Solving Serial Acquirer Puzzles

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Abstract

Using a novel typology of serial acquirers, we examine several puzzles documented in prior literature. We show that acquisitions by different types of acquirers are driven by different factors, they acquire different sizes of targets, and subsequent acquisitions by acquirers are predictable ex ante. Controlling for market anticipation, the most frequent serial acquirers do not earn declining returns as they continue acquiring, while less frequent acquirers do. Our methodology enhances our understanding of serial acquisition dynamics, anticipation, and economic value adjustments. The methodology is likely to be relevant to topics related to event anticipation beyond those covered in this study.

Keywords: Mergers; Acquisitions; M&A; Serial acquirers; Anticipation; Return Persistence; Misvaluation

***JEL* Classification:** G14; G34; G35

1. Introduction

Over the past few decades, a large body of literature has examined whether shareholders benefit when their firms make acquisitions. Most of this literature examines acquirer activity using a cross-sectional approach, typically treating each acquisition as an independent observation. However, acquirers are very different in their propensity to acquire. While most acquirers make but one or two acquisitions, a minority of serial acquirers undertake an extremely large number of acquisitions (Fuller, Netter, and Stegemoller, 2002, Netter, Stegemoller, and Wintoki, 2011, or Aktas, de Bodt, and Roll, 2013, among others).

The literature also documents several findings about these acquirers that pose puzzles if serial acquisition dynamics are not adequately considered. First, there are numerous theories behind acquisition motives, with competing theories often finding support in similar samples over the same time period. Are these competing motivations driven by different acquirer types? Second, serial acquirers earn significantly lower excess returns as they continue acquiring more targets.[1] Why do these acquirers continue acquiring when their returns keep declining? If future acquisition activity can be anticipated ex ante, an explanation for the declining returns is that future acquisition market reactions are lower because expectations of future activity have already been incorporated into acquirer market value. However, the explanatory power of these types of anticipation models in prior studies is low.[2] Furthermore, Wang (2018) notes that the samples and empirical designs limit the generalizability of their prediction models. Third, some acquirers do not follow the pattern above and appear to be "extraordinary" (Golubov, Yawson, and Zhang, 2015). They earn persistently high announcement period returns when making acquisitions, both in past and subsequent acquisitions. The puzzle here lies in understanding why these acquirers are different. Why does the market not anticipate the activity of these acquirers?

We address these serial acquirer puzzles, using a large sample of 55,482 acquisitions of U.S. public, private, and subsidiary targets by 8,640 U.S. publicly listed acquirers during 1989-2018. Prior studies typically exclude a majority of M&A deals because of target size filters commonly

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[1] Studies that document declining abnormal returns for the first 10-15 acquisitions of the acquirer include Karolyi, Liao, and Loureiro (2015), Phalippou, Xu, and Zhao (2015), Gorton, Kahl, and Rosen (2009), Ismail (2008), Doukas and Petmezas (2007), Ahern (2010), Schipper and Thompson (1983), Malatesta and Thompson (1985), Loderer and Martin (1990), Bhagat, Dong, Hirshleifer, and Noah (2005), and Fuller, Netter, and Stegemoller (2002) among others.
[2] See, for example, Cai, Song, and Walkling (2011), Cornett, Tanyeri, and Tehranian (2011), Billett and Qian (2008), Anderson, Huang, and Torna (2017), and Fich, Nguyen, and Officer (2018).

used to derive their samples. While such filters ensure that such studies analyze economically significant transactions, it is plausible that some successful serial acquirers start their acquisition series with small targets and transition to larger targets as they learn more about the process. In contrast, acquirers who may start their acquisitions with large targets may end up failing because they lack the necessary experience in post-merger integration. Such nuances are absent from most M&A studies due to sample selection. In contrast, by not including target size filters during sample selection, we are able to analyze a comprehensive universe of acquisition activity. In addition, we can treat how the market reacts to the acquisition of small targets as an empirical question.[3]

In our paper, we introduce a novel typology of serial acquirers and show that acquirers fall into a number of distinct types. These acquirer types can be predicted ex ante. The typology highlights differences behind the factors that drive acquisitions across acquirer types. It allows us to document differences in the types of targets (large or small, publicly listed or private) that are acquired by different acquirer types. It also significantly improves the explanatory power of anticipation models compared to previous studies. After controlling for the market anticipation of future acquisitions, the pattern in declining returns disappears for the most prolific acquirers. The pattern remains for the later large acquisitions by less prolific acquirers, which is possibly one reason they stop acquiring. While previous studies have introduced anticipation adjustments, our classification of serial acquirers allows us to estimate a specification which incorporates time-varying estimates of acquisition intensity instead of simple indicators of prior acquisition activity. We expect that this new typology of acquirer types can also find applications in topics related to acquisition dynamics beyond those covered in this study.

More specifically, prior research typically uses a binary classification scheme (an arbitrarily chosen x number of acquisitions within z number of years) to classify a firm as a serial or non-serial acquirer.[4] Implicit in this definition is the notion that, if they satisfy the necessary threshold, all serial acquirers represent a homogeneous class. In this paper, we impose no *a priori* restrictions on classifying an acquirer as a serial acquirer. Instead, we use cluster analysis of past acquisition activity to let the data decide, which allows us to show that not all serial acquirers follow the same

[3] Rodrigues and Stegemoller (2007) and Netter, Stegemoller, and Wintoki (2011) discuss issues arising from the choice to exclude small targets in acquisition samples.
[4] Examples include Fuller, Netter, and Stegemoller (2002), Klasa and Stegemoller (2007), Golubov, Yawson, and Zhang (2015), Arikan and Stulz (2016), and Karolyi, Liao, and Loureiro (2015).

acquisition patterns. We find that acquirers make two types of acquisitions – acquisitions that cluster in time (conducted as part of a continuous acquisition block) and acquisitions that do not. While 46% of the acquirers in our sample make one or two acquisitions over the entire period (11% of all acquisitions), 17.5% of acquirers make 60% of all acquisitions.

Based on the total number and concentration of acquisitions within acquisition blocks over the previous five years, we show that acquirers can be classified into four distinct types that we denote as loners, occasional acquirers, sprinters, and marathoners. Acquisition dynamics through time are predictably distinct for each of these acquirer types. Loners are non-serial acquirers, making one or two acquisitions over their lives, occasional acquirers make scattered acquisitions, sprinters make relatively short-lived bursts of acquisitions, and marathoners almost never stop acquiring. These classifications are stable over time. In any given year, 71% of loners, 72% of occasional acquirers, 54% of sprinters, and 85% of marathoners (the most stable type) remain in the same classification type as in the prior year.

Acquisition activity by different acquirer types not only differs in its duration but also in its drivers and the types of targets that are being acquired. As we move from loners to marathoners, acquirer size, operating performance, and firm-specific errors increase monotonically, while the ratio of internal R&D to assets shrinks. Marathoners appear to be larger and more efficient firms who perhaps systematically acquire external growth opportunities. They are also less likely to buy publicly listed targets and conduct fewer acquisitions during M&A waves but more during industry deregulation periods. In contrast, sprinters are more likely to belong in overvalued industries and to acquire during merger waves. Overall, these results indicate that different acquirer types seem to face distinct economic tradeoffs and incentives when making acquisition decisions.

When we concentrate on the 4,338 acquisitions of publicly listed targets, which are typically included in samples analyzing the drivers behind M&A in prior studies, we find that there is significant variation over time in the types of acquirers conducting these deals. In the 1990s, most publicly listed targets were acquired by loners or occasional acquirers, in the 2000s, acquirer types were more balanced, and in the 2010s, these deals were increasingly dominated by marathoners (whereas loners had almost disappeared). These findings appear in line with Grullon, Larkin, and Michaely (2019), who show that since the late 1990s, most US industries have experienced an increase in concentration levels. Given that different acquirer types exhibit different characteristics, the generalizability (or not) of the findings in studies that examine the drivers behind acquisitions from different time periods can be evaluated better if we can identify the acquirer types according to our classification.

Interestingly, acquirers that acquire publicly listed targets are also more likely to end their acquisition activity sooner. This suggests that non-listed targets (that are likely smaller), may be significant in allowing acquirers to learn about post-merger integration and become better at it. The significance of small targets in allowing acquirers to learn is important because as we note above, these targets are often eliminated in studies that employ commonly used target size filters in sample selection. While small targets may not be considered "economically significant" individually, they may affect acquisition activity because they allow acquirers to gain experience in post-merger integration and become better in the process. Marathoners, especially, accumulate significantly large dollar gains in the process of acquiring many small targets.

Can acquisition intensity be predicted ex ante? We find that it can. There are significant differences in firm characteristics *at the time of the first acquisition* for each acquirer type. Multivariate and sequential logistic regressions that examine why acquirers go beyond each acquirer type border, using only information available at their first acquisition, suggest that the firm characteristics of acquirer types are predictable ex ante. Therefore, our acquirer classification can be predicted using ex ante information, which does not require the observation of the firm's entire acquisition series.

Moreover, this ex ante serial acquirer classification significantly increases the accuracy of the out-of-sample probability estimate of the firm conducting a future acquisition as well as the level of acquisition intensity. We follow the innovation literature that has studied patents and innovation events accounting for event arrival intensities (Hausman, Hall and Griliches, 1984, Kogan, Papanikolaou, Seru and Stoffman, 2017). We calculate time-varying estimates of acquisition intensity using Chen, Wu, and Yang's (2019) Poisson count distribution model. We predict the acquisition intensity of each type of acquirer by adding the richer ex-ante information incorporated in serial acquirer types (the specific acquisition dynamics based on number and concentration of acquisitions) and in transition probabilities (either transitioning from one acquisition cluster to the next, or from one serial acquirer type to another). The predictive power of the model increases substantially compared to prior studies. Our new typology of serial acquirer types increases the explanatory power of unconditional anticipation models by nearly five times and of conditional models used in previous studies by 50%. Furthermore, we show that the approaches in the previous literature, which treat serial acquirers as a homogeneous class, are less precise. They overstate the likelihood of future acquisitions by less frequent acquirers and understate the likelihood of future acquisitions by the most frequent acquirers. Our serial acquirer classification also has superior predictive power relative to including the determinants used for deriving the classification individually (i.e., the number of deals, the number of acquisition blocks, and the average intensity of deal-making). The four-type classification seems to sharpen the predictive power beyond the individual elements used for deriving the classification.

We then use the firm-specific predicted acquisition intensity to compute anticipation-adjusted factors around an acquisition announcement. The pre-announcement price for an acquirer incorporates an expectation of future acquisitions. The median net present value (NPV) of the 5th acquisition conducted by a marathoner is 102% larger than the observed market reaction. This percentage increases to 620% as marathoners continue acquiring beyond their 16th acquisition. Overall, the anticipation adjustment factors appear to be consistent with how the market is likely to update its expectation of future acquisitions for the different acquirer types. The anticipation adjustment factors that we estimate with our improved anticipation models are much smaller than those implied in previous studies that use alternative methods to address anticipation.

Using this approach, we show that the decline in unadjusted abnormal returns, observed in prior studies, appears to be the result of ignoring market anticipation of future acquisitions. The anticipation-adjusted abnormal returns that we estimate do *not* decline for marathoners, the most prolific acquirers, whether they conduct small or large deals. They also do not decline for other types of acquirers when they conduct small deals. In contrast, loners, occasional acquirers, and sprinters continue to earn declining anticipation-adjusted returns when they acquire large targets, which may be one reason why they eventually stop their acquisition activity.

The impact on the accrued economic value from acquisitions after adjusting for anticipating future acquisitions is significant. For instance, we find that marathoners accrue the largest cumulative dollar gains over time in their acquisition series, due to the sheer volume of transactions that they undertake, despite experiencing the smallest average abnormal returns at the announcement of each of their deals. The results are robust to focusing only on economically large deals.

The final related serial acquirer puzzle that we address is the existence of extraordinary acquirers who earn persistently high unadjusted abnormal returns, as documented by Golubov et al. (2015). If acquisition activity is indeed predictable, why would the market not be able to predict the acquisition activity of these extraordinary acquirers? We show that the persistence in unadjusted abnormal returns appears to be driven by occasional acquirers. The future average unadjusted one-year abnormal return for extraordinary occasional acquirers is 1.12% compared to 0.79% and 0.03% for extraordinary sprinters and marathoners, respectively. More than half of the marathoners are in the middle tercile based on the average prior three-year abnormal returns distribution, not in the top tercile. Therefore, most marathoners are not extraordinary acquirers, as defined by Golubov et al. (2015). The answer to this puzzle is that extraordinary acquirers are extraordinary because the market does not anticipate their acquisition activity.

We contribute to the literature in several ways. First, we show that serial acquirers, who conduct three-quarters of all U.S. acquisitions, follow distinct ex ante predictable patterns in their acquisition series, driven by different ex ante acquirer characteristics and target types that they acquire. Our study is the first to use an ex ante classification of serial acquirers for predictive purposes. Economically speaking, the predictive power of the acquirer type classification is consistent with how different acquirer types seem to have different intrinsic incentives in making acquisition decisions. Our new classification can find applications in topics related to event anticipation beyond those covered in the current study (e.g., related to CEO styles, changes within an industry depending on its serial acquirer composition, changes in innovation on the acquirer and that of its peers). Second, prior studies have had limited success in predicting unconditional acquisition activity. We show that serial acquirer type and transitions between acquisition clusters and acquirer types, have a great deal of predictive power. Third, there is a body of literature arguing that serial acquirers appear to perform uniformly worse as they continue acquiring. We show that after controlling for the predictability of acquisition patterns, the most prolific acquirers do not earn declining returns over time but the less frequent acquirers do so when they acquire large targets. Furthermore, the value accruing to serial acquirers can be significantly large. While sprinters accumulate large dollar gains through concentrated acquisition activity, marathoners accumulate economically large dollar gains through paced and sustained acquisition activity. This result on the cumulative gains from acquisitions of small targets is consistent with Rodrigues and Stegemoller (2007) and Netter, Stegemoller and Wintoki (2011). Overall, by considering different acquirer types, our methodologies enhance our understanding of acquisition dynamics and its properly adjusted economic impact on serial acquirers compared to previous studies.

The remainder of the paper is organized as follows. The next section discusses prior related literature. Section 3 discusses our data and the methodology for classifying acquirers into different types. Section 4 examines our first serial acquirer puzzle about the drivers of acquisition activity across different acquirer types. We next turn to the analysis of the second serial acquirer puzzle by examining whether acquisition activity can be predicted ex ante (Section 5), estimating anticipation adjustment factors for acquisition announcement stock returns (Section 6), and reporting anticipation-adjusted economic returns earned by serial acquirers (Section 7). Section 8 analyzes the third serial acquirer puzzle, namely extraordinary acquirers and the cumulative accrued value from acquisition activity. Section 9 concludes. We report evidence of the impact of small versus large acquisition targets throughout different parts of the analysis.

