Protection for Sale or Surge Protection?

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Abstract

This paper asks whether the results obtained from using the standard approach to testing the influential Grossman and Helpman "protection for sale" model of political economy might arise from a simpler setting. A model of imports and quotas with protection occuring in response to import surges, but only for organized industries, is simulated and shown to provide parameter estimates consistent with the protection for sale framework. This suggests that the standard approach may be less of a test than previously thought.

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1 Introduction

The Grossman and Helpman (1994) model of "Protection for Sale" (PFS) has become the most influential one in the political economy of trade over the past decade both theoretically and empirically. The PFS model provides a clear-cut prediction on the relationship between the level of protection and the import penetration ratio: protection is positively related to the import penetration for politically unorganized industries, but negatively for politically organized ones. A number of studies have tested this prediction. The first few studies are Goldberg and Maggi (1999) and Gawande and Bandyopadhyay (2000) (GM and GB respectively from here on). While they used the U.S. data, Mitra et al. (2002) and McCalman (2004) used Turkish and Australian data, respectively. Findings in these studies are consistent with the key prediction made by the PFS model.

Recently, researchers have extended the original PFS model in various directions. For example, Bombardini (2004) incorporated firm size into the protection equation. Gawande and Krishna (2004) incorporated foreign lobbies as well as domestic ones while Gawande and Krishna (2005) added lobbying of both upstream and downstream producers. Matschke and Sherlund (2006) added labor unions and labor immobility to the model. Facchini et al. (2006) constructed and estimated the quota version of the PFS model. These extensions leave the basic predictions of the PFS model unchanged and seem to provide more evidence in support of the PFS model.

Despite much evidence favoring the PFS model, the extent to which past studies did a stringent job of testing the PFS model is an open question. This results from the fact that most past studies did not formally test the PFS model. Past studies simply estimated the protection equation derived by the PFS model and examined whether the signs of the key coefficients follow the pattern predicted by the model. However, such an estimation exercise was typically conducted in the absence of a well-specified alternative model.[1] Therefore, it is possible that some alternative model, not the PFS model, may be the correct one.

This paper first shows that a simple setting, where government provides protection for politically organized industries when imports exceed a trigger level (what we call the "Surge Protection" model), is also consistent with the estimates in the literature. In particular, we simulate a simple equilibrium model of domestic consumption and imports, where imports in the politically organized sector are subject to an exogenously and uniformly set quota: if import demand exceeds this quota either because of supply or demand shocks, then there is pressure for protection. This pressure is more likely to get transformed into actual protection if the sector is organized. In fact, we take an extreme position here and assume that the sector is protected only if it is organized. Political organizations are set exogenously and randomly. Obviously, in this simple model, there is no strict protection for sale effect. Parameters are set so the simulated data roughly match the basic statistics of the actual data. Then, we estimate the key equation of the PFS model on the artificial data following the procedures by GM and GB. We obtain coefficient estimates that are consistent with the PFS paradigm. Similar findings are obtained in the analogous tariff-setting version of the model. Our results therefore suggest that estimation of the protection equation, even though sufficient for all the structural parameters, is not enough to test the validity of the PFS model against alternatives such as the simple "Surge Protection"model.

[1] Notable exceptions are Eicher and Osang (2002) and Gawande (1998) who formally tested the PFS model. However, in our view, the results are far from satisfactory. Eicher and Osang (2002) is a good example to make our point. They compared the tariff equation derived by the PFS model and that of the Tariff Function approach by using the Davidson-McKinnon non-nested hypothesis test, concluding that the results are in favor of the PFS model. While this kind of formal approach could be very helpful in making model comparisons, we believe the simplistic approach traditionally being followed can be more misleading than helpful. Even though the tariff equation which they estimated is sufficient for the estimation of the structural parameters, it is a small part of the entire PFS model or the Tariff Function model. Hence, testing the tariff equation only could lead to misleading results; to correctly execute the non-nested model specification tests, one needs to impose all the restrictions of the model on the data. This involves the full solution of the model, which is difficult for the PFS model, and to the best of our knowledge, has not been done in the literature.

To make our point as clear as possible, we use the "Surge Protection" model because to us it seems a simple way to model the institutional side of trade policy. In all countries, membership in the GATT/WTO restricts the ability of countries to protect domestic industries except under certain circumstances, for example, as a safeguard measure, or under anti-dumping law, or in the 80's as a voluntary export restraint. Obtaining protection then involves going through the channels needed to **acquire the status of an exceptional circumstance**. **This is more likely to occur when an industry is threatened with competition.** Given that protection is industry wide, this suggests that organized sectors are likely to have differential access to the protection apparatus relative to unorganized ones so that the mechanism of how protection is set for them might well differ from that of other sectors. This idea is captured in the simplest form by our model. We abstract ourselves from the intricacies of the actual data by using the artificial data for estimation. In that sense, the paper is in the same spirit as the "counterfactual estimation" in Keller (1998), where he created an artificial trade pattern that was not related to R&D spillovers and "verified" the model of international R&D spillovers.

Our results help explain some puzzle in previous work. All studies we are aware of found that political economy factors seem to matter little; the estimate of the weight on contribution relative to welfare (derived from the estimated coefficients) is typically very low.[2] However, given that contributions are small relative to their effects on firm profits and welfare, one would expect a reasonably high weight on contributions, because in the

[2] The estimated low weight on contributions might be partly attributed to the fact that data on contributions is not actually used in the estimation procedure of either GM or GB. The only paper we know that actually used contribution data directly is Kee et al. (2005). They assumed that lobbies have a first mover advantage over government as is the norm in this literature, and looked at foreign lobbying in the US for preferential access (which reduces tariffs to zero or leaves them unchanged) with world prices given. As a result, the welfare cost to the US is the loss of tariff revenue. This loss is, in essence, compared to the contributions received to obtain a weight on contributions relative to welfare. Their results suggest that the government seems to value contributions five times more than welfare: a vast difference from the results using either the GM or GB approach!

PFS model, equilibrium contributions by a group keep the government as well off as in the absence of the lobby group, i.e., just compensate the government.[3] Our results simply suggest that the supposedly low values for the weight on contribution obtained by past studies can be thought of as just a misinterpretation of the parameter estimates; a simpler model than the PFS framework yields similar estimated coefficients, but without the strict PFS interpretation.

Given that findings in the literature favor the PFS model *and* the "Surge Protection" model, one question naturally arises: which model is more plausible? Importantly, the PFS model is not supported by a recent study by Imai et al. (2007). **They use quantile regression and IV quantile regression to take a look at the relationship between the level of protection and the inverse import penetration ratio at various quantiles conditional on the inverse import penetration ratio. Using the data from Gawande and Bandyopadhyay (2000), they provide evidence that at low conditional quantiles of protection measure, the estimated coefficient on the inverse import penetration ratio is zero, and it becomes negative at higher conditional quantiles**[4]. Their results are inconsistent with the PFS model, as at high quantiles of protection where industries should be mostly politically organized, protection should be positively related to inverse import penetration ratio.

