Technology Standards and Cross-Border M&A:

The Role of Standards Setting Organizations

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Does participation in Standards Setting Organizations (SSOs) of a target or an acquirer in an M&A deal influence the value or size of the deal? To answer this question, we look into plausible associations between memberships in SSOs and cross-border M&A. To test the key hypotheses, derived from our theoretical construct, we analyze a unique dataset created by joining the Searle Center database on SSOs with a dataset created by Chakrabarti, Hsieh, and Chang (2017), 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.

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1. Introduction

In this paper, we look into the role of Standard Setting Organizations (SSOs) in Cross-Border Mergers and Acquisitions (M&A). The importance of standardization in the development of complex technologies has been generating increasing interest in technology 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). The prominent role of SSOs, in determining such technology standards, is widely recognized. Yet, the literature on the economic implications of technology standards still remains at its infancy. While this could be attributed to limited availability of data, on large samples of standards from different SSOs, the Searle Center Database (SCD) has lowered such informational barriers. Access to the SCD has opened up a new room for long overdue research on the economic implications, in general, of technology standards. For instance, the vast and growing body of empirical literature on Cross-Border M&A continues to accumulate a wide range of variables of interest that are apparently associated with M&A across countries. Public policy towards cross-border M&A can be informed by in-depth statistical analyses of SCD on SSOs due to the links between technology standards and competition. We join the SCD with a recent data-set constructed by Chakrabarti, Hsieh, and Chang (2015). This provides us a unique data-set that can be used to assess the role of SSOs in firms' merger decisions across borders.

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[1] 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.

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

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

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 M&A across borders, this paper complements the existing literature by recognizing the importance of technology standards in firms' merger decisions across borders.

3. Model

Consider a stylized world containing two countries each with a continuum of atomistic industries, indexed by $z \in [0, 1]$. Each industry supports $N(z) = \left(n(z) + n^*(z)\right)$differentiated goods produced by $n\ (z)$ domestic firms, $n_s(z)$ of which are SSO members, competing (`a la Cournot) with $n^*(z)$ foreign firms, $n_s^*(z)$ of which are SSO members: $n(z)$ and $n^*(z)$ are exogenous but can vary across industries and change due to merger(s). Production of each variety requires a homogeneous intermediate input supplied by one upstream firm located in each country, U at home and U^* abroad, competing (`a la Bertrand) to supply the input (freely traded across borders) to the $n\ (z)$ downstream firms at home and $n_s^*(z)$ downstream firms in the foreign country. The intermediate input is produced at a constant marginal cost $c(z)$ at home and abroad. Production of each variety requires internationally immobile labor, which earns an hourly wage of w and w^* at home and abroad respectively, and one unit of the intermediate input. The unit labor requirements are $\beta_s(z)$ and $\beta_s^*(z)$, for the SSO members, and $\beta(z)$ and $\beta^*(z)$, for the other firms, at home and abroad, respectively. We assume that $\beta_s(z) < \beta\ (z)$ and $\beta_s^*(z) < \beta^*(z)$ i.e. SSOs, in each country, choose efficient technology standards through interactions between standard setting and market competition.[2] For analytical tractability, we assume symmetric differentiation across all varieties. We also assume away any fixed cost which, otherwise, would provide a trivial rationale for mergers. For convenience of exposition, without loss of generality, we sort the firm indices in ascending order of unit labor requirements within each country.

Let the demand side be characterized by a two-tier utility function of consumption levels for 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

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

where, in any industry $z \in [0,\ 1]$, $x_i\,(z)$ is the quantity demanded of a home variety and $x_j^*(z)$ is the quantity demanded of a foreign variety.

Each sub-utility function, in turn, is quadratic

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

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

$$(2) \qquad \int_0^1 \left[\sum_{i=1}^{n} p_i(z)x_i\,(z) + \sum_{j=1}^{n^*} p_j^*(z)x_j^*(z)\right]dz \le I$$

[2] See Spulber (2016) who demonstrates how countervailing effects of voting power and market power induce SSOs to choose efficient technology standards.

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[3] for the k-th domestic variety, in any industry $z \in [0,\ 1]$, is

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

Analogously, the inverse demand for the k^*-th foreign variety in the same industry is

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

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. This specification parameterizes the degree of product differentiation by $\gamma \in [0,\ 1]$: $\gamma = 0$ when the demand for each good is completely independent of other goods; product differentiation declines as $\gamma \to 1$; and the goods are perfect substitutes (homogeneous) if $\gamma = 1$.

