Learning from Repetitive Acquisitions: Evidence from the Time Between Deals

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ABSTRACT

Repetitive acquisitions involve benefits and costs. Benefits accrue from learning about the takeover process while costs involve integrating the combined firms. These benefits and costs are not directly observable from outside the firm but this paper proposes a simple model to infer their relative importance from the time between successive deals. The data requirements are minimal and allow the use of all mergers and acquisitions during 1992–2009 (more than 300,000 deals). The results provide strong and robust evidence that learning dominates integration costs for repetitive acquirers.

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Athletes know that repetition is an essential ingredient of training, but too much repetition can cause damage. Repetitive acquirers face the same sort of trade-off: by repetitively undertaking acquisitions, acquirers may learn,[1] garnering expertise and other knowledge about the takeover process, but successive acquisitions increases firm size and diversity and thus generates integration costs. Do the gains from learning-by-doing dominate the integration costs for repetitive acquirers?

Learning and integration costs in the mergers and acquisitions (M&A) market possibly represent sizeable economic effects. The M&A market is a prime resource allocation channel; as Netter, Stegemoller, and Wintoki (forthcoming) report, the average annual aggregated deal value by U.S. acquirers during 1992–2009 was $928 billion, with a peak value in 1998 of $1,806 billion, or 13% of U.S. stock market capitalization.

Academics have long been aware of repetitive acquirers in the M&A market (e.g., Schipper and Thompson (1983)). Fuller, Netter, and Stegemoller (2002) provide stylized facts about the value creation effects of repetitive acquisitions using a sample of 3,135 deals announced during 1990–2000: buying public firms generate significant negative returns, but buying private targets and subsidiaries generate positive ones. These latter positive returns are even stronger when the deals are financed with equity.

Yet we know little about potential learning associated with repetitive acquisitions.[2] Empirical evidence reported by Fuller, Netter, and Stegemoller (2002) is discouraging: acquirers that completed at least five deals during a three-year period earn 1.7% cumulative abnormal returns (CAR) on average, but from the fifth deal onward, they earn only a 0.52% average CAR.

[1] Throughout this article, we adopt Barkema and Schijven's (2008, p. 596) definition of learning: "the transfer of an organization's experience from one event to a subsequent event."

[2] Management and strategy literature pertaining to learning in an M&A setting is much more developed, but most empirical evidence is limited to case study analyses or focuses on a single or small set of industries with relatively few observations. For example, Hayward (2002) uses a sample of 214 acquisitions made by 120 firms in six industries. Barkema and Scheijven (2008) provide a thorough summary of this literature.

This decline in average CAR during acquisitions programs may indicate growing overconfidence (or related behavioral biases). Billet and Qian (2008), for example, report a negative CAR for deals subsequent to the first among a sample of 3,537 public acquisitions during 1985–2002 and conclude that their results are consistent with a managerial self-attribution bias, leading to overconfidence. However, Aktas, de Bodt, and Roll (2009) argue that the declining CAR during acquisitions programs is not incompatible with learning, because learning-by-doing might lead acquirers to assess expected synergies with the next target more accurately and thus to bid more aggressively to acquire it. Such learning could increase the probability of completing transactions, though at the cost of sharing a higher fraction of the value creation with target shareholders. Consequently, a declining CAR trend is not a conclusive proof of growing overconfidence. Aktas, de Bodt, and Roll (2011) provide empirical evidence consistent with theoretical predictions associated with learning.

All this empirical evidence about repetitive acquirers relies on relatively small samples of large M&A transactions (typically, a few thousand transactions by U.S. public acquirers). A notable exception is Netter, Stegemoller, and Wintoki (forthcoming), who assess the effect of data screens on the scope and characteristics of M&A activity.[3] These authors show in particular that some commonly known results in M&A literature (e.g., acquirers' shareholders do not gain from acquisitions) do not generalize to larger samples. With respect to the question of potential learning associated with repetitive acquisitions, we suspect that such sample biases are relevant. For example, Hayward (2002) suggests that learning depends on the time between successive transactions, such that short periods between successive acquisitions do not allow learning processes to take place, but acquisitions that are too distant in time hamper organizational learning by allowing organizational memory losses.

[3] Two other examples of large-sample M&A research are Erel, Liao, and Weisbach (2010) and Ellis *et al.* (2011) with 56,798 and 37,414 observations, respectively.

If one limits attention to a subsample of large transactions undertaken by serial acquirers, the time between successive transactions cannot be estimated properly, because smaller intermediate transactions are dropped from the sample. The resulting measurement error may bias inferences about learning by repetitive acquirers. Moreover, large deals are significantly more value destroying (Moeller, Schlingemann, and Stulz (2005)) and integration costs relate (at least intuitively) to deal size, so one should expect that subsamples of large transactions are not entirely representative.

We therefore undertake the first, to the best of our knowledge, very large-scale study of learning gains in M&A markets. Our goal is to test whether learning dominates integration costs, or vice versa. If learning dominates integration costs for firms that implement acquisitions programs, structuring learning processes within the organization could be a key driver of value creation. On the contrary, if integration costs overcome learning, strict governance mechanisms to control acquisitions programs are needed – especially if CEO remuneration entails M&A bonuses (see Grinstein and Hribar (2004)).

But investigating the relation between learning and integration costs is challenging, because neither element is directly observable from outside the firm; they are latent factors for the econometrician. We overcome this problem with a structural model that relates the time between successive deals (*TBD*) to the ratio of learning benefits to integrations costs. The *TBD* involves minimal data (i.e., one needs to know only the acquirer's identity and the announcement date or the completion date of the deal). In our model, the acquirer chooses the *TBD* (the time before undertaking a new transaction) that maximizes its expected profit, which is a function of the trade-off between learning benefits and integration costs. We characterize the learning and integration cost functions by a set of assumptions that reflect existing results and economic intuition – in particular, Hayward's (2002) results regarding the optimal time between successive transactions with respect to the learning processes. That is, experience provides positive learning when the time between successive transactions is short, but organizational amnesia generates negative learning effects when it is too long. Using the implicit function theorem, we express the partial derivative of the *TBD* with respect to the deal order number (*DON)* as a function of the relative importance of learning benefits and integration costs. We show that as long as learning is increasing in the *TBD* (experience effects), the *TBD* and the *DON* correlates negatively. This result is central to our method, because it allows us to infer, from an analysis of the relation between the *TBD* and the *DON*, the relative importance of changes in learning with respect to changes in integration costs.

Our main empirical evidence is drawn from a sample of 321,610 deals spanning the period 1992–2009, which are extracted from the Thomson-Reuters Securities Data Company (SDC) database. This very large sample parallels that used by Netter, Stegemoller, and Wintoki (forthcoming) and is designed to reveal M&A market activity as a whole. We impose no restrictions with respect to deal size (known or unknown), acquirer/target status (public or private), acquirer/target nationality (U.S. or non-U.S.), or deal type (merger, acquisition, partial acquisition, etc.). Our results are therefore not likely to be affected by endogenous sample selection. We complement the main analysis using a subsample of transactions with a richer set of information.

Our main measure of the *TBD* is the number of days between the most recent completed deal and the announcement date of the current deal, as reported in the SDC database. Learning and integration costs mostly materialize when transactions are completed.

We compute the *DON* by recomposing, for each acquirer, the history of its M&A activity. The *TBD* is likely affected by industry-wide factors, unrelated to the trade-off between learning and integration costs, as suggested by the well-documented existence of M&A waves (see Mitchell and Mulherin (1996); Harford, (2005)). We control for this source of interference by computing an abnormal *TBD* using two methods. First, we take the difference between the *TBD* and the median *TBD* in the same industry/year. Second, we regress the *TBD* on a set of industry and market-wide potential determinants, then use the estimated residuals of this regression as a second measure of abnormal *TBD*. Most of our results are based on the industry median–adjusted abnormal *TBD*, but we obtain consistent results using the regression-based approach. Finally, we study the relation between the abnormal *TBD* and the *DON* using a linear fixed-effect panel regression model to control for the correlation between successive transactions undertaken by an acquirer.

Our results provide strong and robust evidence that the increase in learning dominates the increase in integration costs for repetitive acquirers. First, for the main sample of 38,887 unique firms that have completed at least two deals during 1992–2009, the abnormal *TBD* is significantly and negatively correlated with the *DON*. This result holds whether we use the industry median–adjusted abnormal *TBD* or the regression-adjusted abnormal *TBD*. We then split our sample into a short *TBD* subsample (i.e., observations for which the *TBD* is less than the sample median *TBD*) and its complement, a long *TBD* subsample. The negative correlation between the abnormal *TBD* and the *DON* is driven by the short *TBD* subsample (experience effect), which provided a clear indication that increases in learning dominate variations of integration costs during acquisition sequences. For the long *TBD* subsample, the results indicate that the memory loss effect is weaker than the decrease in integration costs as the time between successive deals increases.

Second, focusing on a subsample of 8,387 firms (17,655 observations) that undertook transactions classified as M&As by the SDC, we reach the same conclusion. The negative correlation between the abnormal *TBD* and the *DON* therefore is not driven by the presence of acquisitions of majority interests, assets, partial interests, or remaining interests in our main sample.

Third, the presence of several acquisitions by a firm over a period as long as 1992–2009 does not necessarily mean that the firm implemented an acquisitions program, defined as a succession of related acquisitions (Schipper and Thompson (1983)). Therefore, we create another subsample that includes only firms that did not announce any acquisitions during a period of at least 24 months, then engaged in successive acquisitions separated by at most 6 months (a short *TBD*). We identify 1,816 such nearby sequences (13,010 observations) that we define as acquisitions programs. For this sample, the coefficient of the *DON* variable in the fixed-effect panel regression of the abnormal *TBD* on the *DON* is again negative and is ten times larger (in absolute terms) than the coefficient obtained from the main sample. Learning thus appears much stronger for firms that implement acquisitions programs.