2. Literature review

Our paper proceeds in five steps. First, we develop a data-driven cluster analysis method to distinguish serial from non-serial acquirers. Second, we develop insights on how different types of acquirers differ in the factors that drive their acquisition activity. Third, we examine if it is possible to predict acquisition activity by these acquirer types and the intensity of this activity *ex ante*. Fourth, we compute the anticipation adjusted gains to acquirers. Finally, we investigate the remaining two serial acquirer puzzles related to acquirer returns. In this section, we document how the prior literature deals with each of these steps.

2.1. Classifying serial acquirers

There is no consistent definition for serial acquirers although they undertake the vast majority of acquisitions. Fuller, Netter, and Stegemoller (2002, pg. 1771) defines acquirers as *frequent* "if they complete bids for five or more targets in any three-year window during the whole sample period [1990-2000]". Karolyi, Liao, and Loureiro (2015, pg. 2) define serial acquirers in a similar fashion. In contrast, Billett and Qian (2008, pg. 1038) define "CEOs as *frequent* acquirers if they acquire at least two public targets within a five-year period". Implicit in these definitions is the notion that, if they satisfy the necessary threshold, all serial acquirers represent a homogeneous class. In addition, these definitions focus on *ex post* information that the market did not have when the serial acquirer began acquiring.

Furthermore, due mainly to data availability or empirical design, most samples in prior studies include only acquisitions with a reported value for the target, which usually implies publicly listed targets. Though most of these cutoffs exist to limit the scope of the analysis to transactions that are economically meaningful on their own, they result in a significant underestimation of the total number of acquisitions (Netter, Stegemoller, and Wintoki, 2011). The announcement of the acquisition itself, regardless of its size, listing status, or economic impact, provides information to the market relevant to anticipating future acquisitions by the same acquirer. Moreover, analyses over rolling windows that employ "five or more" acquisitions of public targets as a cutoff for identifying serial acquirers do not allow the empirical design to capture the cumulative gains of the acquirers that conduct most of the acquisitions (i.e., sprinters and marathoners).

2.2 What drives acquisitions?

Numerous hypotheses have been advanced on the factors that drive acquisition activity. The efficiency hypothesis says that acquirers acquire for strategic reasons (neoclassical efficiency reasons) (Gort, 1969). Industry-wide factors may also create opportunities to increase efficiency (Andrade, Mitchell, and Stafford, 2001). The overvaluation hypothesis posits that serial acquirers acquire to take advantage of their own or industry overvaluation (Shleifer and Vishny, 2003). Finally, acquirers may learn how to make acquisitions and hence increase the speed with which they acquire and the number of targets they acquire over time (Aktas, de Bodt, and Roll, 2013).

2.3 Predicting acquisition activity

Although several papers have examined the determinants of becoming a target, fewer studies have examined the determinants of becoming an acquirer. Moreover, prior research has not examined whether acquisition intensity can be predicted ex ante. Early papers examine announced programs of acquisition activity (Schipper and Thomson, 1983; Malatesta and Thomson, 1985). Mainly using unconditional models, more recent papers examine whether bidders can be predicted. For instance, Cai, Song, and Walkling (2011) document that the probability of an acquisition is associated with prior acquisitions by rival companies in the same industry. Two papers are closer to our analysis. Billett and Qian (2008) document that prior acquisition activity by a CEO is associated with a higher probability of subsequent acquisitions by the same CEO. Cornett, Tanyeri, and Tehranian (2011) jointly examine the likelihood of three alternatives – a firm choosing not to bid, a firm choosing to bid, and a firm becoming a target in a given year.

With the exception of Cornett et al. (2011), who use an average of annual multinomial models, prior analysis focuses on pooled logit models. Few of these papers report model specification and goodness of fit statistics. Among those that do, the predictive models do not seem to have large explanatory power.

2.4 Excess returns earned by the acquirer

The value gains from acquisitions are commonly estimated by measuring the market reaction at the announcement of the acquisition (Andrade, Mitchell, and Stafford, 2001). Many studies document that acquirers appear not to benefit from acquisitions and offer various explanations (see for example, Karolyi, Liao, and Loureiro, 2015, among others).[5] More relevant to our paper, several studies show that serial acquirers, in particular, appear to perform worse as they continue acquiring (Fuller, Netter, and Stegemoller, 2002, Billett and Qian, 2008, Boubakri, Chan, and Kooli, 2012).

The impact of acquisition anticipation on announcement period returns has been examined in prior studies in different ways.[6] The general idea is that prior actions generate anticipation of future acquisition activity, and therefore, part of the impact of this acquisition activity is reflected on the acquirer's market valuation before the actual acquisition announcement. However, as Wang (2018) notes, the samples and empirical designs in these studies limit the generalizability of the results. Cai, Song, and Walkling (2011) show that prior acquisitions by industry rivals create an anticipation effect that reduces the returns when a new acquirer pursues an acquisition. Consequently, bidder returns within the industry decline over time. The anticipation effect for the acquirer is measured based on past acquisition activity by the acquirer's *rivals*. Cornett, Tanyeri, and Tehranian (2011) estimate a "surprise" measure driven by managerial merger motives.

[5] These explanations include hubris and empire building (Roll, 1985, Jensen, 2005), bidder overconfidence from past successful acquisitions (Billett and Qian, 2008), an optimal target size model leading to lower CARs in subsequent acquisitions (Ahern, 2010; Loderer and Martin 1990), time-varying-changes in an acquirer's growth opportunity set (Klasa and Stegemoller, 2007), and time-varying changes in merger synergies (Dessaint, Eckbo, and Golubov, 2021). Not all these explanations seem relevant for serial acquirers.

[6] See, for example Schipper and Thompson (1983), among others. Although not directly adjusting for anticipation effects, other papers have tried to address anticipation concerns (e.g., Boyson, Gantchev and Shivdasani (2017) and Masulis and Simsir (2018)).

However, this measure is used to address self-selection concerns (mainly based on potential value destruction motives), and not to estimate the probability of announcing a bid. Tunyi (2021) uses a linear model based on firm characteristics to predict acquisition likelihood.

3. Classifying serial acquirers

3.1. Data and descriptive statistics

We obtain our sample of acquisitions of U.S. targets (public, private, and subsidiary firms) announced by U.S. public acquirers during 1989-2018 from the Thomson One's Securities Data Company (SDC) database. We require that the bidder seeks to acquire more than 50% ownership of the target, and that the Center for Research in Security Prices (CRSP) and COMPUSTAT provide information for the acquirer. We obtain stock return and accounting data for the universe of U.S. publicly listed firms from CRSP and COMPUSTAT as of the quarter prior to the announcement date. To alleviate truncation concerns at the start and end of our sampling window, and to avoid concerns about the coverage of SDC in the early 1980s (Netter, Stegemoller, and Wintoki, 2011), we require that (i) the acquirer has not conducted any acquisition in the 4 years prior to the start of our sample period (1985-1988); and (ii) that the acquirer conducts its first acquisition at the latest by the year 2016. Our initial sample consists of 55,482 mergers and acquisitions conducted by 8,640 unique acquirers. Our sample increases to 27,813 unique firms (239,120 firm-year observations) when we include firms that do not conduct any acquisitions within our sample period.

3.2. Classifying serial acquirers

We use cluster analysis to classify acquirers into one of four distinct types that we denote as loners, occasional acquirers, sprinters, and marathoners. Our classification is based on three common-sense dimensions.[7] The first dimension is the total number of acquisitions conducted over the entire sample period. 2,417 acquirers (28% of the acquirers in our sample) conduct just one acquisition in our sample. Another 1,405 acquirers conduct a total of two acquisitions each. In contrast, 1,255 acquirers (16% of all acquirers) conduct more than 10 acquisitions each, 72

[7] To economize on space, we do not tabulate the descriptive statistics reported in this section. All acquirer classification data is available on request from the authors.

acquirers conduct more than 50 acquisitions each, and 17 acquirers conduct over 100 acquisitions each.[8]

The next two dimensions encompass the rolling windows definition used by Billett and Qian (2008). For most acquirers, their acquisitions do not always occur evenly over time. We observe relatively short acquisition windows and spikes of acquisition activity within each window. If acquisitions are widely spaced (for example, if an acquirer conducts one acquisition in 1992 and another four in 2010-2013), the sets of acquisitions may not be comparable. Hence, our second dimension is the number of acquisition blocks. We use 407 days (the 75th percentile of days between two consecutive acquisitions by the same acquirer) as our sample-driven cutoff for classifying acquisitions as part of the same block (our results are similar if we use other durations between blocks, such as one year, 18 months, the 90th percentile, or others). Within acquisition blocks, transactions occur over short periods (median of 90 days).[9] The median time between the end of an acquisition block and the start of the next block (if any) is 2.1 years. We classify our sample into a total of 21,089 acquisition blocks.

Finally, the concentration of acquisitions across blocks is also different across acquirers. While 3,936 acquirers (46% of the acquirers) conduct their acquisitions in only one acquisition block, 3,063 acquirers (35% of the acquirers) conduct them in two or three acquisition blocks. The maximum number of blocks for an acquirer is 14. Acquirers who conduct the most acquisitions do not necessarily conduct them in many blocks. For example, the three firms with the highest number of acquisitions (Arthur Gallagher, Brown & Brown Inc, and Cisco Systems Inc.), carried out all their acquisitions in one continuous block. In comparison, 21 out of the 33 serial acquirers with more than 70 acquisitions conducted them in 2 to 7 acquisition blocks. Hence, the third dimension that we examine is the concentration or intensity of transactions within each block. We define acquisition intensity as the maximum number of acquisitions within an acquisition block divided by the duration of the block in days.

[8] The latter list includes Cisco Systems, Blackstone Group LP, US Bancorp, BB&T Corp., Oracle Corp., Goldman Sachs, Omnicare Inc., JP Morgan Chase & Co., Arthur J. Gallagher, and Brown & Brown Inc, among others.

[9] The average time between acquisitions within a window (127 days) is close to the average time between the announcement of an acquisition and its completion (134 days) as reported in Denis and Macias (2013). A plausible explanation is that a serial acquirer announces the next acquisition when the acquisition team is about to pass the baton to the post-merger integration team.

Based on these three dimensions (total number of acquisitions, number of acquisition blocks and average intensity), we conduct a *k*-median cluster analysis to classify acquirers into different categories, within 5-year rolling windows (starting with 1989-1993 and ending with 2014-2018) as depicted in Figure 1. Our classifications use ex ante information, so we use only acquisition activity from years *t*-6 (or later, if the firm is newly listed) to year *t*-1 to classify acquirer types in year *t*. Cluster analysis groups a set of acquirers in such a way that acquirers in the same cluster are more similar to each other than to those in other clusters (Jain and Dubes, 1988). The *k*-median cluster algorithm identifies *k* centers such that the clusters formed by them are the most compact (Krause, 1986). The median for each attribute is computed in each single dimension in the rectilinear-distance formulation of the *k*-medians problem, so the individual attributes are determined from the dataset. Computing medians makes the algorithm more reliable for discrete or binary data sets, particularly when the distributions have large skewness. The *k*-median cluster analysis, based on the largest value of the Calinski–Harabasz (1974) pseudo-F index, indicates that the most distinct clustering occurs with 4 clusters. The average Calinski–Harabasz pseudo-F index for 4 clusters is 4,941, while the values for the "<4" and ">4" clusters are 2,498 and 3,703 respectively. We allow the classification to be updated with each new 5-year rolling window. In effect, we allow acquirers to transition both to a "higher" type in subsequent rolling windows (for example, from sprinter to marathoner) or to regress to a "lower" type (for example, from sprinter to occasional).

We classify these four distinct types of acquirers as loners, occasional acquirers, sprinters, and marathoners. Loners, who are non-serial acquirers, make one or two acquisitions over their lives, occasional acquirers make scattered acquisitions, sprinters make relatively short-lived bursts of acquisitions, and marathoners almost never stop acquiring. Descriptive statistics are reported in Table 1. A large majority of firms (19,173 unique firms, making up 69% of the firms in our sample or 77% of firm-years) do not conduct any acquisitions. Serial acquirers show marked heterogeneity in acquisitiveness within the four acquirer types. For instance, the 4,409 loners (46.4% of all acquirers) conduct only 10.8% of the acquisitions in the sample (5,993 acquisitions). The 2,493 occasional acquirers (26.2% of all acquirers) conduct 17.5% (9,701) of the acquisitions. The 933 sprinters (9.8% of all acquirers) conduct 11.9% (6,609) of the acquisitions. In contrast, the 1,665 marathoners, while comprising only 17.5% of the acquirer sample, conduct an astonishing 59.8%

(33,179) of all acquisitions. Overall, most firms show limited acquisition activity, and a small proportion of firms conduct most of the acquisitions. [10]

There are significant differences in the characteristics of the targets being acquired, especially for marathoners. While all acquirer types acquire more small targets and more targets that are not publicly listed (private or subsidiary targets), the proportion of non-listed targets increases as we move to higher acquirer types (for example, loners acquire almost 9 times as many private or subsidiary targets than public targets, occasional acquirers acquire 10 times as many, sprinters 11 times, and marathoners 14 times as many). Marathoners, specifically, are much more likely to acquire small and non-publicly listed targets. We follow the literature to classify a deal as small if the target's relative size is less than 1% of the size of the acquirer, and the transaction value is less than $1 million (36% of the deals in our sample). These targets are usually excluded from the samples of prior studies that apply commonly used target size filters to the data.

Table 1 Panel B reports summary statistics at the firm-year observation level. On a firm-year basis, 72% of the sprinters and 82% of the marathoners have conducted at least one acquisition in the prior year; and 54% of the sprinters (69% of the marathoners) conduct one acquisition in the current year. As we move from loners to marathoners, the acquisition intensity increases, the time between acquisitions shrinks, and the number of acquisition blocks increases. Overall, the results from Table 1 suggest that the firm's ex ante acquisitiveness can be informative for subsequent acquisition activity.

Our acquirer classification and the remaining results in the paper are robust to using 7-, 9- and 13-year rolling windows for classifying acquirer types (not reported for brevity). We also examine

[10] We note that the sum of loner, occasional, sprinter, and marathoner acquirers exceeds the number of unique acquirers in the sample (8,640) since our classification allows each acquirer to be classified into more than one type during the sample period. Could a simpler classification based on the number of deals, the time between deals, and acquisition intensity replace the acquirer classification that we use? Prior literature suggests the answer is no. For example, Tunyi (2021) uses a linear model based on firm characteristics to predict acquisition likelihood. The analysis does not report goodness of fit statistics and reports acquisition prediction accuracy at the quintile-level, not the firm-level. However, the extreme skewness of acquisition activity that we observe rules out the use of this type of simple linear model to predict acquisition activity. Most of the loners typically make only one acquisition throughout our sample period. In contrast, half of the occasional acquirers make at least 4 acquisitions, sprinters at least 7, and marathoners at least 14 acquisitions. Moreover, to estimate the adjusted abnormal returns for each acquisition, our classification allows us to estimate a vastly improved Poisson specification which incorporates time-varying estimates of acquisition intensity instead of simple indicators of prior acquisition activity or ad-hoc non-linear models.

