Standard Setting Organizations and Cross-Border Mergers & Acquisitions

in

General Oligopolistic Equilibrium©

Anjishnu Banerjee [1] and Avik Chakrabarti [2]

March 2019

[1] Assistant Professor, Division of Biostatistics, MCW. Email: abanerjee@mcw.edu
[2] Associate Professor, Department of Economics, UWM. E-mail: chakra@uwm.edu

Standard Setting Organizations and Cross-Border Mergers & Acquisitions

in

General Oligopolistic Equilibrium

Does participation in an SSO for a target or an acquirer in cross-border Mergers & Acquisitions (M&A) deal influence the value of deal or the size of the deal in terms of percentage of shares acquired? To answer this question, we derive testable hypotheses on plausible associations between memberships in SSOs and cross-border M&A in a general equilibrium model of oligopolistic competition based on Beladi and Chakrabarti (2019). We then analyze a unique dataset created by joining the Searle Center database on SSOs with a dataset compiled by Banerjee and Chakrabarti (2019), containing detailed information on 40,000 cross border M&A. Most importantly, in our analyses, we address the issue of potential misspecifications of SSO memberships by employing a Bayesian random forest specification for robust quantification of non-linear patterns in regression. We present convincing evidence that SSO membership tends to be associated with larger deals, and that our model is fairly robust for low to moderate miss-specification of covariates.

JEL Classification Code(s): F10, F12, L13

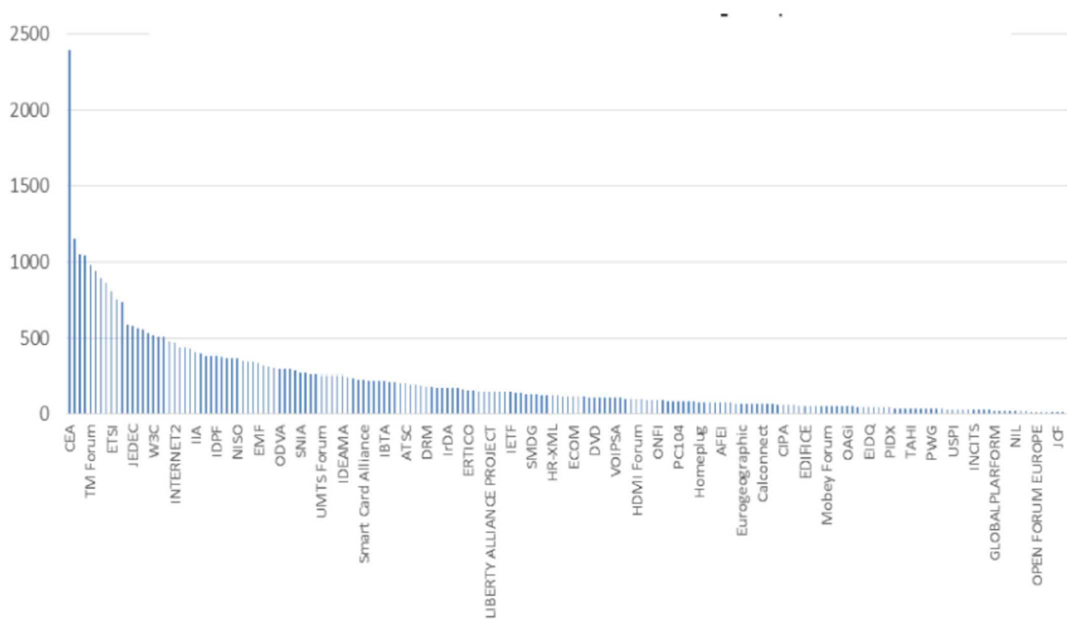
Keywords: Standard Setting Organizations, Technology Standards, Mergers and Acquisitions, Oligopoly, GOLE.

1. Introduction

The significance for standard setting organizations (SSO) is widely recognized across professions as the role of technological standards (i.e. the set of rules and technologies adopted to ensure interoperability between products and services and to ensure that they meet specific industry requirements) has grown tremendously over the recent past. The growing importance of the process of standardization process has been attributed in large part to the growth of the information technology and communications industries. Yet, the empirical literature on the economic linkages of technology standards still remains at its infancy. At the same time, the vast and growing body of empirical literature on Industrial

Organization continues to accumulate a wide range of variables of interest that are apparently associated with market concentration.

Figure 1. Standard Setting Organizations by member count in the Searle Center Database
Source: Baron and Spulber (2018)



While the conspicuous neglect of empirical research on technology standards could be attributed to limited availability of data, on large samples of standards from different SSOs, access to the SCD promises to open up a new room for a long overdue cross-fertilization between economic research on technology standards and market concentration. Public policy towards market concentration can be informed by in-depth statistical analysis of SCD on SSOs due to the links between technology standards and competition. Banerjee and Chakrabarti (2019) constructed a unique data-set (BC-2019, hereinafter), by joining the Searle Center Database (SCD: *ref*. Figure 1) with Security Data Corporation's (SDC) observations on individual firms and augmenting this data with detailed information on competition measures spanning 39,936 firms from 86 countries. With this backdrop, our paper uses BC-2019 to explore any meaningful association between technology standards and cross-border M&A.

Our theoretical construct builds on Beladi and Chakrabarti (2019), taking a cue from Neary (2007) who constructed the first analytically tractable general equilibrium model of oligopolistic competition an early blueprint of which can be traced back to Neary (2003).[1] The key characteristics of a General Oligopolistic Equilibrium (GOLE) model are preserved to the extent that we look at a continuum of atomistic industries within each of which firms have market power and interact strategically. Within the scope of this setting, we derive the following testable hypotheses:

- The incentives for a takeover of a home or a foreign firm, that is not a member of an SSO, by an SSO member from the home or foreign country, rise (fall) with an ex ante rise (fall) in the number of SSO members relative to the number of non-members.
- The incentives for a takeover of an SSO member in the foreign (home) country by a firm at home (abroad), that is not a member of the SSO, rise (fall) with an ex ante rise (fall) in the number of SSO members relative to the number of non-members.
- The incentives for a takeover of an SSO member in the foreign (home) country by another SSO member at home (abroad), rise (fall) with an ex ante rise (fall) in the number of SSO members relative to the number of non-members.

We find convincing evidence in support of these hypotheses and also observe that cross-border M&A between SSO membership tends to be associated with larger deals. The policy relevance of our results follows rather naturally since inferences made from statistical tests of such hypotheses will lead to a better understanding of any effect of changes in the composition of SSOs e.g. resulting from a shift in licensing policy. For illustration, Stoll (2014) observed that the adoption of a stricter licensing policy by the Organization for the Advancement of Structured Information Standards (OASIS), a non-profit standards consortium with more than 5,000 participants from over 600 organizations, had a significant impact on the composition of the organizations joining OASIS as well as on the time period for which component and device manufacturers stay at this SSO. While there was a significant decline in this SSO's membership, since the policy change, the share of software producers dropped significantly and the share of non-profit research organizations and systems integrators rose significantly. The rest of this paper is organized as follows. In the next section, we present our model and propositions. In section 3, we present our empirical analysis. In the final section, we draw our conclusions.