Let $y_s(z)$ be the output supplied by a domestic SSO member (s) and $y_i(z)$ be the output supplied by a home firm (i) that is not a SSO member. Each SSO member, operating at home in any industry $z \in [0,\ 1]$, will

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[3] See Häckner (2000).

$$\underset{\{y_s\}}{Maximize}: \quad \Pi_s = \int_0^1 \left(p_i(z) - c(z) - w\beta_s(z)\right) y_s(z)dz \qquad \forall \quad s = 1,2,\ldots,n_s(z)$$

The other home firms, operating in the same industry, will

$$\underset{\{y_i\}}{Maximize}: \quad \Pi_i(z) = \int_0^1 \left(p_i(z) - c(z) - w\beta(z)\right) y_i(z)dz \qquad \forall \quad i = n_{s+1}(z), n_{s+2}(z),\ldots,n(z)$$

Let $y_{s*}^{\ *}(z)$ be the output supplied by a foreign SSO member (s^*) and $y_j^*(z)$ be the output supplied by a foreign firm (j) that is not a SSO member. Each foreign firm, in industry $z \in [0,\ 1]$, will

$$\underset{\{y_{s*}^*\}}{Maximize}: \quad \Pi_{s*}^* = \int_0^1 \left(p_j^*(z) - c(z) - w^*\beta_s^*(z)\right) y_{s*}^*(z)dz \qquad \forall \quad s^* = 1,2,\ldots,n_s^*(z)$$

The other foreign firms, operating in the same industry, will

$$\underset{\{y_j^*\}}{Maximize}: \quad \Pi_j^*(z) = \int_0^1 \left(p_j^*(z) - c(z) - w^*\beta^*(z)\right) y_j^*(z)dz \quad \forall \quad j = n_{s+1}^*(z), n_{s+2}^*(z),\ldots,n^*(z)$$

Consider now the possibility of bilateral mergers 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 through III follow immediately.

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

Proof. See Appendix.

Proposition II. The incentives for a takeover of a 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 at home and/or abroad.

Proof. See Appendix.

Proposition III. The incentives for a takeover of a SSO member in the foreign (home) country by a 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 at home and/or abroad.

Proof. See Appendix.

4. Data and 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. We join the SCD with a data-set (CHC, hereinafter), recently constructed by Chakrabarti *et al*. (2017) by extracting M&A observations (from Security Data Corporation's (SDC) M&A and Corporate Transactions database) on individual firms and augmenting this data with detailed information on competition measures (which theory suggests should influence firms' M&A decisions, within and across borders), spanning 90,614 M&A (22,600 of which are cross-border M&A with a total transaction value of $3.15 trillion) between firms from 86 countries between 1990 and 2012 with a total transaction value of $10.49 trillion. To effectuate the proposed join between SCD and the CHC dataset, we construct an algorithm which attempts to match, for each M&A deal in the CHC dataset, the participating firms in the deal to names in the SCD. Of the 39983 deals reported in the CHC database, the following table represents the basic distribution of the number of matches found, with a preliminary version of this algorithm.

[Table 1 about here]

Preliminary analysis provides empirical evidence of association between nature of the deal in the CHC database and whether or not the participating firms were SSO members. For example, there is strong evidence that SSO membership tends to be associated with larger deals. Such associations are indicated in tables 2 through 5 (where the dependent variable is the number of bidders for cross-border mergers in an industry and the explanatory variables include the number of SSO firms and concentration ratios measured by HHI), tables 6 through 9 (where the dependent variable is the value of transactions for cross-border mergers in an industry and the explanatory variables include the number of SSO firms and concentration ratios measured by HHI), as well as tables 10 and 11 (using firm-level data) that summarize multivariate regression results.[4]

[Tables 2 – 11 about here]

5. Membership Misspecification

In this section, we underscore and attempt to address an important issue of potential misspecification of SSO membership. The Searle center database of SSO's, while being a large sample, does not possibly cover all possible SSO's that exist. This is likely to lead to false negatives – missed memberships when they actually exist. Also, the join between the SCD and the CHC dataset, we construct an algorithm which attempts to match, for each M&A deal in the CHC

[4] The algorithm to detect SSO memberships may contain false positives; and regression assumptions have not been checked and the appropriate non-parametric and/or non-linearity adjustments have not been made.

dataset, the participating firms in the deal 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 attempt to address this issue by adopting a hierarchical formulation.

Let us focus on the specific question of whether the target or acquirer's SSO membership affects the value of the M&A deal or not. Consider the following set-up for the basic statistical model for this analysis,

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

where

y_{ij} represents the value of the deal between entities represented as acquirer 'i' and target 'j';

I_{ij} is a categorical variable with one of the following categories: a) Both target and acquirer and SSO members; b) Only target is an SSO member; c) Only acquirer is an SSO member; d) None of the target and acquirer are SSO members;

X_i^1 represents acquirer 'i' specific covariates, such as, average wage for acquirer;

X_j^2 represents target 'j' specific covariates;

X_{ij}^3 represents the M&A deal specific covariates, such as indicators of whether it was cross-border or not; and

ϵ_{ij} represents noise.

