A Quantile-based Test of Protection for Sale Model*

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March 8, 2009

Abstract

This paper proposes a new test of the Protection for Sale (PFS) model by Grossman and Helpman (1994). Unlike existing methods in the literature, our approach does not require any data on political organization. We use quantile and quantile IV regressions to do so using the data from Gawande and Bandyopadhyay (2000). Surprisingly, the results do not provide any evidence favoring the PFS model. We also explain why previous work may have inadvertently found support for it.

JEL Classification: F13, F14

Keywords: Protection for Sale; Lobbying; Political Economy; Quantile Regression

*We are grateful to Pol Antras, Kishore Gawande, Penny Goldberg, Elhanan Helpman, Pravin Krishna, Giovanni Maggi, Xenia Matschke, Mark Melitz, James Tybout, Steve Yeaple, and the participants in seminars at Princeton University, Cornell/PSU Macro Conference, 2008 Econometric Society Summer Meetings, NBER ITI Spring Meeting for helpful comments. All errors are ours.

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1 Introduction

There has been much interest in the political economy aspects of trade policy recently. In part, this has been triggered by the theoretical framework in the Grossman and Helpman (1994) "Protection for Sale" (PFS) model. Empirical studies such as Goldberg and Maggi (1999) (hereafter GM) and Gawande and Bandyopadhyay (2000) (hereafter GB) have used US data and shown that as predicted by the PFS framework, protection is positively related to the import penetration ratio for politically unorganized industries, but negatively for organized ones.[1]

In these studies, the key explanatory variable is the dummy variable indicating whether the industry is politically organized. Its construction requires the classification of industries into politically organized and unorganized ones. For this purpose GM and GB used data on contributions along with some simple rules.[2] GM classify an industry as politically organized if its Political Action Committees'(PAC) contribution is greater than a pre-specified threshold level. GB's classification rule is based on the idea that if industries are organized, then industries with higher import penetration ratios are likely to make higher campaign contributions. Several questions naturally arise about their classification rules. First, are their rules consistent with the PFS model? Second, do their rules correctly distinguish between organized and unorganized industries? These issues are of vital importance, because testing and structural estimation of the PFS model requires political organization to be correctly classified and in a manner consistent with the PFS model.

The objective of this paper is two-fold. First, we show that their classification rules may not

[1] Subsequently, Mitra et al. (2002) and McCalman (2004) used Turkish and Australian data respectively, and provided similar evidence.

[2] They could not just say that organized industries were those that made campaign contributions, as is assumed in the PFS model, because in the US data all industries make Political Action Committees'(PAC) contributions. Thus, all industries should be classified as politically organized. But in this case, the PFS model predicts the equilibrium level of protection should be increasing in the inverse import penetration ratio for all industries while in fact, it is decreasing! Moreover, as lobbying efforts could cancel out, protection levels could be quite low. In the small country case, for example, if all industries are taken to be organized, and all agents own some of at most one factor, the equilibrium tariff equals the optimal one, namely zero.

be consistent with the PFS model and consequently their parameter estimates may be biased. We argue that using a cutoff level of contributions may not be advisable as contributions can easily be very small despite the industry being organized. We provide a simple numerical example of the PFS model where the level of the industry's contribution varies greatly depending on its import penetration. We show that organized industries may make very small contributions if their import penetration is high. This implies that using a particular threshold of campaign contribution as a device to distinguish between organized and unorganized industries, as is done in GM, results in mis-classification and is inconsistent with the PFS model. Furthermore, in our numerical example, import penetration and the level of equilibrium campaign contributions are negatively correlated. This is exactly the opposite of the relationship assumed by GB and other papers using their approach to classify industries as organized or not, casting their procedure into doubt as well. We then argue that there is no instrument for the classification errors.

Thus, we have a problem in implementing the usual tests of the PFS model. To deal with it we propose a *new* test of the PFS model. The test is based *not* on the well-known and extensively-examined prediction of the PFS but on other implications past studies have not explored. Importantly, our test does not require classification of industries as organized or not; nor does it require data on contributions made to political parties, data which is available for the US but is not usually available for other countries. Our approach relies on the relationship between observables (i.e., the protection measure, import penetration, and import demand elasticity) implied by the PFS model and thus it is entirely consistent with the PFS framework. In particular, we exploit the following prediction of the PFS model: politically organized industries should have higher protection than unorganized ones given the inverse import penetration ratio and other control variables. This suggests that industries with higher protection are more likely to be politically organized, and thus for these industries, we should expect a positive relationship between the inverse import penetration ratio and the protection measure. Thus, in a quantile

regression, we should see this relationship hold for the higher quantiles of the protection measure conditional on the inverse import penetration ratio and other controls.[3] This prediction is tested on the data used in GB. Contrary to much of the literature, our new test does not provide empirical support for the PFS model.[4]

Below, we review the PFS model, explain and implement our test. We also explain why previous work may have inadvertently found support for it.

2 The PFS Model and Its Estimation

2.1 The PFS Model

The exposition in this section relies heavily on Grossman and Helpman (1994). There is a continuum of individuals, each of infinitesimal size. Each individual has preferences that are linear in the consumption of the numeraire good and are additively separable across all goods. On the production side, there is perfect competition in a specific factor setting: each good is produced by a factor specific to the industry, k_i in industry i, and a mobile factor, labor, L. Thus, each specific factor is the residual claimant in its industry. Some industries are organized, and being organized or not is exogenous to the model. Tariff revenue is redistributed to all agents in a lump sum manner. Owners of the specific factors in organized industries make up the lobby group which can make contributions to the government to influence policy if it raises their total welfare. Government cares about both the contributions made to it and social welfare and puts a relative weight of α on social welfare, $W(\mathbf{p})$ where $\mathbf{p}$ is the domestic price and equals the tariff vector plus the world price $\mathbf{p}^*$.[5]

[3] Note that a quantile regression approach does not involve ordering the endgenous variable and running separate regressions for each quantile. Instead it allows parameter estimates to differ across quantiles while conditioning on explanatory variables. IV quantile regression further deals with endogeneity.

[4] To our knowledge, this is also the first use of quantile IV techniques which are quite new in econometrics (see Chernozhukov and Hansen (2005)) in trade.

[5] We use bold letters for vectors.

The timing of the game is as follows: first, lobbies simultaneously bid contribution functions that specify the contributions made contingent on the trade policy adopted (which determines domestic prices). The government then chooses what to do to maximize its own objective function. In this way, the government is the common agent all principals (organized lobbies) are trying to influence. Such games are known to have a continuum of equilibria. By restricting agents to bids that are "truthful" so that their bids have the same curvature as their welfare, a unique equilibrium can be obtained.[6] The equilibrium outcome in this unique equilibrium is as if the government was maximizing a weighted social welfare function with a greater weight on the welfare of organized industries. In other words, equilibrium tariffs can be found by maximizing

$$G(\mathbf{p}) = \alpha W(\mathbf{p}) + \sum_{j \epsilon J_0} W_j(\mathbf{p}),$$

where J_0 is the set of politically organized industries.