To examine whether the "Surge Protection" model is empirically plausible, this paper follows Imai et al. (2007) and runs the quantile regression and IV quantile regression on the data simulated from the model. The estimated coefficients are zero at low quantiles and negative at higher quantiles, having the same sign as those of the actual data. We thus conclude that the "Surge Protection" model better describes the relationship between the

[3]See Rodrik (1995) for an early survey of political economy models in trade and Gawande and Krishna (2003) for a recent one of the empirical work in the area.

[4]For the rest of the paper, we follow convention and call the conditional quantiles, simply quantiles.

protection and inverse import penetration ratio at various quantiles than the PFS model.

The paper proceeds as follows. The PFS model is laid out in the next section. Section 3 then develops a simple model of imports and quotas with protection occurring in response to import surges, but only for the organized industries, which we calibrate to broadly match the data. We then generate data from it. Section 4 then runs the standard regressions on the simulated data and shows that the standard results are obtained despite the absence of any strict PFS effects. Section 5 verifies that our results go through even with tariffs. Section 6 then explains why this is happening. Section 7 examines and discusses which model is more consistent with the data. Section 8 concludes.

2 The PFS Model and Its Estimation

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. As a result, there are no income effects and no cross price effects in demand which comes from equating marginal utility to own price. 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 can make contributions to the government to try and influence policy if it is worth their while.

Government cares about both social welfare and the contributions made to it and puts a relative weight of α on social welfare. 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 that all principals (organized lobbies) are trying to influence. Such games are known to have a continuum of equilibria.[5] By restricting agents to bids that are "truthful", so that their bids have the same curvature as their welfare, a unique equilibrium is obtained.[6] The equilibrium outcome, thus, is as if the government was maximizing weighted social welfare ($W(p)$ where p is the domestic price and equals the tariff vector plus the world price vector, p^*) with a greater weight on the welfare of organized industries. Thus, equilibrium tariffs can be found by maximizing

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

where J_0 is the set of politically organized industries and the welfare of agents in industry j is

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

where $\pi_j(p_j)$ is producer surplus in industry j, l_j is labor employed in industry j, wage is unity, $\frac{N_j}{N}$ **is the share of industry specific factor owners** in the jth industry, while $T(p) + S(P)$ is the sum of tariff revenue and consumer surplus in the economy.

This is the great charm of the PFS model: not only does it cleanly model where both the demand and the supply of protection are coming from, but the results can be derived from a simple maximization exercise! Small wonder it is so popular.

[5] Given the bids of all other lobbies, each lobby wants a particular outcome to occur, namely, the one where it obtains the greatest benefit less cost. This can be attained by offering the minimal contribution needed for that outcome to be chosen by the government. However, what is offered for other outcomes (which is part of the bid function) is not fully pinned down as given other bids, it is irrelevant. However, bids at other outcomes affect the optimal choices of other lobbies and as their behavior affects the lobby, multiplicity arises naturally. Uniqueness is obtained by pinning down the bids at all outcomes to yeild the same payoff as at the desired one.

[6] For a detailed discussion of this concept, see Bernheim and Whinston (1986).

Differentiating $W_i(p)$ with respect to p_j gives[7]

$$x_j(p_j)\delta_{ij} + \alpha_i \left[-x_j(p_j) + (p_j - p_j^*)m_j'(p_j)\right],$$

where $\delta_{ij} = 1$ if $i = j$ and 0 otherwise, α_i is the **share of industry specific factor owners** in industry i, $m_j'(p_j)$ is the derivative of the demand for imports, and $x_j(p_j) = \pi_j'(p_j)$ denotes supply of industry j. Differentiating $W(p)$ with respect to p_j gives

$$(p_j - p_j^*)m_j'(p_j).$$

Hence, maximizing $G(p)$ with respect to p_j gives

$$\alpha \left[(p_j - p_j^*)m_j'(p_j)\right] + \sum_{i \in J_0} \left[x_j(p_j)\delta_{ij} + \alpha_i \left[-x_j(p_j) + (p_j - p_j^*)m_j'(p_j)\right]\right] = 0.$$

Now $\sum_{i \in J_0} \alpha_i = \alpha_L$, **the share of specific factor owners** in organized industries and $\sum_{i \in J_0} \delta_{ij} = I_j$ is unity if j is organized and zero otherwise. Thus, the above is the same as

$$x_j(p_j)(I_j - \alpha_L) + (p_j - p_j^*)m_j'(p_j)(\alpha + \alpha_L) = 0.$$

Using the fact that $(p_j - p_j^*) = (t_j)\, p_j^*$, the above equation can be rewritten as

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

where $z_j = \frac{x_j(p_j)}{m_j(p_j)}$ and $e_j = -m_j'(p_j)\frac{p_j}{m_j(p_j)}$. This is the basis of the key estimating equation. Note that protection is predicted to be positively related to $\frac{z_j}{e_j}$ if the industry is organized, but negatively related to it if the industry is not organized, and that the sum of the

[7] This follows from the derivative of consumer surplus from good j with respect to p_j being equal to $-d_j(p_j)$, where $d_j(p_j)$ is the demand for good j.

coefficients is positive. Moreover, the coefficients on $\frac{z_j}{e_j}$ and $I_j\frac{z_j}{e_j}$, γ and δ below, can be used to infer the weight on welfare placed by government. It is easy to verify that $\alpha = \frac{1+\gamma}{\delta}$ and $\alpha_L = \frac{-\gamma}{\delta}$. An even stronger prediction is that z_j and e_j do not enter separately once their ratio is controlled for.

GM and GB added an error term to equation (1) to permit estimation:

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

The error term is interpreted as the composite of variables potentially affecting protection that may have been left out, and the measurement error of the dependent variable. Both GB and GM used the coverage ratios for non-tariff barriers as t_j instead of the tariff itself. GB estimated a variant of equation (2) together with the other equations which determine the political contribution and the inverse import penetration ratio. Their protection equation also accounts for tariffs on intermediate goods and adds as explanatory variables the tariff and NTBs on intermediates goods used by the industry. As shown in Grossman and Helpman (1994), protection for the final good is increasing in that of the intermediate inputs used. To consistently estimate equation (2) (since the inverse import penetration ratio and the import elasticity could be endogenous), they used a nonlinear IV estimation technique proposed by Kelejian (1971). It is found that estimates of γ and δ are consistent with those predicted by the PFS model.