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. We discuss this issue in more detail later. Of the covariates included in the model, I_{ij} is the most crucial one for our hypotheses of interest. Unfortunately, I_{ij} is likely to be imperfectly observed, as discussed at the opening of this section. To account for this 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,

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

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

A multivariate model maybe 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 memberships in the industry classification code for the target or acquirer. 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 consider two approaches to circumvent the problems posed by incorrect SSO membership specification:

1. We could use an iterative scheme, where a value $\boldsymbol{\pi_{ij}}$ is estimated from the currently computed I_{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 similary to an expectation-maximization (EM) type algorithm in statistics.
2. Using a Bayesian formulation, when the U_i, V_j, I_{ij} are encoded into prior parameters for quantity of interest, $\boldsymbol{\pi_{ij}}$.

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

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

On the choice of f, 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. We consider three degrees of mis-specification: a) When actual misspecification is 5% or less, termed low, b) When it is about 25%, termed moderate, c) When it is about 50%, and d) When there is no misspecification. Table 12 below compares the performance of the proposed algorithm with mis-specified binary covariates: Worst performers are colored in red, while the best are colored in green; the numbers in the cells represent the percentage of times the actual ground truth (association of covariate with outcome was picked up by the final model).

[Table 12 about here]

It appears that our model is fairly robust to 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 mis-specification, 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. Applying our hierarchical model to the merged dataset, we obtain the following results:

[Table 13 about here]

The coefficients, presented in Table 13, indicates that the posterior probability that SSO membership, be it of the target or acquirer, is not associated with the value of the deal is close to nil.

6. Conclusion

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.

Table 1: Frequencies of matched names in the databases

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: Regression Analysis Summary, when regressing the value of deal with other variables. The first two covariates consider sso membership of the participating firms in the M&A Deal.

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	-2173.15	754.82	-2.88	0.00
chc_companies$TargetIsSsoTRUE	153.58	24.96	6.15	0.00
chc_companies$AcquirorIsSsoTRUE	167.27	25.57	6.54	0.00
chc$Crossborder	65.69	48.43	1.36	0.18
chc$Horizontal	11.23	30.25	0.37	0.71
chc$Contig	-91.56	88.96	-1.03	0.30
chc$Colony	37.00	66.94	0.55	0.58
chc$Dist	0.00	0.01	-0.42	0.67
chc$Proximity	1225.69	154.07	7.96	0.00
chc$Target_Hhi	8.95	67.32	0.13	0.89
chc$Target_Enroll_Pri	12.52	8.81	1.42	0.16
chc$Target_Enroll_Second	-2.75	2.03	-1.36	0.17
chc$Target_Enroll_Tert	3.11	2.44	1.28	0.20
chc$Target_Wage	-3.45	6.81	-0.51	0.61
chc$Target_Total_Emp	-0.05	0.07	-0.77	0.44
chc$Target_Logmarketsize	134.63	105.90	1.27	0.20
chc$Target_Countryskill	-67.42	47.98	-1.41	0.16
chc$Target_Industryskill	2.20	0.84	2.63	0.01
chc$Acquiror_Hhi	0.31	68.83	0.00	1.00
chc$Acquiror_Enroll_Pri	-4.70	9.05	-0.52	0.60
chc$Acquiror_Enroll_Second	0.18	2.05	0.09	0.93
chc$Acquiror_Enroll_Tert	-2.63	2.43	-1.08	0.28
chc$Acquiror_Wage	0.92	6.86	0.13	0.89
chc$Acquiror_Total_Emp	0.23	0.07	3.40	0.00
chc$Acquiror_Logmarketsize	18.67	105.94	0.18	0.86
chc$Acquiror_Countryskill	86.28	48.68	1.77	0.08
chc$Acquiror_Industryskill	3.19	0.77	4.16	0.00

Table 11: Regression Analysis Summary, when regressing the percentage of shares acquired in the deal with other variables. The first two covariates consider sso membership of the participating firms in the M&A Deal.