In their model, the welfare of the lobby group in industry j is

$$W_j(\mathbf{p}) = \pi_j(p_j) + l_j + \frac{N_j}{N}\left[T(\mathbf{p}) + S(\mathbf{p})\right],$$

where $\pi_j(p_j)$ is producer surplus in industry j, l_j is labor income of the owners of the specific factors employed in industry j, wage is unity, $N_j/N = \alpha_j$ is the fraction of agents who own the specific factor j, while $T(\mathbf{p}) + S(\mathbf{p})$ is the sum of tariff revenue and consumer surplus in the economy. Maximizing $G(\mathbf{p})$ gives, after some manipulation:

$$x_j(p_j)(I_j - \alpha_L) + (p_j - p_j^*)m_j'(p_j)(\alpha + \alpha_L) = 0, \tag{1}$$

where I_j is unity if j is organized and zero otherwise, α_L (assuming that each individual owns

[6] For a detailed discussion of this concept, see Bernheim and Whinston (1986). Imai et al. (2008) provide a new elementary proof of their result.

at most one specific factor) corresponds to the fraction of the population that owns the specific capital of organized industries, $z_j = x_j(p_j)/m_j(p_j)$ where $x_j(p_j)$ and $m_j(p_j)$ denote the supply and imports of industry j, while $e_j = -m_j'(p_j)p_j/m_j(p_j)$. Rewriting equation (1) using the fact that $(p_j - p_j^*) = t_j p_j^*$ where t_j is the tariff rate gives:

$$\frac{t_j}{1+t_j} = \left(\frac{I_j - \alpha_L}{\alpha + \alpha_L}\right)\left(\frac{z_j}{e_j}\right).$$

This is the basis of the key estimating equation, which we call the protection equation:

$$\frac{t_j}{1+t_j} = \gamma\frac{z_j}{e_j} + \delta I_j \frac{z_j}{e_j}. \tag{2}$$

This equation provides the well known prediction of the PFS model: $\gamma = [-\alpha_L/(\alpha + \alpha_L)] < 0$, $\delta = 1/(\alpha + \alpha_L) > 0$, and $\gamma + \delta > 0$.[7]

2.2 A Problem in Estimation — the Classification of Industries

To make equation (2) estimable, an error term ϵ_j is added in a linear fashion:

$$\frac{t_j}{1+t_j} = \gamma\frac{z_j}{e_j} + \delta I_j \frac{z_j}{e_j} + \epsilon_j. \tag{3}$$

To allow for the fact that a significant fraction of industries have zero protection in the data, equation (3) can be modified as follows:

$$\frac{t_j}{1+t_j} = Max\left\{\gamma\frac{z_j}{e_j} + \delta I_j \frac{z_j}{e_j} + \epsilon_j, 0\right\}. \tag{4}$$

[7] This holds as long as there are some agents who do not own any specific capital of organized industries, $\alpha_L < 1$.

To test the key prediction (i.e., $\gamma < 0$, $\delta > 0$ and $\gamma + \delta > 0$), equations (3) and (4) have been estimated in a number of previous studies.

Although data on the measure of trade protection, the import penetration ratio, and the import-demand elasticities are often available, it is harder to define whether an industry is politically organized or not. To deal with this problem, GM used data on campaign contributions at the three-digit SIC industry level. An industry is classified as politically organized if the campaign contribution exceeds a specified threshold level. GB use an alternative approach. They run a regression where the dependent variable is the log of the corporate PAC spending per contributing firm relative to value added and the regressors include the interaction of the import penetration from five countries into the sub-industry and the two-digit SIC dummies. Then, industries are classified as politically organized if any of the coefficients on its five interaction terms are found to be positive. This procedure is based on the notion that in organized industries, an increase in contributions would likely occur when import penetration increased.

Both of these procedures are questionable. We offer a formal argument that claims: (1) when industries are misclassified, only under very strong assumptions can we consistently estimate parameters in the protection equation**;** (2) both of the above classification approaches are inconsistent with the PFS model and result in mis-classification of industries, with the likely outcome being inconsistent parameter estimates.

To see the first claim, let η_j be classification error; $\eta_j = I_j - I'_j$ where I_j is the true political organization dummy and I'_j is the political organization dummy used for estimation. Then, the following equation is essentially estimated as the protection equation:

$$\frac{t_j}{1+t_j} = \gamma \frac{z_j}{e_j} + \delta I'_j \frac{z_j}{e_j} + \zeta_j,$$

where $\zeta_j \equiv \delta \eta_j z_j / e_j + \epsilon_j$ is the composite error term. This suggests that we could find in-

struments for z_j/e_j (i.e., variables that are correlated with z_j/e_j but not correlated with ζ_j) only if η_j is mean zero and independent of z_j/e_j; otherwise, instruments for z_j/e_j would be unavailable, as any variable correlated with z_j/e_j will be correlated with $\delta\eta_j z_j/e_j$ and hence ζ_j. Importantly, as we will show below, the classification schemes used by GM and GB may result in classification error that is not mean zero and/or independent of z_j/e_j, thereby making their instruments invalid.[8]

Next, we discuss the second claim. Given the model and the menu auction equilibrium of the PFS model, it is easy to verify that the equilibrium campaign contribution schedule should be such that government welfare in equilibrium should equal the maximized value of the government objective function when industry i is not making any contributions at all. Thus, the equilibrium campaign contribution can be expressed as follows:[9]

$$B_i^*(\mathbf{p}^E) = -\left[\alpha W(\mathbf{p}^E) + \sum_{j\epsilon J_0, j\neq i} W_j(\mathbf{p}^E)\right] + \alpha W(\mathbf{p}(i)) + \sum_{j\epsilon J_0, j\neq i} W_j(\mathbf{p}(i)) = H_i(\mathbf{p}(i)) - H_i(\mathbf{p}^E),$$

where $B_i^*(\mathbf{p}^E)$ is the campaign contribution of industry i at the equilibrium domestic price vector $\mathbf{p}^E$, and $\mathbf{p}(i)$ is the vector of domestic price chosen by the government when industry i is not making any contributions. Since[10] $H_i(\mathbf{p}) = \alpha W(\mathbf{p}) + \sum_{j\epsilon J_0, j\neq i} W_j(\mathbf{p})$, it can be seen that equilibrium contributions are essentially the difference in the value of the function $H_i(\mathbf{p}) : R^N \rightarrow R$ between $\mathbf{p}(i)$ and $\mathbf{p}^E$.

Let $\mathbf{p}(t)$ be a path from $\mathbf{p}^E$ to $\mathbf{p}(i)$ as t goes from zero to unity. Since the line integral is path independent, we can choose this path as desired. In particular, we can choose it so that $\mathbf{p}(t) = \mathbf{p}^E + t\left[\mathbf{p}(i) - \mathbf{p}^E\right]$ so that $\mathbf{p}(t=0) = \mathbf{p}^E$, $\mathbf{p}(t=1) = \mathbf{p}(i)$, and $\mathbf{D}\mathbf{p}(t) = \left[\mathbf{p}(i) - \mathbf{p}^E\right]$.

[8] If their instruments for z_j/e_j are correlated with ζ_j, so are their instruments for I_j'; they used the same instruments as those for z_j/e_j.

[9] As the equilibrium bids of a lobby group equal its welfare of the lobby group less a constant, the constants will cancel out in the expression.

[10] Note that H has to be indexed by i.

Hence,

$$H_i(\mathbf{p}(i)) - H_i(\mathbf{p}^E) = \int_0^1 \frac{dH_i(\mathbf{p}(t))}{dt} dt = \int_0^1 DH_i(\mathbf{p}(t)) \bullet \mathbf{D}\mathbf{p}(t) dt, \tag{5}$$

where $DH_i(\mathbf{p}(t))$ is the vector of partial derivatives of the real valued function $H_i(.)$ with respect to the vector $\mathbf{p}$ and $D\mathbf{p}(t)$ is the vector of the derivatives of $\mathbf{p}$ with respect to t and $\bullet$ denotes their dot product.