2. On Cross-Border M&A

The literature on cross-border M&A, by any standard, is still at its infancy. Notwithstanding the fact that a third of worldwide M&A involve firms from different countries, the vast majority of the academic literature on M&A has been primarily limited to intra-national M&A. Among notable theoretical contributions are the works of Long and Vousden (1995), Head and Ries (1997), Falvey (1998), Reuer *et al*. (2004), Neary (2007), Beladi, Chakrabarti and Marjit (2010, 2013a, 2013b, 2015). Long and Vousden (1995) analyzed the effects of tariff reductions on horizontal M&A in a Cournot oligopoly. They showed that unilateral tariff reductions encourage cross-border M&A which concentrate market power at the expense of M&A which reduce cost, while bilateral tariff reductions have the opposite effect, encouraging M&A which significantly reduce cost. Head and Ries (1997) investigated the welfare consequences of horizontal M&A between firms based in different nations. They demonstrated that when M&A do not generate costs saving, it will be in the national interest for existing competition agencies to block most world welfare-reducing combinations. When M&A generate cost savings, national welfare-maximizing regulators cannot be relied upon to prevent M&A that lower world welfare. Falvey (1998) showed how the rules for approving an international merger should be adapted to account for the fact that the regulator is only concerned with domestic welfare i.e. ignores the effect of the merger on foreign firms and consumers. Reuer *et al*. (2004) have analyzed the role of sector-specific contractual heterogeneity of cross-border M&A in mitigating the problem of adverse selection. They pointed out that, in the case of international M&A, a key contractual variable is whether the parties agree to a performance-contingent payout structure which can mitigate the risk of adverse selection. Bertrand and Zitouna (2006) examined policy designs for international M&A. They showed that the effect of trade liberalization on merger incentives depends on the technological gap: for low and high (medium) gap, there is an inverted U- (W-) shaped relation between trade costs and incentives to merge. Neary (2007) constructed the first analytically tractable general equilibrium model[3] of cross-border M&A where he showed how trade liberalization can trigger international merger waves through bilateral M&A in which it is profitable for low-cost firms to buy out higher-cost foreign rivals. Beladi, Chakrabarti and Marjit (2013) argue that the vertical structure introduces a distinction between the foreign and domestic firm even in the absence of transport costs since M&A can affect competition in input markets creating, in addition to the usual market power motive, an input-market concentration effect.

[3] The foundations can be traced in Neary (2003).

The relevant empirical literature documents a wide range of potential factors that are associated with cross-border M&A. Relatively recent works include Rose (2000) who argue that physical distance can increase the cost of cross border M&A and the level of market development and corporate governance are also likely to affect cross border M&A. Using a large panel data set of cross-border M&A deals for the period 1990–1999, Giovanni (2005) show that the size of financial markets has a strong positive association with domestic firms investing abroad. Jovanovic and Rousseau (2008) find that M&A play an important role in reallocating assets toward an economy's more efficient firms. Chari, Ouimet and Tesar (2009) show that acquirer from developed markets benefit more from weaker governance environments in emerging markets. Alfaro and Charlton (2009) assess the importance of comparative advantage considerations in the determination of FDI. They show that trade costs and an increase in the subsidiary country skill level have negative and significant effects on the level of multinational activity. The interaction term of country skill abundance and industry skill intensity is positively related to FDI. They also show that intra-firm FDI between rich countries in high skill sectors is consistent with the notion that firms in high institution countries with sophisticated inputs engaging more in FDI. Erel, Liao and Weisbach (2012) analyze cross-border M&A in 48 countries between 1990 and 2007. They find that geography, the quality of accounting disclosure and bilateral trade increase the likelihood of M&A between two countries. Bernile, Lyandres and Zhdanov (2012) show that the U-shaped relation between the state of demand and the propensity of firms to merge is driven by horizontal M&A in industries that are more concentrated and characterized by relatively strong competitive interaction among firms. Ahern, Daminelli and Fracassi (2013) find that the volume of cross-border M&A is affected by national culture characteristics such as trust, hierarchy and individualism. Weinberg and Hosken (2013) use a static Bertrand model to directly estimate the price effects of two M&A. Beladi *et al*. (2016) observe a significantly positive and robust association between country upstreamness and cross-border mergers.

While each of these studies has pushed the boundaries of our understanding of what drives M&A decisions across borders, this paper complements the existing literature by recognizing the importance of technology standards in firms' merger decisions across borders.

3. Model and Propositions

2.1 *A Closed Economy*

Consider a country with a continuum of atomistic industries, indexed by $z \in [0, 1]$, employing only one homogeneous factor of production, say labor, the supply of which is exogenously given by L. Each industry supports an exogenous number $(n(z))$ of differentiated goods each of which is produced by a distinct firm competing (`a la Cournot). We allow for symmetric product differentiation across varieties. The total output of any industry $z \in [0, 1]$ is $\tilde{y}(z) = \sum_{i=1}^{n} y_i(z)$ where $i = 1,2,\ldots,n(z)$. Firms, operating in industry z, produce at an average cost $\alpha(z)c(z) = \beta(z)w$ where $\alpha(z) > 1$ for SSO members only and $\alpha(z) = 1$ otherwise; $\left(\frac{\beta(z)}{\alpha(z)}\right)$, sorted to be increasing in z, measures the unit labor requirement; and w is the hourly nominal wage. We assume away any cost of SSO membership. We assume away any fixed cost which, otherwise, would provide a trivial rationale for mergers. The demand side is characterized by a two-tier utility function of consumption levels of all $n(z)$ goods produced in each industry z . The utility function is additive in a continuum of sub-utility functions, each corresponding to one industry

(1) $$U\langle u[x_1(z),\dots,x_n(z)]\rangle = \int_0^1 u[x_1(z),\dots,x_n(z)]dz$$

Each sub-utility function, in turn, is quadratic

(2) $$u[x_1(z),\dots,x_n(z)] = a\sum_{i=1}^{n} x_i - \frac{1}{2}\left(\sum_{i=1}^{n} x_i^2 + 2\gamma \sum_{\substack{i=1 \\ i\neq i'}}^{n} x_i x_{i'}\right)$$

There is a representative consumer, identical across countries, who maximizes (1) subject to the budget constraint

(3) $$\int_0^1 \sum_{l=1}^{n} p_i(z) x_i(z)\, dz \leq I$$

where I is aggregate income which is exogenous in partial equilibrium but can change in general equilibrium due to change in wages and/or profits which, in turn, depend on tastes, technology and market structure.

The resulting inverse demand[2] for the *k*-th differentiated product in industry z is

(4) $$p_k = a - (1-\gamma)x_k - \gamma \sum_{l=1}^{n} x_l$$

where a measures the consumers' maximum willingness to pay, x_k is the quantity demanded, and p_k is the price. This specification parsimoniously parameterizes the degree of product differentiation. $\gamma < 0$ for complementary goods: $\gamma = 0$ when the demand for each good is completely independent of other goods; product differentiation declines as $\gamma \to 1$: $\gamma\ = 1$ for perfect substitutes for complementary goods.

