the two measures of the scope of knowledge flow are. I begin by first reporting the 20 industries with the highest and lowest measures of K_i. This is shown in Table 1.[3]

As shown, the industry with the most international knowledge spillovers measure (lowest K_i) is the "audio and video equipment manufacturing industry". This is the industry into which high definition televisions fall. Therefore, Busch's (1999) assertion that knowledge flows in the high definition television industry were not domestic in scope is confirmed by this measure. Busch also asserts that the semiconductor industry is international in scope. Although, the semiconductor industry does not show up among the 20 lowest measures of K_i, it has the 55th lowest measure of K_i among 386 industries. This also confirms Busch's assertion that knowledge flows in the semiconductor industry are also very international in scope. By contrast, the "aircraft manufacturing" industry ranks as having knowledge spillovers that are very domestic in scope. It ranks as having the 44th highest measure of K_i. Again, this is consistent with Busch's argument.

Unless one has intimate understanding of domestic and foreign innovation in each industry, it is hard to judge whether the measure of K_i for the other industries is reasonable. Although the general ordering seems plausible, it is difficult to determine this objectively. However, I analyze the sensibility of various characteristics of the measures. I first consider the

[3]This measure is constructed using the IPC cSIC concordance based on the sector of use (SOU) concordance.

Table 1: The (agriculture and manufacturing) industries with the lowest and highest measures of domestic knowledge flows.

20 lowest K_i industries		20 highest K_i industries	
K_i	Industry description	K_i	Industry description
.296	Audio & video equip. man.	.727	Natural gas distribution
.397	Photographic services	.731	Support activities for mining
.403	Musical instrument man.	.731	Mayonnaise & dressings
.412	Database, directory publisher	.731	Wet corn milling
.419	Other engine equip. man.	.731	Rice milling
.420	Tobacco farming	.731	Roasted nuts & peanut butter
.432	Recording media man.	.731	Malt manufacturing
.432	Media reproduction	.731	Soybean processing
.432	Software reproducing	.731	Spice & extract man.
.442	Textile & fabric mills	.731	Sanitary paper product man.
.445	Nonferrous forging	.736	Other leather prod. man.
.460	Automobile & light truck man.	.747	Dry pasta man.
.470	Indep. artists, writers, perf.	.748	Burial casket man.
.472	Ophthalmic goods man.	.771	Petroleum refineries
.474	Auto. enviro. control man.	.775	Nonclay refractory man.
.476	Electronic equip. repair	.775	Brick & struct. clay tile man.
.479	Military armored vehicles	.784	Drilling oil & gas wells
.480	Other personal services	.784	Support activ. for oil gas extract.
.484	Household cooking appl. man.	.784	Poultry & egg production
.486	Motion picture industry	.801	Oil gas extraction

Notes: The scope of knowledge flows measure has been rounded to three digits.

Table 2: Summary Statistics for K_i and $\widetilde{K}_i$.

	Mean	Std. dev.	Min.	Max.	Num. obs.
Scope of knowledge spillovers, K_i	.628	.067	.300	.806	386
Scope of knowledge spillovers, $\widetilde{K}_i$	.717	.051	.438	.853	386

Notes: The summary statistics do not include service industries. They only include agriculture and manufacturing industries.

summary statistics of the two measures, which are reported in Table 2.[4] One average 62.8 and 71.7% percent of citations are by U.S. inventors. This suggests that knowledge is more likely to stay within the United States than flow outside of the country. This result seems reasonable and consistent with intuition. The measures range from 30 to 80.6% for K_i and from 43.5 to 85.4% for $\widetilde{K}_i$. The higher average and higher range of values for $\widetilde{K}_i$ suggest that the fraction of U.S. cites is higher when the patents being cited are only U.S. inventor patents. This is also consistent with intuition. If knowledge flows dissipate over space, then when one considers patents by U.S. inventors only, the fraction of cites by foreigners should be lower than if we also include patents that were invented in other countries.