The vector $\mathbf{p}(i)$ must take the same form as $\mathbf{p}^E$ (the domestic price chosen by the government when industry i is making contributions) but with α_L being replaced by $\alpha_L - \alpha_i$. Thus,

$$\frac{p_l(i) - p_l^*}{p_l(i)} = \frac{I(l \in J_0 - \{i\}) - (\alpha_L - \alpha_i)}{\alpha + \alpha_L - \alpha_i} \frac{z_l}{e_l}, \; p_l(i) = \frac{p_l^*}{1 - \frac{I(l \in J_0 - \{i\}) - (\alpha_L - \alpha_i)}{\alpha + \alpha_L - \alpha_i} \frac{z_l}{e_l}},$$

where I is an indicator function. Note the analogy with equation (1). This equation allows us to find $\mathbf{p}(i)$ from the data.

Now using the line integral defined in equation (5) and substituting for $DH_i(\mathbf{p}(t)) = \partial H_i(\mathbf{p})/\partial p_j$ and for $D\mathbf{p}(t) = \left[\mathbf{p}(i) - \mathbf{p}^E\right]$, we get

$$\begin{aligned} B_i^*(\mathbf{p}^E) &= \int_0^1 \sum_j \{(\alpha + \alpha_L - \alpha_i)(p_j(t) - p_j^*) \frac{\partial m_j(p_j(t))}{\partial p_j} \\ &\quad + [I(j \in L - \{i\}) - (\alpha_L - \alpha_i)] x_j(p_j(t))\} \{p_j(i) - p_j^E\} dt \\ &= \sum_j \{p_j(i) - p_j^E\} \int_0^1 \{-(\alpha + \alpha_L - \alpha_i) \frac{(p_j(t) - p_j^*)}{p_j(t)} \left(\frac{z_j(t)}{e_j(t)}\right)^{-1} \\ &\quad + [I(j \in L - \{i\}) - (\alpha_L - \alpha_i)]\} x_j(p_j(t)) \, dt. \end{aligned}$$

Thus, depending on α_i, α, α_L, $x_j(.)$, and z_j/e_j, $B_i^*(\mathbf{p}^E)$ can be small even for politically organized industries. This is evident from a numerical example. We assume there are 400 industries ($N = 400$), of which 200 are politically organized ($N_p = 200$). We set $p_i^* = 2.0$, $\alpha = 50.0$, $\alpha_L = 0.5$, $\alpha_i = \alpha_L/N$, and $x_i = 10000$. We also set $z_i/e_i = i/1000$ for industries $i = 1, ..., N_p$

which are politically organized and $z_{N_p+i}/e_{N_p+i} = i/1000$ for industries $N_p + i = N_p + 1, ..., N$ which are not politically organized.

Figure 1depicts the equilibrium campaign contributions for politically organized industries in the above example[11]. Notice that these contributions vary from 0 to 40 depending on the value of z/e. This illustrates the possibility that GM's classification based on a threshold of campaign contribution could well mis-classify industries with low campaign contribution and low z/e (high import penetration and/or high e) as politically unorganized. Hence, classifying political organization based on a uniform threshold, as done by GM and others, leads to classification error, which is *not* independent of z_j/e_j.

Figure 1 also shows that the equilibrium campaign contributions increase with z/e for politically organized industries[12]. In other words, for politically organized industries, campaign contributions are negatively correlated with import penetration. This is the opposite of the relationship used by GB to classify political organization. Our example therefore suggests that the correct organized industries may be the ones which GB classified as unorganized and vice versa, i.e., $I = 1 - I_{GB}$ where I_{GB} is the politically organization dummy by GB**.**

2.3 Another Look at GB and GM

Mis-classification on the part of GB has an important implication for the interpretation of their parameter estimates: although their estimates seem consistent with the PFS predictions (i.e., $\gamma_{GB} < 0$, $\delta_{GB} > 0$, and $\gamma_{GB} + \delta_{GB} > 0$), they are not, given the *correct* political organization dummy. This can be easily seen by noticing that when $I = 1 - I_{GB}$ is the political organization

[11] We did not plot the campaign contributions of politically unorganized industries becase they obviously are zero.

[12] The positive relationship between campaign contributions and z/e in the simulated model is in line with the PFS model; it predicts that for politically organized industries, protection is positively related to z/e. Hence, campaign contributions and z/e are likely to be positively related as long as greater campaign contributions tend to result in higher protection. However, a *negative* relationship between them is confirmed in the data; in the data used in GB and the data by Facchini et al. (2006) (who reconstructed the GM dataset). In this data, $\log(z/e)$ and log of campaign contributions per dollar of value added are found to be *negatively* correlated. We present these relationships in Figures 2 and 3, respectively.

dummy, the protection equation should be

$$\frac{t_j}{1+t_j} = (\gamma_{GB} + \delta_{GB}) \frac{z_j}{e_j} - \delta_{GB} (1 - I_{GB}) \frac{z_j}{e_j} + \epsilon_j.$$

This implies $\widehat{\gamma} = \gamma_{GB} + \delta_{GB} > 0$, $\widehat{\delta} = -\delta_{GB} < 0$, and $\widehat{\gamma} + \widehat{\delta} = \gamma_{GB} < 0$, which is clearly inconsistent with the PFS framework. In this way, classification error could have led GB to inadvertently conclude that the data supported the PFS model.

We next argue how the approach of GM might be giving a false positive coefficient estimate for z/e for the organized industries due to classification error. In our example, the correlations between protection, contributions and z/e are as in the data and though the true model is clearly inconsistent with the PFS framework, estimation of the protection equation using GM's classification approach provides results in support of the PFS model!

To show this, we generate protection levels that are decreasing in z/e for organized industries as well as for unorganized ones, which is consistent with our quantile estimation results but inconsistent with the PFS model. Specifically, we use the following equation:

$$\frac{t_j}{1+t_j} = \max \left\{ \beta_0 + \beta_1 \frac{z_j}{e_j} + \epsilon_j, 0.0 \right\}$$

where $(\beta_0, \beta_1) = (0.5, -2.5)$ for organized industries, $(\beta_0, \beta_1) = (0.05, -0.25)$ for unorganized ones, and $\epsilon_j \sim N(0, 0.02)$, $z_j/e_j = j/2000$, $j = 1, ..., 200$ for both. Organized industries have higher protection levels but for both organized and unorganized industries, protection falls with z/e. The total number of industries as well as the number of organized industries are set to be the same as the ones used earlier. As observed in the actual data, we set the campaign contributions to be positively correlated with the import penetration ratio[13]. Note that the positive correlation is consistent with a plausible scenario where greater protection requires

[13] See footenote 12.

greater campaign contributions. We normalize the campaign contributions to be equal to the protection measure $t/(1+t)$ and classify industries to be politically organized if the campaign contributions exceed the threshold of 0.25. This results in about 50% of the organized industries being wrongly classified as unorganized.

Using simulated data from the above exercise on protection and z/e, we estimate the protection equation by OLS[14] and then obtain $\widehat{\gamma} = -0.95$ (-9.87) and $\widehat{\delta} = 3.14$ (14.28) where t-statistics are in parentheses. The results are clearly in support of the PFS model even though the simulated model is not. The reason for the result is simple. On the one hand, the simulation setup makes z/e negatively correlated with protection. On the other hand, $I \times z/e$ is positively correlated with the protection measure since $I \times z/e$ is positive only for organized industries with high protection. This is because only the organized industries with low z/e are classified correctly and such industries tend to have high protection.