2.1.1 *Partial Equilibrium without SSO Members*

Absent any possibility of SSO membership, competing `a la Cournot, each domestic firm, operating in industry $z \in [0, 1]$ would

(5) Maximize: $(p_i(z) - c(z))y_i(z) \qquad \forall \;\; i = 1, 2, \ldots, n(z)$

Within any given industry $z \in [0, 1]$, the best-response function of each firm is

(6) $$y_i(z) = \frac{1}{2}\left(a - \gamma \sum_{\substack{l=1 \\ l \neq i}}^{n(z)} y_l(z) - c(z)\right) \qquad \forall \quad i = 1,2,\ldots,n(z)$$

In equilibrium, each firm will produce

(7) $$y_i(z) = \left(\frac{1-\delta(z)}{2-\gamma(z)}\right)(a - c(z)) \qquad \forall \quad i = 1,2,\ldots,n(z)$$

where $\delta(z) = \frac{n(z)\gamma}{n(z)\gamma(z)+(2-\gamma(z))} \in (0,1)$.

The industry output is

(8) $$\tilde{y}(z) = \left(\frac{1-\delta}{2-\gamma}\right) n(z)(a - c(z))$$

The prices are

(9) $$p_i = \left(\frac{1}{2-\gamma(z)}\right)\big((1 - \delta(z))a - (1 - \gamma(z) - \delta(z))c(z)\big) \;\forall \quad i = 1,2,\ldots,n(z)$$

2.1.2 *Partial Equilibrium with SSO Members*

Consider next the possibility that, in each industry $z \in [0, 1]$, $m(z) < n(\mathrm{z})$ firms become members of the SSO and accordingly the unit cost of production is specified (suppressing the notation z , hereinafter, for ease of exposition)) as follows:

(10) $$\beta w = \begin{cases} \alpha c & \forall \quad i = 1,2,\dots,m \\ c & \forall \quad i = (n-m),(n-m+1),\dots,n \end{cases}$$

The best-response functions can be written as

(11) $$y_i = \frac{1}{2}\left(a - \gamma\left[\sum_{\substack{l=1 \\ l\neq i}}^{m} y_l + \sum_{l=(n-m)}^{n} y_l\right] - \alpha c\right) \qquad \forall \quad i = 1,2,\dots,m$$

(12) $$y_i = \frac{1}{2}\left(a - \gamma\left[\sum_{\substack{l=(n-m) \\ l\neq i}}^{n} y_l + \sum_{l=1}^{m} y_l\right] - c\right) \quad \forall \quad i = (n-m),(n-m+1),\dots,n$$

The firms will produce

(13) $$y_i(m,n) = \left(\frac{1}{2-\gamma}\right)\left((a-\alpha c) - \delta(a-\bar{c})\right) \qquad \forall \quad i = 1,2,\dots,m$$

(14) $$y_i(m,n) = \left(\frac{1}{2-\gamma}\right)\left((a-c) - \delta(a-\bar{c})\right) \qquad \forall \quad i = (n-m),(n-m+1),\dots,n$$

where, $\bar{c} = \theta_0 \alpha c + (1-\theta_0)c$, $\theta_0 = \frac{m}{n} \in (0,1)$ is the proportion of SSO members in the industry, and $\delta_0 = \frac{n\gamma}{n\gamma + (2-\gamma)} \in (0,1)$.

The industry output is

(15) $$\tilde{y}(n,n^*) = \left(\frac{1-\delta_0}{2-\gamma}\right) n(a-\bar{c})$$

The prices are

(16) $$p_i = \left(\frac{1}{2-\gamma}\right)\left(a - (1-\gamma)\alpha c - \delta_0(a-\bar{c})\right) \qquad \forall \quad i = 1,2,\dots,m$$

(17) $$p_i = \left(\frac{1}{2-\gamma}\right)\left(a - (1-\gamma)c - \delta_0(a-\bar{c})\right) \qquad \forall \quad i = (n-m),(n-m+1),\dots,n$$

2.1.3 *General Equilibrium*

Having looked at the partial equilibrium analysis, to the extent that wages have been held fixed, let us now turn to a general equilibrium in which wages are determined by equating the supply of labor to the aggregate demand for labor (i.e. is the sum of labor demand across all sectors). Without any SSO members, the full employment condition boils down to

(18) $$L = \frac{1}{2-\gamma}\int_0^1 \beta(z)(1-\delta(z))n(z)(a-c(z))dz$$

The analogous condition with SSO membership is

(19) $$L = \frac{1}{2-\gamma}\int_0^1 \frac{\beta(z)}{\alpha(z)}(1-\delta(z))n(z)(a-\ \alpha c(z)-(1-\theta_0)c(z))dz$$

2.2 *An Open Economy*

Next, consider a stylized world containing two countries each with a continuum of atomistic industries, indexed by $z \in [0,\ 1]$. An industry $z \in (\tilde{z}, \tilde{z}^*)$ supports $N(z) = n(z) + n^*(z)$ differentiated goods produced by $n(z)$ domestic firms competing (`a la Cournot) with $n^*(z)$ foreign firms, where $\tilde{z}$ and $\tilde{z}^*$ are the threshold sectors pinning down the extensive margins of trade[3] at home and abroad respectively. The total output of any industry $z \in [0,\ 1]$ is $\tilde{y}(z) = \left(\sum_{i=1}^{n} y_i\,(z) + \sum_{j=1}^{n^*} y_j^*\,(z)\right)$ where y_i $(i = 1,2,\dots,n)$ is supplied by a home firm and y_j^* $(j = 1,2,\dots,n^*)$ by a foreign firm. In industry z, domestic firms produce at an average cost $\alpha(z)c(z) = \beta(z)w$ and foreign firms at $\alpha(z)c^*(z) = \beta^*(z)w^*$, where w and w^* are nominal wages at home and abroad respectively with $\alpha(z) >$

1 for SSO members only and $\alpha(z) = 1$ otherwise. Any difference in the unit cost of production between countries is justified, as in the Dornbusch-Fischer-Samuelson (DFS) exposition of the Ricardian theory, by differences in unit labor requirements denoted by $\frac{\beta(z)}{\alpha(z)}$ and $\frac{\beta^*(z)}{\alpha(z)}$. $\left(\frac{\beta^*(z)}{\beta(z)}\right) \in (0, \infty)$, sorted to be decreasing in z, can then be interpreted as an index of foreign comparative advantage. Let the demand side be characterized by a two-tier utility function of consumption levels of all $N(z)$ goods produced in each industry z. The utility function is additive in a continuum of sub-utility functions, each corresponding to one industry

(20) $$U\left\langle u\left[x_1(z),..., x_n(z), x_1^*(z),..., x_{n^*}^*(z)\right]\right\rangle = \int_0^1 u\left[x_1(z),..., x_n(z), x_1^*(z),..., x_{n^*}^*(z)\right]dz$$

