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ABSTRACT

Large merger and acquisition (M&A) samples feature the pervasive presence of repetitive acquirers. They offer an attractive empirical context for revealing the presence of acquirer skills (persistent superior performance). But panel data M&A are quite heterogeneous; just a few acquirers undertake many M&As. Does this feature affect statistical inference? To investigate the issue, our study relies on simulations based on real data sets. The results suggest the existence of a bias, such that extant statistical support for the presence of acquirer skills appears compromised. We introduce a new resampling method to detect acquirer skills with attractive statistical properties (size and power) for samples of acquirers that complete at least five acquisitions. The proposed method confirms the presence of acquirer skills but only for a marginal fraction of the acquirer population. This result is robust to endogenous attrition and varying time periods between successive transactions. Claims according to which acquirer skills are a first order factor explaining acquirer cross-sectional cumulated abnormal returns appears overstated.

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Do some acquirers persistently display superior performance? This question is important, because such persistence implies the existence of acquisition skills, achieved through the acquirer's culture, history, expertise, management style, or access to funding sources; skills that are difficult for other firms to replicate. Firms missing this expertise should then focus on internal innovation and organic growth.

A pervasive feature of the market for corporate control is the presence of repetitive acquirers. According to Aktas et al. (2012), in a sample of 321,610 merger and acquisition (M&A) transactions between 1992 and 2009, approximately 25% involved acquirers that had undertaken at least five acquisitions during that period. These repetitive acquirers create a panel data structure in M&A samples, offering a rich opportunity to test various theories and predictions. For example, Schipper and Thompson (1983) and Malatesta and Thompson (1985) investigate investors' anticipation of acquisition programs. Referring to the hubris hypothesis (Roll, 1986) and data that show that acquirers' cumulative abnormal returns (CAR) decline during acquisition programs (Fuller et al., 2002), several authors argue that repetitive acquirers develop overconfidence (e.g., Billett and Qian, 2008), though Aktas et al. (2009) question whether a declining CAR is unambiguous evidence of hubris. Hayward (2002) also examines the conditions in which firms develop acquisition experience.

Building on an econometric approach designed by Bertrand and Schoar (2003; B&S hereafter) to test for the presence of a particular management style, some studies also have begun addressing acquirer skills (Golubov et al., 2015). This setup relies on CEO fixed effects (FE), such that B&S interpret significant CEO FE as evidence of a management style. In particular, they focus on changes in the *R*-square and adjusted *R*-square values when switching from a classical ordinary least squares (OLS) estimator to the data panel FE least squares dummy variable (LSDV) estimator, as well as on Fisher test of the joint significance of FE (FE Fisher Statistic). Yet the importance they attribute to the *R*-square and adjusted *R*-square values is puzzling. These statistics are indeed most often used as goodness of fit measures, not statistical tests. Even if asymptotic distributions exist, these depend on unknown parameters (see Ohtani, 2000). Moreover, without a clear null hypothesis, the interpretation of their results is ambiguous. It is worthwhile also to note that statistical findings using the *R*-square or the adjusted *R*-square offer no insights into the sign associated with skills (i.e., under- or over-performance). The FE Fisher test has the potential to reject the clearly defined null hypothesis of no acquirer skills though.

In the specific case of M&A sample the data sets are panel data sets strongly unbalanced, characterized by attrition as defined in Wooldridge (2002). For example, in Aktas et al.'s (2012) very large sample, more than 50% of the transactions involve acquirers that make only one acquisition. The CAR cross-sectional variation of one-time acquirers then can be captured fully and mechanically by an FE estimator. But does this attrition pattern affect the *R*-square, adjusted *R*-square, and Fisher

test? To what extent does it contaminate empirical findings? In addition to answering these questions, we seek an alternative testing procedure for detecting acquirer skills that might be more robust to the specific attrition pattern.

To do so, our analyses use a sample of 12,707 transactions completed during 1990–2011 by 4,507 unique acquirers. Our sample selection criteria match those of Golubov et al. (2015): domestically controlled transactions, public acquirers, targets of all statuses (public, private, subsidiaries), completed transactions, deal value of at least US $1 million as reported in the Thomson Securities Data Company (SDC) database, relative transaction size at least equal to 1%, and no financial industries (standard industrial classification [SIC] codes 6000–6999). Our sample includes 27.11% fully cash-paid deals and 15.99% public targets. The average deal value is US$ 377 million, and the average acquirer CAR is 1.71%. These statistics are all consistent with previous reports on similar sample types (e.g., Moeller et al., 2004). Of the 4,507 unique acquirers, 1,859 are one-time acquirers (41.25%), whereas 781 (17.33%) engaged in at least five transactions during 1990–2011. These two figures highlight the strong attrition in this typical M&A data set.

To assess the influence of attrition on inferences based on the B&S approach, we conducted simulation studies, in the style of Brown and Warner (1985; B&W hereafter), using our M&A sample and adding simulated acquirer skills. We manipulate the attrition pattern of the generated M&A samples, that is, the percentage of acquirers that complete a particular number of transactions. For example, we simulate samples in which 63.21% of acquirers are one-time acquirers, 23.26% are two-time acquirers, 8.56% are three-time acquirers, and so on. In seven attrition patterns (Figure 1), attrition in the number of transactions shifts from a rapid pace (right-skewed attrition), as typically observed for M&A samples, to a slow pace (left-skewed attrition). Thus we can examine the impact of panel attrition on the ability to detect acquirer skills. Each M&A transaction also is assigned a random acquirer skill level, drawn from a zero mean Gaussian distribution with a given variance. This skill applies to all transactions by a given acquirer (i.e., perfectly persistent). The variance of the Gaussian distribution then drives the importance and heterogeneity of skills in the acquirer sample. We regress the acquirer CAR on acquirer fixed effects (FE) and the set of control variables suggested by Golubov et al. (2015), then analyze the behavior of the FE Fisher test. We report also *R*-square and adjusted *R*-square values, to parallel existing literature. We repeat this process 1,000 times, with different combinations of the variances of abnormal returns and attrition patterns. In turn, we offer three key insights.

First, in the absence of simulated acquirer skills, when switching from the OLS to the LSDV estimator, the *R*-square value increases dramatically in case of right-skewed attrition. With the LSDV estimator, the *R*-square is only weakly reactive to the importance of simulated skills with right-skewed attrition. We conclude that the observation of an increase in the *R*-square value when

switching from OLS to LSDV cannot reveal insights into the presence or absence of acquirer skills in typical M&A samples.

Second, again in the absence of simulated acquirer skills, the increase in the adjusted *R*-square value that results from the switch from the OLS to the LSDV estimator is limited. With the LSDV estimator, the adjusted *R*-square is moreover more reactive to the importance of simulated skills, independently of the attrition pattern. Thus, it is more suited to detect acquirer skills than *R*-square is. But, as mentioned here above, the adjusted *R*-square is essentially goodness of fit measure, with an asymptotic distribution depending on unknown parameters, that offer therefore a limited route to test statistical evidence of the presence of acquirer skills. It also is silent about the sign of the detected skills.

Third, the FE Fisher Statistic, similar to the adjusted *R*-square, displays reactivity to the importance of simulated skills. Yet our B&W simulations highlight that the FE Fisher Statistic size depends on the attrition pattern. In a case of right-skewed attrition (as typically observed in M&A samples), the FE Fisher Statistic is vastly over-sized: in the absence of simulated acquirer skills, the null hypothesis of no acquirer skills is rejected far too often, according to the chosen confidence level (type I error). Therefore, the use of the FE Fisher test to detect acquirer skills leads to potentially strongly biased inferences.

Reflecting these findings regarding the FE Fisher Statistic size issue and the extent to which FE estimation precision depends on the number of acquisitions by the acquirer, we propose a new resampling-based method to detect acquirer skills and designated as RBSD for *Resampling Based Method for Skills Detection*. It builds on a simple idea: reconstruct balanced panels for each number of acquisitions by an acquirer. By construction, the generated M&A samples display no more attrition. We then analyze the size and power of RBSD using the set of B&W simulations adopted for the B&S procedure. Here again, some clear conclusions emerge: the FE Fisher Statistic is correctly sized, even if the sample displays right-skewed attrition. In the power analysis (i.e., ability of the RBSD FE Fisher Statistic to reject the absence of acquirer skills in presence of simulated skills), we observe that power increases with the number of acquisitions by acquirer, which is as expected, because skills by definition are based on persistence. Power also is increasing in the level of simulated skills. Therefore, the RBSD FE Fisher Statistic appears to be a valid statistical test for the presence of acquirer skills in a real-world M&A sample.

Applying the RBSD, we finally test for the presence of acquirer skills in our M&A sample. It confirms the presence of acquirer FE: At a 10% confidence level, for balanced samples of 5 acquisitions per acquirer, in 88.20% of the generated samples, we can reject the absence of significant acquirer FE. At 5% and 1% confidence levels, the corresponding percentages are 73.50% and 36.10%. But the percentages of acquirers displaying statistically significant FE are low. For

balanced samples of 5 acquisitions per acquirer, we find that 6.23%, 3.06%, and 0.65% of acquirer FE are significant at 10%, 5%, and 1% confidence levels, respectively. These results are robust to endogenous attrition due to past performance and controls for the varying time periods between successive transactions. Thus, we assert that the claims presenting acquirer skills as a first-order factor to explain the cross-section of acquirer CAR are overstated.

Our results accordingly contribute to M&A literature. They put into question Golubov et al.'s (2015, p. 315) general conclusions that "acquirer returns are, indeed, best explained by an unobserved, time-invariant, firm-specific factor." Their conclusions rely on the B&S setup and the persistence of acquirer performance throughout acquisition programs. We show that FE Fisher tests for data panels that display strong right-skewed attrition are over-sized and can lead to inaccurate inferences[1]. Golubov et al. (2015) also report the presence of persistence in acquirer performance through acquisition programs—notable, but not enough to validate the presence of skills. As Aktas et al. (2009) show, acquirer performance persistence also might be consistent with learning.

Our results instead support Fee et al.'s (2013) challenges to B&S's results, in which they used evidence from exogenous CEO departures to test whether these shocks affect firm behavior. They find no such effect, in contrast with predictions based on the management style hypothesis. They also assess the power of the B&S approach for uncovering management style, scrambling their data in such a way that, by construction, a management style effect cannot exit. To test for the presence of a management style on this simulated data set, they use the B&S setup. The FE Fisher test in that case led to a spurious conclusion about the presence of a management style effect. We extend this analysis to of the case of data panel attrition patterns that characterize M&A samples. We also offer the RBSD approach as an improved method to detect acquirer skills.

1. Data

1.1. M&A Sample

We collect M&A transactions from the SDC database over the 1990–2011 period, with the same selection criteria used by Golubov et al. (2015):

- Domestic transactions (U.S. acquirers and U.S. targets);
- Completed control transactions (acquirer holds less than 50% of the target shares before the announcement and ends up with 100% of the target shares);

1 Consistent with our simulation results, Golubov et al. (2015) report that for a subsample of acquirers that completed at least two deals during 1990–2011, the Fisher joint test of FE significance drops sharply (in Table 2, from 1.692 in Panel A to 1.287 and 1.261 in Panels B and C). Table 2 also reports that the adjusted *R*-square value drops from 23.1% in the full sample to 12% and 6.8%, respectively, for subsamples of serial acquirers. These results are more consistent with ours.

- Public acquirers and targets of all statuses (private, public, subsidiaries);
- Deal value of at least US$ 1 million;
- Relative transaction size (ratio of the deal value to the acquirer market value) of at least 1%;
- Financial industries (SIC codes 6000–6999) excluded; and
- Necessary information available in the CRSP and COMPUSTAT databases to compute the acquirer CAR and the set of control variables.

Applying these criteria, we collected 12,707 deals. Golubov et al. (2015) obtain 12,491 transactions over the same period. Table 1, Panel A, reports the number of deals by year; Panel B reports them by deal order number (DON), which is the deal number in the sequence of transactions completed by a given acquirer. In Table 1, Panel A, the M&A waves at the end of the 1990s and the mid-2000s are apparent (see also Betton et al., 2008). Furthermore, Figure 1, Panel B, displays the well-known stylized facts about the presence of repetitive acquirers, such that there are many one-time acquirers (41.25% of all acquirers in our sample, or 1,859 out of 4,507), as well as some active repetitive acquirers (781 firms completed at least five deals, or 17.33% of the sample). These statistics coincide with previous reports (e.g., Aktas et al., 2012).