3 A Proposed Approach

3.1 Quantile Regression

Equation (4) and the restrictions on the coefficients have at least two implications. First, z/e has a negative effect on the level of protection for unorganized industries while it has a positive effect for organized ones. Second, given z/e, organized industries have higher protection. These implications lead to the following claim: given z/e, high-protection industries are more likely to be organized and thus the effect of an increase in z/e on protection tends to be that of organized industries.

The logic of this argument is illustrated in Figure 4 where the distribution of $t/(1+t)$ is plotted for given z/e. The variation of $t/(1+t)$ given z/e occurs for two reasons. First, because

[14] Both z/e and the political organization are constructed to be exogenous. Since the classificaton error is correlated with z/e and mean nonzero, we cannot correct for the bias by any instruments as discussed earlier.

some industries are organized while others are not and these two behave differently, and second, because of the error term. As a result, the distribution of $t/(1+t)$ comes from a mixture of two distributions, namely those for the politically organized industries and those for the unorganized. These two distributions for some given values of z/e are plotted in Figure 4. The two dashed lines give the conditional expectations of $t/(1+t)$ for the organized and unorganized industries as a function of z/e. In line with the PFS model, the two lines start at the same vertical intercept point and the line for the organized industries is increasing while the other is decreasing in z/e. For each z/e, if we look at the industries with high $t/(1+t)$, they tend to be the politically organized ones. Thus, at high quantiles, the relationship between $t/(1+t)$ and z/e should be that for organized industries, i.e., should be increasing as depicted by the solid line labelled the 90th quantile in Figure 4.

The relevant proposition (Proposition 1) can be found in Appendix 1. The proposition essentially states that in the quantile regression of $t/(1+t)$ on z/e, the coefficient on z/e should be close to $\gamma+\delta>0$ at the quantiles close to $\tau=1$. To examine this, we use quantile regression (Koenker and Bassett, 1978) and estimate the following equation:

$$Q_T(\tau|Z) = \alpha(\tau) + \beta(\tau) Z/10000, \tag{6}$$

where τ denotes quantile, $T=t/(1+t)$, $Z=z/e$, and $Q_T(\tau|Z)$ is the conditional τ-th quantile function of T. If the PFS model is correct, $\beta(\tau)$ converges to $(\gamma+\delta)>0$ as τ approaches its highest level of unity from below.

3.2 IV Quantile Regression

In the quantile regression, Z is assumed to be an exogenous variable. However, Z is likely to be endogenous as discussed in the literature (e.g., Trefler, 1993) and hence the parameter estimates

of the quantile regression are likely to be inconsistent. It is therefore important to allow for the potential endogeneity of Z. We formally show that even in the presence of this endogeneity, the main prediction of the PFS model in terms of our quantile approach does not change. The relevant proposition (proposition 2), an analogue of proposition 1, is presented in Appendix 1. To test the prediction in the presence of possible endogeneity of Z, we estimate the following equation by using IV quantile regression (Chernozhukov and Hansen, 2004a; 2004b; 2005; 2006):

$$P\left(T \leq \alpha\left(\tau\right) + \beta\left(\tau\right) Z/10000 | W_1\right) = \tau, \tag{7}$$

where W_1 is a set of instrumental variables.

Importantly, nowhere in equations (6) and (7) is the political organization dummy present; these equations involve only variables that are readily available. This way our approach does not require classification of industries in any manner and as a result, we can avoid any biases due to mis-classification.

An issue that we need to deal with is the endogeneity of political organization. We do so by controlling for capital-labor ratios, which is essentially equivalent to allowing the capital-labor ratio to be a determining factor for the probability of political organization. This is motivated by Mitra (1999) who provides a theory of endogenous lobby formation. His model predicts that among others, industries with higher levels of capital stock are more likely to be politically organized.

Even after controlling for the capital-labor ratio, there still could remain a correlation between the error term of the equation determining political organization and the error term of equation (4). Since our method is not subject to classification error, one of the main sources of correlation between the error terms in the two equations in GM and other studies, we are

less subject to this criticism[15]. Moreover, as long as the error term of the equation determining political organization and that of the protection equation are positively correlated, or as long as the negative correlation is not too strong, our quantile IV procedure will still be consistent. This is because only when the negative correlation in the errors is very strong (large positive shocks in protection are correlated with shocks that make an industry unorganized) could the most protected industries be unorganized ones. Plausible scenarios actually would suggest the opposite.

4 Estimation

4.1 Data

We use part of the data used in Gawande and Bandyopadhyay (2000).[16] The data consist of 242 four-digit SIC industries in the United States. In the dataset, the extent of protection, t, is measured by the nontariff barrier (NTB) coverage ratio. z is measured as the inverse of the ratio of total imports to consumption scaled by $10,000$. e is derived from Shiells et al. (1986) and corrected for measurement error by GB. See GB for more details along with the sample statistics of the variables. Of particular note about the data is that 114 of 242 industries (47%) have zero protection, suggesting the potential importance of the corner solution outcome of T in the quantile regression.

We first examine the relationship between the protection measure T and Z using linear regression (OLS). Column 1 row OLS/IV of Table 1 shows that they are negatively and insignificantly correlated in the data**.** After we control for two exogenous variables used in GB, tariffs on intermediate goods ($INTERMTAR$) and NTB coverage of intermediate goods ($INTERMTB$),

[15] In those studies, classification error enters both the disturbance term of the equation determining the political organization and the disturbance term of the protection equation. Thus, classification error necessarily resulted in correlation between the disturbance terms.

[16] We are grateful to Kishore Gawande for kindly providing us with the data.

T and Z remain negatively correlated (Column 2 row OLS/IV). To address the potential endogeneity of Z we use IV estimation. We use three instruments that are found in GB to be strongly correlated with Z: the fraction of employees classified as scientists and engineers ($SCIENTISTS$), the fraction of employees classified as managerial ($MANAGERS$), and cross price elasticity of imports ($CROSSELI$). Again, we find that T and Z are negatively related (Column 3 row OLS/IV). Controlling further for the capital labor ratio does not change the negative relationship (Column 4 row OLS/IV). Next, we examine their relationship at various quantiles, with special attention to high quantiles.

4.2 Quantile Regression

Column 1 of Table 1 presents the estimation results of equation (6)[17]. The results do not appear to provide any supporting evidence for the PFS model; the null hypothesis that $\beta(\tau) \leq 0$ cannot be rejected at high quantiles (in fact, at all quantiles) in favor of the one-sided alternative that $\beta(\tau) > 0$. Moreover, the point estimates indicate that the $\beta(\tau)$ are all negative at high quantiles contrary to the PFS prediction and decrease as τ goes from 0.4 to 0.9.

α and β are estimated to be zero at the 0.1-0.4 quantiles, suggesting that the corner solution ($T = 0$) greatly affects the estimates at lower quantiles. From this evidence, it is conjectured that the existence of corners also affects the estimates at the mean. Thus, findings based on the linear model (i.e., equation (3)) in GB, Bombardini (2005), and others are likely to be subject to bias due to the corner solution problem. In contrast, our method does not suffer from the problem, since the focus is mainly on the higher quantiles where the effect of corner solution is minimal[18].

Following GB, we also control for $INTERMTAR$ and $INTERMNTB$. As Column 2 of

[17] We used stata for all the estimation exercises in this paper except for the IV quantile regression.