Fourth, we study the behavior of a subsample of diversifying transactions undertaken by financial holdings (standard industrial classification [SIC] code 671). We identify 195 such financial holdings and obtain for them 363 acquisitions. Financial holdings that undertake acquisitions in unrelated industries should be less likely to integrate them; rather, these acquisitions essentially constitute portfolios of assets to sell back later. In the absence of post-acquisition integration, we can safely postulate no integration costs. Moreover, if learning materializes, it can only be during the pre-acquisition part of the process (i.e., target identification, negotiation, offer specification), no specific activities taking places after. So by analyzing unrelated acquisitions by financial holdings, we can test whether learning is significant during the pre-acquisition phase. Our results are consistent with the notion that such pre-acquisition phase learning exists for short *TBD* transactions (experience effect).

Fifth, by design, we do not take into account the amounts invested into acquisitions, because our goal is to study the whole M&A market and impose minimal data requirements. Yet we expect that deal size may relate to learning (i.e., acquirers may learn by undertaking small deals; Harding and Rovit (2004)) and integration costs (i.e., large acquisitions require more resources to merge with existing activities), so its omission from our analyses may raise an issue of a correlated missing factor. To investigate this issue, we replicate our analyses using the cumulative deal size of previous transactions, in place of the *DON* variable, which captures both the number of deals already undertaken (similar to the *DON*) and the size of these previous transactions. We obtain a statistically significant negative correlation between the abnormal *TBD* and the cumulative deal size. The negative correlation between the *TBD* and the *DON* is therefore robust to the inclusion of the importance of financial resources invested in an M&A.

These results not only generalizes limited existing empirical evidence about learning but also focuses on the *TBD*, an attribute of acquisition sequences that previously has gone unexplored in finance literature. We provide also several robustness checks of our results with respect to our methodological and econometric choices.

The paper is organized as follows. Section I introduces a simple structural model of the trade-off between learning and integration costs. Section II is devoted to the empirical analysis. Section III provides additional results and robustness checks. Section IV concludes.

I. Learning and Integration Costs in Acquisition Sequences

A. Model Setup

Our goal is to study the trade-off between learning and integration costs faced by a firm undertaking an acquisition. The decision variable is the time the firm waits before making in a new acquisition attempt (*TBD*). We use the deal order number (*DON*) to proxy for the history of transactions already completed by the firm. Note that the *DON* in itself is not a decision variable; rather, it encapsulates past decisions. To keep the model as simple as possible, we abstract from information asymmetry issues and agency conflicts (e.g., among the CEO, shareholders, and/or creditors). We assume that firm decisions are made by the CEO, in the best interest of shareholders and with no budget constraints. The firm shareholders are risk neutral, so the CEO maximizes the firm's expected profit. We finally assume that the timing decision (*TBD*) affects acquisition profit only through the influence of learning and integration costs. Synergies and other sources of value creation are essentially a function of the target selection or the assets under consideration.

B. Learning and Integration Costs

Learning might bear on multiple dimensions of the takeover process (Hitt, Harrison, and Ireland (2001)), including the selection and valuation of targets, due diligence, negotiation, offer specification (e.g., premium, mode of payment), and management of regulatory issues (e.g., intervention of the Federal Trade Commission and/or Department of Justice). Learning also bears on the post-acquisition phase and, at that stage, captures efficiency improvements in integration processes.

We assume that quantity of total learning for a given deal attempt *i*, denoted L_i, is a concave function of the *TBD* (see Figure 1, Panel A). This specification captures Hayward's (2002) ideas: acquisitions made too quickly in succession do not provide enough time to learn (experience effect), while acquisition expertise decays if takeovers are too far apart (memory loss effect). Therefore, there is a *TBD* threshold value denoted $\overline{TBD}$, such that signs of the first and second derivatives of L_i with respect to the *TBD* are:

$$\frac{\partial L_i}{\partial TBD} \geq 0 \text{ if } TBD \leq \overline{TBD} \text{ and } \frac{\partial L_i}{\partial TBD} \leq 0 \text{ if } TBD \geq \overline{TBD}, \tag{1}$$

$$\frac{\partial^2 L_i}{\partial TBD^2} \leq 0. \tag{2}$$

The substantial integration costs faced by acquiring firms also play an important role in merger success or failure. These costs are associated with reconciling various business activities; melting administrative, accounting, controlling, and information systems; and managing corporate culture differences.[4]

[Figure 1 About Here]

We assume that total integration costs for a given deal attempt i, denoted C_i, are a decreasing function of the *TBD* (see Figure 1, Panel B): the more time elapses between two successive deals, the fewer resources used to integrate new activities are saturated, and the lower is the cost of integrating new activities. The first-order derivative of C_i with respect to the *TBD* therefore has the following sign:

$$\frac{\partial C_i}{\partial TBD} < 0. \tag{3}$$

With respect to the firm's acquisition history, the form of the learning gains function depends on whether the *TBD* is short or long:

- Short *TBD* (experience effect): for a given short *TBD*, we assume that L_i is an increasing function of *DON* (see Figure 1, Panel A); i.e., expertise grows with experience:

$$\frac{\partial L_i}{\partial DON} > 0. \tag{4}$$

- Long *TBD* (memory loss effect): for a given level of long *TBD*, we assume that L_i is a decreasing function of *DON* (see Figure 1, Panel A), so the memory loss effect adds up over the number of deals:

$$\frac{\partial L_i}{\partial DON} < 0. \tag{4'}$$

We finally assume that C_i is an increasing function of *DON* (see Figure 1, Panel B), such that the more deals already completed by the firm, the fewer resources it has available to manage the integration process of new activities, such that the integration process is more expensive:

[4] Kaplan, Mitchell, and Wruck (2000) argue that merger success does not only depend on initial due diligence and information gathering but also on postmerger incentives and organizational design. M&A scholars in management document also that the realization of expected synergies and acquisition performance depends on effective post-acquisition integration (see, e.g., Datta (1991); Chatterjee et al. (1992); Larsson and Finkelstein (1999); Weber and Camerer (2003)).

$$\frac{\partial C_i}{\partial DON} > 0. \quad (5)$$

Equations (1) to (5) describe a set of intuitive general assumptions, in the sense that we do not specify a precise functional form for learning gains and integration costs but limit restrictions to the sign of their first- (and second-order in the case of L_i) derivatives. These assumptions rest on previously reported results (Hayward (2002)) or general economic principles (i.e., marginally decreasing profit functions and marginally increasing resource saturation).

C. The Acquirer's Decision Problem

The firm's decision problem is to choose when to undertake the next acquisition, that is, the time between the previous deal and the next deal attempt (*TBD*).[5] Given the characteristics of the selected target, the firm's expected rate of return is:

$$E(\pi) = \Pr(TBD) \times \left(\frac{E\big(L_i(TBD,DON)\big) - E\big(C_i(TBD,DON)\big) + E(S_i) - I_i}{I_i} - k\right) + \big(1 - \Pr(TBD)\big) \times 0, \quad (6)$$

where $\Pr(TBD)$ is the probability of acquiring the target, $E(S_i)$ are the acquisition expected synergies and other sources of value creation, I_i is the acquisition size and k is the firm cost of capital. The more the firm waits for its next acquisition, the higher is the risk of losing the acquisition opportunity ($\frac{\partial \Pr(TBD)}{\partial TBD} < 0$). To simplify the analysis, we assume unit investment ($I_i = 1$) and no costs related to losing the acquisition opportunity.

In the absence of (invertible) functional specifications of learning and integration costs, no explicit expression of the optimal *TBD* can be derived. Our strategy is therefore to develop predictions about the relation between the *TBD* and the *DON*, which are observable, using the implicit function theorem. The derivative of the *TBD* with respect to the *DON* can be expressed as follows:

[5] Recall that the *DON* is not a decision variable but summarizes the history of acquisitions completed by the firm.

$$\frac{\partial TBD}{\partial DON} = -\frac{\frac{\partial E(\pi)}{\partial DON}}{\frac{\partial E(\pi)}{\partial TBD}}. \tag{7}$$

We note that:

- $\frac{\partial E(\pi)}{\partial TBD} = \frac{\partial \Pr(TBD)}{\partial TBD} \times \left(E\left(L_i(TBD, DON)\right) - E\left(C_i(TBD, DON)\right) + E(S_i) - 1 - k\right) +$ $\Pr(TBD) \times \left(\frac{\partial L_i}{\partial TBD} - \frac{\partial C_i}{\partial TBD}\right)$;
- $\frac{\partial E(\pi)}{\partial DON} = \Pr(TBD) \times \left(\frac{\partial L_i}{\partial DON} - \frac{\partial C_i}{\partial DON}\right)$.

In equilibrium, $E\left(L_i(TBD, DON)\right) - E\left(C_i(TBD, DON)\right) + E(S_i) - 1 = k$: the firm achieves its required rate of return. These results lead us to the expression that relates the derivative of the *TBD* with respect to the *DON* to the partial derivatives of learning gains and integration costs:

$$\frac{\partial TBD}{\partial DON} = -\frac{\frac{\partial L_i}{\partial DON} - \frac{\partial C_i}{\partial DON}}{\frac{\partial L_i}{\partial TBD} - \frac{\partial C_i}{\partial TBD}}. \tag{8}$$

Equation (8) in turn allows us to derive empirical testable predictions, because *TBD* and *DON* are observable.

D. Empirical Predictions

Learning gains are increasing for short *TBD* (experience effect) and decreasing for long *TBD* (memory loss effect). Our empirical predictions depend on the sign of $\frac{\partial L_i}{\partial TBD}$.