Although there is a statistically significant difference in the means of K_i and $\widetilde{K}_i$, the two measures are highly correlated. The relationship between the two variables is shown in Figure 1. As shown the measures, with a correlation coefficient of .97, are closely related.

As a further sensibility check of the measure of the scope of knowledge spillovers across industries, I check whether the knowledge measures are correlated with trade-based measures of how global an industry is. If a U.S. industry appears to be isolated from the rest of the world, then it is likely that knowledge flows will also be domestic. I consider two measures of how connected an industry is to the world. The first is the import penetration

[4]I restrict my analysis to agriculture and manufacturing industries only, and do not consider service industries, which tend to be non-traded and therefore do not appear in the antidumping data.

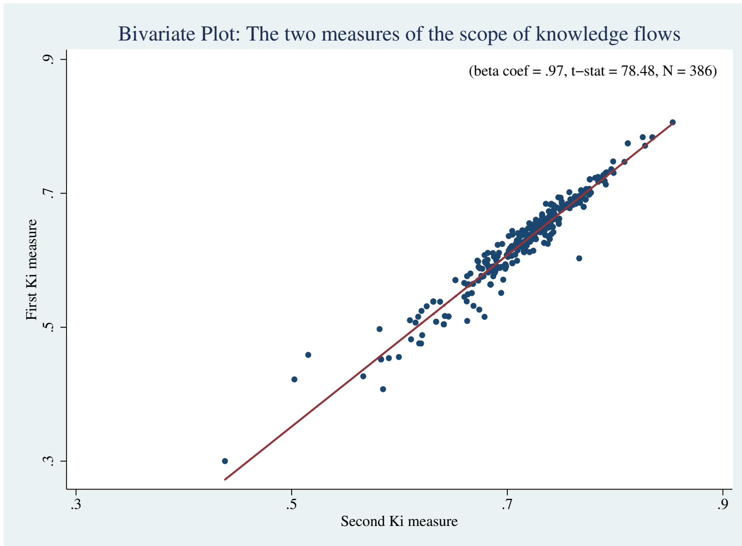

Figure 1: The relationship between the two measures of the scope of knowledge flows.

ratio of an industry, defined as the ratio of imports to domestic production.[5] If an industry faces a large amount of foreign competition, then this indicates that non-US producers are competitive in this industry, and they are likely to be actively involved in knowledge creation. The foreign involvement in purposeful knowledge acquisition will cause knowledge to flow outside of the U.S. to these countries.[6]

The cross-industry relationship between how domestic in scope U.S. knowledge spillovers are and the import penetration ratio is shown in Figure 2. Consistent with this relationship between foreign competitiveness and knowledge flows, there is a negative relationship between the two measures. When foreign firms are competitive in an industry, U.S. knowledge flows tend to be less domestic in scope.

The second measure that I consider is the proportion of an industry's intermediate inputs that are imported. This is calculated as $\sum_j u_{ij}^{imports}/u_{ij}^{total}$ where i indexes industries and j indexes inputs. $u_{ij}^{imports}$ is the value of im-

[5] This is constructed using data from Feenstra *et al.* (2002) and Bartelsman & Gray (1996).

[6] This relationship can also be viewed in the opposite manner. The foreign knowledge acquisition causes the foreign country to be competitive in the production of the goods, causing the U.S import penetration ratio to increase.