GM explicitly considered the corner solution of the protection measure on the LHS. Using full information maximum likelihood, they estimated the following system of equations. First, the "true level of protection" in industry i, the latent variable t_i^*, is related to political organization and z_i.[8]

$$\frac{t_i^* e_i}{1+t_i^*} = \gamma z_i + \delta I_i z_i + \epsilon_i. \tag{3}$$

The true protection level is a multiple of the coverage ratio which lies between zero and unity (to account for the boundedness of the coverage ratio in the data)

$$\begin{aligned} t_i &= \tfrac{1}{\mu} t_i^* \quad if \quad 0 < t_i^* < \mu \\ &= 0 \qquad if \quad t_i^* \leq 0 \\ &= 1 \qquad if \quad t_i^* \geq \mu \end{aligned} \tag{4}$$

where μ is exogenously set at the value 1, 2, or 3.[9] Domestic production to import ratios are related to a variety of factors in

$$z_i = \varsigma_1' R_{1i} + u_{1i}, \tag{5}$$

and whether the industry is politically organized is modelled as

$$I_i = D(\varsigma_2' R_{2i} + u_{2i} > 0), \tag{6}$$

where $D(\cdot)$ is an indicator function, and R_{1i} and R_{2i} are vectors of exogenous variables. GM found that the key parameters γ and δ have the predicted signs and are significant at the 5% level. No matter what level of μ is used, the estimate of α is high (over 49) and α_L is close to unity (over .95), though as expected, a high μ reduces the estimates of α and α_L (a high μ raises true tariffs and this, in turn, is consistent with a higher δ and lower γ and hence, lower weight on welfare and a lower degree of organization).

[8] Note that e_i is moved to the left hand side to alleviate concerns about its endogeneity. Also, they actually use $1 + z_i$ not z_i which results in a few complications as discussed later.

[9] Note, however, that there is no reason for μ not to be less than unity as quotas may be barely binding.

3 A Simple Model of Imports

We now develop a simple model of imports that we will simulate. To match the key statistics of the data, our model has to have several features. First, in the data some industries are politically organized and others are not. In our model we simply assume political organization is randomly determined. Second, in the data some politically organized industries are protected by quota and others are not. To capture that in a simple way, we assume that politically organized industries whose equilibrium imports exceed some level would face a quota.

Consider the domestic and foreign goods equilibrium without quota. For each industry i and subindustry j, there are two types of goods: domestic and foreign goods. To make matters simple, we assume that each good's demand depends only on its own price and random shocks and that home is the only source of demand. Let x_{ij}^H be the equilibrium quantity of home goods in industry i subindustry j, and let p_{ij}^H be its equilibrium price.

The equilibrium is described by the demand and supply equations. The demand for industry i subindustry j of the home good depends on a constant, the price of the good, and random terms as follows:

$$\ln x_{ij}^{Hd} = ahd_1 + ahd_2 \ln p_{ij}^H + xhd_i + uhd_{ij}. \tag{7}$$

Similarly, the supply of the same good follows the supply equation:

$$\ln x_{ij}^{Hs} = ahs_1 + ahs_2 \ln p_{ij}^H + xhs_i + uhs_{ij}. \tag{8}$$

The random terms xhd_i and xhs_i are industry specific demand and supply shocks, and hence, common across all subindustries, while uhd_{ij} and uhs_{ij} are subindustry specific demand and supply shocks and are idiosyncratic to each subindustry. All shocks are assumed to be i.i.d. with normal distributions though the parameters of the distribution differ. Thus, for all i, xhd_i has mean 0 and standard deviation σ_{xhd}, while uhs_i has mean 0 and standard deviation σ_{uhs}. Similarly, for all ij, uhd_{ij} has mean 0 and standard deviation σ_{uhd}, while xhs_i has mean 0 and standard deviation σ_{uhs}. Equilibrium satisfies

$$x_{ij}^{Hd} = x_{ij}^{Hs} = x_{ij}^{H}. \tag{9}$$

Similarly, let import demand be given by

$$\ln x_{ij}^{Md} = amd_1 + amd_2 \ln p_{ij}^{M} + xmd_i + umd_{ij}, \tag{10}$$

and supply by:

$$\ln x_{ij}^{Ms} = ams_1 + ams_2 \ln p_{ij}^{M} + xms_i + ums_{ij}. \tag{11}$$

As before, the random terms xmd_i, xms_i, umd_{ij}, and ums_{ij} are industry and subindustry specific demand and supply shocks. They are distributed i.i.d. normally with means zero and standard errors σ_{xmd}, σ_{xms}, σ_{umd}, and σ_{ums} respectively. Equilibrium satisfies

$$x_{ij}^{Md} = x_{ij}^{Ms} = x_{ij}^{Me}. \tag{12}$$

We assume that there are $n_t = 200$ industries and each industry has $n_j = 6$ subindustries. Each subindustry ij is politically organized with probability Po_i. We allow for some variation in the political organization probability across industries: $Po_i = 0.9$ with probability 0.3,, $Po_i = 0.8$ with probability 0.2, $Po_i = 0.7$ with probability 0.2, and $Po_i = 0.1$ with probability 0.3. This is done to ensure that there is sufficient variation in the numbers of subindustries that are politically organized within industries. If we had only one probability of political organization for every industry, say .6, the fraction of industries that are politically organized will be clustered around .6. We simulate political organization by generating a $(0,1)$ uniformly distributed random variable u_{pi}, and generate independently another $(0,1)$ uniformly distributed random variable u_{oij}. If $u_{pi} \leq 0.3$, then $I_{ij} = 1$ if $u_{oij} \leq 0.1$. $I_{ij} = 0$ otherwise. If $0.3 < u_{pi} \leq 0.5$, then $I_{ij} = 1$ if $u_{oij} \leq 0.7$ and $I_{ij} = 0$ otherwise. If $0.5 < u_{pi}$, then $I_{ij} = 1$ if $u_{oij} \leq 0.8$ and $I_{ij} = 0$ otherwise.

We simulate the output and prices of each industry by first drawing n_t industry demand and supply shocks xmd_i and xms_i for $i = 1, ..., n_t$ and for each industry i, drawing n_s subindustry demand and supply shocks umd_{ij} and ums_{ij} for $j = 1, ..., n_s$. Then, given these shocks and parameters of the demand and supply equations, we compute the equilibrium price and quantities for each subindustry ij.

We now introduce a uniform quota level $\hat{Q}$ for all subindustries. That is, the quota becomes binding in industry ij if the equilibrium output for the foreign goods exceeds $\hat{Q}$. Let d_{ij}^{q} be the indicator for a binding quota. That is, if x_{ij}^{Me} for subindustry ij exceeds $\hat{Q}$, then actual imports, x_{ij}^{M}, equal $\hat{Q}$ and $d_{ij}^{q} = 1$. Otherwise, $x_{ij}^{M} = x_{ij}^{Me}$ and $d_{ij}^{q} = 0$. One way of interpreting this is that there is a trigger level of imports, $\hat{Q}$, above which the relevant agency would restrict imports if asked, but only politically organized agencies ask for such protection. In other words, that there are provisions for preventing a surge of imports, but only organized industries can actually make use of these provisions perhaps because they can overcome the usual free rider problems.