[18] Of course, this advantage comes with a cost. That is, the quantile approach does not allow us to estimate the structural parameters γ and δ separately.

Table 1 shows, our main findings do not change; the null hypothesis that $\beta(\tau) \leq 0$ cannot be rejected at high quantiles, and at the 0.7th quantile the estimate is statistically significant at 5% level. α and β are found to be zero at the 0.1 and 0.2 quantiles, again suggesting the importance of corner solutions.

4.3 IV Quantile Regression

Column 3 of Table 1 presents the estimation results of equation (7)[19]. As in the quantile regression, we cannot reject the null hypothesis that $\beta(0.9) \leq 0$ in favor of the one-sided alternative. The point estimates are not favorable for the PFS model, either; even after correcting for the endogeneity of Z, the estimate of β at the highest quantile is not positive as required by the PFS model. As presented in Column 4 of Table 1, qualitatively similar results are obtained when we further control for the capital labor ratio. For a robustness check, we also use a varied set of instruments: (1) 17 GB's instruments available to us, $INTERMTAR$ and $INTERMNTB$, and their squared terms, (2) instruments in (1) plus their interaction terms, (3) $SCIENTISTS$ only, (4) $MANAGERS$ only, and (5) $CROSSELI$ only. We also examine specifications with/without capital-labor ratios. Our main findings appear to be robust; regardless of which instrument we use and whether we control for capital-labor ratios, the null hypothesis at the highest quantile cannot be rejected. Moreover, the point estimates of $\beta(\tau)$ are all negative at high quantiles[20].

4.4 Alternative Specification

For a further robustness check, we examine a different model specification. Note that by moving e_j to the left hand side of the equation, equation (2) can be re-expressed as:

$$\frac{t_j}{1+t_j} e_j = \gamma z_j + \delta I_j z_j.$$

[19] All the IV quantile regression estimation is done by using a MATLAB code written by Christian Hansen (available at http://faculty.chicagogsb.edu/christian.hansen/research).

[20] For all these results, see Imai et al. (2008).

This provides a basis of an alternative model for our quantile-based test: for quantile regression,

$$Q_{Te}(\tau|z) = \alpha(\tau) + \beta(\tau) z/10000, \tag{8}$$

where $T_e = te/(1+t)$, $Q_{Te}(\tau|z)$ is the conditional τ-th quantile function of T_e; for IV quantile regression,

$$P(T_e \leq \alpha(\tau) + \beta(\tau) z/10000|W_2) = \tau, \tag{9}$$

where W_2 is a set of instrumental variables. As the dependent variable now involves elasticity, we exclude $CROSSELI$ from the set of instrumental variables used earlier.

As presented in Table 2, the results resemble those presented before; point estimates of β at high quantiles are all negative. Our main results therefore do not seem to be driven by the model specification. We also examine the robustness of our results to a varied sets of instruments. Though we tried hard to get the point estimate of β at high quantiles to be positive, we were able to do so in only one case. When the set of instruments included all GB's instruments available to us, except several elasticity-related variables, their squared terms, and their interaction terms, could we get the point estimate of β at 0.9 quantile to be positive[21]. However, even in this case, the estimate was not significant even at the 10% level and hence this could not be seen as strong support of the PFS model.

In Figure 5 and 6, we plot the relationship between the inverse import penetration ratio and the protection measure. In both specifications, with and without the elasticity on the RHS, the relationship is negative, especially if we look at high quantiles of the protection measure, for all values of inverse import penetration ratio. In both figures we can see that the relationship between the inverse import penetration ratio and the protection measure is quite different from the one shown in Figure 4.

[21] The results are available on request.

5 Discussion

There are several possible explanations for our results. The first possibility is heteroskedasticity. If the error term has higher variance when the industry is unorganized, i.e.,

$$\varepsilon_j = w_j + (1 - I_j)\,\zeta_j, \tag{10}$$

then unorganized industries would have error terms with much higher variance. As a result, unorganized industries would dominate in high quantiles as well as in low quantiles, whereas the organized industries would be found mostly around the median. Hence, at high quantiles, the negative quantile regression coefficients correspond to γ, which is negative, and not $\gamma + \delta > 0$. One might think that this could explain the presence of negative slope coefficients in the higher quantiles. While this possibility cannot be completely ruled out, it is hard to reconcile with the fact that almost all industries have positive campaign contributions and both GM and GB report that more than half of the industries are organized, so that it is reasonable to think that a significant fraction of the industries are likely to be organized. If this is so, then it is surprising to find that the slope coefficients of the quantile regressions are negative at almost all quantiles except for the zeros at low quantiles, which comes from the corners. Could hetroskedasticity in terms of z/e account for our results? Simple forms of this clearly cannot. If the variance of the error term increases in z/e, one could actually get a false positive in favor of the PFS model. If the variance of the error term decreases in z/e, then one could obtain the reverse pattern with the slope coefficient rising for lower quantiles. We find neither of these patterns in the data.

Second, the small sample may make it difficult for our approach to provide evidence favoring the PFS model. This problem can be overcome by using more disaggregated data, although such an exercise is beyond the scope of the current paper.

Third, note that when classification error is considered, our results are consistent with part

of GB's results and not inconsistent with those of GM. If political organization were correctly assigned in GB as argued earlier, then GB might also have found no support for the PFS model. Recall that in our example where we computed the relationship between the equilibrium campaign contribution and z/e for organized industries, it was positive instead of negative. If the positive relationship holds in reality, we argued that the industries that were originally classified as organized should be classified as unorganized and vice versa. Then, the true results of the GB estimation should be $\widehat{\gamma} > 0$, $\widehat{\delta} < 0$ and $\widehat{\gamma} + \widehat{\delta} < 0$, part of which (i.e., $\widehat{\gamma} + \widehat{\delta} < 0$) is indeed consistent with our quantile and quantile IV results (i.e., $\beta(\tau) < 0$ for $\tau = 0.9$). We also argued that mis-classification due to the GM's approach could result in evidence favoring the PFS model even when the true model is inconsistent with the PFS framework. This suggests that the GM's results are not inconsistent with our results against the PFS model.

It is worth explaining why we chose to take a quantile (IV) approach rather than some other approach, even though it does not provide estimates of the structural parameters. Given current techniques, there may be another way to satisfactorily estimate the model that does not require classification ex ante of industries into the two groups. This would involve the estimation of GM setup but with organization treated as unobservable.[22] The issue in this case would be identification. The exclusion restriction for identification would require that at least one exogenous variable that determines z/e (i.e., instruments for z/e) does not enter in the political organization equation, and thus does not influence tariffs directly. But such an instrument is likely to be hard to find.

[22] This is equivalent to a switching regression approach where the outcome of the switching regression is not observable. One may also think of this as an unobserved heterogeneity model where the unobserved types are allowed to be endogenous and are estimated in addition to the tariff equation.

6 Conclusion

In this paper, we proposed and implemented a new test of the PFS model that does not require data on political organizations. To our surprise, the findings so far are not supportive of the PFS model. Clearly, more work is needed on this. One fruitful research avenue might be to look at countries other than the United States using our approach as it does not require data on political organization. Another research avenue is to use more disaggregated data so that our approach can provide statistically more clear-cut evidence. Finally, other predictions of the PFS model such as those on equilibrium contribution levels predicted by the PFS model relative to actual contributions need to be tested, and we hope to do so in future work.