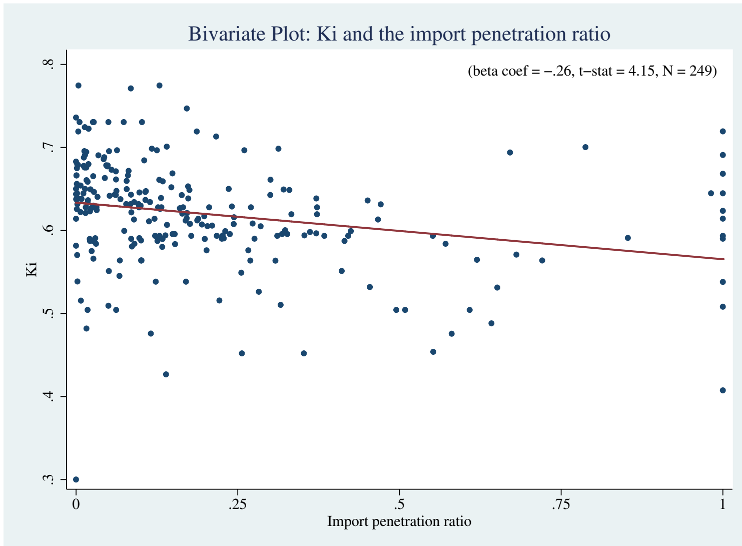

Figure 2: Raw data: K_i and the import penetration ratio.

ported inputs j used by industry i, and u_{ij}^{total} is the total value of inputs j used by industry i.[7] An industry's interaction with foreign input suppliers may facilitate the transfer of knowledge from the domestic producers to the foreign suppliers. In this case, industries that obtain a large proportion of their inputs from foreign suppliers will also be industries for which domestic knowledge tends to flow most freely outside of the country. The upstream relationship with foreign suppliers may facilitate this knowledge flow.

This relationship is shown in Table 3. As shown, industries for which a larger proportion of intermediate inputs are purchased from foreign suppliers are also industries for which knowledge flows tend to be less domestic in scope.

Last, I consider the relationship between the K_i and $\widetilde{K}_i$ and other industry characteristics. I examine the relationship with the skill and capital intensities of production, industry size measured by the number of employees, TFP growth in an industry between 1977 and 1996, and value added as a share of the value of shipments in an industry. A priori, it is difficult to predict a clear relationship between the scope of knowledge spillovers measures and these industry characteristics. Pairwise correlation coefficients between the variables are reported in Table 3. In general, the knowledge spillovers

[7] The data used to construct this measure are from the 1997 United States Input-Output and the import penetration ratio described above.

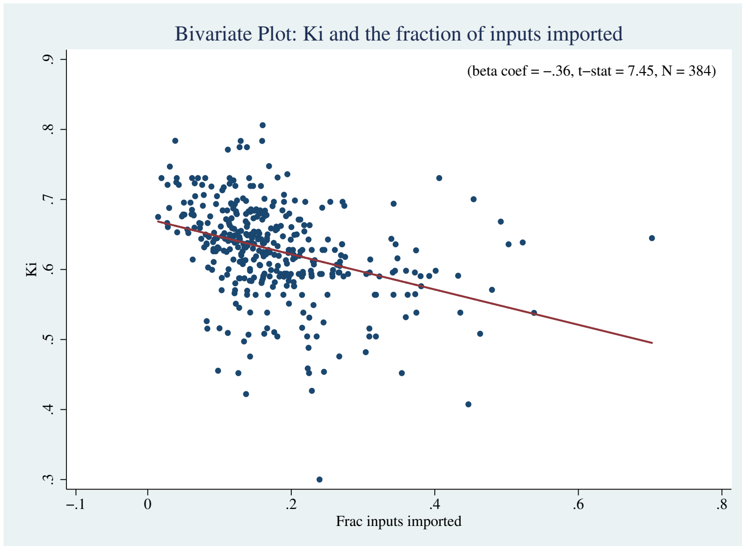

Figure 3: Raw data: K_i and the proportion of an industry's intermediate inputs that are imported.

measures appear uncorrelated with the industry characteristics. The only exception is that in skill-intense industries knowledge flows are less domestic in scope.