Next we aggregate subindustry output to the industry level. Total industry equilibrium output is computed as

$$X_i^H = \sum_{j=1}^{n_j} x_{ij}^H$$

for home goods and

$$X_i^M = \sum_{j=1}^{n_j} x_{ij}^M$$

for foreign goods.

We then generate the variables that we used in the estimation as follows. First, we compute the coverage ratio C_i of industry i to be:

$$C_i = \frac{\sum_{j=1}^{n_j} x_{ij}^M d_{ij}^q}{X_i^M}.$$

That is, coverage ratio is the fraction of industry output i where quota is binding. Furthermore, the inverse import penetration ratio, z_i, for industry i is the ratio of domestic production to imports or

$$\frac{X_i^H + X_i^M}{X_i^M} = 1 + z_i.$$

We also derive the political organization dummy of industry i, I_i, as:

$$I_i = 1 \; if \; \sum_{j=1}^{n_j} I_{ij} > \frac{n_j}{2}$$

$$= 0 \quad otherwise.$$

In other words, we call industry i politically organized if more than half of its subindustries are politically organized.

We chose the parameters of the model so that the simulation is reasonably close to the actual data in several dimensions. The parameters of the home goods demand and supply equations are: $ahd_1 = 4.0$, $ahd_2 = -1.3$, $ahs_1 = 3.4$, $ahs_2 = 1.4$, $amd_1 = 1.4$, $amd_2 = -1.5027$, $ams_1 = 1.4$, $ams_2 = 1.0$. The import demand elasticity, i.e., $-amd_2$, is set at the mean of the industry import demand elasticity from the estimation of Shiells et al. (1986). Furthermore, we set $\sigma_{xhd} = \sigma_{xhs} = 2.0$, $\sigma_{xmd} = \sigma_{xms} = 0.48$, $\sigma_{uhd} = \sigma_{uxhs} = 0.2$, and $\sigma_{umd} = \sigma_{ums} = 0.05$.

Table 1: Summary Statistics

	Simulation	Data
Political organization frequency	0.626	0.680
NTB positive	0.541	0.533
Average log output/import ratio	2.354	2.783
Std. deviation of log output/import ratio	1.347	1.620

In Table 1, we compare the simulation of the model to the data used in GB. The simulation size is 1000.[10] The model matches the average political organization, NTB coverage ratio, log output/import ratio, and the standard deviation of log output import ratio reasonably closely.

Notice that we do not vary the import demand elasticity because, together with the uniform quota level, it would generate correlation between the import demand elasticity and the NTB coverage ratio in the simulation, which we wanted to purge from the model.

4 Estimating the Model Using Simulated Data

Using the data simulated from the simple model, we now estimate the standard protection equation following the procedures of both GB and GM.

[10] We show the average of the 1000 simulations, even though the sample size of the data is only 242. This is because the average over large sample would represent the stochastic model more accurately than that of 242 sample, since it avoids the finite sample variation of the sample average.

4.1 OLS-IV Regression

To replicate the IV estimation done by GB, we estimate the following equation by the three stage least squares:

$$\frac{C_i}{1+C_i} \mid amd_2 \mid = \beta_0 + \gamma \frac{(1+z_i)}{10000} + \delta I_i \frac{(1+z_i)}{10000} + u_i,$$

where we scale variables by dividing by 10000 as done by GB. Importantly, we use $1+z_i$, not z_i, as GB and GM use consumption (which equals domestic production plus imports in the standard homogeneous good model) relative to imports, not production relative to imports. Thus, they in effect use $(1+z_i)$ and we follow their lead for comparability. Note that due to the presence of the interaction term, $I_i(1+z_i)$, this choice of variable results in some mis-specification which could affect the estimates of γ and δ as well as β_0. The impact of using one versus the other turns out to be quite small in GM but larger in our model. We discuss more on this when presenting our maximum likelihood results.

We use two sets of instrumental variables. The first set of instruments includes the exogenous home demand and supply shocks and political organization shocks: xhd_i, xhs_i, and u_{pi} (3SLS1). The second set includes these three instruments, their square terms, and interactions (3SLS2). The sample size is chosen to be 200 which is close to that used in both GB and GM.

Columns 3-5 in Table 2 present the estimation results of OLS, 3SLS1, and 3SLS2, respectively. All the parameter estimates as well as their standard errors are the average of 10 simulation/estimation exercises. Notice that in all the estimates, the coefficient on $(1+z_i)$ is negative and significant, the coefficient on $I_i(1+z_i)$ is positive and significant, and the sum of the two coefficients is positive, just as the PFS model predicts. While our parameter estimates are an order of magnitude larger than those of GB (column 1), they

Table 2: OLS-IV Regression Results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	GB	GM	OLS	3SLS1	3SLS2	OLS	3SLS1	3SLS2
β_0	−0.042		0.315	0.312	0.310	0.306	0.291	0.304
	(0.017)		(0.025)	(0.038)	(0.027)	(0.011)	(0.017)	(0.012)
γ	−3.088	−0.0093	−28.1	−95.8	−47.3	−26.6	−101.0	−58.8
	(1.532)	(0.0040)	(7.91)	(22.9)	(12.3)	(3.56)	(11.2)	(5.68)
δ	3.145	0.0106	35.2	141.4	66.8	35.3	155.6	77.1
	(1.575)	(0.0053)	(9.05)	(31.3)	(15.8)	(3.96)	(14.9)	(7.10)
α	3175	70.43	335.15	73.11	166.50	282.28	63.64	128.98
α_L	0.9819	0.883	0.8308	0.6761	0.6854	0.7540	0.6494	0.6981
Nobs			200	200	200	1000	1000	1000

Note: Standard errors are in parentheses. In columns (3)-(5), the results are the average of 10 simulation/estimation exercises. GB is from the first column in Table 3A (p.145). GM is from the firrst column in Table 1 (p.1145).

are close to those of GM (column 2).[11] These estimates are also close to those estimated for the simulated data following the procedure of GM, as will be prsented later.

Given that the sample size of 200 is a bit small, the IV estimates may be subject to small sample bias. To see if there is a significant bias in the mean, we also run the same simulation/estimation exercise once with the simulation sample size of 1000. The results are reported in columns 6-8 in Table 2. The estimates do differ as expected, but again follow the patterns predicted by the PFS model. It should be stressed that all of these results are obtained in spite of the fact that the data comes from a simple model where the quota is set exogenously at a uniform level in all subindustries, the import elasticity is set constant across all industries, and political organization is completely exogenous to the system – a much less restrictive model than the PFS model.

