# Win-Stay, Lose-Shift: A Strategy of Serial Acquirers<sup>\*</sup>

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January 14, 2019

<sup>\*</sup>We are grateful to Thomas Bates, Hendrik Bessembinder, Oliver Boguth, Ling Cen, Dan Dhaliwal, Matthew Hayes, Michael Hertzel, Stephen Hillegeist, Andrew Karolyi, Laura Lindsey, Michael Matejka, Mike Mowchan, Seth Pruitt, Anand Vijh, Wenyu Wang and seminar participants at the Arizona State University (Finance and Accounting), Auckland Finance Meeting, 2016 Financial Management Association (FMA) Annual Meeting, and 2016 Northern Finance Association (NFA) Annual Meeting for helpful comments and suggestions. This paper won the Best Paper Award at the 2017 Auckland Finance Meeting. Any errors are our own.

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#### Abstract

We show that serial acquirers are likely to repeat (avoid) strategies that produced good (bad) outcomes in the past. This behavior cannot be explained by rational learning because serial acquirers with positive (negative) return experiences are more likely to initiate value-destroying (value-enhancing) mergers in terms of both market reaction and operating performance. We also discover that, following successful acquisition, higher institutional ownership mitigates excessive acquisitiveness of serial acquirers; after bad outcomes, financial expertise on corporate boards helps identify value-enhancing deals. Finally, past successes lead to future mergers by increasing managers' confidence, whereas negative experiences directly curb firms' acquisitiveness.

Keywords: Serial Acquirers, Mergers and Acquisitions, Corporate Gover-NANCE, REINFORCEMENT LEARNING, OVERCONFIDENCE JEL CLASSIFICATIONS: D81, G02, G14, G34

## 1. Introduction

A large majority of mergers and acquisitions (M&As) in the United States are made by serial acquirers. In a sample of 17,083 mergers from 1980 to 2013, 82.92% of deals were made by serial acquirers, accounting for 91.03% of total transaction value.<sup>1</sup> Despite the economic significance of M&A activities by these serial acquirers, few studies have explored the motives and performance of these firms (Karolyi et al., 2015). Notable exceptions are those by Fuller et al. (2002), Klasa and Stegemoller (2007), Billett and Qian (2008), Ahern (2010), and Karolyi et al. (2015). These studies primarily focus on the pattern of decreasing announcement returns from first to subsequent deals and try to find credible explanations for this pattern. Taking a different angle, we investigate behavioral biases of serial acquirers within the dynamics of the acquisition decision to understand who becomes a serial acquirer, what drives their subsequent merger decisions, the value consequences of such decisions, and the role of corporate governance in mitigating these biases.

Using a large sample of U.S. firms from 1980 to 2013, we find that past acquisition return experiences (over 3, 5, or 10 years), measured as the 3-day announcement returns, significantly and strongly predict the likelihood of future acquisitions: positive experiences predict a higher likelihood (*reinforcement*) while negative experiences predict a lower likelihood (*punishment*).<sup>2</sup> These results are robust to standard merger determinants such as Q, size, leverage, and cash flow, and to firm fixed effects that remove the impact of time-invariant firm characteristics. In addition, M&A strategies in previously successful deals, such as acquiring a private target or a within-industry acquisition, are more likely to be repeated in the next acquisition. We interpret

<sup>&</sup>lt;sup>1</sup>There is no consensus on the definition of serial acquirers. In this paper we define serial acquirers as firms that made acquisitions in more than one year over the sample period. We use this definition for two reasons. First, since we examine whether past M&A return experiences affect subsequent merger decisions, we require enough time between prior and subsequent deals to make past announcement returns a feedback in subsequent merger decisions. Second, we want to avoid classifying firms with a single program of acquisitions that includes multiple deals as serial acquirers. Our main results are qualitatively similar once we define serial acquirers as firms that made more than five acquisitions over the sample period, as in Karolyi et al. (2015).

<sup>&</sup>lt;sup>2</sup>The terms, *reinforcement* and *punishment*, are from Skinner (1953).

these findings as reinforcement learning by serial acquirers. Reinforcement learning is a simple model of learning posited by the psychology literature based on the law of effect (Thorndike, 1898; Skinner, 1953): choices that lead to good (bad) outcomes in the past are more likely to be repeated (shunned) in the future, even if this past success (failure) does not logically predict future success (failure).<sup>3</sup> Moreover, we find that firms that experience higher announcement returns in early acquisitions have a greater chance of becoming serial acquirers.