1.2. Dependent Variable

The acquirer CAR is the dependent variable. We calculate it over a three-day event window centered on the deal announcement, as reported in the SDC database. We obtain abnormal returns using the market model. We choose an estimation window from day –300 to day –91 relative to the announcement on day 0. Table 1 displays the descriptive statistics of interest. The acquirer average CAR is 1.71%, a figure typical of large M&A samples that include public and private targets (e.g., Moeller et al. (2004) report 1.10% in a sample of 12,023 transactions during 1980–2001; Betton et al. (2008) report 0.73% for a sample of 9,298 transactions over 1980–2005). As Table 1, Panel A, shows, M&A transactions were more profitable for acquirers during the early 1980s (cf. 1980). Panel B reveals the clearly declining trend of acquirer CAR as a function of the DON, which some authors interpret as a signal of hubris or overconfidence (Billet and Qian, 2008), though Aktas et al. (2009) argue that declining CAR through acquisition programs is not such an unambiguous indicator.

1.3. Control Variables

We collect a set of control variables widely used in M&A literature (Moeller et al., 2004; Golubov et al., 2015):

- Bidder size: the bidder's market value at the end of the fiscal year before the acquisition announcement in millions of U.S. dollars;
- Cash: a dummy variable equal to 1 if the transaction is fully paid in cash;

- Stock: a dummy variable equal to 1 if the transaction is fully paid in stock;
- Private: a dummy variable equal to 1 if the target is a private company;
- Public: a dummy variable equal to 1 if the target is a public company;
- Subsidiary: a dummy variable equal to 1 if the target is a subsidiary;
- Tobin's Q: the acquirer market value of assets (defined as the book value of total assets minus common equity plus the market value of equity) divided by the acquirer book value of assets;
- Run-up: the market-adjusted buy and hold return of the acquirer's stock price from day –210 to day –11 with respect to the announcement date;
- FCF (free cash-flow): the acquirer's operating income before depreciation minus interest expense and income taxes plus changes in deferred taxes and investment tax credit minus dividends on both preferred and common share divided by the book value of total assets;
- Leverage: the acquirer's long-term debt divided by the market value of assets, defined as above;
- Sigma: the standard deviation of the acquirer market-adjusted daily returns from day –210 to day –11 with respect to the announcement date;
- Relative size: the ratio of the deal value to the acquirer market value;
- Relatedness: a dummy variable equal to 1 if the bidder and the target operate in the same industry at the two-digit SIC code level;
- Tender offer: a dummy variable equal to 1 if the deal is classified as a tender offer in the SDC database; and
- Hostile: a dummy equal to 1 if the transaction is classified as hostile in the SDC database.

The acquirer market value and acquirer financial statements items are collected at the end of the fiscal year before the M&A announcement date.

Using the descriptive statistics by year and by DON in Table 1, we can compare our data with Moeller et al.'s (2004), though their sample covers a different period (1980–2001).[2] Our average deal value is US$ 377 million, versus US$ 257 million in Moeller et al. (2004), which matches the secular increase in deal values. A corresponding increase appears in the average acquirer's market value—US$ 2,777 million versus US$ 1,708 million. The percentage of fully cash paid transactions is 27.11% in our sample versus 40.44% in Moeller et al.'s (2004), and the acquirer Tobin's Q is 2.19 in our sample versus 1.89. According to these statistics, our M&A sample does not display unexpected

2 A comparison with Golubov et al. (2015), who analyze the same period, is not possible because they do not report descriptive statistics.

features. Finally, several of the control variables display a clear time trend, including Cash dummy (strongly increasing), Public dummy (decreasing), and Relative size (strongly decreasing).

According to the statistics by DON in Table 1, Panel B (as also reported by Aktas et al., 2012), several variables increase with the DON, including deal values (suggesting that acquirers start with small transactions),[3] acquirer market value (i.e., repetitive acquirers are larger firms or else grow through acquisition), Cash dummy, Leverage, and Tender offers. In contrast, Tobin's Q, Sigma, and Relative size decrease, consistent with the increase in acquirer size in the latter case.

Table 2 contains the results of the multivariate analyses of acquirer CAR. Column 1 reports estimates obtained with the classical OLS estimator, and then in column 2, we add year FE, and in column 3, we present results obtained with the acquirer FE estimator. The comparison of the column 2 results with Golubov et al.'s (2015) table 1, using the same estimator, reveals nearly the same results (though the interactions of *Public* and *Cash* and of *Private* and *Stock* are significant in our case). As we show in column 3, the acquirer FE estimator is relevant for panel data, and bidder size negatively affects acquirer CAR, as does Run-up, Leverage, and the interaction between acquiring a public target and paying in stock. Sigma (i.e., acquirer stock return standard deviation), Relative size, and the interaction between acquiring a private company and paying in stock all have positive impacts on acquirer CAR. Comparisons of the results across columns show that the significance of Bidder size, Run-up, Sigma, the interaction of Public target and Stock acquisition, and the interaction of Private and Stock acquisition are all robust to the chosen estimator. In addition, Leverage changes sign (from positive to negative) when adopting the acquirer FE estimator. The positive relation between acquirer CAR and acquirer leverage is a cross-sectional phenomenon (more leveraged acquirers complete more value-creating transactions on average), not a time-series one (increased leverage for a given acquirer leads to a decrease in CAR on average).

2. Econometric Estimators and Statistics of Interest

The B&S approach relies on a fixed effects (FE) panel data regression. The population regression model takes the following form for the present case:

$$y_{i,t} = \alpha + \boldsymbol{x}_{i,t}\boldsymbol{\beta} + v_i + \varepsilon_{i,t}, \tag{1}$$

3 We note one extremely large transaction, at DON eight: AOL-Time Warner, with a deal size of US$ 168 billion.

where i is the acquirer index, t is the transaction index, $y_{i,t}$ is the variable of interest (eg., a firm performance measure such as the Return On Assets), $\boldsymbol{x}_{i,t}$ is a vector of explanatory variables, $\boldsymbol{\beta}$ is the corresponding vector of coefficients, $v_i + \varepsilon_{i,t}$ is the error term, v_i is acquirer-specific error capturing time-constant unobservable factors, and $\varepsilon_{i,t}$ is the "classic" error term (uncorrelated with $\boldsymbol{x}_{i,t}$ and v_i). B&S use the LSDV regression to estimate firm FEs, which essentially estimates the following regression model:

$$y_{i,t} = c + \alpha_i + \boldsymbol{x}_{i,t}\boldsymbol{\beta} + \varepsilon_{i,t}, \tag{2}$$

where α_i is a dummy variables equal to 1 for acquirer i. The OLS estimates $\hat{\alpha}_i$ are unbiased estimators of v_i,[4] the firm FE of interest.[5]

Next, B&S study the behavior of *R*-square and adjusted *R*-square, two statistics classically used as goodness of fit measures, and of the Fisher joint significance test of FE, computed using LSDV estimates:

$$R^2{}_{LSDV} = 1 - \frac{SSR_{LSDV}}{TSS}, \tag{3}$$

$$Adj\ R^2{}_{LSDV} = 1 - \frac{n-1}{n-k-1} \times (1 - R^2{}_{LSDV}) \text{ , and} \tag{4}$$

$$F = \frac{(\boldsymbol{R}\,\widehat{\boldsymbol{\alpha}} - \boldsymbol{r})'\left[\boldsymbol{R}\,\widehat{\boldsymbol{\Sigma}}_{\widehat{\boldsymbol{\alpha}}}\boldsymbol{R}'\right]^{-1}(\boldsymbol{R}\,\widehat{\boldsymbol{\alpha}} - \boldsymbol{r})}{q}, \tag{5}$$

where $R^2{}_{LSDV}$ refers to the LSDV *R*-square, $Adj\ R^2{}_{LSDV}$ is the adjusted LSDV *R*-square, SSR_{LSDV} is the sum of squared LSDV residuals, TTS is the total sum of squares, n is the number of observations in the sample, k is the number of estimated coefficients, F is the FE Fisher Statistic,[6] $(\boldsymbol{R}\,\widehat{\boldsymbol{\alpha}} - \boldsymbol{r})$ is the matrix of linear restrictions (all FE = 0); $\boldsymbol{R}$ is the matrix of linear restriction coefficients; $\widehat{\boldsymbol{\alpha}}$ is the vector

4 The α_i OLS estimates are not consistent because, for a given T (number of transactions), their asymptotic variance does not converge to zero as N (the number of acquirers) goes to infinity (see Greene, 2011).

5 Other estimators are available to estimate the vector $\boldsymbol{\beta}$ of coefficients. The pooled estimator runs a classical regression, ignoring the presence of time-constant unobservable factors; the within estimator runs a regression on group-demeaned observations; and the between estimator runs on the variation of group means around the overall mean. None of these estimators provides estimates of the α_i of interest though.

6 Even if the OLS α_i estimates are not consistent, the FE Fisher is valid to test the null hypothesis of α_i being jointly equal to zero (see Greene, 2011).

of estimated FE; $\boldsymbol{r}$ is a vector of constants (0 in our case); $\widehat{\boldsymbol{\Sigma}}_{\widehat{\boldsymbol{\alpha}}}$ is the estimated variance–covariance matrix of $\widehat{\boldsymbol{\alpha}}$; and q is the number of restrictions.

Even if asymptotic distributions of the *R*-square and adjusted *R*-square statistics exist, these depend on unknown parameters (see Ohtani, 2000). Moreover, without a clear null hypothesis, their interpretation remains ambiguous. These are most probability the reasons explaining their use restricted to goodness of fit measures. On the contrary, the FE Fisher statistic is classically used for formal statistical inferences because it's asymptotic distribution depends only on parameters that can be estimated using their sample counterparts. It is also important to recognize that the FE Fisher tests the null hypothesis that "all FEs jointly equal 0," which is rejected if even only one of the constraint is rejected while all other ones are satisfied. Although it is informative about the presence of at least one skilled acquirer in our case, the FE Fisher Statistic provides no information about the frequency of the phenomenon (i.e., number of skilled acquirers in the sample). Moreover, the Fisher test is bilateral and reacts to the presence of both positively and negatively significant FE. It does therefore not discriminate between positive (value-creating) and negative (value-destroying) skills.

3. Simulation Procedures

3.1. Attrition Pattern

At the heart of our study is the simulation of different attrition patterns, depicting the percentage of acquirers that complete a given number of deals (we limit ourselves to a maximum of 10 deals, because fewer than 3.6% of the transactions have a DON above 10 during our sample period[7]). We simulate both a rapid pace of attrition (right-skewed attrition) and slow pace of attrition (left-skewed attrition) using Equation 6:

$$\%\, Sample_{ND} = 100 \times \frac{e^{\alpha \times \mathrm{ND}}}{\sum_{i=1}^{N} e^{\alpha \times i}}, \tag{6}$$

where $\%\, Sample_{ND}$ is the percentage of acquirers having completed ND deals in the simulated sample and N is the maximum number of deals completed by any given acquirer in the simulated sample (10 in the present case). We choose α equal to –1, –0.5, and –0.1 for rapid attrition (right-skewed attrition) and to 0.1, 0.5, and 1 for slow attrition (left-skewed attrition).

7 Generating simulated samples containing an important proportion of highly repetitive acquirers leads indeed to incorporate many times the same acquirers in each simulated samples.

We also add the constant repartition of transactions by numbers of deals (10% of the sample). Figure 1, Panel A, presents the different attrition patterns obtained using this procedure. From left to right, we shift from a drastically right-skewed attrition pattern to a drastically left-skewed attrition pattern. The first three columns correspond to α equal to –1, –0.5, and –0.1; the middle column indicates the constant repartition; and the last three columns reflect the corresponding left-skewed attrition patterns. Panel A also displays the corresponding percentages of transactions included in the sample for each number of deals. Figure 1, Panel B, displays the percentage of transactions by number of deals in our actual M&A sample. A comparison of Panels A and B reveals that the attrition pattern featuring our M&A sample closely corresponds to the right-skewed attrition pattern in which α equals –0.5.