Each sub-utility function, in turn, is quadratic

$$u\left[x_1(z),...,x_n(z),x_1^*(z),...,x_{n^*}^*(z)\right] = a\left[\sum_{i=1}^{n} x_i + \sum_{j=1}^{n^*} x_j^*\right] - \frac{1}{2}\left(\sum_{i=1}^{n} x_i^2 + \sum_{j=1}^{n^*} x_j^{*2} + 2\gamma\left(\sum_{\substack{i=1 \\ i\neq i'}}^{n} x_i\, x_{i'} + \sum_{\substack{j=1 \\ j\neq j'}}^{n^*} x_j^* x_{j'}^* + \sum_{i=1}^{n}\sum_{j=1}^{n^*} x_i\, x_j^*\right)\right)$$

There is a representative consumer, identical across countries, who maximizes (1) subject to the budget constraint

(21) $$\int_0^1 \left[\sum_{l=1}^{n} p_i(z) x_i\,(z) + \sum_{l=1}^{n^*} p_j^*(z) x_j^*(z)\right] dz \leq I$$

where I is aggregate income which is exogenous in partial equilibrium but can change in general equilibrium due to change in wages and/or profits which, in turn, depend on tastes, technology and market structure.

The resulting inverse demand[4] for the $k(*)$-th differentiated product in industry z is

(22)
$$p_k^{(*)} = a - (1-\gamma)x_k^{(*)} - \gamma\left(\sum_{l=1}^{n} x_l + \sum_{l=1}^{n*} x_l^*\right)$$

where variables associated with the foreign firm are distinguished, by an asterisk, from those of the home firm: a measures the consumers' maximum willingness to pay, $x_k^{(*)}$ is the quantity demanded, and $p_k^{(*)}$ is the price.

2.2.1 *Partial Equilibrium without SSO Members*

Absent any possibility of SSO memberships, each domestic firm competing `a la Cournot, operating in industries $z \in [0,\ \tilde{z}]$ where $\tilde{z} \in [0,\ 1]$, would

(23)
$$\text{Maximize: } (p_i(z) - c(z))y_i(z) \qquad \forall\ i = 1, 2, \dots, n$$

Each foreign firm, operating in industries $z \in [\tilde{z}^*,\ 1]$ where $\tilde{z}^* \in [0,\ 1]$, would

(24)
$$\text{Maximize: } \big(p_j(z) - c(z)\big)y_j^*(z) \qquad \forall\ j = 1, 2, \dots, n^*$$

Within any given industry $z \in [0,\ 1]$, suppressing the notation z (for ease of exposition), the best-response functions of the domestic and foreign firms can be written as

(25)
$$y_i(n, n^*) = \frac{1}{2}\left(a - \gamma\left[\sum_{\substack{l=1 \\ l \neq i}}^{n} y_l + \sum_{j=1}^{n^*} y_j^*\right] - c\right) \qquad \forall \quad i = 1, 2, \dots, n$$

(26)
$$y_j^*(n, n^*) = \frac{1}{2}\left(a - \gamma\left[\sum_{i=1}^{n} y_i + \sum_{\substack{l=1 \\ l \neq j}}^{n^*} y_l^*\right] - c^*\right) \qquad \forall \quad j = 1, 2, \dots, n^*$$

The domestic and foreign firms will produce

(27) $$y_i(n,n^*) = \left(\frac{1}{2-\gamma}\right)\left((a-c)-\delta(a-\bar{c}_1)\right) \qquad \forall \quad i = 1,2,\ldots,n$$

(28) $$y_j^*(n,n^*) = \left(\frac{1}{2-\gamma}\right)\left((a-c^*)-\delta(a-\bar{c}_1)\right) \qquad \forall \quad j = 1,2,\ldots,n^*$$

where, $\bar{c}_1 = \theta_1 c + (1-\theta_1)c^*$, $\theta_1 = \frac{n}{N} \in (0,1)$, and $\delta_1 = \frac{N\gamma}{N\gamma+(2-\gamma)} \in (0,1)$.

The industry output is

(29) $$\tilde{y}(n,n^*) = \left(\frac{1-\delta_1}{2-\gamma}\right)N(a-\bar{c}_1)$$

The prices of domestic and foreign varieties are

(30) $$p_i = \left(\frac{1}{2-\gamma}\right)\left(a-(1-\gamma)c-\delta_1(a-\bar{c})\right) \qquad \forall \quad i = 1,2,\ldots,n$$

(31) $$p_j^* = \left(\frac{1}{2-\gamma}\right)\left(a-(1-\gamma)c^*-\delta_1(a-\bar{c})\right) \qquad \forall \quad j = 1,2,\ldots,n^*$$

2.2.2 *Partial Equilibrium with SSO Members*

Consider next the possibility that $m < n$ domestic firms and $m^* < n^*$ foreign firms become members of the SSO. The unit cost of production is specified as follows:

(32) $$\beta w = \begin{cases} \alpha c & \forall \quad i = 1,2,\ldots,m \\ c & \forall \quad j = (n-m),(n-m+1),\ldots,n \end{cases}$$

(33) $$\beta^* w^* = \begin{cases} \alpha c^* & \forall \quad j = 1,2,\ldots,m^* \\ c^* & \forall \quad j = (n^*-m^*),(n-m^*+1),\ldots,n^* \end{cases}$$

The best-response functions can be written as

(34) $$y_i = \frac{1}{2}\left(a-\gamma\left[\sum_{\substack{l=1\\l\neq i}}^{m} y_l + \sum_{l=(n-m)}^{n} y_j + \sum_{k=1}^{n^*} y_j^*\right]-\alpha c\right) \qquad \forall \quad i = 1,2,\ldots,m$$

(35) $y_i = \frac{1}{2}\left(a - \gamma\left[\sum_{\substack{l=(n-m)\\ l\neq i}}^{n} y_l + \sum_{l=1}^{m} y_i + \sum_{k=1}^{n^*} y_j^*\right] - c\right)$

$\forall \quad i = (n-m), (n-m+1), \ldots, n$

(36) $y_j^* = \frac{1}{2}\left(a - \gamma\left[\sum_{\substack{l=1\\ l\neq j}}^{m^*} y_l^* + \sum_{l=(n^*-m^*)}^{n^*} y_j + \sum_{i=1}^{n} y_i\right] - \alpha c\right) \qquad \forall \quad j = 1,2,\ldots, m^*$

(37) $y_j^* = \frac{1}{2}\left(a - \gamma\left[\sum_{\substack{l=(n^*-m^*)\\ l\neq j}}^{m^*} y_l^* + \sum_{l=(n^*-m^*)}^{n^*} y_l + \sum_{i=1}^{n} y_i\right] - \alpha c\right)$

$\forall \quad j = (n^* - m^*), (n - m^* + 1), \ldots, n^*$

The firms will produce

(38) $\quad y_i(m, n, m^*, n^*) = \left(\frac{1}{2-\gamma}\right)\left((a - \alpha c) - \delta_1(a - \bar{c}_2)\right) \qquad \forall \quad i = 1,2,\ldots, m$