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Appendix 1: Quantile Regression

Proposition 1 (***Quantile Regression***) *Assume that* (1) Z_j *is bounded below by a positive number, i.e. there exists* $\underline{Z} > 0$ *such that* $Z_j \geq \underline{Z}$, (2) ϵ_j *has a smooth density function which has support that is bounded from above and below,* (3) ϵ_j *is independent of both* Z_j *and and* I_j, *and* (4) $\delta > 0$. *Then, for* τ *sufficiently close to* 1, τ *quantile conditional on* Z_j *can be expressed as*

$$Q_T(\tau|Z_j) = F_\epsilon^{-1}(\tau') + (\gamma + \delta)Z_j \tag{11}$$

where

$$\tau' = \frac{\tau - P(I_j = 0)}{P(I_j = 1)}. \tag{12}$$

Proof. For any $0 < \tau < 1$, for any $\overline{T} > 0$,

$$P\left(T_j \leq \overline{T}|Z_j\right) = P\left(\epsilon_j \leq \overline{T} - \gamma Z_j\right) P(I_j = 0) + P\left(\epsilon_j \leq \overline{T} - (\gamma + \delta)Z_j\right) P(I_j = 1). \tag{13}$$

Let

$$\overline{T} = F_\epsilon^{-1}(\tau') + (\gamma + \delta)Z_j \tag{14}$$

where

$$\tau' = \frac{\tau - P(I_j = 0)}{P(I_j = 1)}, \text{ or } \tau = P(I_j = 0) + \tau' P(I_j = 1). \tag{15}$$

From equation (15), we can see that for $\tau \nearrow 1$, $\tau' \nearrow 1$ as well. Hence, for τ sufficiently close to 1, we have τ' close enough to 1 such that

$$F_\epsilon^{-1}(\tau') + \delta Z_j \geq F_\epsilon^{-1}(\tau') + \delta\underline{Z} > F_\epsilon^{-1}(1).$$

Hence,

$$\overline{T} = F_{\epsilon}^{-1}\left(\tau'\right) + (\gamma + \delta)Z_j > F_{\epsilon}^{-1}\left(1\right) + \gamma Z_j$$

and

$$P\left(\epsilon_j \leq \overline{T} - \gamma Z_j\right) \geq P\left(\epsilon_j \leq F_{\epsilon}^{-1}\left(1\right)\right) = 1$$

which results in

$$P\left(\epsilon_j \leq \overline{T} - \gamma Z_j\right) = 1. \tag{16}$$

Substituting equations (14), (15), and (16) into (13), we obtain

$$\begin{aligned} P\left(T_j \leq \overline{T} | Z_j\right) &= P(I_j = 0) + P\left(\epsilon_j \leq F_{\epsilon}^{-1}\left(\tau'\right)\right) P\left(I_j = 1\right) \\ &= P(I_j = 0) + \tau - P\left(I_j = 0\right) = \tau. \end{aligned}$$

Therefore, for τ sufficiently close to 1,

$$Q_T\left(\tau | Z_j\right) = \overline{T} = F_{\epsilon}^{-1}\left(\tau'\right) + (\gamma + \delta)Z_j.$$

■

We make two remarks on the assumptions. First, we assume that ϵ_j has bounded support (assumption 2). This assumption is reasonable since the protection measure is usually derived from the NTB coverage ratio (e.g., Goldberg and Maggi, 1999; Gawande and Bandyopadhyay, 2000) and therefore it is clearly bounded above and below. Second, we assume that ϵ_j is independent of both Z_j and and I_j (assumption 3). This is rather a strong assumption and will be relaxed next. In particular, we allow Z_j to be correlated with ϵ_j.

Assume the model is as follows:

$$\begin{aligned} T_j^* &= \gamma Z_j + \epsilon_j \text{ if } I_j = 0 \\ T_j^* &= (\gamma + \delta) Z_j + \epsilon_j \text{ if } I_j = 1 \end{aligned}$$

where $Z_j = g(W_j, v_j)$ and W_j is an instrument vector and v_j is a random variable independent of W_j. We will show that $\beta(\tau) \to (\gamma + \delta) > 0$ as $\tau \nearrow 1$.

Let us define u_j as follows:

$$\epsilon_j = E[\epsilon_j | v_j] + u_j, \quad u_j \equiv \epsilon_j - E[\epsilon_j | v_j],$$

where u_j is assumed to be i.i.d. distributed. For the sake of simplicity, we assume that both u_j and $E[\epsilon_j | v_j]$ are uniformly bounded, hence so is ϵ_j. Furthermore,

$$T_j = \max\left\{T_j^*, 0\right\}.$$

Then, for $I_j = 0$ the model satisfies the assumptions A1-A5 of Chernozhukov and Hansen (2006). Similarly for $I_j = 1$. Therefore, from Theorem 1 of Chernozhukov and Hansen (2006), it follows that

$$P\left(T \leq F_\epsilon^{-1}(\tau) + \gamma Z_j | W_j\right) = \tau \text{ for } I_j = 0,$$

and

$$P\left(T \leq F_\epsilon^{-1}(\tau) + (\gamma + \delta) Z_j | W_j\right) = \tau \text{ for } I_j = 1.$$

Proposition 2 (***Quantile IV***) *Assume that Z_j is bounded below by a positive number, i.e.*

there exists $\underline{Z} > 0$ *such that* $Z_j \geq \underline{Z}$. *Then, for* τ *sufficiently close to* 1,

$$P\left(T \leq F_\epsilon^{-1}\left(\tau'\right) + (\gamma + \delta) Z_j | W_j\right) = \tau,$$

where

$$\tau' = \frac{\tau - P\left(I_j = 0\right)}{P\left(I_j = 1\right)}.$$

Proof.

$$\tau' = \frac{\tau - P\left(I_j = 0\right)}{P\left(I_j = 1\right)}, \text{ or } \tau = P\left(I_j = 0\right) + \tau' P\left(I_j = 1\right).$$

Then,

$$\begin{aligned}
& P\left(T_j \leq F_\epsilon^{-1}\left(\tau'\right) + (\gamma + \delta) Z_j | W_j\right) \\
= \; & P\left(\epsilon_j + \gamma Z_j \leq F_\epsilon^{-1}\left(\tau'\right) + (\gamma + \delta) Z_j | W_j\right) P\left(I_j = 0\right) \\
& + P\left(\epsilon_j + (\gamma + \delta) Z_j \leq F_\epsilon^{-1}\left(\tau'\right) + (\gamma + \delta) Z_j | W_j\right) P\left(I_j = 1\right) \\
= \; & P\left(\epsilon_j \leq F_\epsilon^{-1}\left(\tau'\right) + \delta Z_j | W_j\right) P\left(I_j = 0\right) + P\left(\epsilon_j \leq F_\epsilon^{-1}\left(\tau'\right) | W_j\right) P\left(I_j = 1\right) \\
= \; & P\left(\epsilon_j \leq F_\epsilon^{-1}\left(\tau'\right) + \delta Z_j | W_j\right) P\left(I_j = 0\right) + \tau' P\left(I_j = 1\right).
\end{aligned}$$

From the definition of τ', for $\tau \nearrow 1$, $\tau' \nearrow 1$ as well. Because ϵ is uniformly bounded, for τ sufficiently close to 1, we have τ' close enough to 1 such that

$$F_\epsilon^{-1}\left(\tau'\right) + \delta \underline{Z} > F_\epsilon^{-1}\left(1\right).$$