1- and 3-year rolling windows, which unfortunately prove too short for any meaningful classification, mostly because there is not enough time for marathoners to reveal their type.

4. Serial Acquirer Puzzle 1: What drives M&A?

Different studies have found support for numerous factors that drive acquisitions. In this section, we examine acquirer characteristics at the time these acquirers conduct their *first* acquisition, before their type is revealed to the market. Subsequently, we conduct hazard analysis in order to predict how acquirer characteristics affect the time to the next acquisition and what drives the end of acquisition activity. This analysis documents that the acquisitions by different acquirer types are driven by distinct factors. Consequently, different samples can produce different results on the factors that drive acquisitions, based on which acquirer types dominate the sample. Furthermore, our analysis in this section suggests that since the acquisitions by different acquirer types are driven by different factors, their acquisition activity (and future stock returns) can be anticipated, which is the second serial acquirer puzzle that we examine later in the paper.

4.1 Acquirer characteristics at the time of the first acquisition

Table 2 reports acquirer characteristics at the time of the *first* acquisition by each acquirer in the sample, that is, at a time that their "type" has not been revealed by observing their acquisition activity. Our aim is to examine whether the market can predict acquirer types before it can observe their acquisition series. If acquirer types are predictable ex ante, then it is plausible that their acquisition activity can be anticipated. Furthermore, the acquisition activity of different acquirer types may be driven by different factors.

Table 2 reports several firm-specific characteristics that might affect the probability of an acquisition as suggested by prior research (e.g. Bena and Li, 2014; Cai, Song, and Walkling, 2011; Warusawitharana, 2008). We include the market-to-book ratio decomposition proposed by Rhodes-Kropf, Robinson, and Viswanathan (2005) to proxy for overvaluation, and indicators for the dot-com bubble for the 1997-2001 calendar years, and industry-deregulation years (following Ovtchinnikov, 2010, and Harford, 2005) to proxy for industry effects. All continuous variables are winsorized at the 1 and 99 percent levels, and are industry-adjusted where appropriate (based on the 48 Fama-French industry classification). Variable definitions are reported in the Appendix.

As we move from loners to marathoners in columns 2-5, acquirer size, operating performance, and firm-specific errors increase monotonically, while the ratio of internal R&D to assets shrinks. Marathoners appear to be larger and more efficient firms who perhaps systematically acquire external growth opportunities. They are also less likely to buy publicly listed targets and conduct fewer acquisitions during M&A waves but more during industry deregulation periods. In contrast, sprinters are more likely to belong in overvalued industries and to acquire during merger waves.

Overall, it appears that acquirer types are recognizable *ex ante* at the time of their *first* acquisition, even *before* observing their acquisition sequences. They also differ significantly in their efficiency and misvaluation characteristics, suggesting that the acquisition activity of different acquirer types is more likely to be driven by one or the other. Furthermore, marathoners are less likely to acquire public targets, which suggests that they are more likely to acquire *smaller* targets. It is the loners who are more likely to acquire public targets. As we will show later, this may indicate that the most successful acquirers (those that conduct the larger number of deals) may be the ones who learn about target integration by acquiring smaller targets, before embarking on larger acquisitions.

4.2 Hazard analysis on the time between subsequent acquisitions

In this section, we use survival regressions to model the time to the next acquisition.[11] To model the effect of each variable on the acquisition dynamics in event time, we use a semi-parametric Cox model based on a Proportional Hazard (PH) framework (see Wooldridge, 2010, and Cleves, Gould, and Gutierrez, 2004). We define "failure" (the occurrence of the examined hazard) as one at the point the acquirer ends its acquisition activity in our sample period, and zero otherwise. Specifically, we try to determine whether the explanatory variables increase or reduce

[11] We perform survival regressions instead of logit regressions because, although a logit analysis examines acquirer characteristics based on the conditional mean of the probability to stop acquiring at a given point in time (i.e. the absolute risk of not continuing to acquire), it does not consider the length of time to conduct a subsequent acquisition, which is an important driver of our acquirer classification. Moreover, a logit analysis cannot incorporate the notion that the acquirer must survive until reaching the specific time *t* of the analysis for each observation. In untabulated results, we obtain qualitatively similar results when we estimate a parametric log-logistic model based on an Accelerated Failure Time (AFT).

the risk (i.e., the hazard rate) of stopping the acquisition activity. A positive coefficient (larger hazard rate) implies that the risk of stopping the acquisition activity is larger (that is, the firm will likely stop acquiring), while a negative coefficient implies that the risk of stopping the acquisition activity is smaller (the firm will likely continue acquiring). The hazard rate measures the cumulative rate at which a company will stop its acquisitions, conditional on having survived until the current acquisition.[12]

In Table 3, Model 1 reports coefficients for the complete sample, and Models 2-4 use only the subsamples of occasional acquirers, sprinters, and marathoners respectively. The basis for the survival analysis is the sample of 30,564 acquisitions by U.S. publicly listed acquirers that have conducted at least 2 acquisitions during 1989-2018 (a condition required by the duration analysis setting). Across all acquirer types, smaller firms, firms that conduct more internal R&D (or have fewer long-run growth opportunities), firms that are less profitable but have higher sales growth and hold more cash, and those that have made their previous acquisition more recently (or have made their acquisitions in fewer acquisition blocks) are more likely to stop their acquisition activity.[13]

Interestingly, acquirers that acquire publicly listed targets are also more likely to end their acquisition activity sooner. This suggests that non-listed targets (that are likely smaller), may be significant in allowing acquirers to learn about post-merger integration and become better at it. In contrast, when firms acquire publicly listed targets, this is likely the end of their acquisition activity. The significance of small targets in allowing acquirers to learn is important because these targets are often eliminated in studies that employ commonly used target size filters in sample selection. While small targets may not be considered economically significant, they may allow acquirers to gain experience in post-merger integration and become better at acquiring. We note

[12] The hazard function approximates the probability that the failure event occurs in a given interval, divided by the width of the interval. The hazard function describes the instantaneous *rate* of failure and it can increase, decrease, or remain constant.

[13] Our results are robust to deleting acquirers with concurrent transactions announced on the same date. Untabulated analyses indicate that marathoners conduct the vast majority of concurrent transactions, but these concurrent acquisitions do not take place at the end of their acquisition activity. In contrast, most of the concurrent transactions that loners conduct take place at the last M&A transaction date (i.e., loners can acquire two targets on the same date and then end their acquisition activity). This result confirms the accuracy of the cluster analysis procedure in classifying an acquirer who conducts more than one acquisition as a loner when these multiple acquisitions take place on the same date.

that marathoners (the most successful acquirers in terms of number of acquisitions and duration of their acquisition activity) acquire proportionally fewer publicly listed targets, whereas occasional acquirers (who make only a handful of acquisitions in their entire lifetime) acquire proportionally more publicly listed targets (in Table 2, 9.5% of the targets acquired by occasional acquirers are publicly listed – and the fraction of public targets is even larger for loners at 10.6% – whereas only 6.4% of the targets acquired by marathoners are publicly listed).

Despite the similarities, there are also notable differences in the factors that drive acquisition activity between sprinters and marathoners, which suggest that acquisitions by these two types may be driven by different factors. For example, the continuation of acquisition activity by sprinters is less sensitive to R&D, cash holdings, or the type of targets being acquired (public or private) but more sensitive to operating performance. Sprinters are more likely to continue acquiring when their operating performance is good or improving.

Overall, the analysis in this section suggests that though some factors driving acquisitions are common for all acquirers, there are certainly factors that affect acquirers differently, especially when comparing sprinters and marathoners, who together conduct more than 70% of the acquisitions in the sample.

4.3 Representation of acquirer types in M&A samples over time

After documenting differences in acquirer characteristics between different acquirer types, in this section we examine how different acquirer types are represented in M&A samples over time. We focus on the 4,338 acquisitions of publicly listed targets in our sample, since acquisitions of public targets are included in typical samples that examine the drivers behind M&A in prior studies. Every year, we calculate the percentage of all acquisitions of publicly listed targets that are conducted by each of our four acquirer types.

The results are reported in Figure 2. What is striking is that M&A samples from different decades are dominated by different acquirer types. In the 1990s, the vast majority of acquirers of publicly listed targets were loners and occasional acquirers, who conducted 60-100% of these acquisitions every year. In the 2000s, the sample became more balanced. Loners/occasional acquirers and sprinters/marathoners each conducted roughly 50% of the acquisitions of publicly listed targets. In the 2010s, however, the sample is increasingly dominated by marathoners, who conduct most of these deals, up to 60% of the deals in 2011, 2017, and 2018. In contrast, loners, who conducted most of the deals in the 1990s had almost disappeared from the sample by the end of our sample period. We note that we use only 5 years (or less, if the company is newly listed) of past acquisition activity to classify acquirers annually, so the prevalence of marathoners in the later part of our sample is *not* driven by them having accumulated a longer acquisition series over time.

Our findings on the increased representation of marathoner acquirers over time are in line with Grullon, Larkin, and Michaely (2019), who show that since the late 1990s, most US industries have experienced an increase in concentration levels. Their finding that concentration increased more in the most profitable industries is also in line with our evidence that marathoners show better operating performance compared to other acquirer types (see Table 2 above).

What is more significant for our purposes is that, as shown previously, different acquirer types also exhibit differences in firm characteristics and performance. The fact that M&A acquirer samples are dominated by different types of acquirers over different time periods suggests that the studies analyzing these samples may also identify different drivers behind acquisitions over time. Being able to recognize the different acquirer types allows us to evaluate the generalizability of the findings in M&A studies.

5. Serial Acquirer Puzzle 2: Predictability of acquisition activity and declining returns to acquirers

In order to address our second puzzle, the declining returns to acquisitions over time, we first ask the question of whether acquisition activity can be predicted ex ante. If acquisition activity is predictable, then stock returns for future acquisitions may have been anticipated during earlier acquisitions, thus leading to a pattern of declining returns over time. Our analysis so far shows that the four acquirer types have different propensities to acquire and are driven by different factors. Consequently, the market's anticipation of future acquisitions may depend critically on the type of the acquirer. Table 2 in Section 4.1 showed that acquirer types differ in their characteristics at the time they conduct their first acquisition.

In this section, we first show that our acquirer classification is stable over time. A stable classification makes it more likely that acquirer types can be predicted ex ante, and therefore, their acquisition activity can be anticipated. Subsequently, we examine whether the market can predict the probability of conducting one acquisition based on ex ante information. Our results show that our classification of serial acquirers helps predict future acquisition activity better than the approaches in the prior literature. Finally, we present robustness tests for omitted variables.

In subsequent sections, we estimate acquisition anticipation factors, which take into consideration this serial acquirer classification (Section 6). Finally, using these tools, we analyze how anticipation impacts acquisition announcement stock returns and the presence of "extraordinary" acquirers (Sections 7-8).

5.1 Annual transition matrices among the serial acquirer types

Table 4 reports annual transition matrices (Markov chains) from one year to the next which compare the observed serial acquirer type as of the prior year with the eventual acquirer type in the current year. There are two main observations. First, the classification is stable over time. The Markov chain dynamics show that firms tend to stay in the same category as their classification in the prior year: 71% of loners, 72% of occasional acquirers, 54% of sprinters, and 85% of marathoners (the most stable type) remain in the same type as in the prior year. Second, acquirers are slightly more likely to transition to a lower type than to a higher type, although the differences are not large. This analysis suggests that serial acquirers can be classified reliably using a relatively stable classification. A stable classification makes it more likely that acquirer types can be predicted ex ante. To alleviate concerns that the stability of the classification can be mechanically explained by the rolling-windows methodology, untabulated results indicate that the serial acquirer type seems stable even after skipping 4 years for estimating the transition matrices.

5.2 Probability of conducting an acquisition using ex ante information

In Table 5, we estimate various logit model specifications on the probability of conducting at least one acquisition over the year after controlling for acquirer characteristics, which include year and industry fixed effects. The key variables of interest are an indicator as to whether the firm conducted at least one acquisition in the prior year and the serial acquirer type as of the end of the prior year using the closest 5-year rolling window classification process.

In Panel A, models 1 and 2 estimate baseline unconditional specifications, within the universe of all 239,120 U.S. public firm-year observations reported in COMPUSTAT during 1989-2018, without controlling for past acquisition activity or acquirer type. The pseudo-R^2 of the models are

0.040 and 0.043. These values are in line with similar estimates in previous studies (Routledge, Sacchetto and Smith, 2013; Cornett, Tanyen, and Tehranian, 2011; Anderson, Huang and Torna, 2017). Conditional on acquisition activity in the prior year, the pseudo-R^2 in model 3 increases to 0.140, which is again in line with previous such models in the literature (Billett and Qian, 2008). In untabulated analysis, we also replicate the analysis in Golubov, Yawson and Zhang (2015), who classify acquirers into frequent and occasional types (this analysis is conducted on deals with values larger than $1 million, in line with their sample selection criteria). The best predictive model based on their criteria has a pseudo-R^2 of 0.156, which is in line with model 3 above.

However, when we add our acquirer classification in model 4, indicator variables for all the serial acquirer types exhibit significantly positive coefficients, and the pseudo-R^2 increases to 0.20. Adding the interaction indicators for prior acquisitions and the serial acquirer classification marginally improves the pseudo-R^2 to 0.205 in model 5. The control variables have the expected signs (e.g., larger firms, firms with better operating performance, smaller R&D expenses, or larger sales growth, have larger propensities to acquire). The results are similar if we use a panel data specification (model 6). Our results are also similar if we use the actual number of deals in the prior year (instead of a binary indicator) or if we use the square of the number of deals (to capture potential non-linear effects).

Overall, the analysis shows that knowing the acquirer type improves the predictive power of anticipation models. The explanatory power of our models increases by almost five times (compared to the unconditional model) when we control for prior acquisition activity and acquirer type, and increases by 50% compared to conditional models that include only prior acquisition activity or compared to the classification of Golubov, Yawson, and Zhang (2015). This suggests that our serial acquirer classification significantly enhances our understanding of acquirer dynamics. Our specifications improve significantly on results in previous studies.

Table 5 Panel B reports the predicted probability of conducting an acquisition during the year based on the interaction terms of logit model 5 of Panel A (using Stata's *margins* routine). Knowing that the firm conducted an acquisition in the prior year significantly increases the predicted probability of conducting an acquisition over the subsequent year from 10.5% to 43.5%. The increase is economically significant in comparison to the observed proportion of firm-year observations with at least one acquisition (11.5%). However, the acquirer classification as at the end of the prior year is also a significant indicator of whether the firm will conduct an acquisition. The increases in probability are not the same for each acquirer type. For loners, the probability increases by around 6 percentage points (from 25.1% to 31.7%), for occasional acquirers by 12 percentage points (from 32.6% to 45.0%), for sprinters by 15 percentage points (from 42.7% to 57.7%), and for marathoners by more than 23 percentage points (from 49.6% to 73.1%). For example, if a marathoner (loner) conducts an acquisition in a particular year, then there is a 73% (32%) probability that it will announce another acquisition in the subsequent year.