D.1. Short TBD: Experience Effect

When $\frac{\partial L_i}{\partial TBD}$ is strictly positive, the denominator of Equation (8) is strictly positive. Therefore, the sign of $\frac{\partial TBD}{\partial DON}$ depends on the sign of $\frac{\partial L_i}{\partial DON} - \frac{\partial C_i}{\partial DON}$:

- $\frac{\partial L_i}{\partial DON} > \frac{\partial C_i}{\partial DON}$: the increase in learning gains through the acquisition sequence dominates the increase in integration costs. Then, $\frac{\partial TBD}{\partial DON}$ is negative, and the time that elapses between successive deals should decrease during the sequence.

- $\frac{\partial L_i}{\partial DON} < \frac{\partial C_i}{\partial DON}$: integration costs increase at a higher pace than learning gains, and $\frac{\partial TBD}{\partial DON}$ is positive, so *TBD* should be increasing during the acquisition sequence.

For short *TBD*, the sign of $\frac{\partial TBD}{\partial DON}$ allows us to infer whether the increase in learning gains dominates the increase in integration costs during the acquisition sequence, or vice versa.

D.2. Long TBD: Memory Loss Effect

When $\frac{\partial L_i}{\partial TBD}$ is strictly negative, the numerator of Equation (8) is always negative (indeed, $\frac{\partial L_i}{\partial DON} < 0$: memory loss effects add up with greater integration costs). The sign of Equation (8) depends this time on the sign of the denominator:

- $\left|\frac{\partial L_i}{\partial TBD}\right| > \left|\frac{\partial C_i}{\partial TBD}\right|$: the memory loss effect dominates the decrease in integration costs. The denominator of Equation (8) is negative, and the sign of $\frac{\partial TBD}{\partial DON}$ is negative. The time between successive acquisitions should decrease through the deal sequence, because the memory loss effect is prevalent.
- $\left|\frac{\partial L_i}{\partial TBD}\right| < \left|\frac{\partial C_i}{\partial TBD}\right|$: the decrease in integration costs dominates the memory loss effect. The denominator of Equation (8) is positive, and the sign of $\frac{\partial TBD}{\partial DON}$ is positive.

For long *TBD*, we can infer from the sign of $\frac{\partial TBD}{\partial DON}$ whether the memory loss effect dominates the decrease in integration costs during acquisition sequences, or vice versa.

We thus summarize our empirical predictions in Proposition 1.

Proposition 1. Under the assumptions introduced in Sections I.A and I.B,

(a) For short *TBD*: if the increase in learning through the acquisition sequence dominates the increase in integration costs, $\frac{\partial TBD}{\partial DON}$ is negative (and vice versa).

(b) For long *TBD*: if the memory loss effect dominates the decrease in integration costs in *TBD*, $\frac{\partial TBD}{\partial DON}$ is negative (and vice versa).

We are mainly interested in testing prediction (a) for the short *TBD*, which allows us to infer from the relation between the *TBD* and *DON* the relative importance of learning and integrations costs during sequences characterized as short *TBD*. In the theoretical analysis, short *TBD* corresponds to the *TBD* region in which L_i is increasing (left part of Figure 1) and long *TBD*, the region in which L_i is decreasing (right part of Figure 1). In the empirical analysis, we use the sample median *TBD* as a cut-off point to identify short versus long *TBD* at the firm level.

II. Empirical Evidence

A. Sample

The Securities Data Company (SDC) provides the sample of takeovers. To examine all completed transactions, we adopt the selection criteria used by Netter, Stegemoller, and Wintoki (forthcoming). We first select all completed takeovers available from January 1, 1992, to December 31, 2009, including transactions classified by SDC as mergers, acquisitions, acquisitions of majority interest, acquisitions of assets, acquisitions of certain assets, acquisitions of remaining interest, and exchange offers. All these diverse transactions are retained in the sample because our focus is on the acquirer and because SDC's transaction definitions are often vague. For example, almost half the transactions reported by Microsoft as mergers and acquisitions are classified by SDC as acquisitions of assets.[6,7] We have no reason to overlook such transactions. However, to limit the analysis to acquisitions with an explicit change of control, we retain them only when the acquirer purchases 50% or more of the target's shares and owns less than 50% of the target six months prior to the deal announcement.

[6] See http://www.microsoft.com/investor/Stock/AcquisitonHistory/All/default.aspx.

[7] As emphasized by Netter, Stegemoller, and Wintoki (forthcoming), the M&A nomenclature has great meaning when the party of interest is the target firm. From the seller's perspective, the implications of a merger are totally different than those of an asset sale.

No restrictions are imposed with respect to deal size (whether or not SDC reports the deal value), to the status of acquirers and targets (public or private), or to the nationality of acquirers and targets (U.S. or non-U.S.). The earliest sample year is 1992 when SDC begin covering deals of any value, even those with unkown values. This restriction is particularly relevant for our goal of building a complete acquisition history of every firm and minimizing the risk of missing a transaction.

After removing 1,394 duplicate observations, identified by their announcement date, acquirer, and target CUSIP, we retain 321,610 transactions (the main sample). Table I contains summary statistics of the annual acquisition activity by all acquirers and by U.S. acquirers. For both groups of acquirers, the sample exhibits a first peak in the number of transactions between 1997 and 2000, consistent with the well-documented "friendly" M&A wave of the end of the 1990s (Betton, Eckbo, and Thorburn (2008)), and a second peak between 2005 and 2007. The differences between the yearly average and median deal size highlight the impact of large transactions on reported aggregate deal sizes. Forty percent of these 321,610 transactions were undertaken by U.S. acquirers. We report the aggregate deal size for U.S. acquirers in 2008 constant dollars, to provide a direct comparison with Netter, Stegemoller, and Wintoki (forthcoming).[8] These authors report on 128,900 transactions for the period 1992–2009, with an aggregate deal value of $16,702 billion (in 2008 constant dollars). We replicate their sample with 126,878 transactions and an aggregate deal value of $16,032 billion. Our main sample also matches their universe with respect to the form of the deal, according to SDC's classification (unreported results). Most transactions are classified as acquisitions of assets (64.67% for all acquirers; 73.49% for U.S. acquirers). Mergers are the second most common deal form, with more than 20% of transactions classified as such, regardless of the nationality of the acquirer.

[8] Transactions with missing deal value in SDC are not taken into account to obtain aggregate, average and median deal size by year. This creates a downward bias in the reported statistics. But deal value are most often missing for small transactions in SDC.

[Table I About Here]

B. Variables and Methods

B.1. Deal Order Number (DON)

Proposition 1 predicts relations between the deal order number (*DON*) and the time between successive deals (*TBD*), depending on whether the increase in learning dominates the increase in integration costs during acquisition sequences. We therefore start by tracing acquisitions sequences by acquirer to compute the *DON* variable. Specifically, we identify each acquirer using its historical CUSIP code, extract from the main sample all of its acquisitions, and sort the acquisition list by announcement date. A *DON* is assigned to each transaction by increasing announcement date, from 1 for the first acquisition to N for the last acquisition in the main sample.

Table II reports the distribution of deal order numbers. More than 55% of all deals are a first deal for a particular acquirer, though multiple acquisitions are still quite common: 67,387 transactions are associated with a *DON* of at least 5, 36,835 transactions indicate a number of at least 10, and 19,341 transactions have a *DON* of at least 21. Schipper and Thompson (1983) and Fuller, Netter, and Stegemoller (2002) similarly have highlighted the presence of serial acquirers. The average deal size by *DON* in Table II is clearly increasing through the acquisition sequence. For example, the fifth deal in a sequence has an average (median) deal size three (two) times higher than the first deal, and the tenth deal has an average (median) deal size approximately four (three) times higher than the first deal. After the fifteenth deal, the average deal size seems not to increase much more, with an average deal size five times higher than the first. This substantial increase of the deal size throughout the acquisition sequence appears consistent with learning. That is, firms would begin with smaller deals to learn the basics, then as they gain more knowledge, they would risk bigger acquisitions (as indicated in management literature; Harding and Rovit (2004)). But another interpretation is that deal size is correlated with acquirer size and that larger acquirers do more deals. The apparent positive correlation between *DON* and the deal size would then be driven by the acquirer size (a latent factor here). The last two columns of Table II (average and median acquirer market value in millions of dollars) are consistent with this second interpretation.

[Table II About Here]

B.2. Time Between Deals (TBD)

Potentially, learning starts as soon as an acquisition is attempted, whether or not it is completed, because target identification, the choice of buying procedure, the offer specification, etc., can be as informative as the post-acquisition activities. But integration costs arise only after the acquisition is completed. Thus, the choice of whether to compute the *TBD* as the difference between the announcement date of the current transaction and the completion date of the most recently completed transaction or as the difference between announcement dates of successive transactions is an important issue (see Figure 2). We use mostly the *TBD* defined as the days between the announcement date of the current transaction and the completion date of the preceding transaction, which we denote *TBDC*. The *TBDC* spans a conservative interval of learning, because it does not include the earliest part of the potential learning period. We provide also results using the days between the announcement dates of the current deal and the previous deal (denoted *TBDA*) as a robustness check.

[Figure 2 About Here]

M&As exhibit waves at the aggregate and industry levels (Mitchell and Mulherin (1996); Harford (2005)), which should materially influence the *TBD* . However, our model postulates a trade-off between learning gains and integration costs at the firm level. It is firm specific, so we must control for industry and aggregate influences on the *TBD* in empirical tests. Accordingly, we compute the abnormal *TBD* as the difference between the *TBD* and median *TBD* of deals in the same industry/year as the deal under consideration,

$$\text{Abnormal } TBD_d = TBD_d - \text{Median}_{k \in I}(TBD_k), \tag{9}$$

where d is the current deal, and I is the set of deals in the same industry/year. We use the three-digit SIC code to define the industry. (In our robustness checks, we assess the stability of the results using the two-digit SIC code, and we complement this median-adjusted abnormal *TBD* approach with a regression-based approach.)