3.2. Brown and Warner (B&W, 1985) Simulations

We study the interactions between the behavior of the *R*-square, the adjusted *R*-square, the FE Fisher Statistic, and attrition patterns by implementing a B&W-style approach. We refer to B&W because the simulation environment relies on a real data set—namely, our M&A sample—not a simulated one (such that we would have implemented a Monte Carlo approach). The simulation procedure is as follows:

(i) Begin with the actual M&A sample (Section 1). We limit the sample to transactions with DON less than or equal to 10 to match the simulated attrition patterns, leaving a sample of 12,253 transactions.

(ii) Randomly assign M&A transactions to acquirers by shuffling acquirer PERMNOs (i.e., the CRSP database permanent number, which is unique to each firm). We thus create an M&A sample under a null hypothesis of no skills (we break any systematic relationship between a given acquirer and given M&A transactions).

(iii) Model skills as a random drawing in a Gaussian distribution of abnormal returns (denoted $N(0, \sigma_{SK})$).

(iv) Select one attrition pattern and randomly draw 1,000 sub-samples of 500 deals so that the attrition pattern is respected.[8]

(v) For each subsample:

a. For each acquirer i in the subsample:

1. Draw a skill $AR_{i,SK}$ in $N(0, \sigma_{SK})$;

8 In robustness checks, we replicate this exercise with a constant number of acquirers and a constant number of degrees of freedom (see Appendices 1 and 2).

2. Add $AR_{i,SK}$ to the acquirer CAR of all transactions randomly attributed to the acquirer in step (ii).

b. Estimate the same acquirer CAR regression as reported in Table 2, column 3, using the LSDV FE estimator;

c. Collect the *R*-square, adjusted *R*-square, and FE Fisher Statistic obtained in the previous step.

(vi) Compute the average *R*-square, adjusted *R*-square, and FE Fisher Statistic values obtained over the 1,000 subsamples.

We execute this procedure for the combination of seven attrition patterns and for values of σ_{SK} ranging from 0% to 5% in steps of 1 pp. The resulting 42 combinations allow us to analyze in depth the interactions among attrition patterns in M&A samples, acquirer skills, and summary statistics obtained using the LSDV FE estimator. The selected values of σ_{SK} are such that the no simulated skills case is taken into account $(\sigma_{SK} = 0)$, and simulated skills are on an order of magnitude of the average acquirer CAR reported in prior literature. The higher σ_{SK}, the greater the probability that a given acquirer will be imputed a high $AR_{i,SK}$ (in absolute value) for each of its acquisitions, such that more skilled acquirers will be present in the generated sample.

4. Sample Attrition, LSDV *R*-square, Adjusted *R*-square, and FE Fisher Test

Table 3 and Figure 2 summarize our B&W simulation results. Table 3 comprises three panels, focused on the behavior of the *R*-square (Panel A), the adjusted *R*-square (Panel B), and the Fisher joint significance test of acquirer FE (Panel C). In each panel, the first column reports the level of σ_{SK} used to simulate acquirer skills. The first two rows refer to the case of no acquirer skills, and the difference between the two rows reflects the econometric estimator used (except in Panel C, because we cannot compute a Fisher FE test with the OLS estimator). The second column specifies the econometric estimator: OLS pooled regression or the LSDV regression model (see Equation 2). Therefore, row 1 is the benchmark case, row 2 highlights the consequences of switching from OLS to LSDV in the case of no acquirer skills, and rows 3–7 explore the consequences of an increase in σ_{SK} used to simulate acquirer skills. Columns 3–9 correspond to the seven attrition patterns introduced in Section 2 and presented in Figure 1, from right- to left-skewed attrition patterns. Figure 2 displays the evolution of the three statistics of interest (*R*-square, adjusted *R*-square, and Fisher test) along the seven attrition patterns (reproduced in the overlay), in the case of no acquirer skills (Panel A) and when σ_{SK} equals 5% (Panel B).

We comment first on the *R*-square results (Table 3, Panel A). In the case of no acquirer skills (rows 1 and 2), switching from OLS to LSDV dramatically increases the *R*-square in the case of attrition pattern 1 (most right-skewed attrition). The *R*-square goes from 14.66% to 74.44%, a

fivefold increase. In the case of attrition pattern 7 (most left-skewed attrition), the increase is still impressive (from 14.77% to 24.21%) but significantly lower. These results exactly match our expectations, because acquirer FE capture all acquirer cross-sectional variation for one-time acquirers. Thus,

- in the case of a right-skewed attrition pattern, the M&A sample is characterized by the presence of many one-time acquirers, for which FE captures 100% of the cross-sectional variation of acquirer CAR (one constant for each one-time acquirer). An increase in the *R*-square from the OLS to the LSDV estimation thus is no evidence of the presence of acquirer skills;
- in the case of a left-skewed attrition pattern, the M&A sample incorporates many repetitive acquirers (63.21% of acquirers are ten-time acquirers). For these acquirers, the acquirer FE does *not* capture the time variation of acquirer CAR. The more they are present in the sample, the lower is the increase in the explained variance due the presence of acquirer FE.

These results highlight an important phenomenon: attrition patterns drastically affect the behavior of the *R*-square, independent of the presence of acquirer skills, when switching from OLS to LSDV. This *R*-square behavior is clearly apparent in Figure 2, Panel A.

The second striking pattern of behavior for the *R*-square is that, using the LSDV estimator, it is almost insensitive to simulated acquirer skills for right-skewed attrition patterns (it oscillates around 75%). Only for the left-skewed attrition pattern (many repetitive acquirers) does the *R*-square become more sensitive to simulated skills, ranging from 25% for low levels of σ_{SK} to 37% for the highest level. This result again highlights that the LSDV *R*-square is silent about the presence acquirer skills in a situation with a right-skewed attrition pattern.

Regarding the adjusted *R*-square, Table 3, Panel B, reports fundamentally different results. That is, in the case of no acquirer skills, when switching from OLS to LSDV, the adjusted *R*-square moves from 7.83 % to 9.08% for attrition pattern 1. This result is to be expected; the adjusted *R*-square explicitly accounts for the number of estimated parameters (see Equation 4). But is the acquirer *R*-square better able to detect the presence of acquirer skills? Focusing first on the most right-skewed attrition pattern, we observe that the average adjusted *R*-square jumps from 9.08% for no simulated acquirer skills to 26.13% for σ_{SK} equal to 5%. This clear increase reveals a true reactivity of the adjusted *R*-square to simulated acquirer skills. This behavior also is nearly constant across the seven simulated attrition patterns. Figure 2, Panels A and B, highlight this flat behavior of the adjusted *R*-square. Thus, the main shortcomings of the adjusted *R*-square as an indicator of the presence of acquirer skills stem from its primary function, as a measure of the goodness of fit more than a formal statistical test statistic and its indiscriminate responsiveness to value-creating and value-destroying skills.

The FE Fisher test is a formal statistical test with available asymptotic *p*-values, so it offers the most interesting test for the presence of acquirer skills. As highlighted in Section 2, we face a caveat for analyzing acquirer CAR: the underlying null hypothesis is that acquirer FE (acquirer-specific CAR) are jointly equals to 0. The Fisher test is therefore designed to detect the presence of at least one skilled acquirer in the M&A sample under scrutiny, but it offers no input about the nature of the skills (value-creating or value-destroying) or their frequency. Table 3, Panel C, summarizes the B&W simulation, including the average values along the various attrition patterns and σ_{SK} values. With these average percentages, we study the FE test size when we simulate no acquirer skills (i.e., frequency of rejection of the null hypothesis of no acquirer skills when there are none, or type I error), as well as the power of the FE test (frequency of rejection of the null hypothesis when there are acquirer skills, or 1- type II errors).

The analysis of average FE Fisher Statistic values reveals promising features: across all attrition patterns, it is increasing in σ_{SK}. That is, the more intensively we simulate acquirer skills, the higher the FE test values are on average. This increase also is stronger for the left-skewed attrition patterns, which is a desirable result because this sample contains many more repetitive acquirers, such that acquirer skills should be easier to detect.

Turning to the FE Fisher Statistic size, we observe that, at each confidence level for right-skewed attrition patterns, it is vastly over-sized. For example, for attrition pattern 2 (most relevant with respect to the real M&A sample, as highlighted in Figure 1), the null hypothesis of no acquirer skills is rejected 15.5% of the time at a 10% confidence level, 11.30% at a 5% confidence level, and 6.00% at a 1% confidence level. This size issue depends on the attrition pattern, such that for the left-skewed pattern, it almost disappears (rejection rates fall to 11.40%, 6.50%, and 1.40% at the 10%, 5%, and 1% confidence levels). As these results highlight, the LSDV FE test is well suited to test for the presence of at least one significant FE when there are many repeated units of observation in a panel, but it is not well suited when the sample incorporates many one-time (or a limited number of time) units. Yet M&A samples typically contain such units. The use of the B&S setup to detect acquirer skills is therefore potentially highly misleading.

Finally, we observe that the power of the FE test increases with σ_{SK} and from right- to left-skewed attrition patterns (as is clearly observable in Figure 2, Panel B).

5. Testing the Presence of Acquirer Skills

5.1. LSDV FE Test Size Issue

Understanding the origin of the FE Fisher test size issue is a first step towards finding a solution. Some intuition may be obtained starting from the well-known expression that relates the Fisher statistic to the *R*-square:

$$F(J, N-K) = \frac{\frac{R^2 - R_*^2}{q}}{\frac{1-R^2}{N-k}} \tag{7}$$

where R^2 is the *R*-square of the unconstrained regression, R_*^2 is the *R*-square of the constrained regression, q is the number of restrictions, N is the number of observations and k is the number of estimated coefficients in the unrestricted model.

Let us take the simplest setup: a regression with only firm FE, two groups of firms (of size N_1 and N_2 respectively), the first group with firms observed only once and the second group with firms observed t times. The regression equation of the full model takes the following form:

$$y_{i,t} = c + \alpha_2^1 D_{2,t} + \cdots + \alpha_{N_1}^1 D_{N_1,t} + \alpha_1^2\, \gamma_1 D_{N_1+1,t} + \cdots + \alpha_{N_2}^2 D_{N_1+N_2,t} + \varepsilon_{i,t} \tag{8}$$

where α_i^1 are the FE for the first group of firms and α_i^2 for the second. The null hypothesis is therefore:

$$H_0: \alpha_2^1 = \cdots = \alpha_{N_1}^1 = \alpha_1^2 = \cdots = \alpha_{N_2}^2 = 0 \tag{9}$$

In this simplified setup, $N = N_1 + (N_2 \times t)$, $k = N_1 + N_2$, $q = (N_1 - 1) + N_2$, and, for the constrained model, $R_*^2 = 0$. The Fisher statistic becomes therefore:

$$F(J, N-K) = \frac{R^2}{1-R^2} \frac{(1+t)N_2}{(N_1-1)+N_2} \tag{10}$$

If we take the limit when $N_1 \to N$ (the sample is only composed of firms observed only one time), we obtain:

$$\lim_{N_1 \to N} \frac{R^2}{1-R^2} \frac{(1+t)N_2}{(N_1-1)+N_2} = \lim_{N_1 \to N} \frac{R^2}{1-R^2} \times \lim_{N_1 \to N} \frac{(1+t)N_2}{(N_1-1)+N_2} = \infty \times 0 \tag{11}$$

Because the R-square of a fixed-effects regression containing only one observation per firm ($N_1 = N$) is 100% and if $N_1 \to N$, $N_2 \to 0$. So, in the limit, the Fisher statistic is indeterminate.

M&A data panel samples are very specific in that they are characterized by the presence of many one-time acquirers (41.25% in our sample). The indeterminacy in the limiting case of a sample composed only of one-time acquirers suggests that this may be at the origin of the Fisher test size issue.

5.2. Resampling Based Method for Detecting Acquirer Skills (RBSD)

If the presence of one-time acquirers is at the origin of the Fisher test size issue, dropping them from the sample is an easy cure. Starting from this insight, this section introduces a procedure designed to be as powerful as possible to detect acquirer skills if they are present, referred hereinafter to RBSD. Our goal is to make the number of acquisitions by acquirer constant.

A first and obvious solution is to limit the sample to acquirers that completed exactly T acquisitions. Then each acquirer FE can be estimated using the same number of observations, and the FE Fisher test builds on Student laws with the same degrees of freedom. There is a serious caveat to this approach though: the drastic reduction in sample size, affecting the power of the test. In our sample, only 256 acquirers completed exactly 5 acquisitions, but 781 completed 5 or more. To fix this issue, the RBSD resampling algorithm is as follows:

(i) Choose a given number of acquisitions T by an acquirer;

(ii) Select all acquisitions by acquirers having completed <u>at least</u> *T* acquisitions.