3 Estimating Equations and Empirical Results

3.1 The Final Antidumping Duty

As a first cut of the data, I consider the final duty implemented as my measure of administered trade protection. This variable summarizes a number of decisions that are made in the decision making process. It is determined both by the DOC's decision of whether dumping has occurred, the ITC's decision of whether there is material injury. I code cases for which the ITC's final decision is not affirmative and cases that are withdrawn as having a zero final duty.

I motivate my estimating equation by first considering the following

Table 3: Pairwise correlation coefficients.

	Skill intensity	Capital intensity	Number Employees	TFP growth 1977-1996	Value added
Scope of knowledge spillovers, K_i	$-.18$	.02	$-.04$	$-.10$	$-.12$
	(.00)	(.73)	(.55)	(.13)	(.05)
Scope of knowledge spillovers, $\widetilde{K}_i$	$-.16$	$-.04$	$-.03$	$-.08$	$-.10$
	(.00)	(.55)	(.66)	(.18)	(.10)

Notes: Pairwise correlation coefficients are reported with p-values in brackets.

equation,

$$D_{itc} = \sum_{t=1}^{T} \alpha_t I_t + \sum_{c=1}^{C} \gamma_c I_c + \beta_K K_i + \delta_c \widetilde{c}_i^{total}/va_i + \delta_s I_i^{steel} + \delta_m m_{ic}/y_i + \mathbf{X_i}\delta + \varepsilon_{itc} \quad (1)$$

where i indexes industries, t indexes time measured in years, and c indicates the country that the antidumping case is filed against.

The variable K_i is my constructed measure of how domestic in scope knowledge flows are in industry i. If K_i increases the probability that an antidumping petitioner eventually receives protection or the level of the final protection, then we would expect $\hat{\beta}_K > 0$.

The variable $\widetilde{c}_i^{total}/va_i$ is a proxy meant to control for the total volume of knowledge spillovers that flows from an industry. It is measured as the total number of cites of U.S. patents in industry i divided by the total value added in industry i. The variable m_{ic}/y_i is the named country's import penetration ratio: imports from the named country divided by total domestic production, both measured in 1996.[8] I include this measure because this industry characteristic is explicitly considered by the ITC in its material injury decision.

I control for a 'steel industry' fixed effect by including a dummy variable that equals one for NAICS industries listed under the broader classification

[8] The trade data and the production data used to construct this measure are from Feenstra *et al.* (2002) and Bartelsman & Gray (1996).

of "iron and steel mills and manufacturing from purchased steel" in the U.S. I-O tables.[9]

The vector $\mathbf{X_i}$ includes additional industry-level control variables that capture differences in industries' political influence. I include the number of workers employed in an industry, seller concentration, PAC contributions per $1,000 of value added, and the unionization rate. These measures are from Essaji (2005).

A host of other control variables are capture by the time (year) fixed effects I_t and the named country fixed effects I_c included in the estimating equation. Other studies have suggested that economy wide macroeconomic characteristics such as the U.S. trade deficit may affect the ITC's decision making (e.g., Hansen & Prusa, 1997). The time fixed effects will capture these differences, as well as other economy wide differences each year that may influence the ITC and DOC's decision-making.[10]

Similarly, the named country fixed effects capture any differences in the DOC and ITC's rulings which depend on the source of the dumped imports. For example, studies have found that the ITC is much more likely to rule affirmative against Japan, developing countries and non-market economies, and is less likely to rule affirmative against EU countries (Moore, 1992; Hansen & Prusa, 1996, 1997).