These results suggest that it is plausible that the market can predict very precisely if the firm will announce an acquisition based on only two factors – its serial acquirer type and whether it has announced an acquisition in the prior year. It is noteworthy that if we only use the prior deal indicator without also considering the serial acquirer type, as previous studies commonly do, the logit model over-estimates the predicted probabilities of subsequent acquisitions for loners, and underestimates those for sprinters and marathoners. This is not surprising since the approaches in the previous literature treat all serial acquirers as a homogeneous class, and therefore effectively estimate an *average* predicted probability of future acquisition activity. Our results strongly support the hypothesis that acquisitions are predictable ex ante conditional on knowing the serial acquirer type. They also suggest that this predictability differs by acquirer type.[14]

5.3 Robustness tests on the predictability power of the serial acquirer type classification vs its determinants

In untabulated analysis, we find that our serial acquirer classification has superior predictive power relative to the determinants used for deriving the classification. We replicate the specifications in Table 5 by including the information used to derive the serial acquirer classification (i.e., the number of deals, the number of acquisition blocks, and the average intensity of deal-making) all at the same time, individually, or with interactions with the indicator of a deal

[14] Our results are similar if we use a binary prediction (0=No, 1=Yes) with 0.3 as the cutoff threshold for predicting an acquisition over a year equal to one. This cutoff is derived from the intersection of the two statistical measures of the performance of a binary classification test, namely, sensitivity and specificity. Sensitivity measures the proportion of actual positives that are correctly identified as such (i.e., the percentage of firms that end up conducting an acquisition that are correctly predicted to be acquirers in the current year). Specificity measures the proportion of actual negatives that are correctly identified as such (i.e., the percentage of firms that end up not conducting an acquisition that are correctly predicted to be non-acquirers in the current year). Our results are similar if we use other cutoffs close to this intersection (i.e., 0.25 and 0.35). The 0.30 value represents a conservative threshold. The predictive accuracy for marathoners and sprinters improves if we prioritize sensitivity over specificity.

in the prior year. We find that model 5, as reported in Table 5, has the highest pseudo-R^2 compared to all these additional models. The four-type classification seems to sharpen the predictive power beyond the individual elements used for deriving the classification.

5.4 Robustness tests for omitted variables

To alleviate concerns related to omitted variables in our specifications of Table 5, we conduct two sets of confounding analyses (not reported in tables).[15] First, we assess how strong the correlation of the omitted variable with both the outcome and the predictor of interest must be to invalidate our inferences. We find that it would be necessary to replace 92.83% of the observations in Table 5 Panel A with cases for which there is a zero effect of *prior year serial acquirer type* on the probability of conducting an acquisition in order to invalidate the logit estimates. Second, we calculate the impact of an omitted confounding variable necessary to invalidate the inference for the regression coefficient of our main variables of interest. The impact threshold for a confounding variable quantifies the sensitivity of the results to a potentially confounding correlated omitted variable. We find that the interaction of *Prior year serial acquirer type* and *Deal in prior year indicator* greatly increases the predictive power of conducting an acquisition and is robust to omitted variables concerns. None of the other regressors provide evidence that a confounding variable would render the *Prior year serial acquirer type* coefficient statistically insignificant.

We conclude that acquisition activity can be anticipated by the market based on ex ante information. More importantly, the informativeness from the ex ante serial acquirer type is superior to the simpler information of whether the firm conducted an acquisition in the prior year used in previous studies. The results of the confounding analysis alleviate concerns that unobserved heterogeneity from correlated omitted variables drives our inferences.

6. Acquisition dynamics and anticipation adjustment for stock returns

In order to estimate the true economic value (NPV) of acquisitions to the acquirer we need to adjust stock price reactions for the surprise and anticipation elements of the acquisition. Using a more accurate predictive analysis of acquisition dynamics, which is based on the predictability of our acquirer type classification, we first estimate the time-varying acquisition intensity for

[15] See Frank (2000). Recent papers that apply confounding analysis to support inferences from multivariate analysis include Larcker and Rusticus (2010), Call, Martin, Sharp, and Wilde (2018), and Fich, Liu, and Officer (2020).

different types of acquirers. Subsequently, using these estimated acquisition intensities, we estimate anticipation adjustment factors, which proxy for the anticipation component in acquisition announcement stock returns.

6.1. Estimating acquisition values with stock market reactions

We estimate the private value of an acquisition to an acquirer after incorporating the expectation of future acquisitions into the market value of the firm. The intuition is straightforward. The pre-announcement value of a serial acquirer already incorporates an expectation of future acquisitions (Wang, 2018).[16] Therefore, the market reaction at the announcement of a new acquisition will understate the true NPV of this particular acquisition. Each new announcement leads the market to update the probability of more acquisitions in the future, especially as the acquirer type is revealed. Since this probability will never equal exactly one, the observed market reaction will always understate the NPV of future acquisitions.

The literature on innovation has implemented empirical valuation methods that adjust the announcement returns based on a rational anticipation of multiple subsequent events (e.g., Hausman, Hall and Griliches, 1984; Kogan, Papanikolaou, Seru and Stoffman, 2017; Chen, Wu, and Yang, 2019). Our goal is to estimate a similar anticipation-adjusted value for each acquisition. We do so by constructing time-varying estimates of the acquisition intensity for each firm through time (similar to the process by which firms file for multiple patents through time).

Specifically, to estimate the incremental value of an acquisition to an acquirer from observational data of abnormal stock returns, we start by applying the Poisson count distribution model proposed by Chen et. al. (2019), to model the number of acquisitions, *m*, that will occur during a time interval (*t, t+T*) as:

$$\Pr(N = m|I_t) = \frac{\lambda^m e^{-\lambda}}{m!}, m = 0,1, \dots \qquad (1)$$

where I_t is the information set of the investors at time *t* and λ is the acquisition intensity parameter. Let V_0 be the intrinsic value of a firm without an acquisition, V^* the incremental value of one

[16] Wang (2018, pg. 337) posits that "part of the merger market's value is capitalized in firms' pre-merger market values due to the anticipation effect, and this anticipated component of merger gain is not captured by announcement returns." Other approaches that have been used to potentially account for anticipation include Cai, Song, and Walkling (2011), based on bidding activity in the industry, Song and Walkling (2000), based on prior acquisitions of rival companies, and Bhagat, Dong, Hirshleifer and Noah (2005), who, using counterfactuals, employ a probability scaling adjustment method to adjust for the probability of deal failure and potential competing bids in tender offers.

acquisition event to the firm, and mV^* be the incremental time t+T value to the firm if the firm conducts m acquisition events within the time interval T. Then $\bar{V}_0$ is the ex-ante market value of the firm at time 0:

$$\bar{V}_0 = V_0 + \sum_{m=1}^{\infty} \frac{\lambda^m e^{-\lambda}}{m!}(mV^*) = V_0 + \lambda V^* \tag{2}$$

The occurrence of an acquisition event produces a conditional distribution over total end-of-period acquisitions that follows a zero-truncated Poisson distribution:

$$\Pr(N = m | N \geq 1,\ I_t) = \frac{\lambda^m e^{-\lambda}}{(1-e^{-\lambda})m!}, m = 1,2, \ldots \tag{3}$$

Then, the ex-post market value of the firm after an acquisition occurs is

$$\begin{aligned} \bar{V}_1 &= V_0 + \sum_{m=1}^{\infty} \Pr(N = m | N \geq 1,\ I_t)\, mV^* \\ &= V_0 + \sum_{m=1}^{\infty} \frac{\lambda^m e^{-\lambda}}{(1-e^{-\lambda})m!} mV^* \\ &= V_0 + \frac{\lambda}{1-e^{-\lambda}} V^* \end{aligned} \tag{4}$$

Using equations (2) and (4) we estimate the incremental value of an acquisition as

$$V^* = \frac{\Delta\bar{V}}{\frac{\lambda}{1-e^{-\lambda}} - \lambda} = \frac{e^{\lambda}-1}{\lambda}\Delta\bar{V} \tag{5}$$

where $\Delta\bar{V} \equiv \bar{V}_1 - \bar{V}_0$ is the observed change to the market value of the firm when an acquisition occurs.

To estimate the returns and the dollar gains of an acquisition free of anticipation bias, we compute anticipation-adjusted returns as a function of the predicted firm-level acquisition intensity $\bar{\lambda}_{i,t}$, and the number of concurrent acquisitions announced on the same day $n_{i,t}$, derived from the first element in equation (5):

$$Anticipation\ adjustment_{i,t} = \frac{e^{\bar{\lambda}_{i,t}}-1}{\bar{\lambda}_{i,t} \times n_{i,t}} \tag{6}$$

Consequently, the anticipation-adjusted abnormal returns from acquisitions can be estimated as:

$$Anticipation\ adjusted\ abnormal\ return^*_{i,t} = \frac{e^{\lambda_{i,t}}-1}{\lambda_{i,t} * n_{i,t}} CAR_{i,t} \tag{7}$$

The dollar gains for each acquisition can be estimated using equation (7) and the acquirer's market capitalization:

$$V_{i,t}^{*} \; = \frac{e^{\lambda_{i,t}-1}}{\lambda_{i,t} * n_{i,t}} CAR_{i,t} \times MktCap_{i,t} \tag{8}$$

6.2. Estimating acquisition intensity

In order to estimate equations (6), (7), and (8), we first construct the time-varying estimates of the acquisition intensity parameter, $\lambda_{i,t}$, for each firm through time for the universe of 239,120 firm-year observations, including both acquiring and non-acquiring firms. Table 6 Panel A reports coefficients from fitting Poisson regression models of firm-year panel data on the total number of acquisitions within a calendar year. All variables pertain to the quarter prior to the acquisition announcement.

Building on the analysis in Section 5, the independent variables of interest are the acquisitions in the prior year (all models), as well as the acquisition dynamics that the ex-ante serial acquirer types provide (models 3-7). We explore whether the serial acquirer classification as of the prior year (its cluster-specific intensity) can explain future acquisition intensity. Finally, we examine whether the transition probabilities between clusters or serial acquirer types have incremental explanatory power for changes in acquisition intensity.

Following Hausman et al. (1984), and Chen et al. (2019), we solve the models using maximum likelihood estimation (MLE). Highlighting the potential limitations of just looking at cross-sectional or time-series analyses, the large significance for both the overall model and individual coefficients in Table 5 strongly support the use of panel estimation when studying the count intensity of acquisitions per year. [17]

[17] The estimation of time-varying acquisition intensity parameters is infeasible with a cross-sectional analysis, or if we use a simpler pooled model based on a time-series analysis. The empirical estimation of acquisition intensity also highlights the importance of keeping observations of acquisitions announced on the same day in the sample. Most prior research, by design, excludes observations of acquisitions that are announced on the same day (e.g. Golubov, Yawson, and Zhang, 2015). Approximately 5% of the acquisitions in our sample are announced on the same day. Not incorporating this information would lead the acquisition intensity parameter to be biased downwards. Finally, in untabulated analysis, using sequential logit models and logit models of the probability of going beyond a serial acquirer type border lead to similar inferences, and we find no systematic differences in acquirer types across industries.

In all models in Table 6 Panel A, the number of prior acquisitions is significantly positively related to acquisition intensity. Furthermore, acquisition intensity is ex ante predictable conditional on knowing the serial acquirer type. In models 3, 4, 5 and 7, marathoners have the largest coefficient, followed by the sprinters. Models 6-7 show that prior transitions between serial acquirer types have explanatory power for subsequent acquisition intensity. For instance, a firm that has just been classified as a marathoner, exhibits an increase in the predicted acquisition intensity in the current year, especially if the jump was from an occasional acquirer type. A similar increase in the predicted acquisition intensity occurs for a firm that transitions from an occasional acquirer to a sprinter. In contrast, when an occasional acquirer stops acquiring, the model correctly captures the expected predicted decrease in acquisition intensity.

To minimize the loss of observations due to data availability, our main acquisition intensity estimation uses the Poisson count model 4. Table 6 Panel B reports the firm-specific predicted acquisition intensity parameters $\bar{\lambda}_{i,t}$ (i.e., the predicted number of deals in year *t* for firm *i*), from model 4. Finally, Table 6 Panel C reports the average predicted acquisition intensities at particular serial acquirer borders. In addition to quantifying the increase in predicted acquisition intensity for sprinters and marathoners as they have recently increased their acquisition type, we also obtain declines in predicted acquisition intensities as sprinters and occasional acquirers stop acquiring.[18]

6.3. Estimating anticipation adjustment factors for acquisition announcement stock returns

Table 7 reports the mean and median anticipation adjustment (from equation (6)), using the predicted firm-level acquisition intensity $\bar{\lambda}_{i,t}$, winsorized at the 5 and 95 percent levels, classified by serial acquirer type and by the acquisition index number (AIN), that is the total number of acquisitions that the firm has conducted up to that point in time. The median anticipation-adjustment for the overall sample is 1.29, which means that the median NPV to the acquirer of a specific acquisition is 29% larger than the observed market reaction. This value is relatively close to the estimates by Wang (2018, pg. 337), who measures the portion of the firm's market value that can be attributed to an active merger market (13%).

[18] In order to examine what impact the inclusion of small deals has in the estimation of acquisition intensities (deals that are commonly excluded from acquisition samples), in untabulated analysis, we re-estimate Poisson model 4 after controlling for the proportion of large deals conducted by each acquirer during the year. The remaining coefficients in the model are qualitatively similar and the estimated acquisition intensities are not affected significantly.

The breakdown by AIN shows that the Poisson count model regressions capture an increasing expectation of subsequent acquisitions as the firm conducts more acquisitions and reveals its true serial acquirer type. This is especially pronounced for marathoners. A marathoner conducting its 5th to 9th acquisition has a median anticipation adjustment factor of 2.02, which means that the median NPV to the acquirer for this specific acquisition is 102% larger than the observed market reaction. Beyond the 16th acquisition, the median anticipation adjustment for marathoners is 7.20. [19]

We note that we model the anticipation of the timing of future acquisitions but do not take a stance on their incremental value V^*. Our model assumes that the incremental value of future deals to the acquirer will be similar to the current deal. Essentially, the market updates its probability that more acquisitions are likely in the future without changing its estimate of the value of those acquisitions. As a robustness test to assess this assumption, we conduct an untabulated simulation analysis. We assume that the private value of the current transaction is a random variable that is drawn from a normal distribution with mean equal to the observed unadjusted abnormal return for the current transaction and standard deviation equal to the standard deviation of all the transactions in the same year and Fama-French 12-industry classification.[20] We simulate 10,000 trials by bootstrapping the market anticipation of the value of future transactions. In each simulation trial, we calculate the ratio of the estimated anticipation-adjusted abnormal returns to the simulated market value of future transactions. We then calculate the average of this ratio for all the transactions in each simulation trial. The mean average simulated ratio is 3.07, which is similar to the average anticipation adjustment factor of 3.69 reported in Table 7, suggesting that our assumption that the incremental value of future deals to the acquirer will be similar to the value of the current deal is relatively innocuous.