(iii) Repeat 1,000 times:

   a. for acquirers having completed strictly more than *T* acquisitions, random draw exactly *T* acquisitions among their transactions;

   b. using the sample of M&A acquisitions selected in the previous step, compute the FE Fisher statistic and test whether it is significant against the Fisher distribution at 10%, 5%, and 1% confidence levels.

(iv) Report the average FE Fisher Statistic value across the 1,000 generated samples and the percentage of statistically FE Fisher tests at 10%, 5%, and 1% confidence levels.

We replicate the B&W study that applies the B&S approach from Section 3 to study the FE Fisher test size and power computed using our proposed RBSD procedure. We implement it for *T* ranging from 2 (minimum possible value to measure acquirer FE) to 8 (reflecting a marginal percentage of acquirers, 4.46% in our sample). To ensure the comparability of the results with the B&W simulation study, we fixed the number of acquisitions to 500 by randomly drawing $\lfloor 500/T \rfloor$ acquirers from the original sample in step (ii). We limit this investigation to the FE Fisher Statistic, because the *R*-square and adjusted *R*-square goodness of fit statistics do not offer statistical tests.

The results are in Table 4, whose organization follows that of Table 3, Panel C, except that here we report average FE Fisher Statistic values and percentages of statistically significant tests at 10%, 5%, and 1% confidence levels for balanced panels of numbers of acquisitions ranging from 2 to 8. In particular, in Table 4, Panel A, we observe that average FE test values are growing in σ_{SK}, which drives simulated acquirer skills, and in the number of acquisitions. These are expected and desirable features. The FE Fisher test also checks the null hypothesis that no acquirer FE is significantly different from zero. We observe in Table 4, Panel A, that the higher the σ_{SK}, the greater the probability that at least one acquirer FE will be statistically significant. This has again to be expected: the higher the number of acquisitions by the acquirer, the lower are the FE standard errors,[9] and the higher is the FE Fisher Statistic value.

In the size analysis, a striking difference with respect to the B&S size (Table 3, Panel C) emerges. That is, the FE Fisher Statistic average rejection of the null hypothesis when the null hypothesis is true (σ_{SK} = 0%) is in the order of magnitude of the corresponding confidence levels, as verified for all numbers of acquisitions. The FE Fisher test based on RBSD-generated samples thus is correctly sized.

Finally, the improved size of the RBSD-based FE Fisher test does not come at the cost of a loss of power. Comparing average rejection percentages when the null hypothesis is false ($\sigma_{SK} > 0\%$) between the B&S (Table 3) and RBSD (Table 4) approaches, and focusing on attrition pattern 2 (relevant for the M&A sample, Figure 1), we observe similar rejection rates. For example, with $\sigma_{SK} = 3\%$, the B&S average rejection rates are 67.10%, 56.70%, and 37.40% at 10%, 5%, and 1% confidence levels, respectively. The corresponding RBSD-based rejection rates are 72.90%, 61.30%, and 38.80% for M&A samples of four acquisitions. Increasing the number of acquisitions used to detect skills, as we expected intuitively, improves the power of the test. Simulating skills with $\sigma_{SK} = 3\%$ (5% of acquirers, on average, are imputed a positive skill AR of more than 3%) and using sequences of 5 acquisitions, the average rejection rates are 79.90%, 70.80%, and 44.40% at 10%, 5%, and 1% confidence levels, respectively. Using 8 acquisition sequences, the average rejection rates jump to 89.90%, 83.40%, and 66.80%, respectively. Wooldridge (2002, p. 274) emphasizes that "with a large T (number of periods), the $c(i)$ (fixed effects) can be precise enough to learn something about the distribution of $c(i)$. With small T, the $c(i)$ can contain substantial noise." This is exactly what we observe in our simulations.

9 This increase with FE estimation precision as the number of acquisitions by acquirer grows also can be observed when simulating attrition patterns. Figure 3 displays the average values of FE standards errors along the seven attrition patterns simulated in Section 3. They decrease steadily from right-skewed to left-skewed attritions, as expected.

5.3. Acquirer Skills in the M&A Market

Using this correctly sized, powerful procedure to detect acquirer skills, we revisit previous evidence. Our analyses are based on the M&A sample in Section 1. In Table 5, we report the RBSD results using our baseline specification (from Table 2) in Panel A controlling for endogenous sample attrition due to past poor performance in Panel B, and controlling for the time between deals (TBD) in Panel C. In each panel, we report the number of observations and acquirers, then the average Fisher value obtained on 1,000 generated samples, and finally the corresponding percentages of Fisher value significant at 10%, 5%, and 1% confidence levels. This first set of statistics is complemented by the average percentages of significant FE (acquirer skills) at the same confidence levels, with a partition between positive FE (value-creating skills) and negative FE (value-destroying skills). We conduct these analyses for acquisition sequences from 5 to 8 transactions, consistent with the RBSD power analysis results (Section 5.2). Detecting acquirer skills, or the ability to create over-performance consistently, requires a minimum number of transactions by acquirer, especially for our sample spread over 22 years. These analyses therefore are conservative, in that we focus on cases in which acquisition sequences are long enough for a test of acquirer skills to have sufficient power to reject the null hypothesis.

In Table 5, Panel A, at a 10% confidence level and with 8 transactions, the FE Fisher test rejects the null hypothesis of no acquirer skills in 94.20% of cases. This case is clearly the most favorable setup to reject the absence of acquirer skills (minimum level of confidence and longest acquisition sequence), but this first result leads us to conclude that acquirer skills exist. Still, the FE Fisher test offers only low statistical significance. Still using 8 transactions sequences, the average FE Fisher Statistic value is 1.22; with a 1% confidence level, the null hypothesis of no acquirer skills is rejected only in 41.70% of cases. The analysis of the percentages of significant FE complements this picture. With 8 transaction sequences, at a 10% confidence level, 12.63% of the FE are statistically significant. At a 1% confidence level, this percentage drops to 2.32%. Limiting the acquisition sequences to 5 transactions, the percentages drop roughly by half. Therefore, the claims that acquirer skills provide a first-order factor explaining the cross-section of acquirer CAR are overstated. Some acquirers display persistent over- or under-performance, but they represent at best a limited subsample of the repetitive acquirer population.

Figure 4 confirms this diagnostic. It presents the distribution of generated samples by the percentage of statistically significant FE for 5 transaction acquisition sequences and a 5% confidence level. The distribution is spread over the 1%–7% range; observing more than 7% of significant FE in a given generated sample is very rare, and in most cases, this percentage is below 5%. Even if acquirer skills are present, they pertain to a very limited number of acquirers.

In Panel A, Table 5 also delivers the results for acquisition sequences of 5 and 6 transactions, in which scenario a large majority of significant FE are negative. For example, at a 5% confidence level and with 5 acquisition sequences, we observe only 0.95% significant and positive FE (value-creating) and 2.11% significant and negative FE (value-destroying). Apparently, acquirers implementing small acquisition sequences display more negative skills than positive ones. This evidence reverts for longer sequences though. With 8 acquisition sequences, still at a 5% confidence level, 7.26% of FE are significant and positive, and only 0.14% are negative and significant. Two mechanisms may explain these observations: endogenous sample attrition and learning. We provide preliminary explorations of their respective roles in Table 5, Panels B and C.

If those engaged in poor acquisitions halt their activities (e.g., if they become targets, Mitchell and Lehn, 1990; because their CEOs are fired, Lehn and Zhao, 2006), an endogenous sample attrition mechanism comes in to play. Acquirers observable in longer acquisitions sequences will no longer be comparable to acquirers observable in shorter ones. We use previous acquisition CAR in the acquisition sequence to measure acquisition decision quality and include this additional variable in our baseline specification. Table 5, Panel B, summarizes the results. We lose the case of 5 transactions, because for comparability with Panel A, we impose a minimum of 5 transactions in any given sequence. To obtain the CAR of the previous transaction for the first deal of the sequence in addition to the 5 transactions in each sequence, we need therefore at least 6 transactions. The results mimic those from Panel A, with a change in FE distribution asymmetry between 6 and 7 transaction sequences. Endogenous sample attrition, if cured using previous transaction CAR, cannot explain the FE distribution asymmetry along the number of acquisitions in transaction sequences.

A second possible explanation is learning. Aktas et al. (2012) develop a model of the optimal time between successive transactions, to balance learning benefits against integration costs. Their quadratic specification for learning benefits suggests that an overly short TBD does not allow learning to take place, and an overly long TBD leads to losses of know-how. Because our acquisition sequences span 22 years, many years could separate successive observations. The fewer transactions in a sequence, the greater the potential gap, and the more the acquirer risks memory loss. With more transactions, the probability that learning benefits materialize increases. These mechanisms may explain FE distribution behavior along the acquisition sequences in Table 5, Panel A. Thus in Table 5, Panel C, we limit our sample to transactions spaced apart by no more than 24 months. In this case, the FE distribution displays positive skewness along every number of acquisitions, consistent with the notion that learning can help explain FE distribution asymmetry. However, the radical change in the sample composition (i.e., we lose almost one-third of the observations by imposing the 24 months TBD limit) calls for caution at this stage of analysis.

6. Conclusion

Do acquirers display specific skills? Bertrand and Schoar (2003) introduce a test for the presence of skills that relies on a panel data fixed effect estimator; they use it to estimate CEO skills. The presence of repetitive acquirers in large M&A samples suggests the use of such a panel estimator. But M&A samples are characterized by a specific attrition pattern, with the significant presence of many one-time acquirers. Therefore, we challenge the appropriateness of a B&S approach for such data.

Our analysis rests on simulations designed specifically to test whether the attrition pattern affects statistical inferences about acquirer skills when using panel data FE estimators. Our results show without ambiguity that attrition strongly influences the *R*-square statistic. The adjusted *R*-square and Fisher joint significance test of acquirer FE are more robust. But only the latter is classically used as a formal statistical test, suited for testing (in statistical terms) for the presence of acquirer skills, most probably because the *R*-square and adjusted *R*-square distributions depend on unknown parameters. Our simulation results highlight a strong FE Fisher Statistic size issue for samples that display attrition patterns comparable to the one observed in real M&A samples. This over-size issue in turn leads to rejecting far too often the absence of acquirer skills in their actual absence.

We introduce a resampling procedure to test for the presence of acquirer skills, which is robust to sample attrition. After studying its size and power, we apply it to a sample of 12,707 acquisitions between 1990 and 2011. Our results confirm the presence of skilled acquirers (acquirers who display statistically significant over-performance, persistent throughout the acquisition sequences). But these skilled acquirers represent at most a marginal fraction of the repetitive acquirer population. This raises a doubt that acquirer skills represent a primary explanation of heterogeneity in acquirer CARs.