One shortcoming of equation (1) is that if the ITC or DOC's attitude towards a named country changes over time or if the dumping behavior of a named country changes over time, then this will not be captured by the country fixed effects, which are constrained to be constant over time. If, for example, foreign Japanese firms after being hit by antidumping duties change the severity of their dumping behavior, then future DOC and ITC decisions are less likely to be affirmative. I therefore capture named country specific changes in behavior over time by including year-country fixed effects in my estimating equation. That is, I allow for fixed effects that differ for each country *and* year. This estimating equation can be written,

$$\begin{aligned} D_{itc} &= \sum_{t=1}^{T}\sum_{c=1}^{C}\alpha_{tc}I_{tc} + \beta_K K_i \\ &\quad + \delta_c \tilde{c}_i^{total}/va_i + \delta_s I_i^{steel} + \delta_m m_{ic}/y_i + \mathbf{X_i}\delta + \varepsilon_{itc} \qquad (2) \end{aligned}$$

[9]These industries are: 331111, 331112, 331210, 331221, 331222. The results are qualitatively identical if the dummy variable only equals one for the industry 331111, which is the industry that most often petitions.

[10]The time fixed effects will also capture changes in the antidumping law that have occurred between 1980 and 2005, as long as these changes apply equally across all industries.

This specification is more parsimonious than (1). In fact, (1) is a special case of (2), where the estimated time fixed effects are constrained to have the same effect across all countries ($\alpha_{tc} = \alpha_t \, \forall c$), and the estimated country fixed effects are constrained to be the same across all years ($\alpha_{tc} = \gamma_c \, \forall t$).

The dependent variable in (2) is left censored at zero, which suggests that a tobit model is appropriate. However, because of the "incidental parameters problem" associated with tobit models with fixed effects, coefficient estimates and standard errors are biased and inconsistent, and the direction of the bias is unknown (Greene, 2004a,b). Therefore, I estimate (1) by OLS. The other benefit to using OLS is that the data, in the form of partial regression plots, can easily be analyzed. This makes understanding the data and performing regressions diagnostics particularly easy, which is important given that this is a first cut at the data.

OLS estimates of (2) are reported in Table 4. The first two columns report estimates of (1) without the vector of political influence control variables $\mathbf{X_i}$, using both measures of the scope of knowledge flows, K_i and $\widetilde{K}_i$. Using either measure, the coefficients of interest β_K are positive and statistically significant. The measure of knowledge flows $\widetilde{c}_i/va_i$ and the import penetration ratio are positive but statistically insignificant. The steel indicator variable is positive and statistically significant.

In the third and fourth columns, I include the political influence control variables. To save space I do not report the coefficient estimates. The only variable that is consistently significant is the unionization rate, which is estimated to have a positive effect on the final anti-dumping duty. More important for the focus here is that the scope knowledge spillovers measures remain robust to the inclusion of these control variables.

Figure 4 reports the partial correlation plot for K_i from the estimates of column 3. It is clear from the figure that a small number of observations are potentially influencing the results. For this reason, I perform a number of regression diagnostic tests to check for the robustness of the positive coefficient for K_i. I choose to use K_i rather than $\widetilde{K}_i$ only because the estimates are weaker for K_i than for $\widetilde{K}_i$. Therefore, testing the robustness of K_i provides the greatest chance of finding that the relationship is not robust.

The sensitivity checks are reported in Table 5. Each column reports the estimated coefficient of K_i in Equation (2) after influential observations have been identified and omitted from the sample. I use a number of measures of the influence of an observation that have become standard in the literature (Belsley *et al.*, 1980).

Table 4: OLS Estimates. The dependent variable is the final antidumping duty imposed.

	(1)	(2)	(3)	(4)
Knowledge spillovers:				
Scope of knowledge spillovers, K_i	.140*		.186**	
	(.074)		(.075)	
Scope of knowledge spillovers, $\widetilde{K}_i$		.138*		.214***
		(.075)		(.076)
Control variables:				
Cites / value added, $\widetilde{c}_i^{total}/va_i$	.027	.026	.049	.051
	(.034)	(.034)	(.037)	(.038)
Steel dummy variable, I_i^{steel}	.111*	.117*	−.032	−.027
	(.063)	(.069)	(.100)	(.093)
Named country import-pen. ratio, m_{ic}/y_i	.011	.042	.071*	.067*
	(.011)	(.060)	(.038)	(.039)
Political economy variables	No	No	Yes	Yes
Year-country fixed effects	Yes	Yes	Yes	Yes
Number of observations	892	892	868	868
R-squared	.47	.47	.48	.48

Notes: Beta coefficients are reported, with standard errors clustered at the industry level in brackets. ***, **, and * indicate significance at the 1, 5, and 10% levels.