It is crucial to examine value consequences to distinguish reinforcement learning from Bayesian (rational) learning. There are two different types of rational learning that could influence firms' merger decisions. The first type of rational learning assumes that firms' acquisition skills are fixed and that firms learn about their own talent by doing M&As. It may be rational for firms with high (low) skill to initiate more (fewer) acquisitions, which would be consistent with the prediction of reinforcement learning. However, we would expect high (low) past announcement returns to be associated with value-enhancing (value-destroying) subsequent deals, which is contrary to our findings. The second type of rational learning assumes a firm can improve its acquisition skill through serial acquisitions. We would then see more value-enhancing mergers in later acquisitions as serial acquirers become more adept in managing acquisitions.<sup>4</sup> Low past announcement returns, which is consistent with our findings. However, we would not expect to observe the opposite, which we find in this study: negative value consequences of subsequent mergers after deals with high announcement returns.

Consistent with reinforcement learning hypothesis, we find that serial acquirers with higher positive (negative) return experiences are more likely to initiate value-destroying (value-enhancing)

 $<sup>^{3}</sup>$ Erev and Roth (1998) find that a reinforcement learning model outperforms forward-looking models in predicting how games proceed in economics experiments. Charness and Levin (2005) show that when optimal strategies conflict with a reinforcement learning strategy, individuals tend to follow the latter.

<sup>&</sup>lt;sup>4</sup>The prediction of this second type of rational learning is inconsistent with decreasing pattern of announcement returns that is documented in the literature. We confirm the declining pattern of announcement returns in our sample.

mergers and are less likely to engage in value-enhancing (value-destroying) ones in terms of acquirer shareholder wealth. We interpret these findings as good acquisition experiences lead acquirers to overestimate the value of subsequent deals and hence to misclassify a negative net present value (NPV) deal as a positive one. However, poor merger experiences lead firms to be more cautious (e.g., to exert greater due diligence after a run of bad outcomes) in making subsequent decisions; as a result, the subsequent deals turn out to be value-enhancing ones. Further, positive (negative) return experiences are associated with negative (positive) market reactions to subsequent bids. We also find that subsequent mergers by firms with positive experiences underperform those by firms with negative experiences in terms of operating performance over three years after the merger completion. These results provide strong support for reinforcement learning by serial acquirers.

This article is not the first one that points out such behavioral biases of serial acquirers. Billett and Qian (2008) are among the first who made a similar argument as in our paper. While the argument is appealing, the lack of concrete evidence in their paper draws our attention. First, they mostly use the number of previous deals or the order of the current deals to investigate its effects on the likelihood and announcement returns of subsequent deals. Since they do not exploit the performance of previous acquisitions, their empirical evidence is insufficient to support their argument that "... acquisition likelihood increases in the *performance* associated with previous acquisitions ..."<sup>5</sup> In contrast, we investigate dynamic reinforcement learning behavior of frequent acquirers by directly examining the effects of positive and negative experiences. Second, they rely on within-industry variations or univariate tests although such behavioral biases should be tested using within-firm variations. Suppose that a firm is inherently good at doing acquisitions. The firm's superior ability will be associated with both merger announcement returns and the likelihood of engaging in additional deals. Therefore one could observe a spurious positive association between past announcement returns and likelihood of future acquisitions even if the firm do not

 $<sup>^{5}</sup>$ They use the three-year buy-and-hold excess return to investigate its relation to future merger frequency in a univariate test of Table 5.

react to the outcomes of its own previous deals. Third, they claim that poor experiences do not affect subsequent acquisitiveness due to self-attribution bias of CEOs. In line with their view, we provide explicit evidence of self-attribution bias by showing that CEO overconfidence increases after successful acquisitions but do not decrease after the failure. However, contrary to their argument, we find that negative return experiences do discourage firms from initiating future acquisitions, *punishment*, which is consistent with the theories of reinforcement learning. Surprisingly, no prior literature has thoroughly investigated this interesting and important idea raised by Billett and Qian (2008). In this article, we provide a complete picture of serial acquirers' behavior by documenting more concrete evidence for the argument that has been floating around in the literature without sufficient evidence.