In untabulated analysis, we find that the simpler binary classifications used in prior studies (e.g., Golubov et al., 2015, and Netter et al., 2002) cannot incorporate sufficient details of the acquisition dynamics, causing the predictions of acquisition intensity to be over-inflated. For

[19] The results are similar if we use the other Poisson count models and even stronger if we winsorize at the 1 and 99 percent levels. Moreover, since these models are based on the actual occurrence of acquisitions, they take into consideration the potentially smaller set of available targets as the acquirers continue to acquire. This is consistent with Klasa and Stegemoller (2007) who argue that the acquirer's growth opportunity set is time-varying.

[20] Unlike Kogan et al. (2017), we do not truncate the normal distribution at zero, because an acquirer might earn either negative or positive values from an acquisition.

instance, the average predicted acquisition intensity for marathoners (occasional acquirers) in our study is 1.94 (0.59). In contrast, the average predicted acquisition intensity of the frequent (occasional) acquirers, estimated as in Golubov at al. (2015) is 1.51 (0.81), which appears to over-estimate the intensity of the less frequent acquirers. Similarly, Cai, Song, and Walkling (2011), Table 4 and 20, examine anticipation effects based on the occurrence of a prior bid by a *competitor* in the same industry, without considering the acquisition activity by the same acquirer. The implied anticipation adjustment factors in their study are in the 3-4 range, again inflated relative to the ones we estimate. Hence, our granular serial acquirer classification provides a more robust predictive accuracy to estimate the acquisition-adjusted abnormal returns for serial acquisitions.

7. Anticipation-adjusted acquisition stock returns

We next use the anticipation adjustment factors to adjust the stock price reactions to acquisitions for the surprise and anticipation components. Subsequently, we calculate both the individual acquisition gains and the cumulative dollar gains associated with acquisitions.

7.1 Abnormal returns around the acquisition announcement

Table 8 Panel A reports the unadjusted abnormal returns using a 3-day window [-1, +1], around the acquisition announcement. The first column is consistent with the stylized fact documented in previous studies, namely that acquirers earn decreasing abnormal returns on average. This pattern persists when we examine each acquirer type separately. A novel result is that on average, the marathoners seem to start with lower abnormal returns than the other acquirers, right from the start of their acquisition activity.

Table 8 Panel B reports the anticipation-adjusted abnormal returns using equation (7). The average anticipation-adjusted abnormal return, 0.012, is 50% larger than the average unadjusted abnormal return 0.008. For a marathoner conducting its 5^{th} to 9^{th} acquisition (with an average anticipation adjustment factor of 2.36 in Table 7), the NPV to the acquirer of this specific acquisition is 136% larger than the observed market reaction. The results show that, on average, the percentage gains are slightly larger for the loner and occasional acquirers. However, the *difference* between the unadjusted and the anticipation-adjusted abnormal returns is significantly larger for the sprinters and the marathoners (0.0076 vs. 0.0112 and 0.0025 vs. 0.0111 respectively).

While the declining returns to acquirers disappear for the sample after adjusting for anticipation in column 1, when examining different acquirer types, the results are more nuanced. The monotonic declining pattern disappears *only* for marathoners following the anticipation-adjustment. Marathoners, the most frequent acquirers, keep on earning increasing anticipation-adjusted economic values as their acquisition activity continues. In contrast, the last set of acquisitions for loners, occasional acquirers and sprinters earn lower anticipation-adjusted abnormal returns, perhaps one reason why these types of acquirers end their acquisition activity.

In Table 9, we split our sample into large and small deals. There are marked differences between the two. Panel A shows that marathoners appear to focus more on smaller deals. Not surprisingly, Panels B to E show that abnormal returns are larger in the large deals sub-sample. More importantly, however, in Panel C, when we examine large deals, the decline in returns disappears after the anticipation adjustment only for marathoners, in line with the earlier results. Loners, occasional acquirers, and sprinters still earn declining anticipation-adjusted abnormal returns at their final acquisitions. The results when we examine small deals in Panel E are markedly different. With the exception of loners, no other acquirers earn declining returns after we control for anticipation.

These results appear to highlight the importance of small deals in inducing learning among acquirers. When acquirers conduct small deals, which may be less economically significant but help acquirers learn, they earn non-declining anticipation-adjusted returns. When they conduct large deals, most types of acquirers earn declining anticipation-adjusted returns. Only marathoners, the most frequent acquirers, and those with presumably the best expertise in M&A, continue to earn non-declining returns as they continue acquiring large targets. In contrast, the last large acquisitions by loners, occasional acquirers and sprinters earn lower anticipation-adjusted abnormal returns, which may be one reason why these types of acquirers stop acquiring.

These inferences are confirmed in the multivariate regressions in Table 10. Panel A reports coefficients from OLS regressions on unadjusted abnormal returns (models 1, 3, 5, and 7) and on anticipation-adjusted abnormal returns (models 2, 4, 6, and 8) after controlling for variables that have been shown in the prior literature to explain acquirer returns. The main variable of interest is the acquisition index number (AIN). Consistent with a pattern of declining returns, the AIN is significantly negative when the dependent variable is the unadjusted abnormal return for the whole sample and for the sub-sample of marathoners. In contrast, it is insignificant in the regression models where the dependent variable is the anticipation-adjusted abnormal return. In Table 10 Panel B, the results are qualitatively similar for both large and small deals for marathoners. For sprinters and occasional acquirers in contrast, the last few *large* acquisitions earn significantly lower anticipation-adjusted returns than the first few, again suggesting a reason why these firms cease acquiring. However, these two types of acquirers earn higher anticipation-adjusted returns for their later small acquisitions. Since small acquisitions are typically eliminated because of size filters in prior literature, it is not surprising that the literature depicts declining returns to increasing acquisition activity as a puzzle.

7.2. The aggregate economic value of serial acquisitions

A related question is how acquirer type and anticipation affect the aggregate economic value that acquirers earn over their entire acquisition series. To compute this NPV, we multiply the anticipation adjusted CAR for each acquisition with the acquirer's market capitalization using equation (8).

Table 11 reports the anticipation-adjusted dollar gains by serial acquirer type. In Panel A, the distribution of dollar gains is strongly positively skewed. The average dollar gain ($5.36 million) is significantly larger than the median ($0.36 million). Although the loners earn relatively large average anticipation-adjusted dollar gains ($4.03 million), their median gain is the lowest ($0.21 million). Again, there is no evidence of declining gains for marathoners as the acquisition sequence progresses. For example, after their 16th acquisition, marathoners earn an average (median) anticipation-adjusted gain of $8.33 million ($2.90 million), which is in line with the $9.49 million ($1.33 million) they earn in their first acquisition. Untabulated analysis indicates that marathoners earn larger dollar gains regardless of industry.

Panels B and C examine separately the sub-samples of large and small deals. The results show that marathoners earn significant anticipation-adjusted dollar gains regardless of the size of the target ($10.05 million, on average, for large deals and $6.32 million for small deals). Overall, consistent with Rodrigues and Stegemoller (2007) and Netter, Stegemoller, and Wintoki (2011), serial acquirers appear to profit greatly from small deals (on average $4.79 million), that are typically excluded from the samples of prior studies. In untabulated analysis, we find that, whereas both small and large deals exhibit, on average, positive dollar gains, mega-deals with a transaction value over $100 million and relative size over 30% of the acquirer's size, exhibit large *negative* average dollar gains (-$12.1 million), and are driven mainly by acquisitions of public targets. These very large deals comprise 10.8% of the acquisitions of loners and 8.3% of the acquisitions of occasional acquirers but only 2.1% of the acquisitions of marathoners. Overall, marathoners accumulate large dollar gains through acquisitions of small private and subsidiary targets.[21]

8. Serial Acquirer Puzzle 3: Who are the extraordinary acquirers?

Finally, we examine the extraordinary acquirers documented by Golubov, Yawson, and Zhang (2015). These are acquirers who earn persistently high returns on acquisition announcements as they keep acquiring. If acquisition intensity is indeed predictable, why would the market not be able to predict the acquisition activity of these extraordinary acquirers?

Following Golubov et al. (2015), we first estimate the average unadjusted abnormal return to all acquisitions made by an acquirer over the last three calendar years ("avg. past unadjusted CAR") to detect extraordinary acquirers with persistent larger returns. We then split the sample of acquirers into terciles on the basis of past CARs using firm-year level observations. We note that the sample size decreases for this test because the analysis requires multiple acquisitions to compute past and future acquisition performance.

Table 12 Panel A shows the proportion of transactions conducted by each serial acquirer type. Acquisitions by occasional acquirers are evenly distributed among the terciles. In contrast, sprinters and marathoners appear to be mediocre performers, performing neither too well nor too poorly. Marathoners would not be classified as extraordinary acquirers using the above definition. The results are similar if we use quintiles instead of terciles. More than half of the marathoners are in the middle tercile of the abnormal returns distribution, not in the top tercile.

Table 12 Panel B replicates the results in Table 4 in Golubov et al. (pg. 320) and shows the persistence in future average unadjusted abnormal returns for the "extraordinary acquirers" as defined in their paper. The acquirers at the top tercile of average past returns earn larger returns in the future. However, the dispersion in returns is much more modest for the marathoners, and their future returns tend to remain much lower than those for occasional acquirers and sprinters. The

[21] In additional untabulated analysis, consistent with prior research, average dollar gains are larger for subsidiary and private targets compared to public targets.

future average one-year abnormal return for extraordinary occasional acquirers is 1.12% compared to 0.79% and 0.03% for extraordinary sprinters and marathoners, respectively.

Finally, Table 12 Panel C shows that the persistence in returns does not translate into persistence in dollar gains after adjusting for anticipation. Similar to the tale of the tortoise and the hare, marathoners in the *mid tercile* of past unadjusted abnormal returns accumulate, on average, higher anticipation-adjusted dollar gains over the next two years compared to marathoners in the top tercile ($18.99 million compared to $9.48 million). Although they do *not* fall under the "extraordinary" definition, they end up accumulating the largest dollar gains among all marathoners. In contrast, it is the top tercile occasional acquirers and sprinters who receive larger gains compared to their lower terciles ($11.07 million and $27.94 million, respectively). We obtain similar results when we split the sample on past accrued dollar gains, instead of returns (results not reported in tables). Hence, the "extraordinary" acquirers identified by Golubov et al (2015) are not likely to be marathoners, the most frequent acquirers in our sample. They are extraordinary precisely because they are not anticipated.

9. Conclusions

The literature documents several findings about serial acquirers that pose puzzles if serial acquisition dynamics are not properly taken into consideration. These serial acquirer puzzles are related to the motivations behind acquisition activity, why serial acquirers earn significantly lower excess returns as they continue acquiring more targets, why some acquirers do not follow this pattern and appear to be "extraordinary", and finally, whether only large deals are relevant in samples that examine acquisition activity because small deals are not economically significant.

The recent literature has also documented that serial acquirers dominate the acquisition market (making a large number of acquisitions). We use cluster analysis, based on the total number of acquisitions, the number of acquisition blocks, and acquisition intensity within the block, to identify four distinct groups of acquirers, loners, occasional acquirers, sprinters and marathoners. These acquirer types can be reliably classified using a relatively stable classification based on ex ante information. Acquisition activity is driven by different factors for different types of acquirers, and these acquirers appear to acquire targets with different sizes and listing status. Some acquirer types appear to benefit from consistently conducting acquisitions of many small deals and accumulate large dollar gains in the process. Ex ante information on serial acquirer types enables us to predict acquisition activity vastly more accurately compared to previous studies. Once we adjust for market anticipation, we find little evidence of declining returns for the most frequent serial acquirers. On average, serial acquirers seem to experience a positive benefit-cost tradeoff in their serial acquisition dynamics.

We also show that the most frequent and easily predicted acquirers are not extraordinary. Extraordinary acquirers appear to persist because they are not easily predictable by the market. However, through their continuous acquisition activity, the non-extraordinary serial acquirers that we call marathoners end up accumulating large anticipation-adjusted dollar gains.

Overall, our serial acquirer classification and empirical methodology allow us to enhance our understanding of serial-acquisition dynamics well beyond what has been reported in previous related studies. Our results are likely to be useful for traders or hedge fund managers who need to compute ex ante acquisition intensity probabilities. They are also likely to be useful to managers of serial acquirers to demonstrate how simple market excess returns are biased measures of actual private value. Our methodology is applicable to other corporate events such as share repurchases, where firms carry out similar events regularly and predictably. It is also likely to be applicable to models of mutual fund manager performance where the market anticipates future investment strategies by successful mutual fund managers. We leave for further study various additional applications of the serial acquirer classification, for instance, (i) the interaction between serial acquirer types and CEOs (e.g., changes, retirement, styles, etc.); (ii) changes in other firm characteristics for the acquirer and its peers (e.g. changes in innovation, overall efficiency of the firm): and (iii) changes within an industry based on serial-acquisition dynamics (i.e., how innovation or productivity changes as a function of the types of acquirers in such industry). Overall, we expect that our new typology of acquirer types can find applications in academic and practitioner topics related to event anticipation beyond those covered in this study.

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Appendix

Variables used in the paper with descriptions and sources

Variable	Description
Firm and deal characteristics	
Assets	Book value of assets. Source: COMPUSTAT
Market capitalization	Assets – book value of common equity + market value of common equity, measured at end of last calendar year before the acquisition announcement. Source: COMPUSTAT
Long-term debt / Assets	Book value of long-term debt / Assets. Source: COMPUSTAT
R&D/ Assets	Research and development expenditures / Assets. Source: COMPUSTAT
Financial industry	Indicator variable which takes the value of one if the 4-digit SIC industry classification is within the [6000-6799] range (i.e., 48-Fama-French industry [44-47] range. Source: COMPUSTAT.
Public target	Indicator variable which takes the value of one if the stock of the target is publicly traded. Source: SDC.
Private target	Indicator variable which takes the value of one if the stock of the target is not publicly traded. Source: SDC.
Subsidiary target	Indicator variable which takes the value of one if the SDC reports the target as a subsidiary. Source: SDC.
Small target	Indicator variable which takes the value of one if the SDC reports a transaction value smaller than $1 million or the ratio of transaction size over the acquirer's market capitalization is less than 1%. Source: SDC.
Large target	Indicator variable which takes the value of one if the SDC reports a transaction value greater than $1 million and the ratio of transaction size over the acquirer's market capitalization is at least 1%. Source: SDC.
Index in sample	Index starting with one as of the first year in which a firm appears in the sample. Source: SDC and COMPUSTAT
Age	Number of years since founding of the company. If information is not available, then we use the number of years since start of appearance in COMPUSTAT. Source: SDC and COMPUSTAT
Sales	Net annual sales. Source: COMPUSTAT
Sales growth	Ln(Sales/ lagged Sales) based on annual data
Operating performance (EBITDA/Assets)	Earnings before interest, taxes and depreciation / Assets. Source: COMPUSTAT
Market-to-book ratio	Market value of total assets/Book value of total asset following Rhodes-Kropf et al (2005). Source: COMPUSTAT
Firm-Specific error (RRV)	Firm-Specific error estimated with the market-to-book decomposition in Rhodes-Kropf et al (2005).
Industry sector-Specific error (RRV)	Industry sector-Specific error estimated with the market-to-book decomposition in Rhodes-Kropf et al (2005).
Long-run growth opportunities (RRV)	Long-run growth opportunities estimated with the market-to-book decomposition in Rhodes-Kropf et al (2005).
Overall AIN (Acquisition Index) since 1989	Acquisition index number (AIN) starting in 1989
AIN (index within block of acquisitions)	Acquisition index number (AIN) within an acquisition block.
Time since last acquisition	Number of days between two subsequent announced acquisitions.
Acquisition Block Index	We classify acquisitions that cluster in time as part of an acquisition block if the current acquisition takes place within the 75th percentile (i.e., in the

	top quartile, equivalent to 407 days) of the entire distribution of time between acquisitions during our sample period.
Dot-com indicator	Indicator variable equal to 1 if announcement year is between 1997 and 2001
Deregulated year	Indicator variable equal to 1 if a deregulatory activity takes place in the announcement year. We follow Ovtchinikov (2010) to determine deregulatory activity for a given industry.
After 2001	Indicator variable equal to 1 if announcement year is after 2001
Unadjusted abnormal return	Short term cumulative abnormal return (CAR) during a 3-day window, [-1, +1], centered at the announcement date of the current acquisition relative to the value-weighted index return.
Avg. past unadjusted CAR	Average unadjusted abnormal return for all the acquisitions that a firm conducts during the previous 3 years before the current acquisition.
Cum. Adj. dollar gain	Cumulative anticipation-adjusted dollar gain for all the acquisitions that a firm conducts during the previous 3 years before the current acquisition.
Cum. unadjusted CAR over *k* years	Cumulative unadjusted abnormal return for all the acquisitions that a firm conducts over the next *k* calendar years after the current acquisition.
Avg. unadjusted CAR over *k* years	Average unadjusted abnormal return for all the acquisitions that a firm conducts over the next *k* calendar years after the current acquisition.