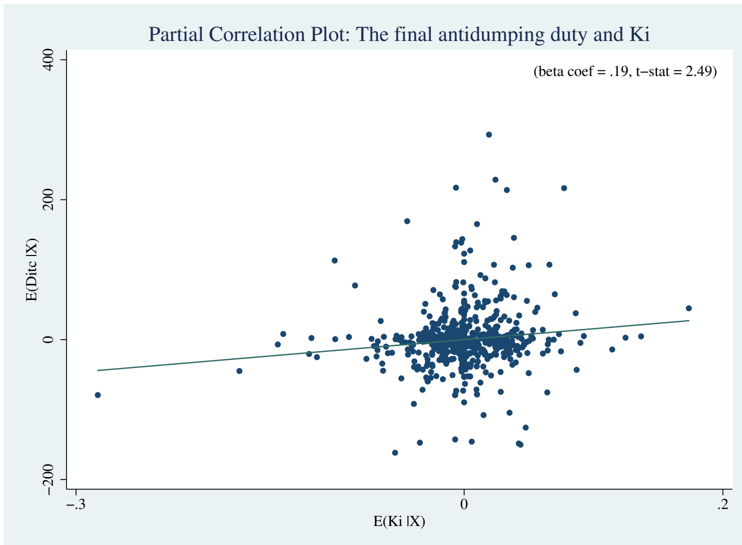

Figure 4: Partial correlation plot for the relationship between D_{itc} and K_i.

Table 5: Omitting influential observations. OLS estimates: the dependent variable is the final antidumping duty imposed.

	K_i		Number	
	coef	s.e.	of obs.	R^2
Baseline	.186**	(.075)	868	.48
DFITS	.192***	(.049)	672	.47
Cooks distance	.211***	(.058)	820	.49
Welsch distance	.145**	(.057)	695	.40

Notes: Beta coefficients are reported, with standard errors clustered at the industry level in brackets. All regressions include year-country fixed effects and the full set of control variables. ***, **, and * indicate significance at the 1, 5, and 10% levels.

3.2 The ITC's Material Injury Decision

The dependent variable in (1) reflects both the DOC and ITC's rulings during the antidumping investigation process. To better understand the reason behind the results of Tables 4 and 5, I separate the different decisions made during antidumping investigations. I first examine the ITC's material injury decision. I do this by estimating the following equation:

$$\begin{aligned}\Pr(\text{Affirmative})_{itc} &= \sum_{t=1}^{T}\sum_{c=1}^{C}\alpha_{tc}I_{tc} + \beta_K K_i \\ &+\delta_c \widetilde{c}_i^{total}/va_i + \delta_s I_i^{steel} + \delta_m m_{ic}/y_i + \mathbf{X_i}\delta + \varepsilon_{itc} \quad (3)\end{aligned}$$

The equation is the same as (2) except that now the dependent variable is the probability that the ITC rules 'affirmative', finding that the domestic industry has been injured. Because of the fixed effects in the estimating equation, I used a logit model to estimate (3).

The logit estimates are reported in Table 6. Here, as before the scope of knowledge spillovers is important. All else equal, the more domestic in scope knowledge spillovers are, the more likely the ITC is to find material injury.

In Table 7, I test the robustness of the logit estimates. The table reports the robustness of the estimates from column 3 of Table 6. I identify influential observations using standard measures of influence when a logit regression is estimated (Hosmer & Lemeshow, 2000). I then omit the 10% of observations with the greatest measures of influence, and re-estimate the logit model.[11] As shown, the results remain robust to the omission of influential observations. In fact, the estimated coefficient for K_i tends to increase and become more statistically significant when influential observations are omitted. This suggests that the relationship in the data is fundamental, and not driven by a small number of influential observations.