After having identified reinforcement learning behavior of serial acquirers, we explore the role of corporate governance in mitigating such behavioral biases. We use institutional ownership and financial expertise on corporate boards as proxies for quality of corporate governance. Firms with higher institutional ownership are less likely to engage in value-destroying deals after positive return experiences, whereas firms with a higher fraction of financial experts on boards are more likely to initiate value-enhancing acquisitions after negative return experiences. Hence institutional ownership mitigates serial acquirers' excessive acquisitiveness following good experiences, while financial expertise on boards helps identify value-enhancing deals after bad outcomes.

To shed some light on a potential channel of these experience effects, we then examine the relative importance of firms and CEOs in explaining our findings. We find that CEO overconfidence can be predicted by the past acquisition experiences of the acquirer. Specifically, positive acquisition experiences increase CEO overconfidence but negative ones have no effect. This result is consistent with one common source of overconfidence documented by the psychology literature: self-attribution bias (Langer and Roth, 1975). CEOs who are subject to self-attribution bias overcredit their role in bringing about good outcomes and overcredit external factors or bad luck with bad outcomes. Our results show that the acquisition experiences of CEOs, coupled

with self-attribution bias, can explain changes in their overconfidence. Interestingly, we find that CEO overconfidence partially subsumes the effect of positive return experiences whereas negative return experiences do predict a significantly lower acquisition likelihood even in the presence of CEO overconfidence. This result suggests that poor acquisition return experiences help prevent future bad deals, perhaps because a management team exerts greater due diligence after a run of bad outcomes.

This study makes three primary contributions to the literature. First, it extends the literature on serial acquirers by investigating their behavior from a new perspective. Prior studies focus primarily on the pattern of decreasing announcement returns from first to subsequent deals and provide evidence for possible explanations of this pattern: agency-cost explanations (Jensen, 2005; Karolyi et al., 2015); an opportunity set hypothesis (Klasa and Stegemoller, 2007); a hubris hypothesis (Billett and Qian, 2008); an anticipation hypothesis (Fuller et al., 2002). In contrast to this literature, we focus on behavioral biases of serial acquirers within the dynamics of the acquisition decisions to understand what drives their future merger decisions and the value consequences of such decisions.

Second, this study builds on the line of research investigating behavioral biases in corporate decisions. Malmendier and Tate (2005) and Malmendier and Tate (2008) document that CEO overconfidence affects capital expenditure and merger decisions. Malmendier et al. (2011) show that managers' early experiences in the Great Depression and in the military influence corporate financing and investment decisions. Dittmar and Duchin (2016) find that a manager's distress experience in a previous firm affects corporate leverage and investment in the current firm. Uniquely, we study the effect of experiences in one domain of corporate policy, M&As, on the subsequent decisions in the *same* domain. In doing so we are able to interpret our findings as strong evidence for reinforcement learning. Corporate takeovers are indeed one area of investigation in which behavioral biases should be investigated seriously for the following three reasons. First, M&A decisions are subject to the reinforcement learning heuristic since takeovers reflect an individual's or a small group's (such as a board of director's) decision (Malmendier and Tate, 2008; Malmendier and Zheng, 2012). Second, corporate mergers are an ideal setting in which to test reinforcement learning because immediate and clear feedback from the market is available at the deal level, which is usually not the case for most corporate decisions. Finally and of greatest importance, the economic impact of serial acquirers' behavioral biases will be stronger than that of individual investors. While a large literature shows decisively that individuals do not always make rational decisions under uncertainty, it usually has little predictive content for market behavior.<sup>6</sup> On the other hand, a firm's behavioral biases have non-trivial economic consequences. Hence our paper also extends a strain of research on reinforcement learning heuristics at the individual level (Benartzi, 2001; Kaustia and Knüpfer, 2008; Choi et al., 2009; Anagol et al., 2015) to the organizational level.