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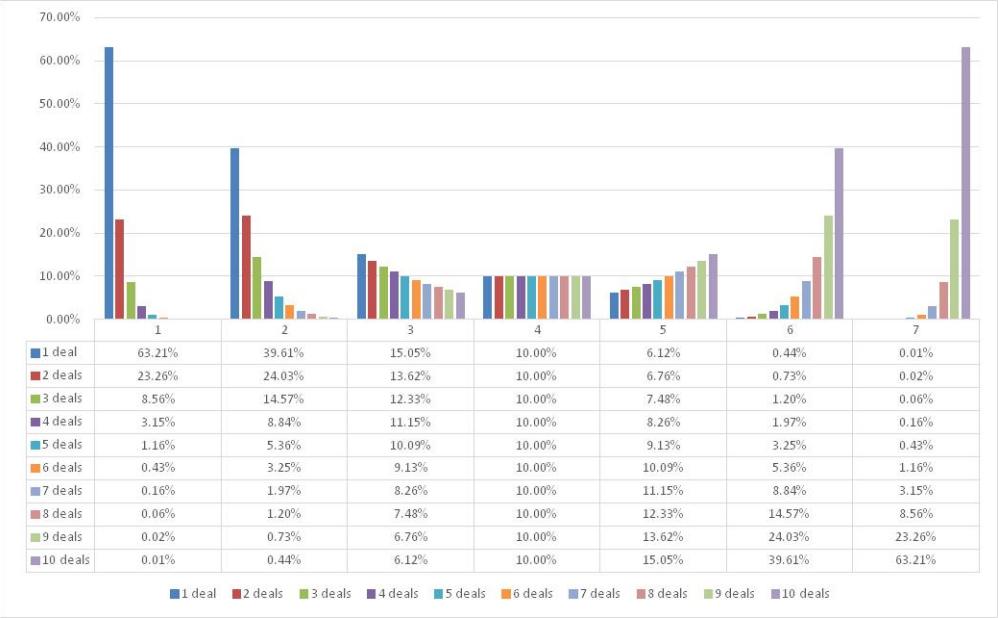
Figure 1: Panel Attrition Patterns

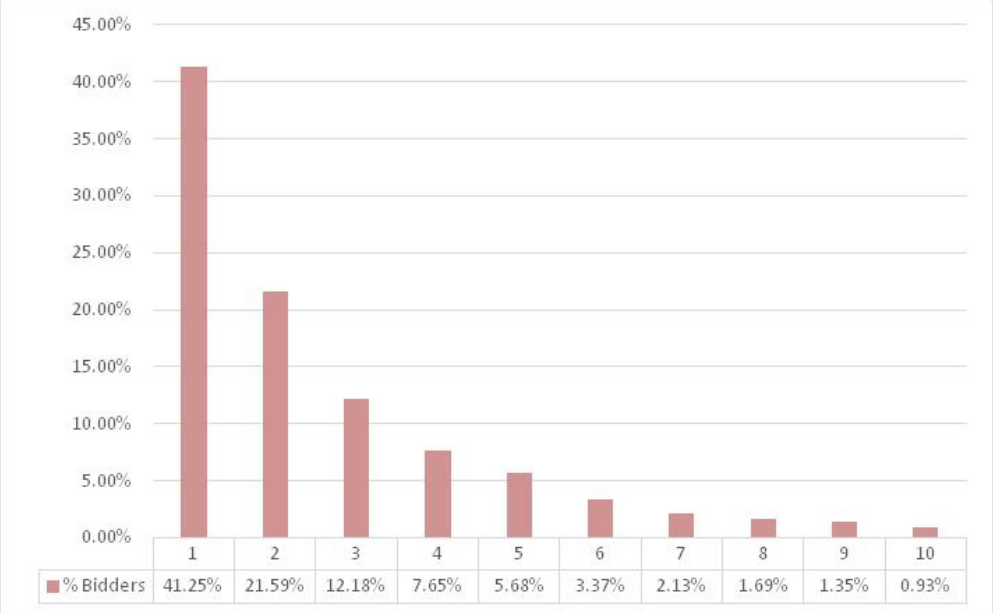
Figure 1 displays a graphical representation of the simulated (Panel A) and actual (Panel B) panel attrition patterns. Simulated attrition patterns obey exponential laws, according to Equation 1. The actual attrition pattern corresponds to the numbers reported in Table 1, Panel B.

Panel A: Simulated Attrition Patterns



	1	2	3	4	5	6	7
1 deal	63.21%	39.61%	15.05%	10.00%	6.12%	0.44%	0.01%
2 deals	23.26%	24.03%	13.62%	10.00%	6.76%	0.73%	0.02%
3 deals	8.56%	14.57%	12.33%	10.00%	7.48%	1.20%	0.06%
4 deals	3.15%	8.84%	11.15%	10.00%	8.26%	1.97%	0.16%
5 deals	1.16%	5.36%	10.09%	10.00%	9.13%	3.25%	0.43%
6 deals	0.43%	3.25%	9.13%	10.00%	10.09%	5.36%	1.16%
7 deals	0.16%	1.97%	8.26%	10.00%	11.15%	8.84%	3.15%
8 deals	0.06%	1.20%	7.48%	10.00%	12.33%	14.57%	8.56%
9 deals	0.02%	0.73%	6.76%	10.00%	13.62%	24.03%	23.26%
10 deals	0.01%	0.44%	6.12%	10.00%	15.05%	39.61%	63.21%

Panel B: Actual M&A Sample Attrition Pattern

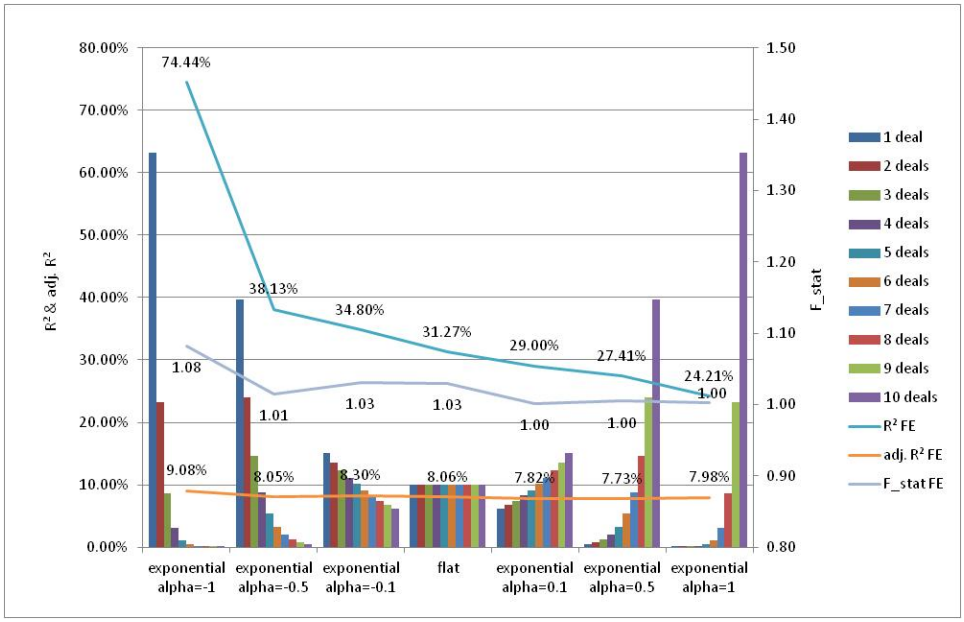


	1	2	3	4	5	6	7	8	9	10
% Bidders	41.25%	21.59%	12.18%	7.65%	5.68%	3.37%	2.13%	1.69%	1.35%	0.93%

Figure 2: Brown and Warner (B&W) Simulations

Figure 2 provides a graphical representation of the Brown and Warner (1985) simulation results in the case of no acquirer skills (Panel A) and acquirer skills (Panel B, 5% abnormal return standard deviation). The simulation procedure is described in Section 2. The M&A sample is introduced in Section 1. The seven attrition patterns correspond to the attrition patterns in Figure 1, Panel A. The three statistics of interest are the *R*-square (R^2 FE), the adjusted *R*-square (adj. R^2 FE), and the Fisher joint significance test of acquirer FE (F_stat FE). The *R*-square and adjusted *R*-square are reported along the left vertical axis; the Fisher test values appear on the right vertical axis.

Panel A: No Acquirer Skills



Panel B: Acquirer Skills ($\sigma_{SK} = 5\%$)

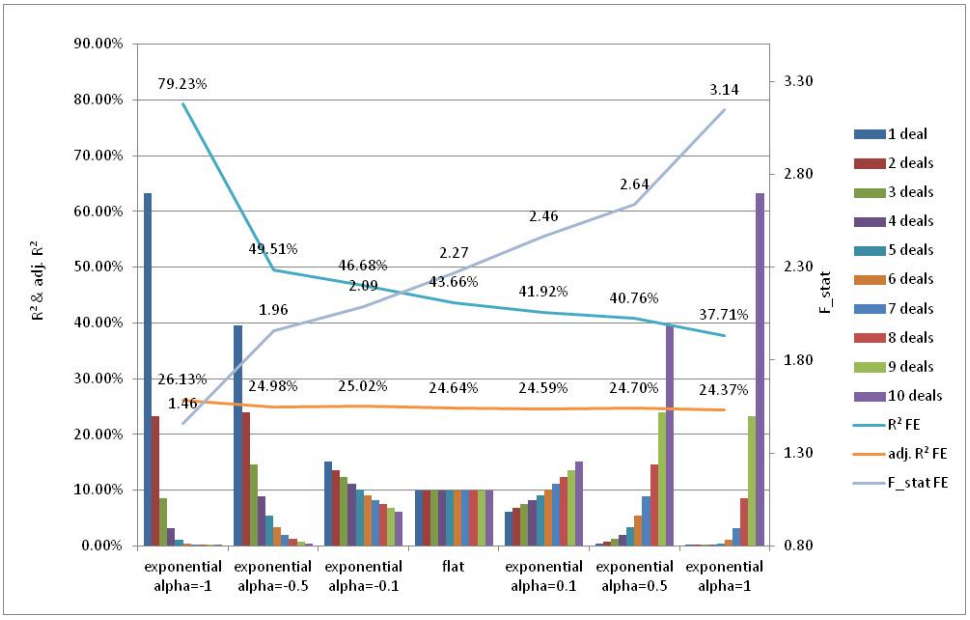


Figure 3: Fixed Effect Standard Errors by Attrition Pattern

Figure 3 shows average values of FE standard errors for each of the seven attrition patterns introduced in Figure 1. These average values result from more than 1,000 randomly selected samples of 500 deals (constant number of transactions for each attrition pattern).

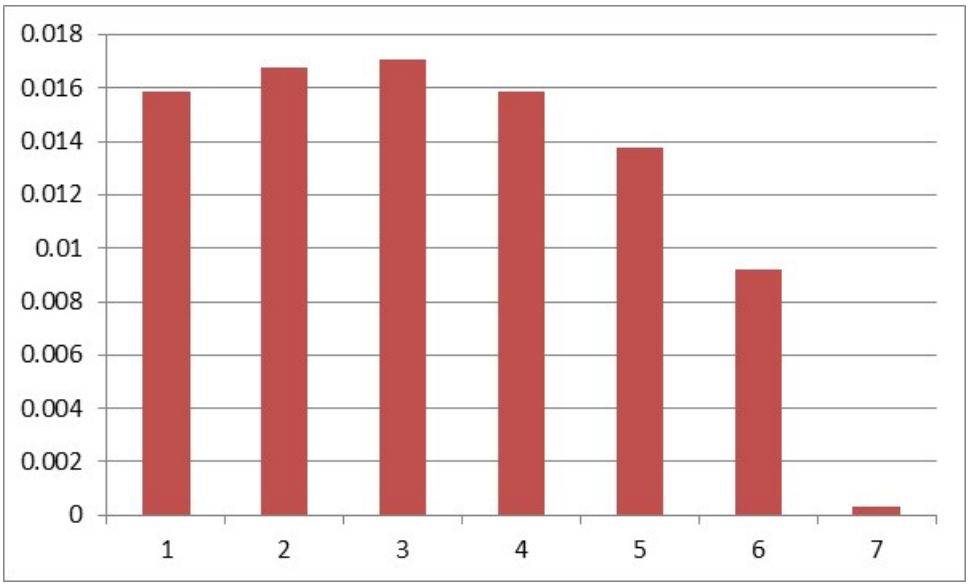
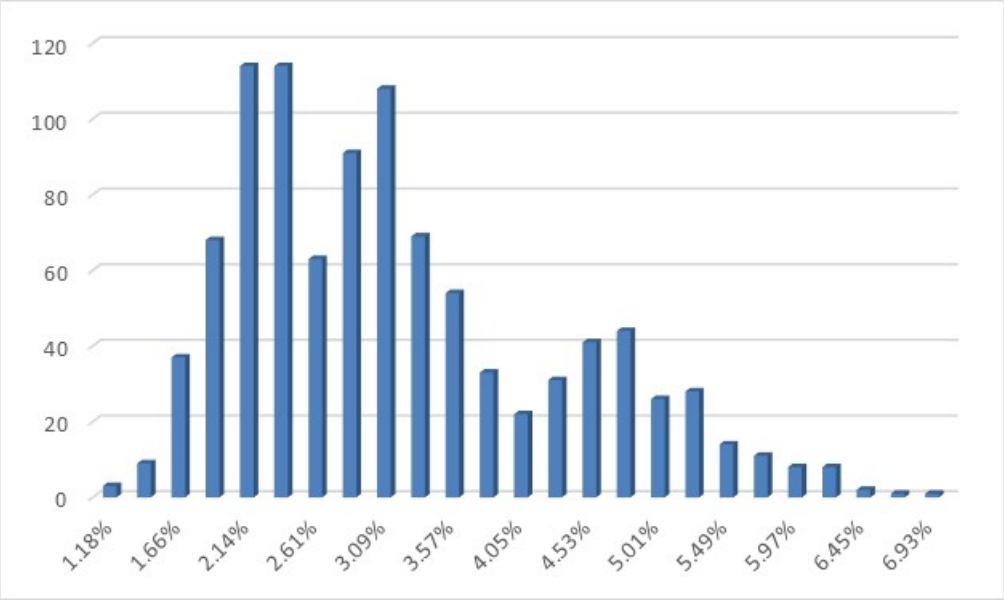


Figure 4: Distribution of Statistically Significant Fixed Effects

Figure 4 reports histograms of the percentage of statistically significant FE. These percentages are computed over 1,000 samples, generated using the resampling based method of detecting acquirer skills (RBSD), as described in Section 5.1. Samples are drawn from the M&A sample introduced in Section 1. The results reflect balanced panels of 5 acquisitions by an acquirer using a 5% statistical confidence level.