Hence,

$$P\left(\epsilon_j \leq F_\epsilon^{-1}\left(\tau'\right) + \delta Z_j | W_j\right) = 1.$$

Therefore,

$$P\left(T_j \leq F_\epsilon^{-1}\left(\tau'\right) + \left(\gamma + \delta\right) Z_j | W_j\right) = P(I_j = 0) + \tau' P\left(I_j = 1\right) = \tau.$$

It follows that for τ sufficiently close to 1,

$$P\left(T \leq F_\epsilon^{-1}\left(\tau'\right) + \left(\gamma + \delta\right) Z_j | W_j\right) = \tau.$$

■

Table 1: Quantile Regression and IV Quantile Regression Results

	(1)		(2)		(3)		(4)	
τ (quantile)	$\alpha(\tau)$	$\beta(\tau)$	$\alpha(\tau)$	$\beta(\tau)$	$\alpha(\tau)$	$\beta(\tau)$	$\alpha(\tau)$	$\beta(\tau)$
0.1	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.004)	0.000 (0.000)	0.000 (0.015)	0.000 (0.000)
0.2	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.009)	0.000 (0.000)	−0.027 (0.019)	11.90 (14.83)
0.3	0.000 (0.000)	0.000 (0.000)	−0.026 (0.001)	−0.099 (0.011)	−0.018 (0.018)	−17.81 (23.37)	−0.032 (0.019)	−4.810 (9.368)
0.4	0.000 (0.000)	0.000 (0.000)	−0.029 (0.002)	−0.020 (0.007)	−0.021 (0.019)	−7.160 (12.05)	−0.036 (0.026)	−4.740 (9.130)
0.5	0.002 (0.003)	−0.003 (0.025)	−0.026 (0.010)	−0.032 (0.035)	−0.019 (0.026)	−7.180 (14.49)	−0.040 (0.043)	−8.320 (18.37)
0.6	0.028 (0.015)	−0.045 (0.103)	−0.053 (0.025)	−0.082 (0.075)	−0.033 (0.026)	−8.500 (13.08)	−0.075 (0.038)	−4.150 (8.596)
0.7	0.077 (0.018)	−0.126 (0.123)	−0.044 (0.023)	−0.125 (0.063)	−0.043 (0.027)	−3.890 (6.624)	−0.056 (0.037)	−3.610 (6.416)
0.8	0.157 (0.036)	−0.258 (0.241)	−0.046 (0.029)	−0.145 (0.082)	−0.029 (0.049)	−4.970 (7.401)	−0.057 (0.077)	−7.360 (11.50)
0.9	0.308 (0.040)	−0.505 (0.343)	−0.001 (0.050)	−0.225 (0.208)	0.079 (0.070)	−5.780 (7.446)	0.090 (0.152)	−10.90 (13.81)
OLS/IV	0.085 (0.009)	−0.165 (0.219)	−0.044 (0.018)	−0.123 (0.194)	−0.027 (0.025)	−2.131 (1.533)	−0.056 (0.027)	−1.826 (0.451)
GB Controls	No		Yes		Yes		Yes	
K/L	No		No		No		Yes	

Note: Columns (1) and (2) provide the estimation results of quantile regressions (equation (6)) and OLS, and columns (3) and (4) the estimation results of IV quantile regressions (equation (7)) and the IV estimation method. Standard errors are in parentheses. For IV quantile regressions, standard errors are calculated by 200 bootstrap resampling. GB Controls and K/L indicate whether $INTERMTAR$ and $INTERMNTB$ are controlled for and whether capital-labor ratios are controlled for, respectively. For details of these variables, see Gawande and Bandyopadhyay (2000).

Table 2: Quantile Regression and IV Quantile Regression Results: An Alternative Specification

	(1)		(2)		(3)		(4)	
τ (quantile)	$\alpha(\tau)$	$\beta(\tau)$	$\alpha(\tau)$	$\beta(\tau)$	$\alpha(\tau)$	$\beta(\tau)$	$\alpha(\tau)$	$\beta(\tau)$
0.1	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.006)	0.000 (0.478)	0.000 (0.025)	0.000 (2.896)
0.2	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.018)	0.000 (6.696)	−0.051 (0.034)	−3.800 (11.16)
0.3	0.000 (0.000)	0.000 (0.000)	−0.044 (0.003)	−0.019 (0.013)	−0.026 (0.022)	−25.00 (23.64)	−0.047 (0.030)	−18.30 (18.50)
0.4	0.000 (0.000)	0.000 (0.000)	−0.058 (0.003)	−0.035 (0.012)	−0.043 (0.031)	−18.33 (21.26)	−0.067 (0.038)	−8.200 (20.54)
0.5	0.002 (0.005)	−0.004 (0.041)	−0.063 (0.017)	−0.052 (0.060)	−0.015 (0.046)	−17.51 (22.92)	−0.070 (0.059)	−11.45 (22.82)
0.6	0.046 (0.021)	−0.065 (0.153)	−0.070 (0.032)	−0.099 (0.101)	−0.014 (0.066)	−22.65 (23.72)	−0.104 (0.085)	−14.95 (21.59)
0.7	0.133 (0.025)	−0.189 (0.188)	−0.071 (0.045)	−0.176 (0.140)	−0.012 (0.076)	−9.150 (17.33)	−0.055 (0.101)	−8.850 (18.90)
0.8	0.236 (0.048)	−0.335 (0.405)	−0.068 (0.037)	−0.220 (0.135)	0.018 (0.091)	−12.59 (12.08)	0.030 (0.114)	−13.55 (15.83)
0.9	0.454 (0.061)	−0.645 (0.704)	−0.029 (0.103)	−0.350 (0.531)	0.133 (0.123)	−8.770 (6.242)	0.067 (0.243)	−10.70 (12.98)
OLS/IV	0.126 (0.014)	−0.119 (0.279)	−0.068 (0.027)	−0.072 (0.247)	−0.004 (0.060)	−5.599 (3.274)	−0.044 (0.078)	−5.041 (3.739)
GB Controls	No		Yes		Yes		Yes	
K/L	No		No		No		Yes	

Note: Columns (1) and (2) provide the estimation results of quantile regressions (equation (8)) and OLS, and columns (3) and (4) the estimation results of IV quantile regressions (equation (9)) and the IV estimation method. Standard errors are in parentheses. For IV quantile regressions, standard errors are calculated by 200 bootstrap resampling. GB Controls and K/L indicate whether $INTERMTAR$ and $INTERMNTB$ are controlled for and whether capital-labor ratios are controlled for, respectively. For details of these variables, see Gawande and Bandyopadhyay (2000).