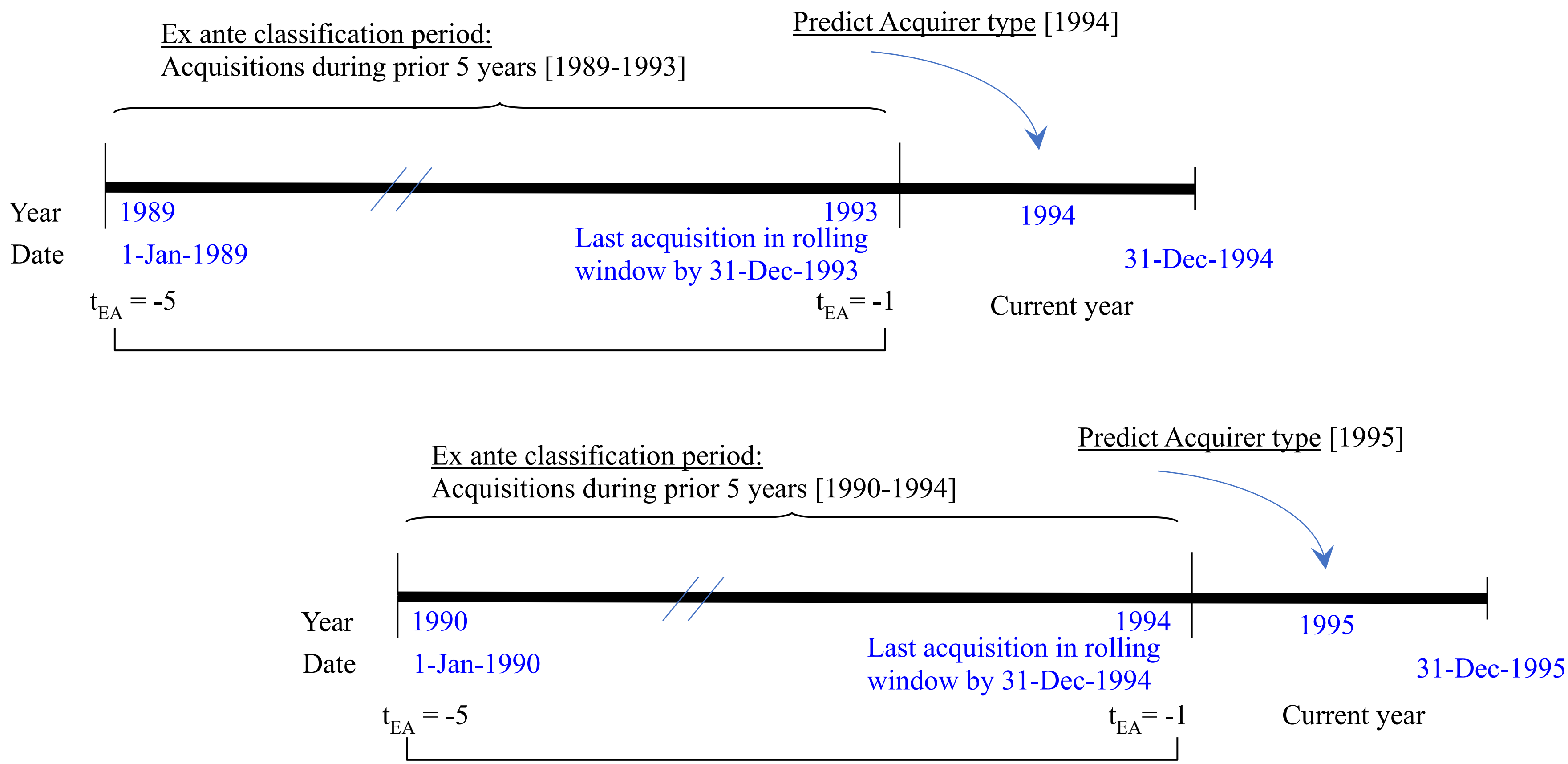

Figure 1. Example of ex ante serial acquirer type classification using 5-year rolling windows

This figure illustrates the process of building the ex ante serial acquirer type classification based on 5-year rolling windows during 1989-2018. The figure shows two examples of ex ante classification, one for the year 1994 and one for the year 1995. We use the parameters (total acquisitions, number of acquisition-blocks and average intensity) over the entire prior 5 years (or less, if the company is newly listed) for the serial acquirer ex ante classification used for the subsequent year. The ex ante classification for the year 1994 (1995) is based on the information from the years 1989-1993 (1990-1994). We allow the classification to be updated annually if the firm changes acquirer type.

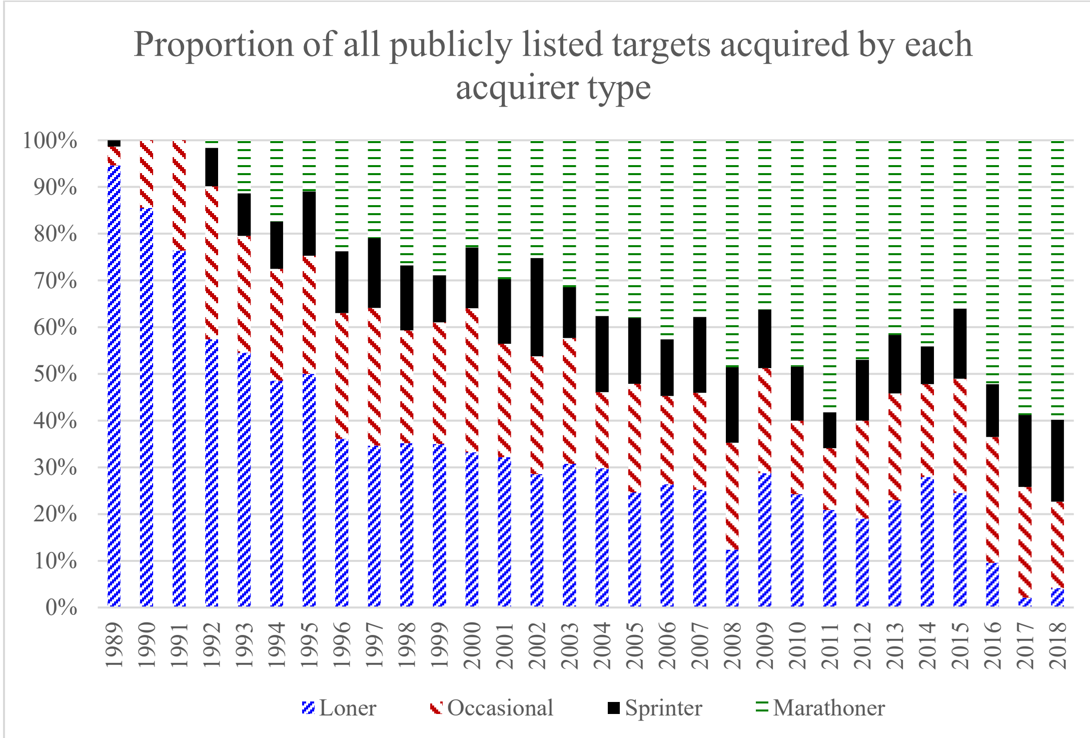

Figure 2. Proportion of acquisitions of publicly listed targets by different acquirer types

This figure illustrates the proportion of all publicly listed targets acquired by each of the different acquirer types annually. The sample consists of the 4,338 acquisitions of publicly listed targets conducted during 1989-2018. The process of building the ex ante serial acquirer type classification based on 5-year rolling windows is described in Fig 1. The ex ante classification for each year is based on acquisition activity in the past 5 years (or less, if the company is newly listed). We allow the acquirer classification to be updated annually if the firm changes acquirer type.

Table 1. Acquisition activity by serial acquirer type

This table describes the acquisition dynamics and activity for the serial acquirer types as classified by the k-median cluster analysis. The serial acquirer classification uses the total number of acquisitions and total number of acquisition blocks for each acquirer in the sample based on the entire sample of 55,482 announced acquisitions of U.S. public, private and subsidiary targets by U.S. public acquirers during 1989-2018. We require that (i) the acquirer has not conducted any acquisition in the 4 years prior to the start of our sample period, i.e. 1985-1988; and (ii) that the acquirer conducts its first acquisition at least by the year 2016. To classify an acquisition as part of an acquisition block, we use as our threshold the 75th percentile (i.e., 407 days) of the entire distribution of time between two subsequent acquisitions during our sample period. All transactions conducted by an acquirer are classified as part of a specific acquisition block as a function to the time between acquisitions. Panel A reports unique firm observations and Panel B firm-year observations. We note that the sum of loner, occasional, sprinter, and marathoner acquirers in Panel A ("All acquirers") exceeds the number of unique acquirers in the sample, since our classification allows each acquirer to be classified into more than one type during the sample period.

Panel A. Unique firm observations

	All Firms	Acquirers									Targets				
	Firms (#)	Acquirers (%)	Acquisitions (#)	Acquisitions (%)	Mean (#)	Min (#)	p25 (#)	Med (#)	p75 (#)	Max (#)	Public (#)	Private (#)	Subsidiary (#)	Large (#)	Small (#)
Total (N firms)	27,813														
Non-acquirers	19,173	0.0%	0	0.0%	0	0	0	0	0	0					
All acquirers	9,500	100.0%	55,482	100.0%	6.2	1	1	3	7	380	4,338	33,623	17,521	20,036	35,446
Loner	4,409	46.4%	5,993	10.8%	1.4	1	1	1	2	2	600	3,327	1,921	2,112	4,788
Occasional	2,493	26.2%	9,701	17.5%	3.9	3	3	4	5	6	842	5,345	2,986	3,312	4,880
Sprinter	933	9.8%	6,609	11.9%	7.1	6	6	7	8	10	559	3,777	2,094	2,322	3,424
Marathoner	1,665	17.5%	33,179	59.8%	19.9	9	11	15	23	380	2,337	21,174	10,520	12,290	22,354

Panel B. Firm-year observations

	Total	Non-acquirer	Loner	Occasional	Sprinter	Marathoner
Total (N firm-years)	239,120	183,890	26,913	19,739	4,322	4,256
N firm-years with an acquisition in prior year	26,588		9,743	10,258	3,096	3,491
Proportion with an acquisition in prior year out of total	11%		36%	52%	72%	82%
N firm-years with an acquisition in current year	29,412	9,820	6,902	7,422	2,326	2,942
Proportion with an acquisition in current year out of total	12%	5%	26%	38%	54%	69%
Number of acquisitions within blocks of acquisitions	5.19		3.35	5.54	8.68	10.83
Time since last acquisition (days)	534		629	535	404	369
Number of acquisition blocks	2.01		1.30	2.19	2.81	4.40

Table 2. Acquirer characteristics and acquirer types at the time of the *first* acquisition

The table reports acquirer characteristics at the time of the *first* acquisition by each unique acquirer during 1989-2018. We report industry-adjusted variables, where appropriate, based on the 48 Fama-French industry classification. The serial acquirer type as of the prior year is estimated based on the ex-ante classification that used the 5-year rolling window which ended in the year prior to the current year. Variables are defined in the Appendix. ***, **, * denote significance at 1%, 5% and 10% levels, respectively.

	1	2	3	4	5	*t*-test for difference in means			
	Total	Loner	Occasional	Sprinter	Marathoner	Loner to occasional	Occasional to sprinter	Sprinter to marathoner	Loner to marathoner
[N]	8,640	3,846	2,256	896	1,642	2 vs 3	3 vs 4	4 vs 5	2 vs 5
Firm and deal characteristics									
Assets	1,347	639	837	1,757	2,499	*	***	*	***
Long-Term Debt / Total Assets	0.0841	0.0876	0.0658	0.0555	0.0645	**			**
Public Target	0.0949	0.1061	0.0953	0.0926	0.0639	*		**	***
Private Target	0.5814	0.5681	0.5811	0.5938	0.5877				
Subsidiary Target	0.3237	0.3258	0.3236	0.3136	0.3484			*	
Efficiency and growth opportunities									
Operating performance	-0.0586	-0.0905	-0.0465	-0.0345	0.0176	***		***	***
Sales Growth	0.3533	0.3639	0.3704	0.4053	0.2869			**	**
R&D / Total Assets	0.0261	0.0335	0.0248	0.0140	0.0096	***	***		***
Long-term Growth Opportunities (RRV)	0.6473	0.6540	0.6433	0.6361	0.6403				
Overvaluation variables									
Firm-specific error	0.1511	0.0957	0.1889	0.1921	0.2298	***			***
Industry sector-specific error	0.0672	0.0646	0.0603	0.0802	0.0493			**	
Industry effects									
Dot-com bubble	0.2344	0.2561	0.2380	0.2444	0.2314	*			**
Industry Deregulation	0.0273	0.0218	0.0297	0.0290	0.0426	**		*	***

Table 3. Hazard analysis on the time between two subsequent acquisitions by acquirer type

This table reports duration analysis results for semi-parametric Cox models by acquirer type, where a positive (negative) coefficient implies a higher (lower) probability that the acquisition activity will stop (i.e., a larger hazard rate).The serial acquirer classification uses 30,564 announced acquisitions of U.S. public, private and subsidiary targets by U.S. public acquirers that have conducted at least 2 acquisitions during 1989-2018 (a condition required by the duration analysis setting). The table reports hazard ratios from Cox Proportional Hazard (PH) models on the hazard of stopping the acquisition activity. Model 1 uses all observations, and models 2, 3, and 4 use only the subsamples of occasional acquirers, sprinters, and marathoners, respectively. Raw level variables (i.e., non-industry-adjusted), are used, winsorized at the 1%-99% percentile. Year and industry fixed effects are included in the regressions. P-values are reported in parentheses. The regressions use Eicker-Huber-White-Sandwich heteroskedastic-robust standard errors clustered by industry. ***, **, * denotes significance at 1%, 5% and 10% levels, respectively.