Our final contribution is to provide potential explanations for one particularly interesting observation reported in Table V of Moeller et al. (2005). They state, "The firms that make large loss deals are *successful* with acquisitions until they make their large loss deal." Specifically, it documents that before making large loss deals, firms successfully make public target and/or equity-financed acquisitions. Interestingly, an overwhelming portion of large loss deals use the same strategies. But after a large loss, the firms avoid engaging in future M&As. They argue that these large loss deals cannot be fully reconciled with firm and deal characteristics, misvaluation-driven acquisitions, or signals of lack of internal growth opportunities. This article echoes a potential explanation for this observation through reinforcement learning behavior of frequent acquirers.

<sup>&</sup>lt;sup>6</sup>Choi et al. (2009) find individuals increase their savings rate after a high average and/or low variance return and interpret this behavior as consistent with reinforcement learning. See also Benartzi (2001), Kaustia and Knüpfer (2008), Anagol et al. (2015), and Dittmar and Duchin (2016) for the applications in the finance.

## 2. Data

We use the Securities Data Company (SDC) U.S. Mergers and Acquisitions database for the analysis of corporate acquisition decisions. We consider a sample of firms that announced *at least* one acquisition between fiscal years 1980 and 2013.<sup>7</sup> We require that the acquirer is a U.S. public company; that the target is public, private, or a subsidiary; that the acquirer has annual financial statement information available from the Compustat and stock return data from the Center for Research in Securities Prices (CRSP) Daily Stock Price and Returns file; and that the acquisition was completed. Following Harford et al. (2012) and Erel et al. (2012), we further require that the acquirer owns 100% of the target shares after the acquisition; we omit acquisitions in which the acquirer already holds more than 50% of the target shares before the announcement. We exclude leveraged buyouts (LBOs), spinoffs, recapitalizations, self-tender offers, exchange offers, repurchases, partial equity stake purchases, acquisitions of remaining interest, and privatizations. Finally, we require the transaction value to exceed \$1 million and to be at least 1% of the acquirer's market capitalization 11 days before the announcement date.

We measure cash flow as earnings before extraordinary items (IB) plus depreciation (DP), and capital as property, plants, and equipment (PPENT). We normalize cash flow with beginning-of-year capital. We measure Q as the ratio of market value of assets to book value of assets. The market value of assets is defined as total assets (AT) plus market equity minus book equity. Market equity is defined as common shares outstanding (CSHO) times fiscal-year closing price (PRCC\_F). Book equity is calculated as stockholders' equity (SEQ) minus preferred stock liquidating value (PSTKL) plus balance sheet deferred taxes and investment tax credit (TXDITC) when available minus post-retirement assets (PPROR) when available.<sup>8</sup> The book value of assets is total assets, and earnings is income before extraordinary items. Leverage is total debt (DLTT + DLC) over total assets at the beginning of the year. Size is the log of total assets at the beginning of the year where total assets is converted into December 2012 constant dollars using

<sup>7</sup>We start our analysis in 1983 because the shortest window for past acquisition experiences is three years.

<sup>&</sup>lt;sup>8</sup>We closely follow the definitions of Q and its components, as in Fama and French (2002)

the Consumer Price Index for All Urban Consumers (CPI-U) inflation rates.

Relative size is the deal value divided by the market value of the bidding firm's equity 11 days prior to the announcement date; relatedness is an indicator variable set to one if the acquirer and target are operating in the same industries with a common two-digit Standard Industrial Classification code and zero otherwise; and friendly is a binary variable with a value of 1 if the bid is reported as friendly. Public, private, and subsidiary are indicator variables with a value of 1 if the bid is for a public, private, or subsidiary target; and cash (stock) is a binary variable where 1 indicates that the 100% of the acquisition was financed with cash (stock). To ensure that our results are not driven by outliers, we winsorize all relevant variables at the 1% level.

## 3. Measuring Past Acquisition Return Experiences

We construct three different measures for acquisition return experiences over the previous 3-, 5-, and 10-year windows: *Transaction Value Weighted Return*, *Equally Weighted Return* and *Success Ratio*.