[11] Note that we need to divide our coefficients by 10000 to make them comparable to GM's.

4.2 Maximum Likelihood Estimation

Next we follow GM and assume the error terms of the equations (3), (5), and (6) are jointly normally distributed. That is, $(\epsilon_i, u_{1i}, u_{2i}) \sim N(0, \Sigma)$.[12] We use full-information maximum likelihood to estimate the parameters of the model. The instruments for $(1 + z_i)$ are the exogenous home demand and supply shocks and political organization shocks: $\mathbf{R}_{1i} = (xhd_i, xhs_i, u_{pi})$. Also, the instruments for the political organization dummy are the exogenous demand and supply shocks as well as the political organization shocks: $\mathbf{R}_{2i} = (xhd_i, xhs_i, xmd_i, xms_i, u_{pi})$. Again, we conduct 10 simulation/estimation exercises with the sample size of 200 and then take the average of those results.

Table 3: Maximum Likelihood Results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	GM	GM-A3	Model 1	Model 2	Model 3	Model 1	Model 2	Model 3
β_0		−0.2545		0.178	−0.435		0.127	−0.393
		(0.241)		(0.070)	(0.127)		(0.033)	(0.059)
β_I		0.3851			0.951			0.820
		(0.347)			(0.156)			(0.071)
γ	−0.0093	−0.0092	−0.007	−0.010	−0.003	−0.012	−0.015	−0.004
	(0.0040)	(0.0044)	(0.003)	(0.003)	(0.004)	(0.002)	(0.002)	(0.002)
δ	0.0106	0.0089	0.011	0.012	0.003	0.019	0.020	0.006
	(0.0053)	(0.0089)	(0.004)	(0.003)	(0.004)	(0.002)	(0.002)	(0.002)
α	93.46		88.46	83.62	396.4	51.57	48.56	163.03
α_L	0.8773		0.651	0.867	1.033	0.633	0.748	0.656
l			−972.0	−968.6	−950.2	−4755.9	−4749.2	−4685.7
Nobs			200	200	200	1000	1000	1000

Note: Standard errors are in parentheses. β_I is the coefficient on I_i. l is the log-likelihood. In columns (3)-(5), the results are the average of 10 simulation/estimation exercises. GM is from the first column in Table 1 (p.1145). GM-A3 is from Table A3 (p.1152).

Column 3 of Table 3 presents the result when taking $\mu = 1$ (Model 1). The coefficient on $(1 + z_i)$ is negative and significant, the coefficient on $I_i(1 + z_i)$ is positive and significant, and the sum of the two coefficients is positive, which is totally consistent with the PFS

[12] For nomalization, the variance of u_{2i} is set to one.

model and also in line with those of GM (column 1). Note also that the estimate of α is "too high" to be reasoable. In Model 2, we add a constant term to equation (3). The estimates of γ and δ are nearly the same as before, while the intercept is found to be positive and significant. Similar results are obtained when the sample size is increased to 1000 (see columns 6-7).

Model 3 further adds the political organization dummy to Model 2, allowing the intercept to differ for organized and unorganized industries. As column 5 indicates, the intercepts differ in sign: positive for organized industries and negative for unorganized ones. The coefficients on $(1 + z_i)$ and $I_i(1 + z_i)$ are found to be insignificant. **This appears to suggest that organized industries are protected and the remainder gets negative protection, which, in the probit model implies that most of the unorganized industries have zero protection. Similar results hold when the sample size increases to 1000 (column 8).**

Overall, the results are consistent with the PFS model: γ is positive and significant, δ is negative and significant, and their sum is positive. Also, as in GM, α is estimated to be "too high." These findings are robust to the inclusion of the constant term and the political organization dummy. One small inconsistency is worth noting. In Model 3, it is found that the constant term is negative and the coefficient on the political organization dummy is positive. If the true model is equation (3) but we use $z_i^* = 1 + z_i$ instead of z_i, then the estimating equation can be expressed as follows:

$$\frac{t_i^* e_i}{1 + t_i^*} = \gamma \left(z_i^* - 1\right) + \delta I_i \left(z_i^* - 1\right) + \epsilon_i$$
$$= -\gamma - \delta I_i + \gamma z_i^* + \delta I_i z_i^* + \epsilon_i.$$

Because $\gamma < 0$ and $\delta > 0$, the constant term should be estimated to be positive and the coefficient on the political organization dummy to be negative. However, that is not the case either in our results or GM's and in this sense, one could argue that our and GM's results are not in line with the PFS model.

It is also noteworthy that there are some discrepancies between our and GM's findings. First, the constant term and the coefficient on the political organization dummy are significant in Model 3 (columns 5 and 8), while they are not in GM (column 2). GM's small sample size (107), which results in large standard errors, may explain this discrepancy. Another possible reason is that the simulated data and the actual data differ in the variations in the dependent variable and the import penetration ratio. More variation exists in the dependent variable in the data than in our simulated data, as we keep e constant. The data on the inverse import penetration ratio in GM is clustered away from origin, since US, a large country, has a low ratio of imports to domestic production in most industries. As a result, greater variation in the dependent variable is being explained by a small variation in the explanatory ones in GM, leading to the insignificance of the constant term in GM.

The second discrepancy is that adding the constant and dummy for organization affects their estimates of γ and δ less than ours. Why does this difference arise? If the true model is

$$\frac{t_i}{1+t_i} e_i = \beta_0 + \beta_I I_i + \gamma\left(1+z_i\right) + \delta I_i\left(1+z_i\right),$$

then the omission of I_i will result in overestimate of δ (as occurs in Table 3) due to the positive correlation between I_i and $I_i\left(1+z_i\right)$. The correlation is smaller in the data (0.105) than the one in the simulation (0.325), which explains why our results change more than those of GM. The higher correlation in the simulated data is because of the uniform quota level; when quota is binding for a subindustry, its import is constant. We find it noteworthy that even in the simple setting, we obtain a significant and negative value for γ and a significant and positive value for δ despite allowing for different intercepts for organized and unorganized industries as required by the PFS model when $1+z$ is used instead of z!

5 Tariffs instead of Quotas

Although most of the empirical work estimating the PFS model uses NTB's as proxies for tariffs, there are some notable exceptions such as McCalman (2004), who used Australian data on tariffs. In this section, we simulate a simple equilibrium model of trade with exogenously determined tariff levels, which has the same spirit as our equilibrium model with quotas. We solve the model and estimate the protection for sale equation using the simulated data. As before, equations (7)-(9), and (10)-(12) define the demand, supply, and equilibrium for domestic goods and imports respectively.