Acquirer type	All	Occasional	Sprinter	Marathoner
Model	(1)	(2)	(3)	(4)
Firm and deal characteristics				
log(assets)	-0.235***	-0.155***	-0.185***	-0.240***
	(0.000)	(0.000)	(0.000)	(0.000)
Long-term debt / assets	0.033	0.410***	0.194	0.207
	(0.805)	(0.001)	(0.341)	(0.444)
Public Target	0.210***	0.154**	0.212	0.251***
	(0.000)	(0.035)	(0.245)	(0.000)
Private Target	-0.120**	-0.003	0.026	-0.146***
	(0.044)	(0.961)	(0.726)	(0.000)
Efficiency and growth opportunities				
Operating performance (EBITDA / assets)	-0.189***	-0.333***	-0.252**	-0.198
	(0.002)	(0.000)	(0.031)	(0.588)
Sales Growth	0.058***	0.039*	0.245***	0.143**
	(0.001)	(0.096)	0.000	(0.016)
R&D / assets	0.930***	0.981**	1.200	2.148***
	(0.000)	(0.021)	(0.161)	(0.008)
Cash and cash-equivalents / assets	0.537***	0.365**	0.035	0.851***
	(0.000)	(0.021)	(0.884)	(0.005)
Long-run growth opportunities (RRV)	-0.129**	-0.190**	-0.166*	-0.247***
	(0.033)	(0.043)	(0.050)	(0.001)
Industry effects				
Dot-com indicator	0.084	0.345	0.394	-0.196
	(0.509)	(0.206)	(0.250)	(0.764)
Deregulation year	0.147***	-0.092	0.338	0.158
	(0.003)	(0.269)	(0.133)	(0.611)
Financial Industry	-0.315***	-0.139***	0.022	-0.425***
	(0.000)	(0.002)	(0.799)	(0.000)
Overvaluation variables				
Firm-specific error (RRV)	0.007	-0.068*	-0.019	-0.106
	(0.868)	(0.058)	(0.873)	(0.252)
Industry sector-Specific error (RRV)	-0.033	0.126	-0.089	-0.221
	(0.614)	(0.296)	(0.643)	(0.317)
Prior acquisition history				
ST CAR [-1, +1] in prior acquisition	-0.087	-0.313	0.687	-0.657
	(0.766)	(0.377)	(0.315)	(0.477)
Change in operating perf. since prior deal	0.060	-0.107	-1.084*	0.049
	(0.679)	(0.671)	(0.084)	(0.959)
log(Time since last acquisition)	-0.735***	-0.912***	-0.839***	-0.657***
	(0.000)	(0.000)	(0.000)	(0.000)

Acquis. block index by acquirer since 1989	-0.113***	-0.466***	-0.178***	0.010
	(0.000)	(0.000)	(0.000)	(0.690)
Intercept, year and industry FE	Yes	Yes	Yes	Yes
log-likelihood	-30,600	-8,749	-2,957	-5,152
N	30,564	7,751	4,659	13,693

Table 4. Annual transition matrix from ex-ante to ex-post acquirer type

This table reports the annual transition matrix from one year to the next by acquirer type. The initial sample contains all 239,120 U.S. public firm-year observations reported in COMPUSTAT during 1989-2018. Variables are defined in the Appendix.

	% [N]	Non-acquirer	Loner	Occasional	Sprinter	Marathoner
Lag type=non-acquirer	100% [173631]	**95% [164585]**	4% [7333]	1% [1582]	0% [81]	0% [50]
Lag type=Loner	100% [23634]	9% [2191]	**71% [16894]**	19% [4391]	1% [129]	0% [29]
Lag type=Occasional	100% [17486]	2% [361]	15% [2613]	**72% [12677]**	9% [1594]	1% [241]
Lag type=Sprinter	100% [3824]	0% [7]	2% [59]	26% [976]	**54% [2064]**	19% [718]
Lag type=Marathoner	100% [3794]	0% [1]	0% [12]	3% [112]	12% [454]	**85% [3215]**

Table 5. Predicting the probability of an acquisition

Panel A reports the results of logit models on the probability of conducting an acquisition in the current year based on firm classifications and characteristics over the prior year, within the universe of all 239,120 U.S. public firm-year observations reported in COMPUSTAT during 1989-2018. Models 1-5 are logit models. Model 6 is a panel-data logit model. We report industry-adjusted variables, where appropriate, based on the 48 Fama-French industry classification. All the continuous control variables are standardized to have a mean equal to zero and standard deviation equal to one. The base for serial acquirer type is the acquirers with no acquisitions within the prior 5 years. The serial acquirer type as of the prior year is estimated based on the ex-ante classification that used the 5-year rolling window which ended in the year prior to the current year. The regressions use robust standard errors (reported in parentheses). Panel B reports the observed and predicted probability of conducting an acquisition in a given year, estimated using Stata's margins routine that properly incorporates the interaction terms in the logit model 5 of Panel A. Variables are defined in the Appendix. ***, **, * denote significance at 1%, 5% and 10% levels, respectively.

Panel A. Logit models on probability of conducting an acquisition in the current year

Specification	Logit	Logit	Logit	Logit	Logit	Panel data Logit
Model	(1)	(2)	(3)	(4)	(5)	(6)
Prior year serial acq type: Loner				1.714***	1.560***	1.307***
				(0.045)	(0.051)	(0.031)
Prior year serial acq type: Occasional				2.278***	1.950***	1.503***
				(0.055)	(0.068)	(0.039)
Prior year serial acq type: Sprinter				2.887***	2.405***	1.774***
				(0.064)	(0.093)	(0.078)
Prior year serial acq type: Marathoner				3.592***	2.700***	2.035***
				(0.092)	(0.114)	(0.100)
Deal in prior year indicator			1.945***		1.076***	0.941***
			(0.025)		(0.123)	(0.102)
Loner × Deal in prior year indicator					-0.734***	-0.679***
					(0.134)	(0.107)
Occasional × Deal in prior year indicator					-0.524***	-0.481***
					(0.136)	(0.107)
Sprinter × Deal in prior year indicator					-0.438***	-0.401***
					(0.127)	(0.129)
log(Assets)	0.177***	0.105***	0.079***	0.075***	0.069***	0.090***
	(0.009)	(0.009)	(0.008)	(0.008)	(0.008)	(0.006)
Index in sample		-0.129	-0.305***	-0.788***	-0.745***	-0.699***
		(0.106)	(0.096)	(0.092)	(0.091)	(0.037)
$[\text{Index in sample}]^2$		0.029	0.072***	0.179***	0.170***	0.160***
		(0.027)	(0.025)	(0.026)	(0.025)	(0.010)
Long-Term Debt / Assets		0.309***	0.124**	-0.107	-0.098	-0.047
		(0.062)	(0.055)	(0.067)	(0.064)	(0.052)
R&D / Assets		-1.941***	-1.781***	-1.656***	-1.640***	-1.782***
		(0.259)	(0.233)	(0.221)	(0.219)	(0.153)
Operating performance (EBITDA /		0.323***	0.247***	0.216***	0.209***	0.213***
assets)		(0.039)	(0.038)	(0.043)	(0.043)	(0.023)
Sales Growth (annual)		0.584***	0.469***	0.661***	0.613***	0.605***
		(0.040)	(0.046)	(0.045)	(0.046)	(0.024)
Firm-Specific error (RRV)		0.202***	0.212***	0.235***	0.232***	0.237***
		(0.020)	(0.016)	(0.015)	(0.015)	(0.013)
Long-run Growth Opportunities (RRV)		0.051**	0.075***	0.115***	0.109***	0.121***
		(0.020)	(0.022)	(0.024)	(0.024)	(0.021)

Industry sector-Specific error (RRV)		0.193***	0.235***	0.283***	0.282***	0.286***
		(0.030)	(0.030)	(0.029)	(0.029)	(0.031)
Dot-com indicator		0.965***	0.487***	-0.056*	-0.041	0.154**
		0.000	0.000	(0.071)	(0.186)	(0.035)
Deregulation year		-0.109*	-0.097*	-0.095	-0.091	-0.083*
		(0.061)	(0.058)	(0.061)	(0.061)	(0.048)
Intercept	-3.897***	-3.489***	-3.119***	-2.744***	-2.727***	-3.074***
	(0.070)	(0.124)	(0.103)	(0.087)	(0.086)	(0.088)
Industry and Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R^2	0.040	0.043	0.140	0.200	0.205	
N	239,120	164,792	164,792	164,792	164,792	164,792

Panel B. Observed and predicted probability of an acquisition in the current year

		Predicted Pr[Acq in Yr] {continuous}				
	Actual		Deal in prior year			
	proportion	Total	No	Yes	Diff Y-N	
Prior Year Serial Acquirer Type	With acq. in year					
All	0.1154	0.1467	0.1054	0.4352	0.3298	***
Non-acquirer	0.0000	-	0.0688	-		
Loner	0.0941	0.2604	0.2506	0.3166	0.0660	***
Occasional	0.2048	0.3444	0.3263	0.4495	0.1232	***
Sprinter	0.3645	0.4485	0.4270	0.5765	0.1495	***
Marathoner	0.6031	0.5289	0.4959	0.7312	0.2353	***

Table 6. Estimating acquisition intensity

Panel A reports coefficients from fitting Poisson regressions of acquirer-year panel data on the total number of acquisitions within a calendar year. The final sample contains all observations with required data based on the entire sample of 239,120 firm-year observations of firms in COMPUSTAT during 1989-2018. Panel B reports the firm-specific predicted acquisition intensity $\bar{\lambda}_{i,t}$ (i.e., the predicted number of deals in year t for firm i), from the Poisson count model 4 by serial acquirer type. Panel C reports the firm-specific predicted acquisition intensity $\bar{\lambda}_{i,t}$, from the Poisson count model 4 at particular serial acquirer type borders. Variables are defined in the Appendix. The regressions use Eicker-Huber-White-Sandwich heteroskedastic-robust standard errors (clustered by year in the OLS regressions). Standard errors are reported in parentheses. ***, **, * denote significance at 1%, 5% and 10% levels, respectively.

Panel A. Poisson count models on number of acquisitions per year

Dep. Var: Count intensity of acquisitions by year	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Number of public targets acquired in prior year	0.296***	0.294***	0.268***	0.270***	0.249***	0.255***	0.250***
	(0.011)	(0.012)	(0.012)	(0.012)	(0.013)	(0.013)	(0.013)
Number of private targets acquired in prior year	0.441***	0.446***	0.428***	0.436***	0.427***	0.418***	0.428***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.003)	(0.004)
Number of subsidiary targets acquired in prior year	0.349***	0.339***	0.328***	0.321***	0.309***	0.305***	0.310***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)
Prior year serial acq type: Loner			0.084***	0.098***	0.105***		0.106***
			(0.006)	(0.006)	(0.007)		(0.007)
Prior year serial acq type: Occasional			0.146***	0.169***	0.175***		0.177***
			(0.007)	(0.007)	(0.008)		(0.008)
Prior year serial acq type: Sprinter			0.283***	0.327***	0.338***		0.307***
			(0.014)	(0.014)	(0.016)		(0.020)
Prior year serial acq type: Marathoner			0.472***	0.586***	0.588***		0.630***
			(0.017)	(0.017)	(0.020)		(0.022)
Change from Sprinter (Yr-2) to Marathoner in prior year						0.160***	-0.210***
						(0.035)	(0.038)
Change from Occasional (Yr-2) to Sprinter in prior year						0.211***	0.082***
						(0.023)	(0.028)
Change from Occasional (Yr-2) to Marathoner in prior year						0.386***	0.045
						(0.061)	(0.063)
After being a Sprinter (Yr-2) with no acquisitions in prior year						-0.267	-0.103
						(0.399)	(0.401)
After being an Occasional (Yr-2) with no acquisitions in prior year						-0.089*	0.023
						(0.050)	(0.050)
log(assets)	0.030***	0.028***	0.023***	0.022***	0.024***	0.033***	0.024***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)
Index in sample		-0.009		-0.117***	-0.107***	-0.062***	-0.107***
		(0.006)		(0.007)	(0.009)	(0.009)	(0.009)
[Index in sample]^2		0.004**		0.028***	0.026***	0.018***	0.026***
		(0.002)		(0.002)	(0.003)	(0.003)	(0.003)

Cont.	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Long-term debt / assets		-0.003		-0.002	0.029**	0.042***	0.028**
		(0.004)		(0.004)	(0.013)	(0.014)	(0.013)
R&D / assets		-0.118***		-0.122***	-0.271***	-0.269***	-0.271***
		(0.016)		(0.017)	(0.030)	(0.031)	(0.030)
Operating performance (EBITDA / assets)		0.004		0.007**	0.010**	0.011**	0.010**
		(0.003)		(0.003)	(0.005)	(0.005)	(0.005)
Sales growth (annual)					0.150***	0.137***	0.150***
					(0.006)	(0.006)	(0.006)
Firm-specific error (RRV)					0.047***	0.046***	0.047***
					(0.003)	(0.003)	(0.003)
Long-run growth opportunities (RRV)					0.030***	0.029***	0.030***
					(0.005)	(0.005)	(0.005)
Industry sector-specific error (RRV)					0.059***	0.057***	0.060***
					(0.007)	(0.008)	(0.007)
Dot-com indicator					0.011	0.044***	0.010
					(0.016)	(0.016)	(0.016)
Deregulation year					-0.047***	-0.050***	-0.046***
					(0.012)	(0.012)	(0.012)
Intercept	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry and Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
$\chi2$	37,231	34,019	31,989	30,288	24,448	23,350	24,488
AIC	536,866	489,793	511,400	468,141	397,035	399,532	397,004
N	239,120	219,627	222,369	205,829	164,262	164,792	164,262

Panel B. Predicted acquisition intensity

Predicted (Acquisition intensity)	N	Mean	Standard deviation	p25	Median	p75	p90	p99
All	222,369	0.25	0.40	0.09	0.15	0.24	0.54	1.82
Non-acquirer	167,145	0.13	0.08	0.07	0.12	0.18	0.23	0.34
Loner	26,911	0.35	0.19	0.20	0.28	0.50	0.62	0.94
Occasional	19,738	0.59	0.38	0.29	0.52	0.78	1.10	1.81
Sprinter	4,322	1.01	0.56	0.60	0.87	1.27	1.73	2.85
Marathoner	4,253	1.94	1.57	0.99	1.50	2.34	3.64	8.05

Panel C. Predicted acquisition intensity at particular serial acquirer type borders

Predicted (Acquisition intensity)	Mean
Change from Sprinter (Yr-2) to Marathoner in prior year	1.55
Change from Occasional (Yr-2) to Sprinter in prior year	0.95
Change from Occasional (Yr-2) to Marathoner in prior year	1.88
After being a Sprinter (Yr-2) no acquisitions in prior year	0.21
After being an Occasional (Yr-2) no acquisitions in prior year	0.20

Table 7. Anticipation adjustment factors

The table reports the mean [and median] anticipation-adjustment factor using the predicted firm-level acquisition intensity, $\bar{\lambda}_{i,t}$, based on equation (6). Variables are winsorized at the 5 and 95 percent level. The serial acquirer type as of the prior year is estimated based on the ex-ante classification that used the 5-year rolling window which ended in the year prior to the current year. Variables are defined in the Appendix.