Average: 0.0306; SD: 0.0112; skewness: 0.7882; kurtosis: -0.1129

Table 1: Sample and Variable Descriptive Statistics

Table 1 reports the descriptive statistics for the M&A sample in our study. We collected M&A transactions from the Thomson SDC database for the 1990–2011 period, using the same criteria as Golubov et al. (2015): transactions between U.S. acquirers and U.S. targets, completed control transactions (acquirer holds less than 50% of the target shares before the announcement and 100% of the target shares after), public acquirers and targets of all statuses (private, public, subsidiaries), deal value at least equal to US$1 million, relative transaction size (deal value divided by the acquirer market value) at least equal to 1%, no financial industries (SIC codes 6000–6999), and information necessary to compute the acquirer CAR and the set of control variables available in the CRSP and COMPUSTAT databases. Panel A displays statistics by year, and Panel B provides the corresponding figures by the deal number in the sequence of transactions completed by a given acquirer (DON). In both panels, the columns reflect the *# Deals*, or number of deals; *Avg Deal Value,* or average deal value in millions of U.S. dollars; *Med Deal Value,* the corresponding median; *Avg Market Value*, which is the average market value of the acquirer at the end of the fiscal year before the acquisition announcement in millions of U.S. dollars; *Cash*, a dummy variable equal to 1 for transactions fully paid in cash; *Stock*, a dummy variable equal to 1 for transactions fully paid in stock; *Private*, a dummy variable equal to 1 if the target is a private company; *Public,* a dummy variable equal to 1 if the target is a public company; *Subsidiary,* a dummy variable equal to 1 if the target is a subsidiary; *Tobin's Q,* the acquirer market value divided by the acquirer book value of assets; *Run-Up,* the market-adjusted buy-and-hold return of the acquirer from day –210 to day –11 with respect to the announcement date; *FCF,* the acquirer's operating income before depreciation minus interest expenses minus income taxes plus changes in deferred taxes and investment tax credits minus dividends on both preferred and common share divided by the book value of total assets; *Leverage,* the acquirer's long-term debts divided by the market value of assets, defined as the book value of total assets minus common equity plus the market value of equity; *Sigma,* the standard deviation of the acquirer market-adjusted daily returns from day –210 to day –11 with respect to the announcement date; *Relative Size,* the deal value divided by the acquirer market value; *Relatedness,* a dummy variable equal to 1 if the bidder and target are active in the same industry (2-digit SIC); *Tender Offer,* a dummy variable equal to 1 if the transaction is classified as a tender offer in the Thomson SDC database; *Hostile,* a dummy equal to 1 if the transaction is classified as hostile in the Thomson SDC database; and *CAR,* which is the three-day acquirer cumulative abnormal returns. For dummy variables, the percentages correspond to sample proportions.

Panel A

Year	*# Deals*	*Avg Deal Value*	*Avg Market Value*	*Cash*	*Public*	*Tobin's Q*	*Run-Up*	*FCF*	*Leverage*	*Sigma*	*Relative Size*	*Relatedness*	*Tender Offer*	*CAR*
1990	273	104,600	830,100	25.27%	15.38%	1.87	1.0408	7.45%	14.24%	3.09%	42.52%	56.04%	2.93%	0.61%
1991	269	73,893	724,600	21.19%	15.24%	1.83	1.3169	6.53%	13.96%	3.98%	37.76%	63.20%	3.72%	4.15%
1992	366	80,195	668,800	18.31%	10.38%	2.30	1.1488	7.41%	12.16%	3.68%	42.87%	63.11%	2.19%	3.16%
1993	519	119,200	686,100	18.11%	10.21%	2.04	1.1572	6.48%	14.49%	3.98%	38.01%	60.12%	1.93%	3.53%
1994	608	148,200	1,022,000	20.39%	15.13%	2.11	1.0839	6.86%	11.37%	3.52%	80.45%	57.07%	3.29%	2.32%
1995	707	191,900	1,104,000	20.37%	17.96%	2.07	1.1137	8.60%	12.94%	3.26%	38.70%	62.23%	4.67%	2.21%
1996	867	217,100	1,228,000	17.88%	16.49%	2.42	1.2098	8.95%	13.29%	3.50%	30.04%	59.05%	3.23%	2.52%
1997	1067	217,900	1,474,000	18.74%	15.75%	2.33	1.0355	6.99%	13.53%	3.60%	36.17%	59.79%	3.94%	2.58%
1998	1060	396,700	2,138,000	20.47%	19.15%	2.38	1.0548	6.53%	13.50%	3.56%	30.14%	59.06%	3.11%	1.61%
1999	881	635,300	4,335,000	19.30%	21.23%	2.50	1.2091	6.39%	13.09%	4.47%	34.39%	63.56%	4.31%	2.10%
2000	688	952,800	5,543,000	20.78%	21.51%	3.01	1.4635	4.43%	12.64%	4.92%	30.51%	62.50%	5.09%	-0.19%
2001	539	492,500	2,670,000	23.56%	20.04%	2.23	1.2518	4.63%	12.57%	5.01%	31.63%	64.19%	4.27%	0.97%
2002	580	259,000	2,414,000	31.90%	13.10%	2.04	1.2373	3.14%	12.33%	4.17%	20.85%	64.48%	3.62%	1.11%
2003	509	203,200	2,014,000	31.63%	15.52%	1.66	1.3042	3.83%	12.75%	3.64%	21.50%	65.62%	3.54%	2.05%
2004	590	317,200	1,658,000	40.85%	12.71%	2.13	1.2092	5.26%	11.44%	2.93%	23.36%	68.31%	1.36%	1.40%
2005	570	599,400	4,251,000	38.25%	14.91%	2.19	1.0624	7.92%	11.16%	2.58%	22.40%	66.49%	1.05%	1.24%
2006	572	542,400	4,543,000	41.78%	13.81%	2.15	1.0836	8.08%	11.08%	2.46%	21.13%	61.36%	0.87%	0.87%
2007	590	387,900	5,018,000	42.37%	14.75%	2.12	1.0811	6.50%	11.39%	2.44%	24.61%	62.88%	3.22%	1.05%
2008	399	334,600	2,840,000	38.85%	12.28%	2.02	1.0448	6.30%	12.25%	3.13%	35.29%	65.91%	3.51%	0.24%
2009	306	791,300	7,074,000	39.87%	17.65%	1.63	1.1966	7.01%	15.15%	4.71%	24.99%	65.69%	4.58%	1.95%
2010	366	545,100	6,943,000	42.90%	16.39%	1.66	1.1088	6.76%	14.91%	2.61%	23.51%	65.03%	4.10%	1.14%
2011	381	551,300	4,395,000	39.37%	9.97%	1.82	1.0853	8.75%	13.94%	2.52%	22.26%	61.42%	1.31%	0.45%
Total	12,707	377,277	2,777,919	27.11%	15.99%	2.19	1.1557	6.59%	12.83%	3.57%	32.53%	62.27%	3.25%	1.71%

Panel B

don	# Deals	Avg Deal Value	Avg Market Value	Cash	Public	Tobin's Q	Run-Up	FCF	Leverage	Sigma	Relative Size	Relatedness	Tender Offer	CAR
1	4507	207,200	1,431,000	21.77%	14.56%	2.33	1.1441	3.93%	10.59%	4.09%	45.36%	60.82%	2.64%	2.57%
2	2648	346,400	2,193,000	25.79%	14.77%	2.23	1.1586	6.83%	12.22%	3.68%	31.66%	61.86%	3.29%	1.84%
3	1675	342,100	2,778,000	27.94%	16.12%	2.17	1.1804	8.30%	13.48%	3.32%	26.96%	62.63%	3.28%	1.51%
4	1126	508,500	3,380,000	30.28%	16.34%	2.07	1.1605	8.37%	13.90%	3.17%	21.97%	63.23%	3.64%	1.23%
5	781	515,900	3,977,000	34.19%	17.29%	2.04	1.1733	9.00%	15.12%	3.13%	23.16%	66.45%	4.23%	0.84%
6	525	608,600	4,777,000	35.05%	19.24%	2.06	1.1507	9.02%	15.64%	2.96%	19.66%	62.67%	3.05%	0.41%
7	373	759,300	5,586,000	37.80%	20.64%	2.00	1.1723	9.64%	16.48%	2.92%	18.32%	65.42%	3.22%	0.07%
8	277	1,339,000	8,142,000	35.02%	22.38%	1.96	1.1456	9.29%	16.50%	2.87%	19.40%	65.34%	5.78%	0.39%
9	201	491,200	7,025,000	38.31%	17.41%	1.85	1.1281	8.30%	16.37%	2.88%	17.21%	61.19%	4.48%	0.67%
10	140	390,100	5,479,000	35.00%	19.29%	1.87	1.1471	8.43%	17.80%	2.81%	14.78%	70.71%	5.00%	0.92%
more	454	588,900	5,397,000	34.58%	20.70%	1.86	1.1324	8.44%	18.09%	2.60%	19.96%	61.23%	3.96%	0.29%

Table 2: Multivariate Analysis of Acquirer CAR

Table 2 displays the results of the acquirer CAR regression on a set of determinants comparable to Golubov et al.'s (2015) table 1. The M&A sample is presented in Table 1. Column 1 is obtained using the classic OLS estimator. In column 2, we add year FE, and in column 3, we use the panel data least squares dummy variable (LSDV) estimator, combined with year FE. Variables are defined in the Table 1 legend and in Section 1. The *# Observations* is the number of observations, *adj R-square* is the adjusted *R-square*, *FE Fisher* is the Fisher statistic corresponding to the null hypothesis that all FE jointly equal 0. Standard errors are robust to heteroskedasticity. The *p*-values are reported in parentheses, under the corresponding coefficients.

	(1)	(2)	(3)
Log Bidder Size	-0.006	-0.005	-0.016
	(0.000)	(0.000)	(0.000)
Tobin's Q	-0.002	-0.002	0.000
	(0.018)	(0.017)	(0.900)
Run-Up	-0.006	-0.006	-0.007
	(0.003)	(0.003)	(0.003)
FCF	0.003	0.002	0.000
	(0.797)	(0.890)	(0.986)
Leverage	0.015	0.016	-0.030
	(0.045)	(0.032)	(0.066)
Sigma	0.504	0.613	0.483
	(0.000)	(0.000)	(0.029)
Relative Size	0.002	0.001	0.007
	(0.204)	(0.213)	(0.013)
Relatedness	-0.002	-0.002	-0.001
	(0.302)	(0.305)	(0.688)
Tender Offer	-0.001	-0.001	-0.001
	(0.811)	(0.884)	(0.883)
Hostile	-0.005	-0.007	-0.015
	(0.631)	(0.540)	(0.276)
Public x Cash	0.008	0.008	0.003
	(0.058)	(0.070)	(0.558)
Public x Stock	-0.030	-0.030	-0.033
	(0.000)	(0.000)	(0.000)
Private x Cash	0.000	0.001	0.002
	(0.943)	(0.761)	(0.469)
Private x Stock	0.014	0.012	0.021
	(0.002)	(0.008)	(0.000)
Subsidiary x Cash	0.007	0.007	0.004
	(0.005)	(0.003)	(0.207)
# Observations	12,707	12,707	12,707
R-square	4.90%	5.40%	51.90%
adj. R-square	4.80%	5.20%	25.14%
Year FE	*no*	*yes*	*yes*
Acquirer FE	*no*	*no*	*yes*
FE Fisher	-	-	1.75
			(0.000)

Table 3: Brown and Warner (B&W) Simulation Results with a Constant Number of Transactions

Table 3 reports results of the Brown and Warner (1985) simulation results. The simulation procedures are described in Section 2. We use the M&A sample introduced in Section 1 (see Table 1 for descriptive statistics). Panel A presents the average *R*-square obtained by estimating the Table 2 regression model over 1,000 randomly selected samples of 500 deals (constant number of transactions for each different attrition pattern), Panel B provides the corresponding average adjusted *R*-square, and Panel C offers the corresponding average Fisher joint significance test of acquirer FE (with percentages of statistically significant FE tests at 10%, 5%, and 1% confidence levels). In each panel, *Skills* is the standard deviation σ_{SK} of the Gaussian distribution from which the acquirer skills are drawn (additional abnormal returns added to the acquirer CAR around the announcement date). *Est* is either OLS for ordinary least squares or LSDV for the least squares dummy variable estimator. The *Panel attrition pattern* specifies the form of attrition pattern imposed on the selected random sample (columns 3–9 correspond to patterns displayed in Figure 1). In Panel C, the tables provide the FE Fisher statistic tests and the proportion of significance obtained among the 1,000 randomly selected samples at 10%, 5%, and 1% confidence levels.