The parameterization is the same as in the quota case except for the inclusion of the uniform tariff t in the import demand equation. We set a uniform import tolerance level $\hat{Q}$ for all sub industries. We assume that if the equilibrium output for the foreign goods exceeds $\hat{Q}$, then government imposes an uniform tariff $t = 0.1$. Otherwise, the tariff is set to be 0. Let d_{ij}^t be the indicator that takes on the value of one if the tariff is positive. That is, $d_{ij}^t = 1$ if x_{ij}^{Me} exceeds $\hat{Q}$ and $d_{ij}^t = 0$ and $x_{ij}^M = x_{ij}^{Me}$, otherwise. For industries with positive tariffs, the industry demand equation becomes as follows:

$$\ln x_{ij}^{Md} = amd_1 + amd_2 \ln\left[(1+t)\, p_{ij}^M\right] + xmd_i + umd_{ij}.$$

Equilibrium under the tariff is computed by equalizing industry demand and supply. The output, $(1+z_i)$, and political organization for each industry are computed by aggregating over subindustries, just as in the quota model. The industry level tariff is the simple average of the subindustry tariffs, $t_i = \sum_{j=1}^{n_i} t_{ij}/n_i$.

Generating data from our model, we estimate the following equation by OLS and 3SLS:

$$\frac{t_i}{1+t_i} \mid amd_2 \mid = \beta_0 + \gamma \frac{(1+z_i)}{10000} + \delta I_i \frac{(1+z_i)}{10000} + u_i.$$

Table 4: Regression Results

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS	3SLS1	3SLS2	OLS	3SLS1	3SLS2
β_0	0.051	0.049	0.049	0.049	0.046	0.048
	(0.004)	(0.006)	(0.004)	(0.002)	(0.003)	(0.002)
γ	−4.927	−16.04	−7.753	−4.504	−16.72	−6.792
	(1.310)	(3.84)	(2.02)	(0.585)	(1.90)	(0.948)
δ	5.482	24.34	11.16	5.399	26.77	13.05
	(1.540)	(5.40)	(2.68)	(0.669)	(1.62)	(1.22)
α	2285.4	427.4	984.9	1872.3	373.0	765.5
α_L	0.939	0.659	0.675	0.844	0.625	0.674
Nobs	200	200	200	1000	1000	1000

Note: Standard errors are in parentheses. In columns (1)-(3), the results are the average of 10 simulation/estimation exercises.

Estimation results are presented in Table 4. The results in columns 1-3 are the average of 10 simulation/estimation exercises with the sample size of 200, while those in columns 4-6 are based on the sample size of 1000. Estimates are fully consistent with the PFS model, although the simple tariff model from which we generated data is quite different from the PFS one. It is also found that the estimate of α is "too high". Qualitatively similar results (available upon request) are obtained when we estimate the model by the maximim likelihood.

6 Why the Simulation Results?

Why is it that we spuriously estimate a protection for sale effect from the simulated data? In this section, we try to explain the reason by using an even simpler model of protection, which does not even have any aggregation over subindustries. Suppose that the demand for and supply of home goods have no random component:

$$\ln X_i^{Hd} = ahd_1 + ahd_2 \ln p_i^H$$
$$\ln X_i^{Hs} = ahs_1 + ahs_2 \ln p_i^H.$$

Then, the home goods equilibrium quantity is:

$$\ln X_i^H = \frac{ahd_2 ahs_1 - ahs_2 ahd_1}{ahd_2 - ahs_2}.$$

We choose parameters so as to set the home goods equilibrium quantity to unity. That is,

$$\ln X_i^H = \frac{ahd_2 ahs_1 - ahs_2 ahd_1}{ahd_2 - ahs_2} = 0.$$

For imported goods in the same industry, however, demand and supply are random. Furthermore, let

$$\ln X_i^{Md} = amd_1 + amd_2 \ln p_i^H + xmd_i$$
$$\ln X_i^{Ms} = ams_1 + ams_2 \ln p_i^H + xms_i.$$

Thus, the equilibrium of the foreign goods market is

$$\ln X_i^M = \frac{amd_2 ams_1 - ams_2 amd_1}{amd_2 - ams_2} + \frac{amd_2 xms_i - ams_2 xmd_i}{amd_2 - ams_2}.$$

We set the parameters so as to set the foreign goods equilibrium to be as follows.

$$\ln X_i^M = -1.0 + 2.0U_i,$$

where U_i is assumed to be uniformly distributed on [0,1]. This gives the desired level of imports. Also, we set the uniform quota level, $\hat{Q} = 1$, so $\ln\hat{Q} = 0$. As before, organization is random and there is a .5 chance of being organized. Protection occurs if the quota is binding and the industry is organized. There is, of course, no strict PFS.Then, the coverage ratio, C_i , the ratio of trade under quota to total trade is:

$$C_i = 0 \text{ so } \frac{C_i}{1 + C_i} = 0, \text{ if } \ln(X_i^M) = -1.0 + 2.0U_i < 0,$$

and

$$C_i = 1 \text{ so } \frac{C_i}{1 + C_i} = 0.5, \text{ if } \ln(X_i^M) = -1.0 + 2.0U_i \geq 0.$$

Since the probability of being organized is .5, with a large enough number of industries, half of them will be organized and half will not. For the half that are not organized, the consumption to import ratio is:

$$\frac{X_i^H + X_i^M}{X_i^M} = 1 + z_i = 1 + \frac{1}{e^{(-1.0 + 2.0U_i)}}.$$

For the other half of the industries, which are politically organized, it is:

$$
\begin{aligned}
1 + z_i &= 1 + \frac{1}{e^{(-1.0+2.0U_i)}}, \text{ if } \ln(X_i^M) = -1.0 + 2.0U_i < 0, \\
&= 2, \qquad\qquad\qquad\quad \text{if } \ln(X_i^M) = -1.0 + 2.0U_i \geq 0.
\end{aligned}
$$

Now consider that we have drawn 2000 industries. For a large enough sample size, in any realization, roughly half will be organized. To illustrate the intuition, we take exactly half to be organized. Number the industries that are not organized by integers between 1 and 1000 with a higher index given to the industry with a larger U_i. Similarly, number the industries that are organized by integers between 1001 and 2000 with a higher index given to the industry with a higher U_i. Only industries with an index above 1000 will ever get protection. As the number of draws gets large enough, we would expect to see a uniform empirical distribution of the realizations of U_i. To capture this in our picture below, we place one firm at each integer. That is, we assume that industry i has $U_i = \frac{i}{1000}$ for $i = 1, ..., 1000$, and $U_i = \frac{i-1000}{1000}$ for $i = 1001, ..., 2000$. Industries with an index higher than or equal to 1500 will have the quota invoked and be binding while industries with an index below the cutoff, while organized, never have the quota invoked.