(39) $\quad y_i(m, n, m^*, n^*) = \left(\frac{1}{2-\gamma}\right)\left((a - c) - \delta_1(a - \bar{c}_2)\right)$

$\forall \quad j = (n-m), (n-m+1), \ldots, n$

(40) $\quad y_j^*(m, n, m^*, n^*) = \left(\frac{1}{2-\gamma}\right)\left((a - \alpha c) - \delta_2(a - \bar{c}_2)\right) \qquad \forall \quad i = 1,2,\ldots, m^*$

(41) $\quad y_j^*(m, n, m^*, n^*) = \left(\frac{1}{2-\gamma}\right)\left((a - c) - \delta_2(a - \bar{c}_2)\right)$

$\forall \quad j = (n^* - m^*), (n - m^* + 1), \ldots, n^*$

where, $\bar{c}_2 = \theta_0 \alpha c + (1 - \theta_0)c + \theta_1 \alpha c^* + (1 - \theta_1)c^*$, $\theta_0 = \frac{m}{n} \in (0,1)$ is the proportion of domestic SSO members in the industry, $\theta_1 = \frac{m^*}{n^*} \in (0,1)$ is the proportion of foreign SSO members in the industry, $\delta_1 = \frac{n\gamma}{n\gamma + (2-\gamma)} \in (0,1)$, and $\delta_2 = \frac{n^*\gamma}{n^*\gamma + (2-\gamma)}$.

The industry output is

(42) $$\tilde{y}(m,n,\ m^*,n^*) = \left(\frac{1-\delta_1-\delta_2}{2-\gamma}\right) N(a-\bar{c}_2)$$

The prices of domestic and foreign varieties are

(43) $$p_i = \left(\frac{1}{2-\gamma}\right)\left(a-(1-\gamma)\alpha c - \delta_1(a-\bar{c}_2)\right) \qquad \forall \quad i = 1,2,\ldots,m$$

(44) $$p_i = \left(\frac{1}{2-\gamma}\right)\left(a-(1-\gamma)c - \delta_1(a-\bar{c}_2)\right) \qquad \forall \quad i = (n-m),(n-m+1),\ldots,n$$

(45) $$p_j^* = \left(\frac{1}{2-\gamma}\right)\left(a-(1-\gamma)\alpha c^* - \delta_3(a-\bar{c}_2)\right) \qquad \forall \quad i = 1,2,\ldots,m^*$$

(46) $$p_j^* = \left(\frac{1}{2-\gamma}\right)\left(a-(1-\gamma)c^* - \delta_3(a-\bar{c}_2)\right)$$

$$\forall \quad j = (n^*-m^*),(n-m^*+1),\ldots,n^*$$

2.2.3 *General Equilibrium*

In an open economy general equilibrium, without any SSO members, wages are determined by full employment conditions

(47) $$L = \int_{\tilde{z}}^{\tilde{z}^*} \beta(z)\tilde{y}(W,W^*,z,n,n^*)dz + \int_0^{\tilde{z}^*} \beta(z)\tilde{y}(W,W^*,z,n,0)dz$$

(48) $$L^* = \int_{\tilde{z}^*}^{\tilde{z}} \beta^*(z)\tilde{y}^*(W,W^*,z,n,n^*)dz + \int_{\tilde{z}}^{1} \beta^*(z)\tilde{y}^*(W,W^*,z,0,n^*)dz$$

where wages are normalized to $W = \lambda w$ and $W^* = \lambda w^*$ by choosing λ, the marginal utility of income, as the *numeraire*. L and L^* denote the supply of labor and $\tilde{z}$ and $\tilde{z}^*$ are the threshold sectors for the extensive margins of trade, at home and abroad respectively. Analogously, the full employment conditions with SSO membership are

(49) $$L = \int_{\tilde{z}}^{\tilde{z}^*} \frac{\beta(z)}{\alpha(z)} \tilde{y}(W, W^*, z, n, n^*)dz + \int_{0}^{\tilde{z}^*} \frac{\beta(z)}{\alpha(z)} \tilde{y}(W, W^*, z, n, 0)dz$$

(50) $$L^* = \int_{\tilde{z}^*}^{\tilde{z}} \frac{\beta^*(z)}{\alpha(z)} \tilde{y}^*(W, W^*, z, n, n^*)dz + \int_{\tilde{z}}^{1} \frac{\beta^*(z)}{\alpha(z)} \tilde{y}^*(W, W^*, z, 0, n^*)dz$$

In the home country's labor market, full employment ensures that home labor supply matches the sum of labor demands from sectors $z \in [0, \ \tilde{z}^*]$ in which home firms face no foreign competition (i.e. $n^* = 0$) and from the sectors $z \in [\tilde{z}, \ \tilde{z}^*]$ in which both home and foreign firms operate. Analogously, in the foreign country's labor market, full employment ensures that foreign labor supply matches the sum of labor demands from sectors $z \in [\tilde{z}, \ 1]$ in which foreign firms face no foreign competition (i.e. $n = 0$) and from the sectors $z \in [\tilde{z}^*, \tilde{z}]$ in which both home and foreign firms operate.

Consider now the possibility of bilateral mergers, within or across borders, that result in the closing down of one of the firms as long as the net gain from the merger is sufficient to compensate each participating firm. Propositions I, II, and III follow immediately.

Proposition I. The incentives for a takeover of a home or a foreign firm, that is not a member of an SSO, by an SSO member from the home or foreign country, rise (fall) with an *ex ante* rise (fall) in the number of SSO members relative to the number of non-members.

Proof. Follows from (13), (14), and (38) – (41).

Proposition II. The incentives for a takeover of an SSO member in the foreign (home) country by a firm at home (abroad), that is not a member of the SSO, rise (fall) with an *ex ante* rise (fall) in the number of SSO members relative to the number of non-members.

Proof. Follows from (13), (14), (27), (28), and (38) – (41).

Proposition III. The incentives for a takeover of an SSO member in the foreign (home) country by another SSO member at home (abroad), rise (fall) with an *ex ante* rise (fall) in the number of SSO members relative to the number of non-members.

Proof. Follows from (13), (14), (27), (28), and (38) – (41).

4. Data & Empirics

The SCD includes quantifiable characteristics of 762,146 standard documents, institutional membership in a sample of 195 SSOs, and the rules of 36 SSOs on standard-essential patents, openness, participation, and standard adoption procedures. First, we joined the SCD with a data-set (CHC-2017, hereinafter) compiled by Chakrabarti *et al*. (2017) after extracting observations from Security Data Corporation (SDC) and Corporate Transactions (CT) databases on individual firms and augmenting this data with detailed information on competition measures spanning firms from 86 countries between 1990 and 2012 with a total transaction value of $10.49 trillion. To effectuate the proposed join, we construct an algorithm which attempts to match the observations SCD and the CHC-2017 dataset. Of the 39,983 observations reported in the CHC-2017 database, a match of 23,158 (i.e. ~ 58%) was feasible.