Mean [median]	Total	Loner	Occasional	Sprinter	Marathoner
Total	3.69 [1.29]	1.08 [1.08]	1.29 [1.21]	1.60 [1.41]	7.75 [2.10]
AIN					
1	1.14 [1.11]	1.06 [1.08]	1.18 [1.15]	1.22 [1.17]	1.37 [1.25]
2-4	1.34 [1.32]	1.13 [1.11]	1.31 [1.32]	1.42 [1.40]	1.54 [1.45]
5-9	2.10 [1.85]		1.57 [1.53]	1.98 [1.79]	2.36 [2.02]
10-15	3.77 [2.63]				3.77 [2.63]
>=16	19.13 [7.20]				19.13 [7.20]

Table 8. Acquirer abnormal returns

Panel A reports the unadjusted abnormal returns using a 3-day window [-1, +1], around the acquisition announcement by serial acquirer type and by acquisition index number (AIN). Panel B shows the anticipation-adjusted abnormal returns based on equation (7). Variables are winsorized at the 1 and 99 percent level. The serial acquirer type as of the prior year is estimated based on the ex-ante classification using the 5-year rolling window which ended in the year prior to the current year. Variables are defined in the Appendix.

Panel A. Average unadjusted abnormal returns by serial acquirer type

	Total	Loner	Occasional	Sprinter	Marathoner
Total	0.0078	0.0129	0.0110	0.0076	0.0025
AIN					
1	0.0115	0.0138	0.0122	0.0086	0.0042
2-4	0.0080	0.0102	0.0107	0.0065	0.0025
5-9	0.0056		0.0087	0.0078	0.0029
10-15	0.0022				0.0022
>=16	0.0017				0.0017

Panel B. Average anticipation-adjusted abnormal returns by serial acquirer type

	Total	Loner	Occasional	Sprinter	Marathoner
Total	0.0123	0.0138	0.0133	0.0112	0.0111
AIN					
1	0.0126	0.0147	0.0138	0.0102	0.0053
2-4	0.0031	0.0109	0.0109	0.0136	0.0084
5-9	0.0080		0.0091	0.0091	0.0139
10-15	0.0132				0.0132
>=16	0.0188				0.0188

Table 9. Acquirer abnormal returns for large and small deals

This table replicates Table 6 Panels B and C after splitting the sample based on large and small deals. We classify a deal as a large deal if the target's relative size is at least 1% of the acquirer, and if the transaction value is at least $1 million dollars. Panel A reports the proportion of all deals that are large-size deals in the sample. Panels B and D report the unadjusted abnormal returns using a 3-day window [-1, +1], around the acquisition announcement. Panels C and E show the anticipation-adjusted abnormal returns derived from the first element of equation (5). The serial acquirer type as of the prior year is estimated based on the ex-ante classification using the 5-year rolling window which ended in the year prior to the current year. Variables are winsorized at the 1 and 99 percent level. Variables are defined in the Appendix.

Panel A. Proportion large-size deals by serial acquirer type

	Total	Loner	Occasional	Sprinter	Marathoner
Total	0.37	0.46	0.44	0.42	0.26
AIN					
1	0.46	0.47	0.50	0.47	0.37
2-4	0.33	0.43	0.43	0.42	0.43
5-9	0.29		0.39	0.39	0.37
10-15	0.29				0.29
>=16	0.14				0.14

Panel B. Large deals: Unadjusted abnormal returns by serial acquirer type

	Total	Loner	Occasional	Sprinter	Marathoner
Total	0.0111	0.0148	0.0131	0.0097	0.0053
AIN					
1	0.0139	0.0161	0.0139	0.0094	0.0077
2-4	0.0104	0.0104	0.0136	0.0093	0.0043
5-9	0.0083		0.0065	0.0104	0.0068
10-15	0.0033				0.0033
>=16	0.0043				0.0043

Panel C. Large deals: Anticipation-adjusted abnormal returns by serial acquirer type

	Total	Loner	Occasional	Sprinter	Marathoner
Total	0.0162	0.0165	0.0160	0.0155	0.0162
AIN					
1	0.0159	0.0178	0.0157	0.0120	0.0113
2-4	0.0068	0.0120	0.0120	0.0181	0.0127
5-9	0.0184		0.0032	0.0032	0.0209
10-15	0.0124				0.0124
>=16	0.0368				0.0368

Panel D. Small deals: Unadjusted abnormal returns by serial acquirer type

	Total	Loner	Occasional	Sprinter	Marathoner
Total	0.0058	0.0113	0.0093	0.0060	0.0015
AIN					
1	0.0095	0.0118	0.0106	0.0079	0.0021
2-4	0.0064	0.0100	0.0086	0.0043	0.0016
5-9	0.0043		0.0101	0.0063	0.0013
10-15	0.0018				0.0018
>=16	0.0013				0.0013

Panel E. Small deals: Anticipation-adjusted abnormal returns by serial acquirer type

	Total	Loner	Occasional	Sprinter	Marathoner
Total	0.0100	0.0115	0.0111	0.0081	0.0092
AIN					
1	0.0098	0.0120	0.0120	0.0086	0.0017
2-4	0.0012	0.0100	0.0100	0.0103	0.0052
5-9	0.0039		0.0129	0.0129	0.0098
10-15	0.0135				0.0135
>=16	0.0158				0.0158

Table 10. Regressions of acquirer abnormal returns

Panel A reports coefficients from OLS regressions of unadjusted abnormal returns (models 1 and 3) and of anticipation-adjusted abnormal returns derived from the first element of equation (5) (models 2 and 4) on the acquisition index number by deal size. Panel B reports the coefficients from OLS regressions for the large size and small-size subsamples. The list of other controls is market-to-book ratio, private target, subsidiary target, log(assets), sales growth, long-term debt / assets, R&D / assets, operating performance, number of firms in industry, cash / assets, log (age), after 2001, cash-only, and stock-only. The serial acquirer type as of the prior year is estimated based on the ex-ante classification using the 5-year rolling window which ended in the year prior to the current year. Variables are defined in the Appendix. The regressions use Eicker-Huber-White-Sandwich heteroskedastic-robust standard errors, reported in parentheses (clustered by year). ***, **, * denote significance at 1%, 5% and 10% levels, respectively.

Panel A. OLS regressions of acquirer abnormal returns on acquisition index number by serial acquirer type

Model								
Subsample	All	All	Occasional	Occasional	Sprinter	Sprinter	Marathoner	Marathoner
Dependent variable	Unadjusted CARs	Anticipation Adjusted CARs	Unadjusted CARs	Anticipation Adjusted CARs	Unadjusted CARs	Anticipation Adjusted CARs	Unadjusted CARs	Anticipation Adjusted CARs
Model	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
log(AIN)	-0.155***	0.000	-0.146	-0.003	0.410	0.003	-0.144**	-0.003
	(0.054)	(0.008)	(0.345)	(0.004)	(0.739)	(0.014)	(0.058)	(0.015)
Other controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Intercept	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry and Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.027	0.002	0.041	0.037	0.029	0.026	0.019	0.003
N	31,911	30,373	9,089	9,089	5,259	5,259	16,025	16,025

Panel B. OLS regressions of acquirer abnormal returns on acquisition index number by deal size

Subsample	Large deals	Large deals	Small deals	Small deals
Dependent variable	Unadjusted CARs	Anticipation Adjusted CARs	Unadjusted CARs	Anticipation Adjusted CARs
Model	(1)	(2)	(3)	(4)
log(AIN)	-0.166	0.008	-0.126**	-0.002
	(0.103)	(0.008)	(0.049)	(0.010)
Other controls	Yes	Yes	Yes	Yes
Intercept	Yes	Yes	Yes	Yes
Industry and Year Fixed Effects	Yes	Yes	Yes	Yes
R^2	0.052	0.011	0.016	0.003
N	10,773	10,198	21,138	20,175

Table 11. Dollar gains from acquisitions

The table reports anticipation-adjusted dollar gains from acquisitions by serial acquirer type and number of acquisitions. Panel A reports the mean and median for the whole sample. Panel B and C report the mean and median for the large-and small-deal subsamples respectively. The serial acquirer type as of the prior year is estimated based on the ex-ante classification using the 5-year rolling window which ended in the year prior to the current year.

Panel A. All deals

Mean{median] $mil	Total	Loner	Occasional	Sprinter	Marathoner
Total	5.36 [0.36]	4.03 [0.21]	3.61 [0.36]	5.27 [0.56]	7.29 [1.01]
AIN					
1	5.09 [0.29]	4.21 [0.20]	3.39 [0.45]	6.71 [0.43]	9.49 [1.33]
2-4	4.27 [0.37]	3.44 [0.25]	3.83 [0.35]	6.14 [0.69]	4.67 [1.01]
5-9	6.76 [0.51]		3.07 [0.01]	3.68 [0.65]	10.41 [0.85]
10-15	3.42 [0.37]				3.42 [0.37]
>=16	8.33 [2.90]				8.33 [2.90]

Panel B. Large deals

Mean{median] $mil	Total	Loner	Occasional	Sprinter	Marathoner
Total	6.31 [0.65]	6.15 [0.4]	3.5 [0.58]	4.83 [0.83]	10.05 [2.56]
AIN					
1	7.81 [0.53]	7.16 [0.41]	3.87 [0.64]	7.55 [0.61]	17.98 [2.11]
2-4	3.6 [0.66]	2.62 [0.34]	4.77 [0.65]	1.24 [1.28]	3.81 [2.23]
5-9	6.18 [1.05]		-7.33 [-0.04]	5.87 [0.86]	12.12 [3.33]
10-15	3.42 [1.7]				3.42 [1.7]
>=16	14.29 [6.81]				14.29 [6.81]

Panel C. Small deals

Mean{median] $mil	Total	Loner	Occasional	Sprinter	Marathoner
Total	4.79 [0.21]	2.22 [0.14]	3.7 [0.23]	5.6 [0.43]	6.32 [0.41]
AIN					
1	2.78 [0.18]	1.6 [0.12]	2.91 [0.34]	5.97 [0.26]	4.49 [0.81]
2-4	4.72 [0.24]	4.07 [0.21]	3.14 [0.21]	9.86 [0.35]	5.1 [0.44]
5-9	7.05 [0.35]		9.8 [0.04]	2.36 [0.51]	9.72 [0.19]
10-15	3.42 [-0.24]				3.42 [-0.24]
>=16	7.33 [1.3]				7.33 [1.3]

Table 12. Extraordinary acquirers and persistence in cumulative abnormal returns and dollar gains.
Panel A reports the proportion of transactions conducted by each serial acquirer type. Future dollar gains are anticipation-adjusted. Panel B, replicates Table 4 of Golubov, Yawson, and Zhang (2015) (pg. 320), and reports the persistence in future average unadjusted abnormal returns for the "extraordinary acquirers". Panel C reports the average and the persistence in cumulative anticipation-adjusted dollar gains over *k* years by past return performance. The initial sample contains all observations with required data based on the entire sample of 239,120 firm-year observations of firms in COMPUSTAT. The serial acquirer type as of the prior year is estimated based on the ex-ante classification using the 5-year rolling window which ended in the year prior to the current year. Variables are defined in the Appendix.

Panel A. Proportion of acquisitions conducted by serial acquirer type

Avg. past unadjusted CAR		Total	Occasional	Sprinter	Marathoner
Bottom tercile		0.31	0.33	0.29	0.24
Mid tercile		0.39	0.33	0.45	0.59
Top tercile	"Extraordinary acquirers"	0.30	0.33	0.26	0.18

Panel B. Persistence of average unadjusted abnormal returns

	Average future unadjusted CAR measured over	All	Occasional	Sprinter	Marathoner
Total	1 year	0.52%	0.72%	0.42%	0.14%
	2 years	0.53%	0.70%	0.45%	0.13%
Avg. past unadjusted CAR terciles (measured over prior 3 years)					
Bottom tercile	1 year	0.44%	0.51%	0.41%	0.24%
	2 years	0.46%	0.53%	0.42%	0.25%
Mid tercile	1 year	0.34%	0.54%	0.24%	0.13%
	2 years	0.37%	0.56%	0.34%	0.08%
Top tercile	1 year	0.91%	1.12%	0.79%	0.03%
	2 years	0.85%	1.01%	0.68%	0.14%

Panel C. Average cumulative anticipation-adjusted dollar gains over *k* years by past return performance

	Average future cumulative dollar gain measured over	All	Occasional	Sprinter	Marathoner
Total	1 year	3.39	-0.21	8.82	7.71
	2 years	6.52	0.17	18.37	14.22
CAR terciles measured over past 3 years					
Bottom tercile	1 year	-2.98	-8.06	8.53	2.94
	2 years	-3.67	-9.67	10.24	5.16
Mid tercile	1 year	6.04	-0.35	6.75	14.41
	2 years	8.94	-0.96	18.27	18.99
Top tercile	1 year	6.02	7.72	13.07	-10.61
	2 years	13.65	11.07	27.94	9.48

Solving Serial Acquirer Puzzles

ANTONIO J. MACIAS
Baylor University

P. RAGHAVENDRA RAU
University of Cambridge

ARIS STOURAITIS
Hong Kong Baptist University

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Macias: Hankamer School of Business, Baylor University, USA (e-mail: Antonio_Jesus@baylor.edu; tel. +1(254)710-4140); Rau: University of Cambridge, Judge Business School, Trumpington Street, Cambridge CB2 1AG, UK. (email: r.rau@jbs.cam.ac.uk; tel. +44 (0)1223 761079); Stouraitis: School of Business, Hong Kong Baptist University, Renfrew Road, Kowloon Tong, Hong Kong, People's Republic of China (stoura@hkbu.edu.hk; tel. (852) 3411 7561). We would like to thank Goutham Abotula, Eli Fich, Andrey Golubov, David Hirshleifer, Sandy Klasa, Kai Li, Peter Limbach, Marc Lipson,, Irvin C. Notting, Dimitris Petmezas, Mike Stegemoller, Wenyu Wang, Morad Zekhnini, participants at the 2021 FMA Annual Meeting, the Universidad de los Andes Corporate Finance Conference, and seminar participants at Baylor University, Indian School of Business, and Nursultan Nazarbayev University for helpful comments.