Figure 1 plots the U_i and the import quantity. Notice that for industry $i = 1001, ..., 2000$, which are politically organized, the quota binds and import quantity equals the quota when U_i is large (industries 1500 to 2000).

(Figure 1 in here)

Figure 2 plots the protection measure. The coverage ratio is positive only for industries that are politically organized and whose quota is binding, i.e., industries 1500 to 2000. Their protection measure is .5. Thus, the protection measure in Figure 2 is what we need to fit.

(Figure 2 in here)

Figure 3 plots 1+ z_i. As we can see, this is high for industries with small imports and low for industries with large imports. It is constant for industries with index 1500 to 2000 because of the binding quota.

(Figure 3 in here)

We next plot the $1+z_i$ times the political organization dummy in Figure 4, i.e., $I_i\,(1+z_i)$. Notice that for industries 1 to 1000, $I_i\,(1+z_i)$ is zero because they are never politically organized.

(Figure 4 in here)

Let us try to fit the protection measure in Figure 2 by using $(1+z_i)$ (Figure 3) and $I_i(1+z_i)$ (Figure 4) by OLS. We obtain

$$\begin{aligned}\widehat{\left(\frac{C}{1+C}\right)} &= \hat{\beta}_0 + \hat{\gamma}\,(1+z) + \hat{\delta} I\,(1+z) \\ &= \underset{(0.0160)}{0.3728} - \underset{(0.0072)}{0.1571}(1+z) + \underset{(0.0035)}{0.0921} I\,(1+z)\,.\end{aligned}$$

Again, note the opposite signs of γ and δ as in the PFS model. Figure 5 plots the dependent variable and the model prediction.

(Figure 5 in here)

There seems to be a positive correlation between protection and $(1 + z_i)$ for politically organized industries but a negative one between protection and $(1 + z_i)$ for non organized industries. This is what the regression is picking up.

We can confirm the above insight by looking at the regression results from a different angle, i.e., by using the partitioned regression. Let RIP_i be the component of $(1 + z_i)$ that is orthogonal to $I_i\,(1 + z_i)$. It is obtained by regressing $(1 + z_i)$ on the constant term and $I_i\,(1 + z_i)$ and taking the residual. The blue line in Figure 6 plots this orthogonal component.

(Figure 6 in here)

Due to the properties of the partitioned regression, the coefficients of the OLS regression of the protection measure on the orthogonal component gives the coefficient on $(1 + z_i)$ back. As can be seen from the figure, the thin line is the orthogonal component of the $(1 + z_i)$, which clearly is negatively correlated with the protection measure, which is the reason for the negative coefficient of the $(1 + z_i)$ in the original OLS.

The dotted line in Figure 7 is the prediction by the constant term and the orthogonal component. Similarly, let $RIIP_i$ be the component of $I_i\,(1 + z_i)$ that is orthogonal to $(1 + z_i)$. It is obtained by regressing $I_i\,(1 + z_i)$ on the constant term and $(1 + z_i)$ and taking the residual. The thin line in Figure 7 plots the orthogonal component.

(Figure 7 in here)

Again, the coefficient of the OLS regression of the protection measure on the orthogonal component gives the coefficient on $I_i\,(1 + z_i)$ back. As can be seen from the graph, the thin line is the orthogonal component of $I_i(1 + z_i)$, which clearly is positively correlated with the protection measure, which is the reason for the positive coefficient of $(1 + z_i)$ in the original OLS.

The qualitative aspects of the results do not change when we use IV estimation with U_i and U_i^2 as instruments. γ and δ are estimated to be -0.610 and 1.008 along with the standard errors of 0.280 and 0.645, respectively. In this case, not only are the signs right but $\gamma + \delta > 0$, which is even more consistent with the PFS model.

Conventional empirical studies in trade estimating the political economy effects use non-tariff barriers as a proxy for tariff protection measures, even though non-tariff barriers could be better interpreted as quotas. The above results show that the real reason behind the results in support of PFS models could be the difference between the quota being binding and non-binding. That is, $\delta > 0$ fits well for the industries under quota (1500 to 2000) and industries that are not politically organized, but does not fit well for industries that are politically organized but not under quota (1001 to 1499). On the other hand, $\gamma < 0$ fits well for industries that are politically organized since those with high equilibrium imports face binding quotas, but fits very poorly for those that are not politically organized. Hence, it is natural that combining both would give the best fit, and these results correspond to the signs obtained by GM, GB, and others. Similar interpretations can be offered for the tariff version in Section 6.

7 Which Model is More Plausible?

We have shown that (1) data simulated from a simple model of import, Surge Protection (SP) model, are reasonably close to actual data and (2) estimation of the protection equation using the simulated data provides coefficients that are consistent with those predicted by the PFS framework. This suggests that numerous past findings in favor of the PFS model are also in favor of the SP model. Clearly, estimation of the PFS equation is in-sufficient to conclude the validity of the PFS model. This problem was indeed noticed by Goldberg and Maggi (1999); they mentioned that "(s)trictly speaking, we do not test the G-H model, because we do not have a well-specified alternative hypothesis" (p.1135).

Given our results along with past findings in the literature, it is important to ask which model is (more) correct. Our conclusion is that the SP model is more empirically plausible than the PFS model. This is made on the basis of two results: one result recently provided by Imai et al. (2007) that the PFS is not empirically plausible, and the other result that the SP model appears to match data well, which we will presnt.

Imai et al. (2007) recently propose a new approach to testing the PFS model. An important feature of their approach is that it does not require the classification of industries into organized and unorganized ones[13]. Their approach exploits 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 given z/e industries with higher protection are more likely to be politically organized, and thus for those industries, one should expect a positive relationship between the inverse import penetration ratio and the protection measure. Imai et al. (2007) provide a formal proof of this argument within the framework of recent works on quantile regression (Koenker and Bassett, 1978) and instrumental variable quantile regression (Chernozhukov and Hansen, 2004a; 2004b; 2006). Their proposition (proposition 1) essentially states that in the quantile regression of $t/(1+t)$ on z/e, the coefficient on z/e should be close to $(\gamma+\delta)$ at the quantile close to 1. To empirically examine this, they use quantile regression (Koenker and Bassett, 1978) and estimate the following equation:

$$Q_T(\tau|Z) = \alpha(\tau) + \beta(\tau) Z/10000, \tag{13}$$

[13] Imai et al. (2007) also argue that the conventional classificaton of political organization by Goldberg and Magee (1999) and Gawande and Bandyopadhyay (2000) are inconsistent with the PFS model, and relying on those arbitrary classification could result in wrong coefficient estimates of the protection equation.