Table III lists the summary statistics for the *TBD* variables for the entire sample as well as the short and long *TBD* subsamples. Because the predictions in the previous section depend on the presence of a short or long *TBD*, the sample is divided according to *TBD* length, around the median.

[Table III About Here]

Panel A of Table III reports on *TBDC*, the number of days between the announcement date of the current deal and the completion date of the previous deal (*TBDC*). In total there are 129,400 *TBDCs*, because there must be at least two deals for any given firm. The average *TBDC* is 420 days (about 14 months), and the corresponding median is 174 days (almost 6 months). The *TBDC* is clearly decreasing throughout the deal sequence: from 577 days (19 months) on average during the first five transactions to 61 days (2 months) for deal order numbers greater than 20. The same decreasing pattern emerges for both the short and long *TBD* subsamples.

Panel B of Table III reports on *TBDA*, the number of days between the announcement dates of the current and previous deals. The patterns of *TBDA* and *TBDC* are similar, which suggests that the analyses might not be seriously affected by the particular way TBD is computed.

Panel C of Table III focuses on the abnormal *TBDC*. Removing the industry median *TBDC* significantly affects our results in one key respect: for the short *TBD* subsample, the abnormal *TBDC* is almost constant from *DON* = 1 to *DON* = 20, then drops substantially for

DON greater than 20. This indicates that industry determinants play a role in the decreasing trend shown by *TBD* in Panels A and B.

It is tempting to interpret the trends in the *TBDC*, *TBDA*, and abnormal *TBDC* in light of Proposition 1, but successive transactions by a given acquirer are not independent observations. Statistical inference therefore could be difficult, a concern we address in Section II.C.

B.3. Control Variables

Some of our analyses require the use of additional control variables. We collect several transaction-level control variables: a dummy variable identifying horizontal deals (at the four-digit SIC industry level), a dummy variable identifying private targets, a dummy variable identifying U.S. targets, and deal size in millions of dollars. Panel A of Table IV provides the number of observations in our main sample for which these variables are available, the fraction of horizontal transactions, the fractions of private targets and domestic targets, and the average and median deal sizes. Panels B and C contain the corresponding figures for the short and long *TBD* subsamples, respectively. Although the three dummy variables are available for all transactions, the SDC reports deal size for less than half of them (see also Netter, Stegemoller, and Wintoki (forthcoming)). The percentage of horizontal transactions appears slightly higher for the long *TBD* subsample, whereas domestic targets seem slightly more present in the short *TBD* subsample. The percentage of private targets is stable between the two subsamples. The average deal size is substantially higher for short *TBD* transactions (a difference of almost $40 million), but this difference likely driven by a few large transactions, because the median deal sizes are comparable.

[Table IV About Here]

B.4. Econometric Specifications

Successive transactions by a given acquirer are not necessarily independent observations. We therefore control for the possible correlation of successive acquisitions by a given firm. Our baseline approach is to adopt a fixed-effect panel data specification:

$$\text{Abnormal}\ TBD_{i,j} = \alpha_j + \beta\ DON_{i,j} + \varepsilon_{i,j}, \tag{10}$$

where *i* is the acquisition index, *j* is the firm index, and α_j is the firm-fixed effect that captures unobservable factors that remain constant through time. The section on robustness checks reports additional results using a pooled estimator and clustered standard errors (Petersen (2009); Thompson (2011)).

C. Results

Our main results, the estimation of Equation (10), are reported in Table V. The dependent variable is the industry-adjusted abnormal *TBDC*. The first column in Panel A of Table V summarizes the main sample results for 129,400 observations, a significant reduction in sample size relative to the 321,610 transactions identified in Table I. But we need at least two transactions to compute the *TBD*, and 179,057 transactions are for the first deal (see Table II). The 129,400 observations involve 38,887 unique acquirers, for an average of 3.3 observations per acquirer. Fixed-effect coefficients are therefore not included in Table V (there are 38,887). The Fisher statistic is highly significant, with a value of 109.08. The estimated coefficient of the *DON* variable is –2.08, and the corresponding t-statistic is highly significant with a value of –10.44. The abnormal *TBDC* decreases on average throughout the acquisition sequences.

[Table V About Here]

Proposition 1, on the relation between the *TBD* and the *DON*, depends on whether the context is the experience effect part of the learning function (short *TBD*) or the memory loss effect part (long *TBD*), which are reported separately after splitting the sample at the median in columns 2 and 3. For the short *TBD* in column 2, the *DON* coefficient is –1.36 and highly significant with a t-statistic of –22.93. This is a clear indication that learning in acquisition sequences dominates increase in integration costs. In contrast, for the long *TBD* subsample in column 3, *DON* has a positive coefficient (0.90) that is also significant (t-stat = 2.27).

The contrast in the *DON* coefficients between columns 2 and 3 is striking. It indicates that for long *TBD*, the decrease in integration costs obtained by waiting longer before undertaking a next deal dominates the adverse effect due to memory loss.

The results in column 2 and 3 refer to subsamples formed by selecting observations on the dependent variable (*TBDC*). This procedure might raise concerns about endogenous subsampling, but our aim is not to generalize these results to the whole population of transactions (which are in column 1). Rather, columns 2 and 3 offer direct tests of Proposition 1. We note finally that the results for the full sample seem driven mainly by the short *TBDC* subsample: in both cases, the *DON* coefficient is negative and highly significant, whereas for the long *TBDC* subsample, the *DON* coefficient is positive.

These results pertain to a long period of time (1992 to 2009), and it is possible that acquirers undertaking a few transactions (e.g., 2 or 3) over a 18-year period are not really implementing acquisitions programs (Schipper and Thompson (1983)). Therefore, to refine our analysis, Panel B of Table V reports results for a subsample of acquisitions sequences that clearly reflect acquisitions programs, according to two criteria. First, the acquirer must remain quiet for 24 months (no acquisition attempts in our main sample), similar to Song and Walkling's (forthcoming) dormant period (though they use a period of 12 months). This makes it likely that we capture the starts of new acquisitions programs. Second, the maximum time elapsed between two successive transactions is 6 months and thus includes only sequences of related transactions. With respect to our main sample, in which the median *TBD* is 174 days (see Panel A, Table III), we select only sequences of short *TBD* transactions. In comparison, Fuller, Netter, and Stegemoller (2002) demand that "the acquirer completes bids for five or more targets in any three-year window during the sample period" (p. 1771), which implies a six-month maximum average time between transactions for the window of three years. Their criterion is thus somewhat less strict than ours, because we apply the six-month threshold on a transaction-by-transaction basis.

The results in Panel B of Table V confirm our initial evidence: the *DON* coefficient is negative (–25.68) and highly significant (t-stat = –22.16). The coefficient's value (in absolute terms) is more than 10 times higher than the coefficients reported in Panel A of Table V for the total sample (column 1) and the short *TBD* subsample (column 2), and the associated t-statistic is as high for the short *TBD* subsample (column 2), despite the drastic reduction in the sample size. The increase in learning through acquisition sequences thus seems to be particularly pronounced. Perhaps acquirers starting an acquisitions program focus more on putting learning processes into place throughout their organization.

Does learning occur during the pre-acquisition phase? To seek an answer to this question, we study a subsample of unrelated acquisitions by financial holdings, which likely engage in buying and reselling in the general course of their business. It seems less likely that financial holdings bother much to integrate unrelated acquisitions. Without post-acquisition integration costs, learning can occur, if at all, during the pre-acquisition phase.

We therefore form another subsample applying two criteria to our main sample. First, acquirers are firms from SIC code 671, "Offices and Bank Holding Companies." Second, the transactions involve targets outside the financial industy (SIC codes 6000–6999). Given these constraints, we can identify a sample of 363 deals, undertaken by 192 financial holdings acquirers, for which we can compute the *TBD* (see column 1, Panel C, Table V). The *DON* coefficient for this sample (column 1, Panel A, Table V) is not significant, but when the 363 observations are divided into two subsamples using the median abnormal *TBD*, the *DON* coefficient is negative (–11.08) and marginally significant (t-stat = –1.64) for the short *TBD* subsample (column 2). This result should not be dismissed just because the sample is small and the fixed-effect panel approach requires that we estimate numerous coefficients (118 fixed-effect coefficients, slope, and variance of the residuals). Despite the low statistical power of this test, there is significant evidence of learning during the pre-acquisition phase by financial holdings.

III. Robustness Checks

This section checks the robustness of our results with respect to various potential issues, including the computation of the *TBD*, the sample composition, the stability and form of the learning function, and the correlation between successive observations for a given acquirer. For brevity, results are given only for the main sample (i.e., the sample discussed in column 1, Panel A, Table V).[9]

A. TBD Computation

The results in Table V are based on the *TBDC*, the number of days between the current transaction announcement date and the completion date of the most recent transaction (see Figure 2). An alternative computation would use the number of days between successive announcement dates (*TBDA*). The first column of Table VI provides the results when *TBDA* is the dependent variable. The *DON* coefficient is negative (–2.00) and very close to the value reported in Panel A of Table V (column 1), as well as highly significant (t-stat = –9.97). Hence, defining the time elapsed between two successive deals, commencing with the announcement date or the completion date of the previous deal, does not affect the results.

[Table VI About Here]

[9] The full set of results are available on request.

The range of the *TBDC* is large (from 1 to 6,430 days in the main sample). We check whether the results are affected by using the natural logarithm of the *TBDC* before computing the abnormal *TBDC*. The second column of Table VI displays the results. The *DON* coefficient is again negative (–0.02) and highly significant (t-stat = –29.40). Using the log(*TBDC*) increases the statistical significance of the *DON* coefficient.

We also compute the industry median–adjusted *TBDC* using the three-digit rather than the two-digit SIC code. The results are in column 3 of Table VI. The *DON* coefficient and its associated t-statistic are almost unaffected by this change.