[Tables 1 – 10 about here]

Next, we looked into the possibility of potential misspecification of SSO membership. We joined the SCD with BC-2019: the SCD of SSOs, while spanning a large sample, does not possibly cover all existing SSOs. This is likely to lead to false negatives – missed memberships when they actually exist. Also, the join between the SCD and the BC-2019 dataset, we construct an algorithm which matches the firms to names available in the SCD. However, the same corporation could be referred to by different variants in the databases, an example being, 'Alcatel Cable', 'Alcatel' and 'Alcatel Corporation' all referring to the same entity. These algorithms attempting to match phrases or strings that approximately match each other is often referred to as "fuzzy matching" in computer science literature. We use a novel modification of Seller's algorithms, identification of the most likely keyword and approximate distance computation techniques to adapt into a probabilistic matching technique for our purpose. This matching technique is not perfect (as is any probabilistic technique) – matches could be incorrectly specified due to incorrectly tagged keywords or missing potential matches, therefore possibly leading to both false positives and false negatives in the matches. We address this issue by adopting a hierarchical formulation. To do so, we consider the following set-up for the basic statistical model for this analysis,

$$y_{ij} = f\left(I_{ij}, X_i^1, X_j^2, X_{ij}^3\right) + \epsilon_{ij}.$$

We use a generic functional form 'f(.)' for the regression model since it is not clear that a standard least squared linear regression model would provide the best fit. Of the covariates included in the model, I_{ij} is the most crucial one for our hypotheses of interest.

To account for such potential uncertainty in the main covariate of interest I_{ij}, we propose the following hierarchical formulation. Let T_{ij} be the true unobserved value of the covariate and I_{ij} the deduced value from the probabilistic matching algorithm, possibly incorrectly specified As with I_{ij}, the variable T_{ij} could be in one of four categories, based on the target and acquirer's SSO membership. Consider the vector of conditional probabilities

$$\boldsymbol{\pi_{ij}} = \{\pi_{ij}^{a}, \pi_{ij}^{b}, \pi_{ij}^{c}, \pi_{ij}^{d}\}$$

where

$$\pi_{ij}^{a} = \Pr\left(T_{ij} \in a \;\middle|\; I_{ij}\right)$$

and, similarly, for the other elements $\pi_{ij}^{b}, \pi_{ij}^{c}, \pi_{ij}^{d}$.

A multivariate model is constructed for estimation of these conditional probabilities, such as,

$$\boldsymbol{\pi_{ij}} = g(U_i, V_j, I_{ij})$$

where U_i, V_j represent acquirer and target specific characteristics respectively, such as observed proportion of SSO membership in the industry classification code for the target or acquirer. We observe that mergers between SSO member tend to be associated with a higher degree of product differentiation relative to mergers between a member of the SSO and a non-member. However, the estimated value of the proportion of SSO memberships itself depends on the covariate I_{ij}, rendering estimation of $\boldsymbol{\pi_{ij}}$ difficult. We considered two alternative approaches to circumvent the problems posed by incorrect SSO membership specification: we could use an iterative scheme, where a value $\boldsymbol{\pi_{ij}}$ is estimated from the currently computed I_{ij}, or use a Bayesian formulation, when the U_i, V_j, I_{ij} are encoded into prior parameters for quantity of interest, $\boldsymbol{\pi_{ij}}$**.**

Using this value of $\boldsymbol{\pi_{ij}}$ in the probability matching scheme, new values of I_{ij} are computed. This iteration then continues until updates or changes to either set of values is minimal. This scheme is conceptually similar to an expectation-maximization (EM) type algorithm in statistics. The expectation maximization scheme is difficult to implement in practice since the computation of I_{ij} is quite burdensome and doing this at each iteration of algorithm would represent infeasible computation time. We resort to the Bayesian approach instead for the estimation of $\boldsymbol{\pi_{ij}}$'s. Once these conditional probabilities are estimated, they replace their counterparts in the basic model mentioned at the start of this subsection, so that the basic model now becomes:

$$y_{ij} = f\left(\pi_{ij}, X_i^1, X_j^2, X_{ij}^3\right) + \epsilon_{ij}$$

Our preliminary investigations reveal the presence of non-linear patterns as well as higher order interaction terms in the merged data. We use a Bayesian random forest specification for robust quantification of non-linear patterns in the regression. In general, random forests represent a regression technique that work by averaging estimates over a collection of individual regression trees. To investigate how well our proposed algorithm works, we devise a simulation study with mock-up data. This mock-up data investigates how well our algorithm is able to pick up associations with imperfect specification of covariates. In doing so, we consider three degrees of misspecification (*ref*. table above):

a) Low i.e. actual misspecification is 5% or less;

b) Moderate i.e. actual misspecification is about 25%; and

c) High i.e. actual misspecification is at least 50%.

It turns out that our model is fairly robust for low to moderate misspecification of covariates whereas standard regression is not. It is also worth noting that in case of perfect specification, our proposed model performs at least as well as the standard methods. In instances of high misspecification, when it may be argued that attempting the regression analysis itself may be dubious for the main covariate of interest, since the little information is present, our model is able to beat the standard linear model but remains comparable to a hierarchical linear model taking into account estimated conditional probabilities.

5. Conclusion

We complement the vast and growing literature on market concentration by identifying statistically significant associations between the composition of SSOs and market concentration. In doing so, we recognize that the Searle center database of SSOs, while being a large sample, does not possibly cover all SSOs that exist. Our analysis provides convincing evidence of association between the nature of a deal in the CHC database and whether or not the participating firms were SSO members: SSO membership tends to be associated with larger deals. We recognize that the Searle center database of SSOs, while being a large sample, does not possibly cover all SSOs that exist. We also acknowledge that the join between the SCD and the CHC dataset, inaccurately specify matches due to incorrectly tagged keywords or missing potential matches, possibly leading to both false positives and false negatives in the matches. We address this issue by employing a Bayesian random forest specification for robust quantification of non-linear patterns in our regression analyses. Our model is fairly robust for low to moderate miss-specification of covariates.

Appendix

Table 1

Type	Number Matched To SCD	Percentage of total number matched
Matched Target	18343	45.88
Matched Acquiror	23158	57.92
Matched both	11462	28.67

Table 2

```
   Huber iteration 1:  maximum difference in weights =     .95706586
   Huber iteration 2:  maximum difference in weights =     .31021567
   Huber iteration 3:  maximum difference in weights =     .11141612
   Huber iteration 4:  maximum difference in weights =     .08882252
   Huber iteration 5:  maximum difference in weights =     .06122824
   Huber iteration 6:  maximum difference in weights =     .03692159
Biweight iteration 7:  maximum difference in weights =     .28826186
Biweight iteration 8:  maximum difference in weights =     .05580931
Biweight iteration 9:  maximum difference in weights =     .05352545
Biweight iteration 10:  maximum difference in weights =     .06796745
Biweight iteration 11:  maximum difference in weights =     .040394
Biweight iteration 12:  maximum difference in weights =     .00789165

Robust regression                                     Number of obs =        149
                                                         F(  1,   147) =   216.49
                                                         Prob > F      =   0.0000
```

number_of_~s	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
nssofirms	.1054134	.0071643	14.71	0.000	.0912551	.1195717
_cons	6.738669	.9156753	7.36	0.000	4.929081	8.548257