Panel A. *R-square*

		Panel attrition pattern						
Skills	*Est.*	1	2	3	4	5	6	7
(0%)	OLS	14.66%	15.00%	14.96%	14.47%	14.87%	14.66%	14.77%
(0%)	LSDV	74.44%	38.13%	34.80%	31.27%	29.00%	27.41%	24.21%
(1%)	LSDV	74.83%	38.65%	34.97%	31.78%	29.68%	28.31%	25.05%
(2%)	LSDV	75.77%	40.33%	36.58%	33.65%	31.61%	30.19%	27.18%
(3%)	LSDV	76.68%	42.85%	39.55%	36.32%	34.19%	32.87%	29.97%
(4%)	LSDV	77.79%	46.12%	42.87%	39.68%	38.01%	36.78%	33.72%
(5%)	LSDV	79.23%	49.51%	46.68%	43.66%	41.92%	40.76%	37.71%

Panel B. Adj. R-square

		Panel attrition pattern						
Skills	*Est.*	1	2	3	4	5	6	7
(0%)	OLS	7.83%	8.06%	8.01%	7.80%	7.93%	7.75%	8.01%
(0%)	LSDV	9.08%	8.05%	8.30%	8.06%	7.82%	7.73%	7.98%
(1%)	LSDV	10.49%	8.83%	8.53%	8.75%	8.70%	8.89%	8.99%
(2%)	LSDV	13.81%	11.34%	10.82%	11.24%	11.21%	11.28%	11.58%
(3%)	LSDV	17.04%	15.08%	14.99%	14.81%	14.57%	14.68%	14.97%
(4%)	LSDV	21.01%	19.93%	19.65%	19.32%	19.52%	19.65%	19.52%
(5%)	LSDV	26.13%	24.98%	25.02%	24.64%	24.59%	24.70%	24.37%

Panel C. Fisher joint significance test of acquirer FE

		Average Fisher Test						
		Panel attrition pattern						
Skills	*Est.*	1	2	3	4	5	6	7
(0%)	LSDV	1.08	1.01	1.03	1.03	1.00	1.00	1.00
(1%)	LSDV	1.09	1.07	1.04	1.06	1.07	1.07	1.09
(2%)	LSDV	1.16	1.17	1.19	1.23	1.24	1.27	1.35
(3%)	LSDV	1.23	1.35	1.40	1.48	1.52	1.59	1.78
(4%)	LSDV	1.33	1.62	1.71	1.81	1.95	2.06	2.40
(5%)	LSDV	1.46	1.96	2.09	2.27	2.46	2.64	3.14

		Percentage of significant Fisher Test at 10%						
		Panel attrition pattern						
Skills	*Est.*	1	2	3	4	5	6	7
(0%)	LSDV	24.80%	15.50%	16.40%	15.00%	11.60%	10.10%	11.40%
(1%)	LSDV	27.50%	21.30%	16.90%	19.20%	17.30%	18.60%	18.80%
(2%)	LSDV	34.70%	35.70%	38.90%	44.40%	45.40%	45.60%	55.30%
(3%)	LSDV	43.40%	67.10%	70.10%	77.40%	81.50%	84.10%	89.60%
(4%)	LSDV	56.40%	90.80%	92.10%	95.00%	97.20%	97.20%	99.10%
(5%)	LSDV	73.00%	97.50%	98.80%	99.00%	99.80%	99.70%	99.60%

		Percentage of significant Fisher Test at 5%						
		Panel attrition pattern						
Skills	*Est.*	1	2	3	4	5	6	7
(0%)	LSDV	20.60%	11.30%	11.70%	9.90%	7.40%	5.80%	6.50%
(1%)	LSDV	21.50%	13.50%	10.80%	11.10%	10.90%	11.50%	10.90%
(2%)	LSDV	27.00%	28.60%	28.30%	33.00%	32.40%	33.20%	42.30%
(3%)	LSDV	34.80%	56.70%	59.50%	68.60%	71.90%	75.50%	82.60%
(4%)	LSDV	47.90%	86.40%	87.70%	91.70%	94.10%	95.20%	98.10%
(5%)	LSDV	64.70%	96.60%	97.70%	98.50%	99.60%	99.50%	99.60%

		Percentage of significant Fisher Test at 1%						
		Panel attrition pattern						
Skills	*Est.*	1	2	3	4	5	6	7
(0%)	LSDV	12.90%	6.00%	5.60%	4.80%	2.30%	2.00%	1.40%
(1%)	LSDV	12.30%	7.20%	4.60%	5.20%	4.30%	3.00%	1.60%
(2%)	LSDV	16.30%	15.00%	15.30%	17.00%	14.50%	17.40%	20.30%
(3%)	LSDV	22.00%	37.40%	39.80%	47.70%	50.60%	57.50%	66.80%
(4%)	LSDV	33.50%	74.90%	76.70%	83.70%	86.60%	89.10%	94.30%
(5%)	LSDV	47.40%	91.20%	94.60%	96.70%	97.10%	98.50%	98.90%

Table 4: Resampling Based Method of Detecting Acquirer Skills: Size and Power Analysis

Table 4 reports the Brown and Warner (1985) simulation results studying the size and power of a Fisher joint significance test of acquirer FE, built using our resampling based method of detecting acquirer skills (RBSD). The RBSD procedure is introduced in Section 5. We use the M&A sample introduced in Section 1 (see Table 1 for descriptive statistics). We report the average FE Fisher value and percentages of statistically significant FE tests at the 10%, 5%, and 1% confidence levels obtained by estimating the Table 2 regression model over 1,000 randomly generated samples of 500 deals. *Skills* provides the standard deviation σ_{SK} of the Gaussian distribution from which acquirer skills are drawn (additional abnormal returns added to the acquirer CAR around the announcement date). LSDV refers to the least squares dummy variable estimator. *Number of acquisitions* is the number of transactions by the acquirer in the generated random sample.

Panel A. Average Fisher value

		Number of acquisitions						
Skills	*Est.*	2	3	4	5	6	7	8
(0%)	LSDV	1.01	1.01	1.01	1.01	1.00	1.00	1.00
(1%)	LSDV	1.03	1.04	1.04	1.05	1.06	1.07	1.08
(2%)	LSDV	1.09	1.12	1.16	1.19	1.23	1.27	1.30
(3%)	LSDV	1.17	1.27	1.35	1.42	1.51	1.58	1.69
(4%)	LSDV	1.32	1.46	1.62	1.77	1.90	2.06	2.18
(5%)	LSDV	1.48	1.70	1.96	2.18	2.41	2.65	2.89

Panel B. Percentage of significant Fisher Test

		10% Confidence Level						
		Number of acquisitions						
Skills	*Est.*	2	3	4	5	6	7	8
(0%)	LSDV	10.60%	9.20%	10.20%	9.80%	8.00%	8.30%	8.50%
(1%)	LSDV	11.60%	14.00%	15.10%	15.90%	15.90%	17.80%	18.00%
(2%)	LSDV	26.00%	31.70%	36.90%	42.30%	46.90%	52.40%	52.20%
(3%)	LSDV	43.90%	66.00%	72.90%	79.90%	86.10%	85.10%	89.90%
(4%)	LSDV	75.70%	90.60%	94.80%	97.50%	98.00%	99.30%	99.50%
(5%)	LSDV	94.50%	98.40%	99.60%	99.70%	99.90%	99.80%	100.00%
		5% Confidence Level						
		Number of acquisitions						
Skills	*Est.*	2	3	4	5	6	7	8
(0%)	LSDV	6.00%	5.10%	5.60%	4.20%	4.40%	3.60%	4.70%
(1%)	LSDV	6.40%	6.70%	6.80%	8.30%	8.90%	9.60%	10.10%
(2%)	LSDV	16.10%	20.10%	25.90%	29.00%	34.50%	37.70%	38.80%
(3%)	LSDV	31.00%	51.00%	61.30%	70.80%	78.10%	78.90%	83.40%
(4%)	LSDV	63.80%	84.20%	91.30%	94.60%	96.40%	98.40%	98.80%
(5%)	LSDV	88.50%	97.00%	98.90%	99.20%	99.50%	99.70%	99.90%

		1% Confidence Level						
		Number of acquisitions						
Skills	*Est.*	2	3	4	5	6	7	8
(0%)	LSDV	1.70%	1.40%	0.50%	1.10%	1.30%	0.40%	1.10%
(1%)	LSDV	1.80%	1.30%	1.80%	1.90%	2.20%	2.50%	2.80%
(2%)	LSDV	4.90%	6.20%	10.20%	11.60%	14.30%	17.00%	17.90%
(3%)	LSDV	10.80%	25.90%	38.80%	44.40%	57.30%	59.00%	66.80%
(4%)	LSDV	39.30%	64.90%	77.80%	87.40%	89.80%	92.40%	93.20%
(5%)	LSDV	70.40%	91.10%	96.40%	97.60%	99.00%	99.30%	98.60%

Table 5: Real Data Set Analysis

Table 5 reports the results of our resampling based method of detecting acquirer skills (RBSD), applied to the real M&A sample introduced in Section 1. The RBSD procedure is introduced in Section 5.1. Panel A presents results obtained using our baseline specification (Table 2), Panel B adds the previous transaction CAR as an additional control variable to control for endogenous sample attrition, and Panel C contains only the subsample of acquisitions with a time between deal (TBD) inferior or equal to 24 months. In each panel, the average Fisher test reports the corresponding average Fisher joint significance test of acquirer FE. The percentages of significant Fisher tests in the generated samples are reported at the 10%, 5%, and 1% confidence levels, as are the percentages of statistically significant FE tests at these confidence levels. The corresponding statistics are reported by the sign of the FE. *Number of acquisitions* is the number of transactions by acquirer. #Observations is the number of observations in each sample. #Acquirers is the number of acquirers (FE) in each sample.