In column 4 of Table VI, we also assess the robustness of the results by computing the abnormal *TBD* using a regression-based approach. We start by regressing the *TBDC* on a set of industry- and market-wide determinants: *HHI*, industry concentration (i.e., the Herfindahl-Hirschman index for firms with a given three-digit SIC code, computed using firm total assets reported in the Compustat database); *Median Firm Size*, (estimated using firm market value from the CRSP database); *Median ROA*, or the industry median return on assets; *Median Growth Rate*, the industry median sales-based growth rate; *Liquidity*, the liquidity index introduced by Schlingemann, Stulz, and Walkling (2002) to capture the intensity of corporate asset transactions within an industry; *Aggregate Market-to-Book*, or the aggregate market-to-book ratio; and *C&I spread*, the commercial and industrial loan rate spreads used by Harford (2005).[10] All these variables are measured as of year-end when the transaction was announced. The first-step regression is therefore:

$$TBDC_{i,j} = \gamma_0 + \gamma_1 HHI_{Ind,Year} + \gamma_2 Median\ Firm\ Size_{Ind,Year} + \gamma_3 Median\ ROA_{Ind,Year}$$
$$+\gamma_4 Median\ Growth\ Rate_{Ind,Year} + \gamma_5 Liquidity_{Ind,Year}$$
$$+\gamma_6 Aggregate\ Market\ to\ Book_{Year} + \gamma_7\ C\&I\ Spread_{Year} + \varepsilon_{i,j}, \tag{11}$$

[10] http://www.federalreserve.gov/releases/e2/e2chart.htm.

where *i* is the acquisition index, *j* is the firm index, and *Ind* and *Year* are the corresponding industry and year indices, respectively.

The residuals of this first-step regression become our new measure of the abnormal *TBDC*:

$$\text{Abnormal}\, TBDC_{i,j} = TBDC_{i,j} - \widehat{TBDC_{i,j}}, \tag{12}$$

where $\widehat{TBDC_{i,j}}$ is the fitted value from Equation (11).

The estimation results for Equation (11), in Panel A of Table VII, refer to a sample of 136,910 observations. All coefficients are highly significant except the M&A market liquidity index. The *TBDC* is increasing with industry concentration, industry median firm size, and industry median *ROA*. These three variables seem to characterize industries with fewer transaction opportunities. The median industry growth variable instead reveals a negative coefficient: growing industries offer more opportunities for acquirers. The *C&I Spread* has a positive and statistically significant coefficient, which indicates that, consistent with Harford (2005), tighter financing conditions slow down M&A market activity. Surprisingly, the aggregate market-to-book ratio has also a positive and significant coefficient. Periods of high valuations may delay acquisition activity if targets are more expensive or there is more potential competition in the M&A market (see Aktas, de Bodt, and Roll (2010)).

Column 4 of Table VI, provides the results obtained with the regression-adjusted abnormal *TBDC*. The *DON* coefficient is negative (–4.56) and highly statistically significant (t-stat = –22.43), as well as two times larger (in absolute value) than the coefficient estimated with the industry median–adjusted *TBDC* (column 1, Panel A, Table V). We therefore consider the results in Table V cautious estimates with respect to the procedure chosen to adjust the *TBDC* to industry- and market-wide determinants.

A last concern that might be raised about the computation of *TBDC* is the presence of a private portion in the M&A process, as recently emphasized by Boone and Mulherin (2007).

The issue is potentially serious, because private negotiations between parties make the announcement date an imperfect measure of the transaction starting point. If this measurement error is correlated with our independent variable, we face a endogenous errors-in-variables problem. We check it using a sample of 1,573 transactions for which we collected the length of the private process by hand, using the SEC filings S4 and 14D for mergers and 14A for tender offers (see also Aktas, de Bodt, and Roll (2010)). This sample of M&A transactions spanned 1994–2007 among U.S. listed firms, featured a minimum deal size of $100 million, and required that the percentage held by the acquirer was less than 50% before the deal announcement and more than 50% after its completion. The private process length is the time elapsed, in days, between the initiation of the takeover process and the announcement date of the takeover agreement. For these 1,573 transactions, we regress the private process length on the *DON* variable (computed using our main sample):

$$Private\ Process\ Length_{i,j} = \alpha + \beta\ DON_{i,j} + \varepsilon_{i,j}, \tag{13}$$

where *i* is the acquisition index, and *j* is the firm index.

Panel B of Table VII features the estimation results for Equation (13). The *DON* coefficient is negative (–0.15) but not statistically significant (t-stat = –0.43). We thus conclude that private process-generated errors in the *TBD* variable are mainly innocuous noise that might affect test power but do not influence our inferences.[11]

[Table VII About Here]

B. Sample Composition

The main sample includes transactions classified by SDC as acquisitions of assets, majority of interest, certain assets, remaining interests, and exchange offers, as well as those

[11] It could be argued that the private part in the M&A process generates signed errors in the *TBDC* computation, because the announcement date by definition is the last day of the private period. Signed errors of measurement might be a source of an estimation bias, but this concern only holds for the *TBDC* variable. For the *TBDA* variable, the errors of measurement may be positive or negative. Column 1 of Table VI shows that *TBDC* and the *TBDA* give similar results.

strictly classified as mergers or acquisitions. This choice is motivated by the goal of computing the *DON* variable as precisely as possible and to study the M&A market as a whole. However, including transactions not clearly identified as mergers or acquisitions may raise questions about the real nature of the observed phenomena. It also limits the possibility of including control variables in multivariate analyses (though the fixed-effect panel estimator controls for acquirer characteristics that are stable through time). Nonetheless, the robustness of the results presented thus far can be checked against sampling choices by studying three subsamples: (1) transactions classified as mergers or acquisitions in the SDC database (M&A subsample); (2) transactions classified as mergers or acquisitions in the SDC database and for which the following control variables are available: horizontal transaction (acquirer and target in the same four-digit SIC code industry), private target, deal size, and U.S. target (M&A subsample with controls); and (3) acquirers that completed at least five transactions during 1992–2009 (repetitive acquirers subsample).

Panel A of Table VIII reports on the M&A subsample (column 1). The subsample includes 17,655 transactions and produces a *DON* coefficient that is negative (–6.63), three times higher (in absolute value) than the estimate obtained with the main sample (–2.08, see column 1, Panel A, Table V), and strongly significant (t-stat = –4.86). Adding the control variables in column 2 reduces the sample to 12,769 observations (column 2) but increases both the *DON* coefficient estimate (–17.52) and its statistical significance (t-stat = –14.81). For the sake of brevity, the coefficients of the control variables are not reported, because none of them is significant. Focusing on repetitive acquirers in column 3 generates a sample of 84,637 observations. Almost the same coefficient estimate is obtained for the *DON* variable (–2.07) as in the main sample, and it is again highly statistically significant with a t-statistic of –12.24. These results together confirm that the results presented thus far do not depend on sampling choices.

C. Learning Gains Function

In Section I, learning and integration costs functions are assumed to be stable throughout acquisitions sequences. But in practice, exogenous shocks can transform the shape of these functions. In particular, information technology has modified profoundly the way people communicate and collaborate in the past two decades. In 1992, the Internet was virtually absent in the business environment; today, it is ubiquitous. The information technology revolution also has created a massive disintermediation movement, affecting many industries (e.g., travel and leisure, computers and software, banking and insurance). These exogenous shocks might change the learning gains and information costs functions of acquirers.

To deal with this issue, we select, for each acquirer, transactions after the point at which *DON* = 5. This selection criterion yields 57,149 observations (column 1, Panel B, Table VIII). With this sample, the *DON* coefficient is negative (–0.78) and highly significant (t-stat = –5.16). However, the *DON* coefficient estimate is significantly smaller than the one obtained with the main sample (–2.08, column 1, Panel A, Table V): the increase in learning continues to dominate the increase in integration costs even for later transactions undertaken by each acquirer. The change in the estimated slope is more difficult to interpret though. It may be due to the concave/convex form of learning and integration costs functions (see Figure 1) or to structural changes in the shape of these functions. The limited number of observations by acquirer does not allow one to disentangle these interpretations.

Another potential shortcoming of the model in Section I relates to financial resources committed to acquisitions. A key characteristic of M&A transactions is the deal size (Fuller, Netter, and Stegemoller (2002)), which the theoretical analysis presented in Section I ignores. Yet one may suspect relations among deal size, integration costs, and learning. In particular, integration costs should increase with deal size, and undertaking small acquisitions may be a good path to mastering the acquisition process (Harding and Rovit (2004)). To check whether omitting the financial resources committed to acquisitions affects our results, the cumulative deal size through the acquisition sequence replaces the *DON* variable used in Equation (10):

$$\text{Abnormal } TBDC_{i,j} = \alpha_j + \beta \; Cumulative\ Deal\ Size_{i,j} + \varepsilon_{i,j}, \tag{14}$$

where i is the acquisition index, j is the firm index, and *Cumulative Deal Size*$_{i,j}$ is the cumulative deal size from the first to the most recent transaction i – 1 for acquirer j. If the deal size is not reported by SDC, the transaction is skipped, such that the real amount of financial resources committed is underestimated.

Column 2 in Panel B of Table VIII contains the results. The coefficient of the cumulative deal size variable is negative (–0.002) and highly significant (t-stat = –5.47). Taking into account financial resources committed to the sequence of acquisitions thus does not change the conclusions.

Do integration costs increase with deal size, as intuition would suggest? To test whether it is the case, the deal size of the most recent transactions (when available) is used in replacement of the cumulative deal size. Panel B of Table VIII reports the result (see column 3). The lagged deal size coefficient is positive (0.002) and significant (t-stat = 2.2), consistent with the notion of increasing integration costs with deal size, as expected. The change of sign between the cumulative and lagged deal size coefficients is also indicative of the importance of learning during acquisitions sequences. The increase in learning is significant enough to overcome the increases in integration costs due to the accumulation of transactions.