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, it is expected that $\beta(\tau)$ converges to $(\gamma+\delta) > 0$ as τ approaches to 1 from below. Using the data from Gawande and Bandyopadhyay (2000), Imai et al. (2007) find that the null hypothesis of $\beta(\tau) = 0$ cannot be rejected at high quantiles (in fact, all quantiles) in favor of the one-sided alternative of $\beta(\tau) > 0$. Moreover, the point estimates indicate that contrary to the PFS prediction, $(\gamma+\delta)$ are all negative at high quantiles and decrease as goes from 0.4 to 0.9. The results do not provide any evidence favoring the PFS model.

In the quantile regression, Z is assumed to be an exogenous variable. However, Z is likely to be endogenous as discussed in the literature and hence the parameter estimates of the quantile regression are likely to be inconsistent. Imai et al. (2007) therefore allow for the potential endogeneity of Z. They formally show that even in the presence of this endogeneity, the main prediction of the PFS model in terms of their quantile approach does not change. See Imai et al. (2007) for the relevant proposition (proposition 2). To test the prediction in the presence of possible endogeneity of Z, they estimate the following equation by using IV quantile regression (Chernozhukov and Hansen, 2004a; 2004b; 2006):

$$P(T \leq \alpha(\tau) + \beta(\tau) Z/10000|W) = \tau, \tag{14}$$

where W is a set of instrumental variables. As in the quantile regression, Imai et al. (2007) find that the null hypothesis of $\beta(\tau) = 0$ in favor of the one-sided alternative cannot be rejected. The point estimates are not favorable for the PFS model, either; even after correcting for the endogeneity of Z, the estimate of at the highest quantile is not found to be positive as required by the PFS model. Imai et al. (2007) also show the robustness of their findings; regardless of which instrument they use and whether they control for capital-labor ratio, the null hypothesis at the highest quantile cannot be rejected. Moreover, the point estimates of $\beta(\tau)$ are negative at high quantiles; in fact, zero at low quantiles and negative at any other quantiles, which is inconsistent with the PFS's prediction.

Next, we examine the validity of the SP model. We conduct the following exercise: using simulated data from the SP model, we estimate equations (13) and (14). We ask whether the parameter estimates from the simulated data resemble those reported in Imai et al. (2007). If the SP model is valid, then the patterns exhibited in the former are expected to be similar with those in the latter.

In the original SP model, all politically organized subindustries are assumed to have a uniform level of quota. Since this is rather a strong assumption, we slightly extend it by allowing the quota to be stochastically determined. Specifically, we add some randomness to the quota, i.e.,

$$\hat{Q}_{ij} = \widehat{Q} + \varsigma, \varsigma \sim N(0, 1),$$

where $\hat{Q}_{ij}$ is the quota level for politically organized subindustries ij. Using simulated data from this model (the modified SP model), we estimate equations (13) and (14) again.

The results are presented in Table 5. The coefficients on Z are found to be zero at lower quantiles and thereafter negative, which is consistent with those in Imai et al. (2007). Moreover, in the modified SP model, the coefficients on Z decrease with quantile; this pattern is also observed in Imai et al. (2007).

Similar results are obtained for the IV quantile regression (Table 6). It is also noteworthy that the size of β's is by and large similar to that obtained by Imai et al. (2007) when they use three instruments that are highly correlated with Z.

The results overall suggest that the feature of the SP model is more consistent with the actual data than the PFS model. The intuition behind the negative coefficient estimate of the SP model is simple. A surge in imports, which increases the import penetration ratio, tends to result in the quota being binding, which corresponds to an increase in the

Table 5: Quantile Regression Results of the Surge Protection Model

	SP		Modified SP	
τ (quantile)	$\alpha(\tau)$	$\beta(\tau)$	$\alpha(\tau)$	$\beta(\tau)$
0.1	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
0.2	0.000 (0.000)	0.000 (0.091)	0.000 (0.000)	0.000 (0.030)
0.3	0.000 (0.006)	0.000 (2.658)	0.000 (0.002)	−0.045 (0.696)
0.4	0.020 (0.066)	−6.672 (5.798)	0.006 (0.006)	−1.973 (1.985)
0.5	0.042 (0.007)	−11.33 (2.641)	0.020 (0.006)	−5.125 (1.759)
0.6	0.044 (0.001)	−9.615 (1.618)	0.033 (0.006)	−6.686 (1.721)
0.7	0.046 (0.001)	−7.841 (1.479)	0.049 (0.006)	−7.854 (2.022)
0.8	0.046 (0.000)	−6.076 (1.388)	0.072 (0.008)	−8.666 (2.469)
0.9	0.047 (0.000)	−4.276 (1.186)	0.111 (0.013)	−9.214 (3.103)

Note: Standard errors are in parenthese.

NTB coverage ratio. A similar mechanism has been considered in the literature. Findlay and Wellisz (1982), for example, argued that an increase in import in an industry triggers lobbying efforts which result in higher protection. That is, like in the SP model, a negative relationship is predicted between the change in inverse import penetration ratio and the NTB coverage ratio. This prediction is indeed borne out in the data; Trefler (1993) found that the relationship between import penetration ratio and protection is insignificant but a change in import penetration has a positive and significant effect on protection.

8 Conclusion

In this paper, we suggest that the usual tests of the PFS model are actually also consistent with a simpler model where protection tends to occur when imports surge and the industry is organized. Since our model does not allow the estimates of γ and δ to be used to construct a weight on welfare placed by the government, there is no puzzle regarding the high weight on welfare generated by these "tests" of the PFS model.

Table 6: IV Quantile Regression Results of the SP Model

	SP		Modified SP	
τ (quantile)	$\alpha(\tau)$	$\beta(\tau)$	$\alpha(\tau)$	$\beta(\tau)$
0.1	0.000 (0.001)	0.000 (0.000)	0.000 (0.000)	0.000 (0.000)
0.2	0.004 (0.008)	−2.000 (4.755)	0.000 (0.031)	−0.093 (0.009)
0.3	0.031 (0.015)	−15.33 (7.286)	0.000 (0.002)	−2.931 (0.292)
0.4	0.042 (0.004)	−17.00 (2.153)	0.006 (0.670)	−7.210 (0.718)
0.5	0.043 (0.001)	−14.24 (1.613)	0.018 (1.921)	−8.934 (0.891)
0.6	0.044 (0.000)	−11.54 (1.349)	0.038 (1.836)	−9.866 (0.985)
0.7	0.044 (0.000)	−9.450 (1.141)	0.053 (2.162)	−10.83 (1.082)
0.8	0.045 (0.000)	−7.430 (1.138)	0.073 (2.618)	−11.08 (1.109)
0.9	0.045 (0.003)	−5.390 (1.074)	0.110 (3.342)	−10.53 (1.078)

Note: Standard errors are in parenthese.

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