3.3 Looking only at Positive Antidumping Duties

I next consider the relationship between the scope of knowledge flows and the level of final antidumping duty among cases for which a final duty was imposed. That is, I omit from the sample cases for which the DOC's ruling was negative, cases that were withdrawn, and cases for which the ITC's

[11] In practice, because observations are omitted if there is only one observation in a country-year pair, more than 10% of the observations are omitted. As well, this explains why the number of observations is different in each regression.

Table 6: Logit Estimates. The dependent variable is the probability of an affirmative injury decision by the ITC.

	(1)	(2)	(3)	(4)
Knowledge spillovers:				
Scope of knowledge spillovers, K_i	5.42**		9.31**	
	(2.78)		(3.86)	
Scope of knowledge spillovers, $\widetilde{K}_i$		4.41		9.60**
		(3.09)		(4.71)
Control variables:				
Cites / value added, $\widetilde{c}_i^{total}/va_i$	.549	.537	.726	.720
	(.389)	(.407)	(.447)	(.450)
Steel dummy variable, I_i^{steel}	1.24**	1.12	.766	.737
	(.603)	(.573)	(.735)	(.718)
Named country import-pen. ratio, m_{ic}/y_i	6.19***	6.04***	6.09***	5.79***
	(2.03)	(2.00)	(2.03)	(1.95)
Political economy variables	No	No	Yes	Yes
Year-country fixed effects	Yes	Yes	Yes	Yes
Number of observations	522	522	491	491
Pseudo R-squared	.14	.14	.14	.14

Notes: Coefficients are reported, with standard errors clustered at the industry level in brackets. ***, **, and * indicate significance at the 1, 5, and 10% levels.

Table 7: Omitting influential observations. Logit estimates: the dependent variable is the probability of an affirmative injury decision by the ITC.

	K_i coef	K_i s.e.	Number of obs.	R^2
Baseline	4.91**	(3.86)	491	.14
Deviance	22.3***	(5.35)	344	.23
D χ^2	18.4***	(4.40)	359	.20
D-deviance	13.7***	(4.23)	369	.19
D-beta	10.3**	(2.53)	433	.16

Notes: Coefficients are reported, with standard errors clustered at the industry level in brackets. All regressions include year-country fixed effects and the full set of control variables. ***, **, and * indicate significance at the 1, 5, and 10% levels.

Table 8: OLS Estimates. The dependent variable is the final anti-dumping duty imposed.

	(1)	(2)	(3)	(4)
Knowledge spillovers:				
Scope of knowledge spillovers, K_i	.095		.189	
	(.109)		(.129)	
Scope of knowledge spillovers, $\widetilde{K}_i$		.103		.219*
		(.103)		(.118)
Control variables:				
Cites / value added, $\widetilde{c}_i^{total}/va_i$	−.062	−.061	−.049	−.045
	(.057)	(.053)	(.036)	(.031)
Steel dummy variable, I_i^{steel}	−.081	−.071	−.112	−.104
	(.093)	(.100)	(.127)	(.127)
Named country import-pen. ratio, m_{ic}/y_i	−.023	−.026	−.009	−.016
	(.076)	(.078)	(.072)	(.075)
Political economy variables	No	No	Yes	Yes
Year-country fixed effects	Yes	Yes	Yes	Yes
Number of observations	396	396	380	380
R-squared	.68	.68	.69	.69

Notes: Beta coefficients are reported, with standard errors clustered at the industry level in brackets. ***, **, and * indicate significance at the 1, 5, and 10% levels.

injury decision was negative. Looking at the remaining cases, I ask whether there is a relationship between the scope of knowledge flows and the final duty imposed.