Table 3

```
   Huber iteration 1:  maximum difference in weights =     .92780473
   Huber iteration 2:  maximum difference in weights =     .36563917
   Huber iteration 3:  maximum difference in weights =     .18270908
   Huber iteration 4:  maximum difference in weights =     .07265588
   Huber iteration 5:  maximum difference in weights =     .02604644
Biweight iteration 6:  maximum difference in weights =     .27859103
Biweight iteration 7:  maximum difference in weights =     .0641862
Biweight iteration 8:  maximum difference in weights =     .0405317
Biweight iteration 9:  maximum difference in weights =     .02937173
Biweight iteration 10:  maximum difference in weights =     .01650225
Biweight iteration 11:  maximum difference in weights =     .01367514
Biweight iteration 12:  maximum difference in weights =     .00616366

Robust regression                                      Number of obs =        149
                                                          F(  2,    146) =   110.96
                                                          Prob > F      =   0.0000
```

number_of_~s	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
nssofirms	.101813	.0072327	14.08	0.000	.0875187	.1161074
acquiror_hhi	-9.615448	4.039476	-2.38	0.019	-17.59885	-1.632046
_cons	12.3692	2.374043	5.21	0.000	7.677274	17.06113

Table 4

```
   Huber iteration 1:  maximum difference in weights =     .92622255
   Huber iteration 2:  maximum difference in weights =     .40131545
   Huber iteration 3:  maximum difference in weights =     .16799405
   Huber iteration 4:  maximum difference in weights =     .06732042
   Huber iteration 5:  maximum difference in weights =     .02412928
Biweight iteration 6:  maximum difference in weights =     .29427237
Biweight iteration 7:  maximum difference in weights =     .08626125
Biweight iteration 8:  maximum difference in weights =     .04202793
Biweight iteration 9:  maximum difference in weights =     .03374201
Biweight iteration 10:  maximum difference in weights =     .02253379
Biweight iteration 11:  maximum difference in weights =     .01235837
Biweight iteration 12:  maximum difference in weights =     .00788352

Robust regression                                      Number of obs =        149
                                                          F(  3,    145) =    72.83
                                                          Prob > F      =   0.0000
```

number_of_~s	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
nssofirms	.101585	.0073197	13.88	0.000	.0871179	.116052
acquiror_hhi	-9.285057	4.265759	-2.18	0.031	-17.71616	-.8539572
target_hhi	-.9855631	4.49333	-0.22	0.827	-9.866448	7.895322
_cons	12.70702	2.963106	4.29	0.000	6.850565	18.56348

Table 5

```
   Huber iteration 1:  maximum difference in weights =     .9317479
   Huber iteration 2:  maximum difference in weights =     .40494237
   Huber iteration 3:  maximum difference in weights =     .18140675
   Huber iteration 4:  maximum difference in weights =     .08102307
   Huber iteration 5:  maximum difference in weights =     .04365277
Biweight iteration 6:  maximum difference in weights =     .29584696
Biweight iteration 7:  maximum difference in weights =     .08214019
Biweight iteration 8:  maximum difference in weights =     .04686977
Biweight iteration 9:  maximum difference in weights =     .03544554
Biweight iteration 10:  maximum difference in weights =     .01801222
Biweight iteration 11:  maximum difference in weights =     .01115683
Biweight iteration 12:  maximum difference in weights =     .00724617

Robust regression                                      Number of obs =        149
                                                          F(  4,   144) =    53.69
                                                          Prob > F      =   0.0000
```

number_of_bidders	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
nssofirms	.1016035	.0073858	13.76	0.000	.087005	.116202
acquiror hhi	-8.832032	9.435547	-0.94	0.351	-27.4821	9.818034
target_hhi	-.3993775	10.21967	-0.04	0.969	-20.59932	19.80056
acquiror target hhi	-.9413482	15.71352	-0.06	0.952	-32.0003	30.1176
_cons	12.45294	5.560926	2.24	0.027	1.46135	23.44452

Table 6

```
   Huber iteration 1:  maximum difference in weights =     .99276599
   Huber iteration 2:  maximum difference in weights =     .70750153
   Huber iteration 3:  maximum difference in weights =     .73776636
   Huber iteration 4:  maximum difference in weights =     .60844318
   Huber iteration 5:  maximum difference in weights =     .42487127
   Huber iteration 6:  maximum difference in weights =     .65519962
   Huber iteration 7:  maximum difference in weights =     .0802087
   Huber iteration 8:  maximum difference in weights =     .0668683
   Huber iteration 9:  maximum difference in weights =     .01952989
Biweight iteration 10:  maximum difference in weights =     .2930441
Biweight iteration 11:  maximum difference in weights =     .12541948
Biweight iteration 12:  maximum difference in weights =     .05341069
Biweight iteration 13:  maximum difference in weights =     .02670788
Biweight iteration 14:  maximum difference in weights =     .00910233

Robust regression                                      Number of obs =        150
                                                          F(  1,   148) =  1027.21
                                                          Prob > F      =   0.0000
```

value_of_t~_	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
nssofirms	13.38881	.4177459	32.05	0.000	12.56329	14.21432
_cons	217.947	70.39335	3.10	0.002	78.84108	357.0529

Table 7

```
   Huber iteration 1:  maximum difference in weights =    .98102558
   Huber iteration 2:  maximum difference in weights =    .70392375
   Huber iteration 3:  maximum difference in weights =    .56478207
   Huber iteration 4:  maximum difference in weights =    .61727705
   Huber iteration 5:  maximum difference in weights =    .37153352
   Huber iteration 6:  maximum difference in weights =    .42718438
   Huber iteration 7:  maximum difference in weights =    .05784221
   Huber iteration 8:  maximum difference in weights =    .04132751
Biweight iteration 9:  maximum difference in weights =    .29251503
Biweight iteration 10:  maximum difference in weights =    .18975048
Biweight iteration 11:  maximum difference in weights =    .06185846
Biweight iteration 12:  maximum difference in weights =    .04026461
Biweight iteration 13:  maximum difference in weights =    .01918044
Biweight iteration 14:  maximum difference in weights =    .0098116

Robust regression                                     Number of obs =        150
                                                         F(  2,    147) =   394.93
                                                         Prob > F      =   0.0000
```

value_of_t~_	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
nssofirms	13.0601	.4804915	27.18	0.000	12.11054	14.00966
acquiror hhi	-327.8671	361.3514	-0.91	0.366	-1041.982	386.2476
_cons	430.0583	211.2303	2.04	0.044	12.61783	847.4987