Figure 1: Equilibrium Campaign Contribution of Politically Organized Industries

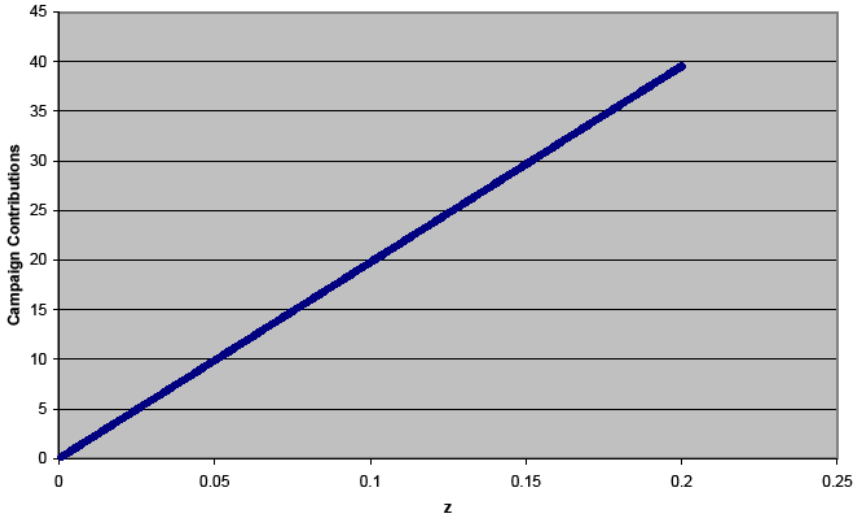

Figure 2: Campaign Contributions and z/e

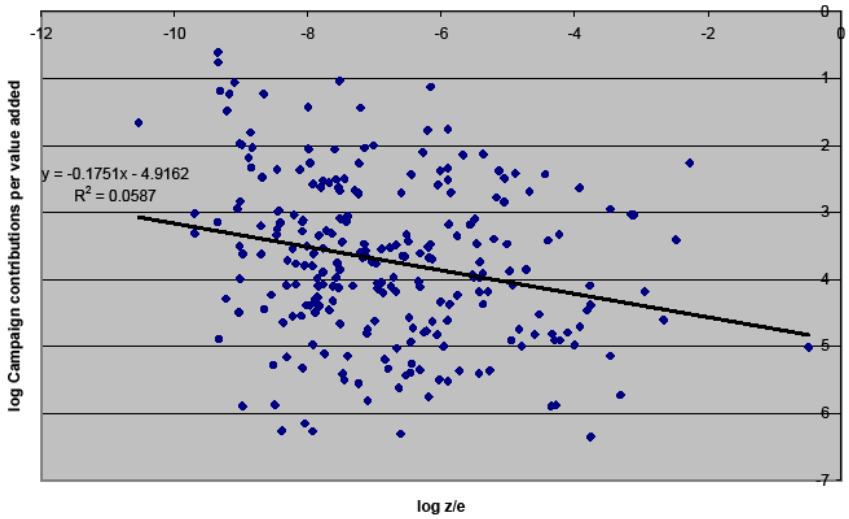

Figure 3: log z/e and log campaign contributions

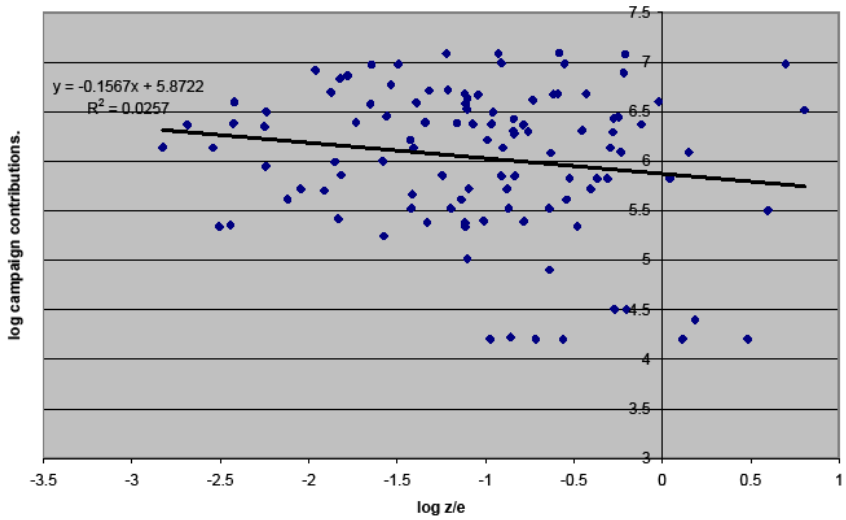

Figure 4: PFS Protection Equation: $\frac{t}{1+t} = \beta + \gamma \frac{z}{e} + \delta I \frac{z}{e} + u$

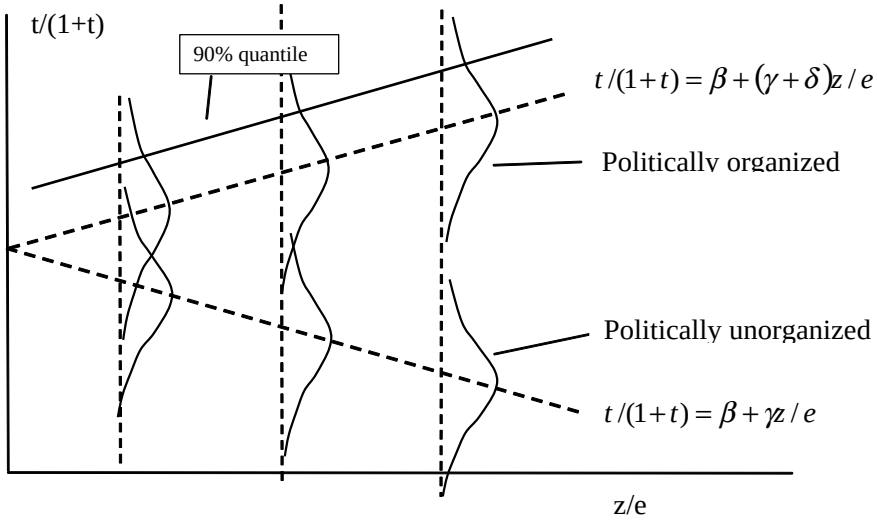

Figure 5:Plot of inverse import penetration (z/e) ratio and protection measure NTB/(1+NTB)

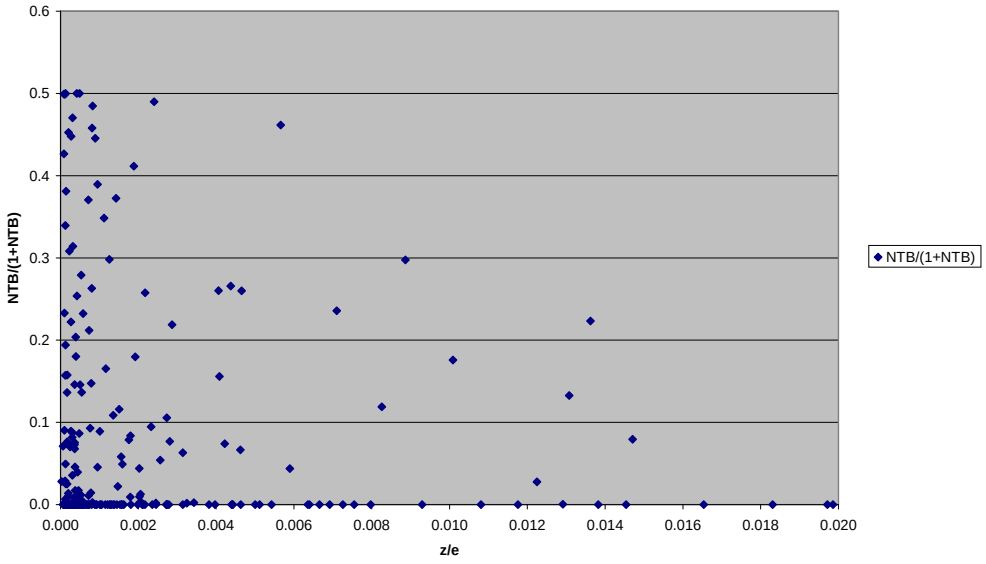

Figure 6:Plot of inverse import penetration ratio z and protection measure [NTB/(1+NTB)]*e