[Table VIII About Here]

D. Correlation of Observations

Because successive transactions by an acquirer are not independent observations, a fixed-effect panel estimator is used to generate the results reported in Tables V, VI, and VIII. To check the robustness of the results against this choice, Panel C of Table VIII reports results obtained using the standard pooled ordinary least square (OLS) estimator with asymptotic standard error (column 1) and clustered standard error (column 2), as suggested by Petersen (2009) and Thompson (2011).

The classic pooled OLS estimator yields a negative estimate for the *DON* coefficient (–8.92), confirming the results obtained with the fixed-effect panel estimator. The *DON* is highly significant, whether we rely on an asymptotic (t-stat = –59.84) or clustered (t-stat = –2.88) standard error. However, the impact of the correlation between successive observations for a given acquirer on the standard errors estimates is strong (i.e., the *DON* coefficient clustered standard error is more than 20 times greater than the asymptotic one).

Equation (10) is fundamentally a univariate regression of the abnormal *TBDC* on the *DON* variable. This opens the possibility to compare graphically the pooled OLS estimator and the fixed effect panel estimator. Figure 3 displays the distribution of the number of observations (dotted red line) and the average abnormal *TBDC* (plain blue line) by *DON* for the pooled OLS estimator (Panel A) and the fixed-effect panel estimator (Panel B). In Panel B, to obtain a graphical representation of the *DON* slope coefficient in a fixed-effect panel context, we use group demeaned data. The distribution of observations is consistent with descriptive statistics in Table II: most acquirers undertake fewer than 10 transactions. The abnormal *TBDC* decreases with the *DON*, especially where observations cluster, in both panels. However, Panel A exhibits a larger (and regular) decrease in the abnormal *TBDC* than Panel B, which may explain the difference in the *DON* coefficient estimates obtained between the pooled OLS estimator (–8.92, Panel C, Table VIII) and the fixed-effect panel estimator (–2.08, Panel A, Table V). Interpretation of the *DON* coefficient estimate obtained using the pooled OLS estimator must be done with care though, because it is unclear whether the negative slope reflects a decrease in the abnormal *TBDC* for a given acquirer or indicates that acquirers that engage in more deals perform them faster.

[Figure 3 About Here]

IV. Conclusions

Acquirers that undertake sequences of acquisitions may benefit by learning from deal to deal, but they also are potentially exposed to integration costs that become larger impediments with more deals. We study this trade-off. But because learning and integration costs are not observable from outside the firm, we model the acquirer's decision to undertake new transactions as a function of the time elapsed since its previous acquisition (*TBD*). The model's main result is a testable empirical prediction that relates *TBD* in acquisitions sequences to the relative importance of learning and integration costs.

Computing the *TBD* imposes minimal data requirements (i.e., only acquirer identity and announcement date). Thus, one can observe *TBD* for the all acquisitions in the entire M&A market during 1992–2009, more than 300,000 transactions. The empirical evidence uncovers a clear and significant decrease in the *TBD* during acquisitions sequences. This negative trend in the *TBD* is consistent with learning benefits that dominate integration costs.

To the best of our knowledge, this paper is the first to address the relative importance of learning and integration costs for a sample that is not potentially biased by selection criteria (see Netter, Stegemoller, and Wintoki (forthcoming)). Results show that for firms that engage into repetitive acquisitions, learning dominates integration costs . This has potentially important managerial implications. It reveals the importance of learning-by-doing through repetitive acquisitions and emphasizes the need to implement organizational structures designed to encourage and develop learning processes as much as possible.

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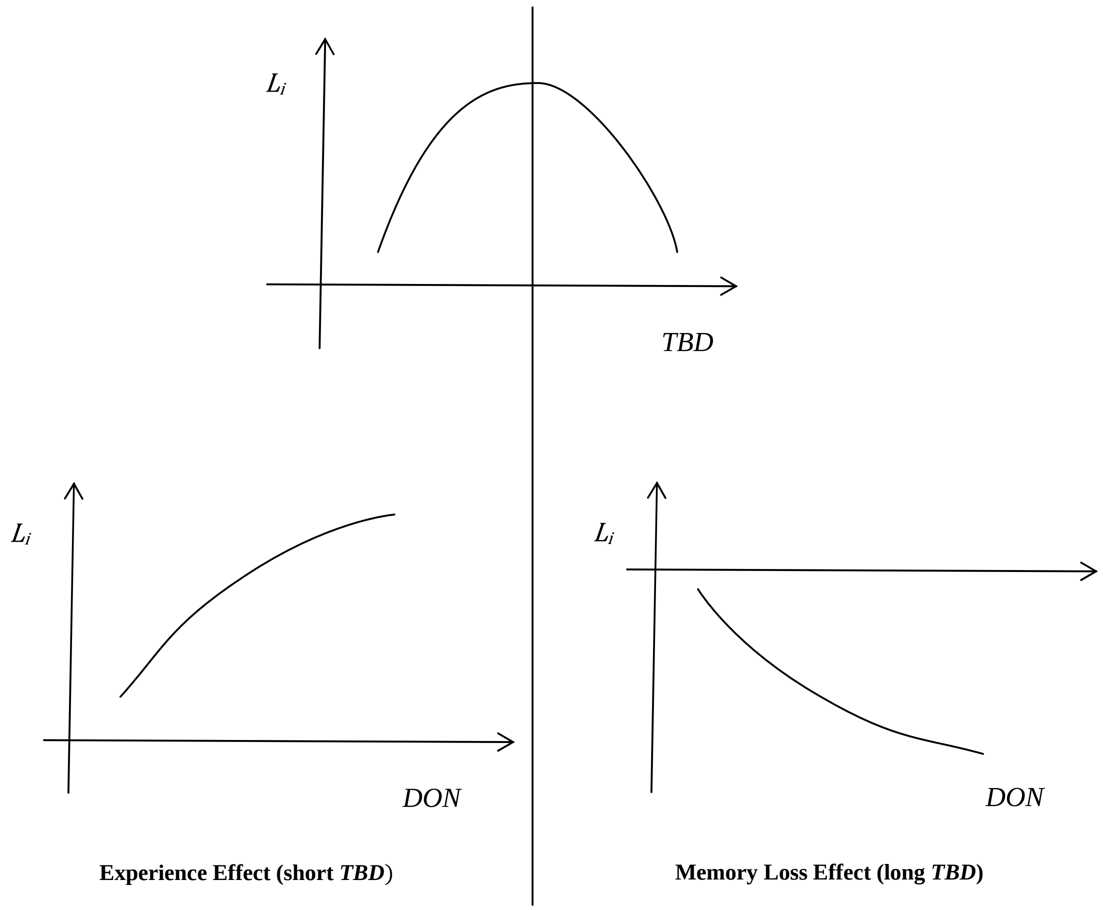
Figure 1: Learning Gains and Integration Costs

Figure 1 depicts our assumptions about total learning gains L_i and total integration costs C_i for a given deal attempt i as a function of the time elapsed since the previous deal (*TBD*) and the number of deal already completed by the firm (*DON*). Assumptions on the signs of second-order derivatives of L_i with respect to *DON* (in Panel A), and C_i with respect to both *TBD* and *DON* (in Panel B) are made only for graphical representation purpose.

Panel A. Learning Gains



Panel B. Integration Costs

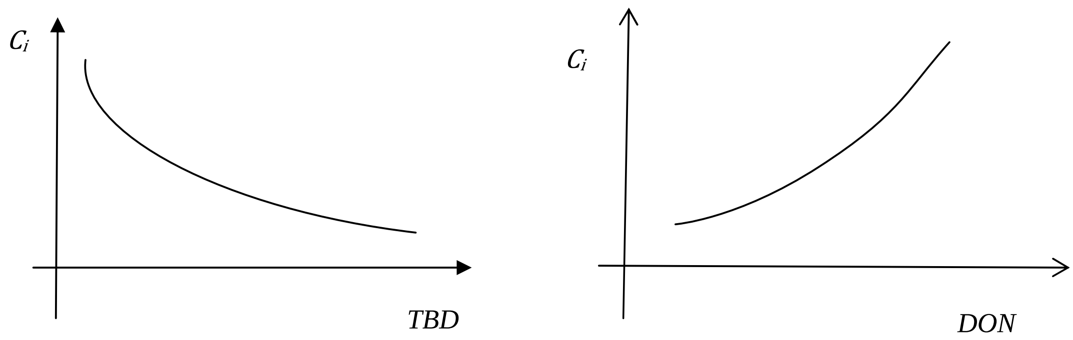


Figure 2: Time Between Deal Computation

Figure 2 provides a graphic depiction of the computation of the time between successive deals as the difference between (a) the current transaction announcement date and the previous transaction completion date (*TBDC*) and (b) announcement dates of successive transactions (*TBDA*).