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	0.55	6.69	0.08	0.93
chc_companies$TargetIsSsoTRUE	-0.44	0.22	-2.00	0.05
chc_companies$AcquirorIsSsoTRUE	-0.67	0.22	-2.99	0.00
chc$Crossborder	-0.01	0.43	-0.02	0.98
chc$Horizontal	0.67	0.26	2.51	0.01
chc$Contig	2.16	0.78	2.77	0.01
chc$Colony	1.78	0.58	3.04	0.00
chc$Dist	0.00	0.00	2.70	0.01
chc$Proximity	-2.88	1.35	-2.13	0.03
chc$Target_Hhi	-0.11	0.59	-0.19	0.85
chc$Target_Enroll_Pri	0.09	0.08	1.20	0.23
chc$Target_Enroll_Second	-0.04	0.02	-2.21	0.03
chc$Target_Enroll_Tert	0.11	0.02	4.95	0.00
chc$Target_Wage	0.39	0.06	6.43	0.00
chc$Target_Total_Emp	0.00	0.00	3.85	0.00
chc$Target_Logmarketsize	1.13	0.93	1.22	0.22
chc$Target_Countryskill	2.47	0.42	5.86	0.00
chc$Target_Industryskill	-0.05	0.01	-6.93	0.00
chc$Acquiror_Hhi	-1.20	0.60	-1.99	0.05
chc$Acquiror_Enroll_Pri	0.20	0.08	2.55	0.01
chc$Acquiror_Enroll_Second	-0.07	0.02	-3.65	0.00
chc$Acquiror_Enroll_Tert	0.10	0.02	4.85	0.00
chc$Acquiror_Wage	0.35	0.06	5.70	0.00
chc$Acquiror_Total_Emp	0.00	0.00	0.77	0.44
chc$Acquiror_Logmarketsize	-4.16	0.93	-4.47	0.00
chc$Acquiror_Countryskill	1.57	0.43	3.67	0.00
chc$Acquiror_Industryskill	-0.07	0.01	-9.89	0.00

Table 12: 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%**

Table 13. Estimates

Explanatory Variable	Coefficient	Standard Error
Target is SSO member	123.21	45.23
Acquiror is SSO member	117.33	41.11

Appendix

Proofs of propositions I through III follow from equations A1 through A4 below. In the pre-merger equilibrium, the firms' profits are

$$\text{(A1)} \qquad \Pi_s = \int_0^1 \left(y_s(z)\right)^2 dz \qquad \forall \quad s = 1,2,\ldots,n_s(z)$$

$$\text{(A2)} \qquad \Pi_i = \int_0^1 \left(y_i(z)\right)^2 dz \qquad \forall \quad i = n_{s+1}(z), n_{s+2}(z),\ldots,n(z)$$

$$\text{(A3)} \qquad \Pi^*_{s*} = \int_0^1 \left(y^*_{s*}(z)\right)^2 dz \qquad \forall \quad s^* = 1,2,\ldots,n^*_s(z)$$

$$\text{(A4)} \qquad \Pi^*_j = \int_0^1 \left(y^*_{s*}(z)\right)^2 dz \qquad \forall \quad j = n^*_{s+1}(z), n^*_{s+2}(z),\ldots,n^*(z)$$

where the outputs of firms operating in industry $z \in [0,\ 1]$ are

$$y_s(z) = \frac{(2-\gamma) - [2+\gamma(N(z)-2)]\left[c(z) + w\beta_s(z)\right] + \gamma[(n_s(z)-1)w\beta_s(z) + (n(z)-n_s(z))w\beta(z) + n^*_s(z)w^*\beta^*_s(z) + (n^*(z)-n^*_s(z))w^*\beta^*(z) + \left(N(z)-1\right)c(z)]}{(2-\gamma)[2+\gamma(N(z)-1)]}$$

$$\forall \quad s = 1,2,\ldots,n_s(z)$$

$$y_i(z) = \frac{(2-\gamma) - [2+\gamma(N(z)-2)]\left[c(z) + w\beta(z)\right] + \gamma[n_s(z)w\beta_s(z) + (n(z)-n_s(z)-1)w\beta(z) + n^*_s(z)w^*\beta^*_s + (n^*(z)-n^*_s(z))w^*\beta^*(z)\left(N(z)-1\right)c(z)]}{(2-\gamma)[2+\gamma(N(z)-1)]}$$

$$\forall \quad i = n_{s+1}(z), n_{s+2}(z),\ldots,n(z)$$

$$y^*_{s*}(z) = \frac{(2-\gamma) - [2+\gamma(N(z)-2)]\left[c(z) + w^*\beta^*_s(z)\right] + \gamma[n_s(z)w\beta_s(z) + (n(z)-n_s(z))w\beta(z) + (n^*_s(z)-1)w^*\beta^*_s(z) + (n^*(z)-n^*_s(z))w^*\beta^*(z)\left(N(z)-1\right)c(z)]}{(2-\gamma)[2+\gamma(N(z)-1)]}$$

$$\forall \quad s^* = 1,2,\ldots,n^*_s(z)$$

$$y^*_j(z) = \frac{(2-\gamma) - [2+\gamma(N(z)-2)]\left[c(z) + w^*\beta^*(z)\right] + \gamma[n_s(z)w\beta_s(z) + (n(z)-n_s(z))w\beta(z) + n^*_s(z)w^*\beta^*_s(z) + (n^*(z)-n^*_s l(z)-1)w^*\beta^*(z) + \left(N(z)-1\right)c(z)]}{(2-\gamma)[2+\gamma(N(z)-1)]}$$

$$\forall \quad j = n^*_{s+1}(z), n^*_{s+2}(z),\ldots,n^*(z)$$

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