Panel A. Baseline Specification

	Number of acquisitions by acquirer			
	5	6	7	8
# Observations	3,830	3,066	2,652	2,168
# Acquirers	766	511	379	271
Average Fisher value	1.12	1.17	1.20	1.22
Percentage of Fisher value significant				
10%	88.20%	94.70%	95.40%	94.20%
5%	73.50%	83.20%	87.50%	83.00%
1%	36.10%	47.10%	48.90%	41.70%
	Number of acquisitions by acquirer			
	5	6	7	8
Average percentage of FE significant				
10%	6.23%	5.46%	11.91%	12.63%
5%	3.06%	2.59%	6.64%	7.26%
1%	0.65%	0.27%	1.92%	2.32%
Average percentage of FE significant & positive				
10%	1.98%	1.98%	10.90%	12.16%
5%	0.95%	0.96%	6.23%	7.12%
1%	0.17%	0.12%	1.87%	2.31%
Average percentage of FE significant & negative				
10%	4.25%	3.47%	1.00%	0.47%
5%	2.11%	1.63%	0.41%	0.14%
1%	0.47%	0.15%	0.05%	0.01%

Panel B. Controlling for Endogenous Attrition

	Number of acquisitions by acquirer			
	5	6	7	8
# Observations	-	2,555	2,196	1,897
# Acquirers	-	511	366	271
Average Fisher value	-	1.19	1.25	1.20
Percentage of Fisher value significant				
10%	-	95.60%	99.00%	90.70%
5%	-	89.90%	95.20%	74.50%
1%	-	57.50%	75.20%	32.70%
	Number of acquisitions by acquirer			
	5	6	7	8
Average percentage of FE significant				
10%	-	11.36%	8.68%	9.22%
5%	-	5.99%	4.51%	5.02%
1%	-	1.20%	1.06%	1.41%
Average percentage of FE significant & positive				
10%	-	0.93%	6.28%	8.27%
5%	-	0.64%	3.46%	4.69%
1%	-	0.06%	0.92%	1.37%
Average percentage of FE significant & negative				
10%	-	10.43%	2.40%	0.95%
5%	-	5.35%	1.05%	0.33%
1%	-	1.15%	0.14%	0.04%

Panel C. Controlling for Time Between Deals

	Number of acquisitions by acquirer			
	5	6	7	8
# Observations	2,760	2,376	2,002	1,600
# Acquirers	552	396	286	200
Average Fisher value	1.13	1.15	1.11	1.10
Percentage of Fisher value significant				
10%	77.60%	78.90%	43.30%	27.30%
5%	62.10%	63.00%	24.10%	13.40%
1%	27.70%	25.30%	4.10%	1.90%
	Number of acquisitions by acquirer			
	5	6	7	8
Average percentage of FE significant				
10%	9.38%	10.83%	9.11%	8.91%
5%	4.76%	5.69%	4.65%	4.69%
1%	1.05%	1.36%	1.09%	1.14%
Average percentage of FE significant & positive				
10%	6.67%	8.73%	7.66%	8.03%
5%	3.52%	4.75%	4.09%	4.35%
1%	0.87%	1.24%	1.03%	1.09%
Average percentage of FE significant & negative				
10%	2.71%	2.10%	1.44%	0.89%
5%	1.24%	0.95%	0.56%	0.35%
1%	0.18%	0.12%	0.06%	0.05%

Appendix 1. Brown and Warner (B&W) Simulation Results, Constant Number of Acquirers

Appendix 1 reports the results obtained by replicating the analyses for Table 3 but with a constant number of 100 acquirers for each attrition pattern.

Panel A. *R-square*

		Panel attrition pattern						
Skills	*Est.*	1	2	3	4	5	6	7
(0%)	OLS	31.53%	17.07%	15.41%	13.79%	13.03%	12.32%	10.98%
(0%)	LSDV	89.67%	40.47%	35.08%	30.28%	27.34%	25.15%	20.71%
(1%)	LSDV	89.57%	41.17%	35.38%	31.00%	28.00%	26.02%	21.08%
(2%)	LSDV	89.96%	43.11%	37.59%	32.73%	30.02%	27.76%	23.16%
(3%)	LSDV	90.28%	45.78%	40.26%	35.27%	32.63%	30.92%	26.25%
(4%)	LSDV	90.98%	48.05%	42.98%	39.17%	36.52%	34.61%	30.00%
(5%)	LSDV	91.65%	51.48%	47.17%	43.26%	40.65%	38.88%	34.85%

Panel B. Adj. R-square

		Panel attrition pattern						
Skills	*Est.*	1	2	3	4	5	6	7
(0%)	OLS	10.41%	8.22%	8.13%	7.78%	7.65%	7.40%	7.39%
(0%)	LSDV	14.16%	8.27%	8.22%	7.60%	7.52%	7.29%	7.43%
(1%)	LSDV	13.35%	9.34%	8.65%	8.56%	8.37%	8.38%	7.87%
(2%)	LSDV	16.47%	12.33%	11.78%	10.85%	10.93%	10.53%	10.29%
(3%)	LSDV	19.40%	16.44%	15.56%	14.22%	14.25%	14.44%	13.90%
(4%)	LSDV	25.28%	19.95%	19.41%	19.38%	19.21%	19.01%	18.28%
(5%)	LSDV	30.64%	25.22%	25.32%	24.80%	24.47%	24.30%	23.95%

Panel C. Fisher joint significance test of acquirer FE

		Average Fisher value						
		Panel attrition pattern						
Skills	*Est.*	1	2	3	4	5	6	7
(0%)	LSDV	1.25	1.02	1.02	1.00	1.00	1.00	1.01
(1%)	LSDV	1.30	1.06	1.04	1.06	1.07	1.07	1.09
(2%)	LSDV	1.34	1.19	1.20	1.22	1.24	1.26	1.34
(3%)	LSDV	1.40	1.39	1.43	1.46	1.53	1.60	1.79
(4%)	LSDV	1.50	1.61	1.69	1.85	1.95	2.05	2.37
(5%)	LSDV	1.65	1.92	2.11	2.32	2.49	2.67	3.20

		Percentage of significant FE at 10%						
		Panel attrition pattern						
Skills	*Est.*	1	2	3	4	5	6	7
(0%)	LSDV	18.60%	14.30%	15.10%	12.70%	11.20%	10.10%	10.20%
(1%)	LSDV	17.50%	17.60%	15.90%	21.40%	20.30%	20.70%	22.40%
(2%)	LSDV	21.70%	34.60%	36.80%	45.30%	49.50%	57.10%	73.50%
(3%)	LSDV	24.10%	63.90%	71.80%	78.60%	86.40%	92.80%	98.80%
(4%)	LSDV	30.00%	84.40%	91.80%	97.50%	98.80%	99.80%	99.90%
(5%)	LSDV	36.60%	96.00%	98.20%	99.30%	100.00%	100.00%	100.00%

		Percentage of significant FE at 5%						
		Panel attrition pattern						
Skills	*Est.*	1	2	3	4	5	6	7
(0%)	LSDV	10.80%	9.00%	10.40%	8.10%	7.20%	6.40%	6.30%
(1%)	LSDV	11.60%	11.60%	10.70%	13.80%	13.40%	12.30%	13.90%
(2%)	LSDV	13.60%	26.00%	28.20%	34.60%	37.00%	45.30%	61.20%
(3%)	LSDV	15.50%	52.70%	60.70%	70.50%	80.30%	87.50%	97.50%
(4%)	LSDV	19.00%	76.50%	87.30%	95.50%	97.60%	99.00%	99.90%
(5%)	LSDV	25.10%	92.90%	97.30%	99.10%	100.00%	100.00%	100.00%

		Percentage of significant FE at 1%						
		Panel attrition pattern						
Skills	*Est.*	1	2	3	4	5	6	7
(0%)	LSDV	2.90%	4.60%	5.00%	4.00%	3.20%	2.70%	1.70%
(1%)	LSDV	4.50%	5.50%	4.20%	6.30%	5.30%	4.40%	3.90%
(2%)	LSDV	4.70%	13.80%	14.30%	16.00%	18.60%	23.60%	37.50%
(3%)	LSDV	5.60%	33.80%	41.00%	50.70%	63.90%	72.20%	91.30%
(4%)	LSDV	7.90%	59.10%	74.70%	87.60%	93.40%	96.00%	99.60%
(5%)	LSDV	9.80%	86.10%	93.20%	98.20%	98.80%	99.50%	100.00%

Appendix 2. Brown and Warner (B&W) Simulation Results, Constant Degrees of Freedom

Appendix 2 reports the results obtained by replicating the analyses from Table 3 but with a constant number of degrees of freedom for each attrition pattern.

Panel A. *R-square*

		Panel attrition pattern						
Skills	*Est.*	1	2	3	4	5	6	7
(0%)	OLS	8.78%	11.93%	12.62%	12.58%	13.02%	13.03%	13.55%
(0%)	LSDV	68.96%	35.34%	32.44%	29.20%	27.33%	25.84%	23.12%
(1%)	LSDV	69.15%	36.01%	32.84%	29.82%	27.99%	26.64%	23.65%
(2%)	LSDV	69.92%	37.88%	34.69%	31.55%	29.99%	28.43%	25.67%
(3%)	LSDV	71.22%	40.70%	37.70%	34.19%	32.62%	31.57%	28.62%
(4%)	LSDV	72.77%	43.41%	40.66%	38.23%	36.53%	35.28%	32.41%
(5%)	LSDV	74.61%	47.17%	44.94%	42.27%	40.64%	39.34%	37.12%

Panel B. Adj. R-square

		Panel attrition pattern						
Skills	*Est.*	1	2	3	4	5	6	7
(0%)	OLS	6.42%	7.13%	7.52%	7.56%	7.65%	7.54%	7.85%
(0%)	LSDV	7.35%	7.26%	7.54%	7.46%	7.50%	7.45%	7.88%
(1%)	LSDV	7.91%	8.22%	8.08%	8.28%	8.35%	8.46%	8.51%
(2%)	LSDV	10.22%	10.91%	10.62%	10.52%	10.89%	10.69%	10.94%
(3%)	LSDV	14.12%	14.96%	14.74%	13.99%	14.25%	14.61%	14.47%
(4%)	LSDV	18.72%	18.84%	18.79%	19.27%	19.22%	19.24%	19.01%
(5%)	LSDV	24.21%	24.23%	24.64%	24.55%	24.45%	24.30%	24.65%

Panel C: *FE Fisher*

		Average Fisher value						
		Panel attrition pattern						
Skills	*Est.*	1	2	3	4	5	6	7
(0%)	LSDV	1.04	1.02	1.01	1.00	1.00	1.00	1.01
(1%)	LSDV	1.05	1.05	1.03	1.06	1.07	1.07	1.09
(2%)	LSDV	1.09	1.17	1.19	1.22	1.24	1.26	1.34
(3%)	LSDV	1.17	1.36	1.42	1.46	1.53	1.60	1.79
(4%)	LSDV	1.27	1.61	1.68	1.86	1.95	2.06	2.38
(5%)	LSDV	1.41	1.94	2.11	2.31	2.49	2.66	3.22

		Percentage of significant FE at 10%						
		Panel attrition pattern						
Skills	*Est.*	1	2	3	4	5	6	7
(0%)	LSDV	30.30%	17.20%	15.20%	14.40%	10.90%	10.40%	9.40%
(1%)	LSDV	32.00%	21.50%	19.00%	20.80%	20.10%	19.30%	19.70%
(2%)	LSDV	40.60%	43.80%	44.70%	49.60%	48.20%	53.50%	58.20%
(3%)	LSDV	57.70%	78.00%	80.50%	83.90%	86.80%	90.40%	94.00%
(4%)	LSDV	77.80%	95.50%	96.50%	99.10%	98.90%	99.60%	99.70%
(5%)	LSDV	91.70%	99.60%	99.30%	99.60%	100.00%	99.90%	100.00%

		Percentage of significant FE at 5%						
		Panel attrition pattern						
Skills	*Est.*	1	2	3	4	5	6	7
(0%)	LSDV	24.90%	12.50%	10.70%	10.30%	7.00%	6.20%	4.70%
(1%)	LSDV	26.30%	15.00%	12.90%	14.30%	13.50%	12.40%	11.00%
(2%)	LSDV	35.00%	34.00%	32.00%	36.20%	37.10%	41.10%	45.00%
(3%)	LSDV	51.50%	70.10%	72.70%	74.60%	80.10%	84.90%	88.90%
(4%)	LSDV	71.40%	92.90%	93.40%	97.50%	97.70%	99.20%	98.90%
(5%)	LSDV	86.80%	98.90%	98.90%	99.60%	100.00%	99.70%	100.00%

		Percentage of significant FE at 1%						
		Panel attrition pattern						
Skills	*Est.*	1	2	3	4	5	6	7
(0%)	LSDV	15.70%	6.60%	5.10%	4.80%	3.50%	2.60%	0.70%
(1%)	LSDV	18.90%	8.00%	5.60%	6.80%	5.30%	3.70%	2.40%
(2%)	LSDV	23.40%	19.20%	16.30%	18.90%	18.40%	21.30%	23.00%
(3%)	LSDV	38.50%	51.50%	54.50%	57.30%	63.60%	67.60%	74.90%
(4%)	LSDV	58.90%	85.10%	85.70%	94.10%	93.50%	94.80%	96.40%
(5%)	LSDV	79.80%	97.20%	97.80%	98.70%	98.80%	99.50%	99.80%
(5%)	LSDV	63.00%	95.10%	94.70%	95.20%	96.50%	96.40%	96.90%