OLS estimates of this relationship are reported in Table 8. Overall, the evidence for a positive relationship between how domestic knowledge flows are and the final duty is weak at best. Although the estimated coefficients for K_i and $\widetilde{K}_i$ are positive, they are only statistically significant in one of the four specification reported. Further robustness tests, not reported here, confirm that the relationship is not robustly significant.

4 Alternative Explanations for the Relationship

The importance of K_i and $\widetilde{K}_i$ in explaining the probability that the ITC finds material injury (and therefore the final antidumping duty that is imposed) may be the result of a spurious correlation between the measures and other industry characteristics that are important. As I illustrated in Section 2.3, K_i and $\widetilde{K}_i$ are significantly correlated with the import-penetration ratio in an industry and with the fraction of an industry's inputs that are imported. It may be that these are the industry characteristics that matter for antidumping investigation decisions. I check for this by re-estimating (2) and (3), while controlling for an industry's import penetration ratio and the fraction of its inputs that are imported. As reported in columns 1 and 3 of Table 9, the estimated coefficient for K_i remains positive and statistically significant. In columns 2 and 4, I also include an industry's skill and capital intensity. These are important industry characteristics that may bias the results if omitted. Including these controls does not alter the robustness of the results.

The result are identical if one uses $\widetilde{K}_i$ rather than K_i as the measure of the scope of knowledge flows. One can also control for other industry characteristics such as an industry's TFP growth rate, the ratio of value added to value of shipments, Herfindahl index of input concentration, or the geographic concentration of production in an industry. Overall, the results remain robust to controlling for these additional industry characteristics as well. This result is not surprising given that, as shown in Section 2.3, these variables tend to be uncorrelated with K_i and $\widetilde{K}_i$.

Table 9: Adding additional industry-level control variables.

	(1)	(2)	(3)	(4)
	OLS		Logit	
Knowledge spillovers:				
Scope of knowledge spillovers, K_i	.209**	.203**	8.84**	9.87**
	(.088)	(.089)	(4.08)	(4.60)
Other industry characteristics:				
Import-penetration ratio	−.029	−.043	−.661	−.497
	(.088)	(.088)	(1.27)	(1.29)
Fraction of inputs imported	.068	.092	−.307	−.691
	(.110)	(.107)	(3.09)	(3.23)
Skill-intensity		−.053		−.365
		(.063)		(1.63)
Capital-intensity		−.042		.384
		(.076)		(1.63)
Control variables: $\widetilde{c}_i^{total}/va_i$, I_i^{steel}, m_{ic}/y_i	Yes	Yes	Yes	Yes
Political economy variables	Yes	Yes	Yes	Yes
Year-country fixed effects	Yes	Yes	Yes	Yes
Number of observations	868	868	491	491
R-squared	.48	.48	.14	.15

Notes: In columns 1 and 2, beta coefficients are reported, and in columns 3 and 4, coefficients are reported. Standard errors clustered at the industry level are given in brackets. ***, **, and * indicate significance at the 1, 5, and 10% levels. The dependent variable in columns 1 and 2 is the final antidumping duty D_{itc}, and in columns 3 and 4 is the probability that the ITC finds material injury $\Pr(\text{Affirmative})_{itc}$.

5 Conclusions

I have tested whether the scope of knowledge spillovers in an industry affects administrated trade protection. I found that, all else equal, the final antidumping duty imposed is higher in industries where domestic knowledge spillovers are primarily domestic in scope. This is true even when one controls for difference in political influence across industries. These results appear to be driven by the ITC's material injury decision. The ITC is more likely to rule affirmative when the petitioning industry has knowledge spillovers that are domestic in scope. I do not find evidence that conditional on a final duty being imposed, the scope of an industry's knowledge flows affect the level of the final duty.

Overall, these results provide preliminary evidence for the possibility of a strategic motive in administered protection. All else equal, industries for which the benefits of knowledge creation tend to remain in the country are also the industries that tend to fair better in the antidumping investigation process.

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