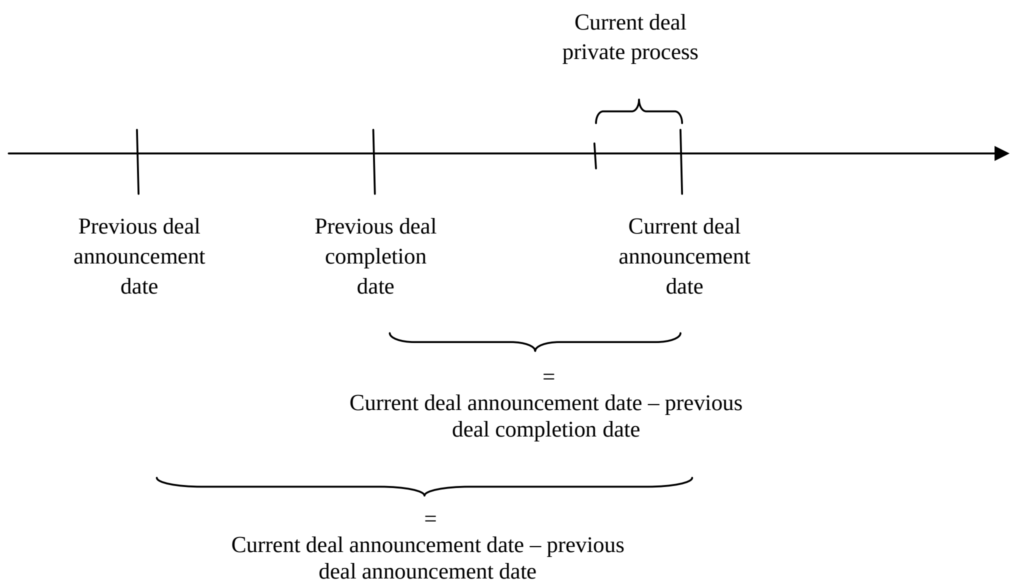
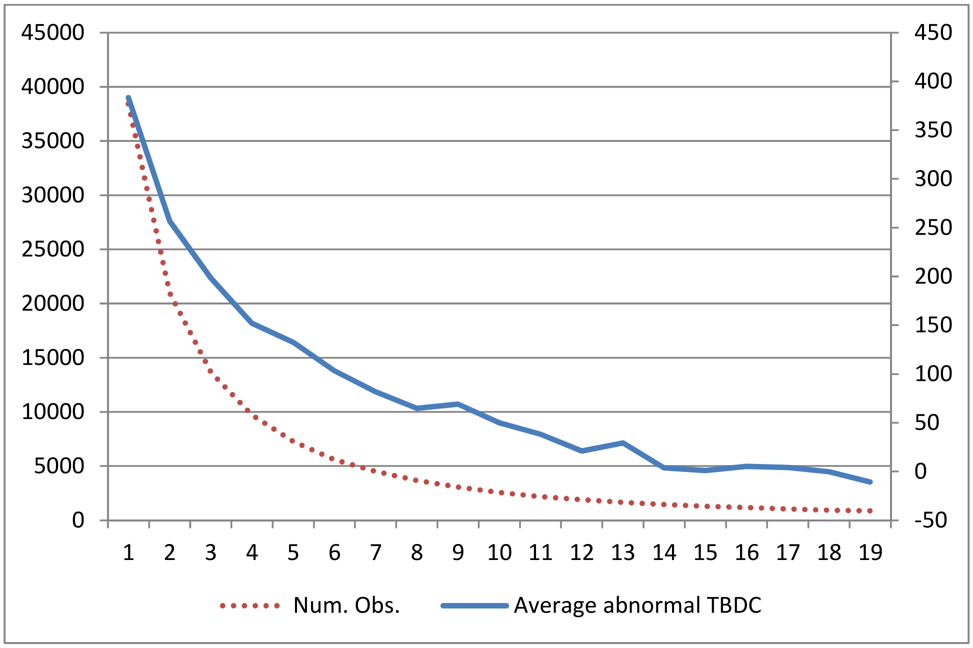


Figure 3: Pooled Ordinary Least Square Estimator versus Fixed-Effect Panel Estimator

Figure 3 displays the distribution of the number of observations (dotted red line) and the average abnormal time between deals (*TBDC*) (plain blue line) as functions of the number of deals already completed by the firm (*DON)* for the pooled OLS estimator (Panel A) and the fixed-effect panel estimator (Panel B). In Panel B, to obtain a graphical representation of the *DON* slope coefficient in a fixed-effect panel context, we use group demeaned data (removing from each abnormal *TBDC* and *DON* the corresponding acquirer average value). In both panels, the horizontal axis is the *DON*, the left vertical axis is the number of observations, and the right vertical axis is the average abnormal *TBDC*.

Panel A. Pooled Ordinary Least Square Estimator



Panel B. Fixed Effect Panel Estimator

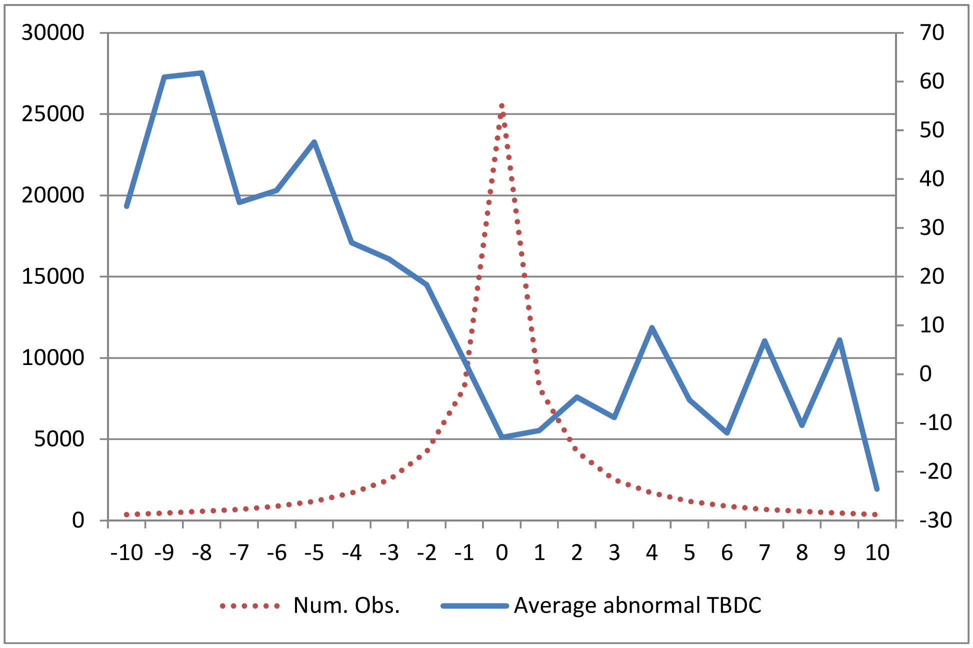


Table I

Acquisition Activity by Year

Table I reports the annual acquisition activity of all acquirers and U.S. acquirers from 1992 to 2009. The sample includes completed transactions denoted by SDC as mergers, acquisitions, acquisitions of majority interest, acquisitions of assets, acquisitions of certain assets, acquisitions of remaining interest, and exchange offers, in which the acquirer owned less than 50% of the target prior to the purchase and then acquired a 50% stake or more. *N* corresponds to the number of acquisitions in each year. The aggregate deal size is the sum of all deal values for a particular year in 2008 constant dollars.

Year	All Acquirers				U.S Acquirers			
	N	Aggregate deal size ($mil)	Average deal size ($mil)	Median deal size ($mil)	*N*	Aggregate deal size ($mil)	Average deal size ($mil)	Median deal size ($mil)
1992	9,691	422,543	70.44	10.00	4,042	197,888	69.97	10.60
1993	9,954	523,011	77.44	10.20	4,675	310,278	92.76	12.40
1994	11,422	656,947	84.13	10.88	5,533	408,685	103.39	13.08
1995	14,287	1,080,137	130.14	12.84	6,538	644,792	157.27	17.60
1996	15,394	1,204,267	130.05	15.00	7,622	710,880	148.78	20.78
1997	18,188	1,770,847	148.38	15.07	8,970	1,086,959	182.25	21.10
1998	20,630	2,765,667	216.15	16.63	10,195	1,741,123	283.96	24.95
1999	21,283	3,597,271	293.16	17.65	8,709	1,634,014	330.73	29.69
2000	22,124	3,336,984	276.49	17.15	8,309	1,652,025	373.14	28.00
2001	17,240	1,609,742	177.07	12.82	5,994	821,470	258.69	22.50
2002	15,406	1,075,634	133.41	12.91	5,633	446,576	152.30	21.70
2003	16,238	1,182,574	141.98	13.74	6,245	617,541	204.56	25.00
2004	18,290	1,663,072	185.92	15.65	7,093	820,407	263.86	32.30
2005	21,199	2,310,680	233.41	19.00	7,863	1,132,984	339.74	34.73
2006	23,174	3,019,205	290.76	21.20	8,494	1,427,557	439.99	41.00
2007	24,922	3,199,357	297.54	20.07	8,510	1,209,494	397.26	39.93
2008	22,392	1,651,928	198.22	14.39	6,973	564,519	267.80	23.90
2009	19,776	1,139,851	165.06	9.68	5,480	605,136	349.56	18.50
Total	321,610	32,209,716			126,878	16,032,329		
Mean	17,867	1,789,429			7,049	890,685		

Table II

Sample Distribution by Deal Order Number

Table II provides the sample distribution by deal order number. For each firm in the sample, we sort acquisitions by announcement date, and we assign a deal order number equal to 1 for the firm's first deal, then increase the deal order number by one unit for each successive transaction. *N* and % denote, respectively, the number of acquisitions and the percentage of the sample for each deal order number. We also report the average and median deal sizes by deal order number (in millions of dollars) and the average and median acquirer size (market value in millions of dollars).