Table 8

```
   Huber iteration 1:  maximum difference in weights =    .97712698
   Huber iteration 2:  maximum difference in weights =    .82919434
   Huber iteration 3:  maximum difference in weights =    .63846953
   Huber iteration 4:  maximum difference in weights =    .60802062
   Huber iteration 5:  maximum difference in weights =    .39004363
   Huber iteration 6:  maximum difference in weights =    .39745598
   Huber iteration 7:  maximum difference in weights =    .05912203
   Huber iteration 8:  maximum difference in weights =    .03899446
Biweight iteration 9:  maximum difference in weights =    .29391202
Biweight iteration 10:  maximum difference in weights =    .15256491
Biweight iteration 11:  maximum difference in weights =    .0490188
Biweight iteration 12:  maximum difference in weights =    .04893493
Biweight iteration 13:  maximum difference in weights =    .02388416
Biweight iteration 14:  maximum difference in weights =    .01294248
Biweight iteration 15:  maximum difference in weights =    .00580872

Robust regression                                     Number of obs =        150
                                                         F(  3,    146) =   245.93
                                                         Prob > F      =   0.0000
```

value_of_t~_	Coef.	Std. Err.	t	P>|t|	[95% Conf.	Interval]
nssofirms	12.97759	.496779	26.12	0.000	11.99578	13.9594
acquiror_hhi	-373.144	389.134	-0.96	0.339	-1142.207	395.9194
target_hhi	141.7597	409.8193	0.35	0.730	-668.1849	951.7043
_cons	383.2831	269.0751	1.42	0.156	-148.5023	915.0684

Table 9

```
   Huber iteration 1:  maximum difference in weights =     .97918916
   Huber iteration 2:  maximum difference in weights =     .6163138
   Huber iteration 3:  maximum difference in weights =     .77048485
   Huber iteration 4:  maximum difference in weights =     .27785906
   Huber iteration 5:  maximum difference in weights =     .31684987
   Huber iteration 6:  maximum difference in weights =     .16659548
   Huber iteration 7:  maximum difference in weights =     .08309542
   Huber iteration 8:  maximum difference in weights =     .05528054
   Huber iteration 9:  maximum difference in weights =     .03341017
Biweight iteration 10:  maximum difference in weights =     .30379682
Biweight iteration 11:  maximum difference in weights =     .34850829
Biweight iteration 12:  maximum difference in weights =     .1567207
Biweight iteration 13:  maximum difference in weights =     .12579286
Biweight iteration 14:  maximum difference in weights =     .15688647
Biweight iteration 15:  maximum difference in weights =     .44358351
Biweight iteration 16:  maximum difference in weights =     .31105817
Biweight iteration 17:  maximum difference in weights =     .05970394
Biweight iteration 18:  maximum difference in weights =     .01424925
Biweight iteration 19:  maximum difference in weights =     .00354958

Robust regression                                      Number of obs =        151
                                                          F(  4,   146) =    88.70
                                                          Prob > F      =   0.0000

------------------------------------------------------------------------------------
value_of_transact~_ |      Coef.   Std. Err.      t    P>|t|     [95% Conf. Interval]
--------------------+---------------------------------------------------------------
          nssofirms |   6.705663   .3731909    17.97   0.000     5.968108    7.443217
       acquiror hhi |  -335.6996   820.6589    -0.41   0.683    -1957.605    1286.206
         target_hhi |   98.83451   889.2499     0.11   0.912    -1658.631      1856.3
acquiror target hhi |    63.1294    1365.51     0.05   0.963    -2635.591     2761.85
              _cons |   460.6895   483.7797     0.95   0.343    -495.4264    1416.805
------------------------------------------------------------------------------------
```

Table 10: Performance of the proposed algorithm with mis-specified binary covariates

Performance Criterion	**Low mis-specification**	Moderate mis-speciation	High mis-specification	With perfect specification
Linear model without hierarchy	**58%**	**41%**	**42%**	**93%**
Linear model with hierarchy	**71%**	**63%**	**52%**	**93%**
Bayesian random forests	**81%**	**75%**	**51%**	**96%**

References

Banerjee, A. and A. Chakrabarti (2019). Technology standards and cross-border M&A: The role of standards setting organizations, *mimeo*.

Baron, J. and D. F. Spulber (2018). "Technology standards and standard setting organizations: Introduction to the Searle center database." *Journal of Economics & Management Strategy*, 27(3): 462-503.

Beladi, H. and A. Chakrabarti (2019). Multidivisional firms, internal competition, and comparative advantage, *Journal of International Economics*, 116(1): 50-56.

Beladi, H., Chakrabarti, A., and Marjit, S. (2010). "Cross-border Merger, Vertical Structure and Spatial Competition", *Economics Letters* 109 (2): 112 – 114.

_______________ (2013a). "Cross-border Mergers in Vertically Related Industries", *European Economic Review* 59, 97 – 108.

_______________ (2013b). "Privatization and Strategic Mergers Across Borders", *Review of International Economics* 21(3): 432 – 446.

_______________ (2015). "On Cross-Border Mergers and Product Differentiation", The BE Journal of Economic Analysis and Policy: *Advances*, Volume 15(1): 37 – 51.

Chakrabarti, A., Y. Hsieh, Y., and Y. Chang, Y. (2017). "Cross-border M&A and Market Concentration in a Vertically Related Industry: Theory and Evidence", The Journal of *International Trade & Economic Development* 26(1): 111-130.

Häckner, J. (2000): "A Note on Price and Quantity Competition in Differentiated Oligopolies", *Journal of Economic Theory*, 93, 233-239.

Head, K. and J. Ries, (1997). "International Mergers and Welfare under Decentralized Competition Policy", *Canadian Journal of Economics*, 30, 1104-1123.

Jovanovic, B. and P.L. Rousseau (2008). "Mergers as Reallocation." *The Review of Economics and Statistics*, 90, 765-776.

Long, N.V. and N. Vousden (1995). "The Effects of Trade Liberalization on Cost-reducing Horizontal Mergers", *Review of International Economics*, 3, 141-155.

Neary, J. P. (2003). "Globalization and Market Structure," *Journal of the European Economic Association*, 1: 245-271.

_______________ (2007). "Cross-border M&A as Instruments of Comparative Advantage," *Review of Economic Studies*, 74: 1229-1257.

______________ (2016). "International Trade in General Oligopolistic Equilibrium." *Review of International Economics*, 24, 669-698.

Perry, M. and R. Porter (1985). "Oligopoly and the Incentive for Horizontal Merger", *American Economic Review*, 75, 219-227.

Reuer, J.J. et al. (2004). "Mitigating Risk in International Mergers and Acquisitions: The Role of Contingent Payouts," *Journal of International Business Studies*, 35, 19–32.

Spulber, D. F. (2018). "Standard Setting Organizations and Standard Essential Patents: Voting Power versus Market Power." *Economic Journal*.

Stoll, T. P. (2014). "Are You Still in? The Impact of Licensing Requirements on the Composition of Standards Setting Organizations." The Impact of Licensing Requirements on the Composition of Standards Setting Organizations, Max Planck Institute for Innovation & Competition Research Paper 14-18.

Endnotes

[1] See Beladi, Chakrabarti, and Marjit, S. (2010, 2013a, 2013b, and 2015).
[2] See Häckner (2000).
[3] The extensive margins of trade are defined in terms of the varieties exported from each country.
[4] See Häckner (2000).