Deal order number	*N*	%	Average deal size	Median deal size	Average acquirer size	Median acquirer size
1	179,057	55.68%	103	12	1,311	162
2	40,012	12.44%	133	14	1,541	204
3	21,402	6.65%	165	17	1,982	285
4	13,752	4.28%	241	21	2,350	370
5	9,706	3.02%	325	24	2,863	465
6	7,237	2.25%	234	28	3,250	570
7	5,564	1.73%	274	30	3,659	664
8	4,428	1.38%	339	34	4,302	768
9	3,617	1.12%	381	33	4,969	892
10	3,002	0.93%	378	35	5,766	987
11	2,505	0.78%	348	45	6,119	1,107
12	2,148	0.67%	496	45	6,669	1,126
13	1,853	0.58%	639	41	7,373	1,265
14	1,600	0.50%	371	43	7,722	1,261
15	1,407	0.44%	547	43	8,099	1,382
16	1,228	0.38%	324	46	8,544	1,432
17	1,088	0.34%	365	52	9,662	1,644
18	979	0.30%	426	52	10,689	1,820
19	881	0.27%	429	63	11,835	1,887
20	803	0.25%	498	75	12,807	2,042
21 and higher	19,341	6.01%	498	32	29,142	3,981
Total	321,610	100.00%				

Table III

Summary Statistics for the Time Between Successive Deals

Here are summary statistics for different definitions of the time between deals (*TBD*) by deal order number. *TBDC* is the difference (in days) between the current deal announcement date and the most recent deal completion date. *TBDA* is the difference (in days) between the announcement dates of two successive transactions. The abnormal *TBDC* is the difference between the *TBDC* and the median *TBDC* in the corresponding industry/year. Panel A reports average *TBDC* by deal order number for ranges of values ([2-5], [6-10], [11-20], [>20]). Panels B and C report the corresponding average *TBDA* and abnormal *TBDC*, respectively. Column 1 contains average values for the sample of all observations; columns 2 and 3 display statistics for *TBDs* below the sample median (short *TBDs*) and above the sample median (long *TBDs*), respectively.

Panel A. *TBDC* (*N* = 129,400)

Deal order number	All	Short *TBD*	Long *TBD*
2-5	577	75	864
6-10	303	70	582
11-20	205	64	484
>20	61	25	413
Average	420	60	782
Median	174	48	493

Panel B. *TBDA* (*N* = 132,277)

Deal order number	All	Short *TBD*	Long *TBD*
2-5	570	94	868
6-10	299	81	560
11-20	202	71	462
>20	60	26	385
Average	418	71	779
Median	171	54	501

Panel C. Abnormal *TBDC* (*N* = 129,400)

Deal order number	All	Short *TBD*	Long *TBD*
2-5	330	– 116	584
6-10	85	– 110	319
11-20	–5	– 113	209
>20	–38	– 57	147
Average	202	– 100	505
Median	0	– 73	252

Table IV

Summary Statistics on Deal Characteristics

Here are summary statistics for the following deal characteristics: whether it is horizontal (in the same four-digit SIC code), whether the target is a private company, whether the target is a U.S. firm, and the deal size in millions of dollars. Panel A includes all observations. Panels B and C report, respectively, for *TBD* below and above the sample median (short and long *TBD*). For dummy variables, the mean indicates the proportion of deals.

Panel A. Total sample

Variable	Number of observations	Mean	Median
Horizontal, dummy	321,610	33%	
Private target, dummy	321,610	54%	
U.S. target, dummy	321,610	38%	
Deal size ($mil)	137,626	196.70	15.00

Panel B. Short *TBD* subsample

Variable	Number of observations	Mean	Median
Horizontal, dummy	69,912	26%	
Private target, dummy	69,912	56%	
U.S. target, dummy	69,912	47%	
Deal size ($mil)	33,341	291.83	20.90

Panel C. Long *TBD* subsample

Variable	Number of observations	Mean	Median
Horizontal, dummy	69,716	31%	
Private target, dummy	69,716	55%	
U.S. target, dummy	69,716	42%	
Deal size ($mil)	34,272	255.64	23.71

Table V

Repetitive Acquirers and Learning: Evidence from the TBD

This table reports the estimated coefficient of the deal order number variable (*DON*) using a fixed-effects panel regression in which the dependent variable is the abnormal time between successive deals (*TBDC*), the number of days between the announcement date of the current deal and the completion date of the previous deal. To compute the abnormal *TBDC*, we remove the median *TBDC* of the industry from the firm's *TBDC*. Three-digit SIC codes define industries. Panel A reports on the main sample. Panel B includes transactions embedded within an acquisitions program. We assume that an acquisitions program starts if the company undertakes a transaction after a 24-month dormant period, but it ends if the company does not undertake another acquisition within 6 months of the announcement of a given transaction. Panel C consists of transactions undertaken outside the finance industry (SIC code 6000–6999) by financial holdings. Column 1 includes results for the entire sample; columns 2 and 3 contain results for subsamples of observations with *TBD* below and above the sample median (short and long *TBD*), respectively.

Panel A. Main sample

Variable	All	Short TBD	Long TBD
DON	–2.08	–1.36	0.90
t-stat	–10.44	–22.93	2.27
p-value	0.00	0.00	0.02
Fisher statistic	109	526	526
Number of observations	129,400	59,527	69,873
Number of unique acquirers	38,887	20,352	31,994

Panel B. Acquisitions programs

Variable	Short TBD
DON	–25.68
t-stat	–22.16
p-value	0.00
Fisher statistic	491
Number of observations	13,010
Number of unique acquirers	1,816

Panel C. Diversifying acquisitions by financial holdings

Variable	All	Short TBD	Long TBD
DON	–27.49	–11.08	17.98
t-stat	–0.98	–1.64	0.27
p-value	0.32	0.00	0.78
Fisher statistic	0.98	2.71	0.07
Number of observations	363	185	178
Number of unique acquirers	192	118	122

Table VI

Repetitive Acquirers and Learning Gains: Robustness Checks

Here are robustness checks with respect to measurement of the dependent variable. The table reports the estimated coefficient of the deal order number variable (*DON*) using a fixed-effect panel regression. The dependent variable changes across columns. The *TBDA* is the number of days between the announcement dates of the current deal and the previous deal. The *TBDC* is the number of days between the announcement date of the current deal and the completion date of the previous deal. "ln" is the logarithm operator. In columns 1 and 2, the abnormal *TBDA* and abnormal *ln(TBDC)* are industry adjusted using the three-digit SIC code industry median *TBDA* and *ln(TBDC)*, respectively. In column 3, the abnormal *TBDC* is computed using the two-digit SIC code industry median *TBDC*. In column 4, the abnormal *TBDC* is computed using the regression-based approach described in Section III.A.

Variable	(1) Abnormal *TBDA*	(2) Abnormal *ln(TBDC)*	(3) Abnormal *TBDC* (two-digit SIC)	(4) Abnormal *TBDC* (regression-based)
DON	–2.00	–0.02	–2.29	–4.56
t-stat	–9.97	–29.40	–11.34	–22.43
p-value	0.00	0.00	0.00	0.00
Fisher statistic	99.52	864.76	128.61	503.42
Number of observations	132,277	129,400	129,400	126,682
Number of unique acquirers	92,284	38,887	38,887	38,176

Table VII

Additional Results

In Panel A, the time between successive deals is regressed on a set of industry- and market-wide determinants. The dependent variable is the *TBDC*, the number of days between the announcement date of the current deal and the completion date of the previous deal. The explanatory variables are as follows: *HHI*, the sales-based industry concentration computed using firm total assets; *Median Firm Size*, the industry median firm size (estimated using the firm market value, obtained from the CRSP database); *Median ROA*, or the industry median return on assets; *Median Growth Rate*, the industry median sales-based growth rate; *Liquidity*, the liquidity index introduced by Schlingemann, Stulz, and Walkling (2002) to capture the intensity of corporate asset transactions within an industry; *Aggregate Market-to-Book*, or the aggregate market-to-book ratio; and *C&I Spread*, the commercial and industrial loan rate spreads used by Harford (2005). Industry variables are computed using the three-digit SIC code. In Panel B, the private process length is the number of days between the initiation of the takeover process and the announcement of the takeover agreement; it is regressed on the deal order number (*DON*). The details of the private takeover process are hand collected from the merger background section of SEC filings (see Aktas, de Bodt, and Roll (2010)).

Panel A. Industry determinants of *TBDC*

Variable	Coefficient	t-Statistic	*p*-Value
Intercept	–314.95	–23.56	*0.00*
HHI	201.75	25.20	*0.00*
Median firm size	0.01	4.26	*0.00*
Median ROA	498.05	19.56	*0.00*
Median growth rate	–19.74	–5.11	*0.00*
Liquidity	0.004	0.13	*0.89*
Aggregate market-to-book	170.58	15.22	*0.00*
C&I spread	241.82	61.11	*0.00*
Fisher statistic	810.65		
R^2	0.04		
Number of observations	136,910		

Panel B. Private process length regression

Variable	Coefficient	t-Statistic	*p*-Value
Intercept	212.81	35.92	0.00
DON	–0.15	–0.43	0.66
Fisher statistic	0.19		
R^2	0.00		
Number of observations	1,573		

Table VIII

Additional Robustness Checks

Table VIII provides additional robustness checks relative to the sampling procedure (Panel A), learning functions (Panel B), and estimation methods (Panel C). In each panel and column, the dependent variable is the industry-adjusted abnormal *TBDC* (see Table V).

Panel A. Alternative samples of transactions

Variable	(1) M&A sample	(2) M&A sample with control variables	(3) Acquirers with at least five deals
DON	–6.63	–17.52	–2.07
t-stat	–4.86	–14.81	–12.24
p-value	0.00	0.00	0.00
Fisher statistic	23.71	50.44	149.95
Number of observations	17,655	12,769	84,637
Number of unique acquires	8,387	6,311	9,494

Panel B. Learning function

Variable	(1) From fifth deal	(2) All sample	(3) All sample
DON	–0.78		
t-stat	–5.16		
p-value	0.00		
Cumulative deal size		–0.002	
t-stat		–5.47	
p-value		0.00	
Lagged deal size			0.002
t-stat			2.20
p-value			0.03
Fisher statistic	26.65	29.98	441.30
Number of observations	57,149	129,400	51,732
Number of unique acquires	8,701	38,887	10,302

Panel C. Estimation methods

Variable	(1) All sample Pooled estimation	(2) All sample Clustered standard errors
DON	–8.92	–8.92
t-stat	–59.84	–2.88
p-value	*0.00*	*0.00*
Fisher statistic	3,581.85	3,581.85
Number of observations	129,400	129,400
Number of unique acquires	38,887	38,887