Transaction Value Weighted Return is a transaction value weighted average of announcement returns during the corresponding experience windows where announcement returns are either raw returns or abnormal returns of the acquiring firm's stock over a three-day window starting one day before the announcement date (Equation (1)). Abnormal returns are the difference between raw returns and value-weighted market index returns. Similarly, we define *Equally Weighted Return* as an equally weighted average of announcement returns (Equation (2)).

$$Transaction Value Weighted Return_{i,t}$$
(1)  
= 
$$\frac{\sum_{j=1}^{n_{i,t}^{(w)}} Transaction Value_{i,j} \times Announcement Return_{i,j}}{\sum_{j=1}^{n_{i,t}^{(w)}} Transaction Value_{i,j}}$$

$$Equally Weighted Return_{i,t} = \frac{\sum_{j=1}^{n_{i,t}^{(w)}} Announcement Return_{i,j}}{n_{i,t}^{(w)}}$$
(2)

where  $n_{i,t}^{(w)}$  is the total number of merger announcements of firm i at time t over the past w year window and j indicates corresponding past mergers. Stock market reaction may or may not be a correct measure of merger synergy; however, it is clear, immediate, and observable feedback from the market. Hence firms perceive it as an indicator of past acquisition performance (experience) and do care about it when they make a merger decision.

From an economic point of view, *Equally Weighted Return* might be a more appropriate measure of past acquisition experiences than *Transaction Value Weighted Return* in the sense that the economic impact of announcements on acquiring firms can be directly measured by announcement returns of their stocks *regardless* of transaction values of the corresponding acquisitions. In other words, announcement returns already take into account the economic effect of transaction values on acquiring firms' values. For instance, an abnormal announcement return would be close to zero if the transaction value of the announced deal was negligible relative to the size of the acquirer.

On the other hand, past acquisition experiences could be formed by a *salience-weighted* announcement return where corresponding transaction values proxy for the salience of past acquisitions. Large deals are salient not only because they are more likely to be deeply implanted in one's memory but also because such deals are more likely to be covered by leading business publications, which increases their salience. Therefore we use *Transaction Value Weighted Return* as another measure of past acquisition experiences.

One shortcoming of the above-mentioned two measures is that they can be dominated by one extreme announcement return. For this reason we construct an alternative measure, *Success*  *Ratio*, as follows:

Success Ratio<sub>i,t</sub> = 
$$\frac{\sum_{j=1}^{n_{i,t}^{(w)}} \mathbb{1}_{\{Announcement Return_{i,j} > 0\}}}{n_{i,t}^{(w)}}$$
(3)

where  $n_{i,t}^{(w)}$  is the total number of merger announcements of firm i at year t over the past w year window and j indicates corresponding past mergers. It is a ratio of the number of successful deals to the total number of deals during the previous 3-, 5-, and 10-year windows. We define successful deals as those with positive announcement returns.

## 4. Do Past Acquisition Return Experiences Lead to More Mergers?

## 4.1. Baseline Specification

We first test whether a firm exhibits reinforcement learning behavior when it makes a merger decision. Using the following fixed effects logit regression, we test if there is a positive association between acquisition return experiences and propensity to engage in subsequent mergers:

$$Pr\{Y_{i,t} = 1 | Past \ Acquisition \ Experiences_{i,t}, \ X_{i,t}\}$$

$$= F(\beta_i + \beta_t + \beta_1 Past \ Acquisition \ Experiences_{i,t} + X'_{i,t}B)$$

$$(4)$$

where  $Y_{i,t}$  is a binary variable having the value 1 if the firm i announced at least one merger bid in year t that was eventually completed; *Past Acquisition Experiences*<sub>i,t</sub> is our main variable, one of the following three measures over the previous 3-, 5-, and 10-year windows: *Transaction Value Weighted Return, Equally Weighted Return,* and *Success Ratio*;  $X_{i,t}$  is a set of controls, including size, Q, leverage, and cash flow following the literature;  $\beta_i$  and  $\beta_t$  are firm and year fixed effects respectively; and F(.) is the logistic cumulative distribution function. We cluster standard errors by firm. We predict  $\beta_1$ , the coefficient on the past acquisition experiences, to be positive. We estimate Equation (4) with a conditional logit regression to include firm fixed effects and to avoid the incidental parameter problem (see Wooldridge, 2011 for more detail). Conditioning the likelihood on the total number of fiscal years with at least one merger in each firm, we avoid estimating the coefficients of fixed effects and estimate parameters of interest consistently.

Our main variable, past acquisition experiences, has two types of variations: cross-sectional and within-firm variations. Since we employ logit regressions with firm fixed effects, our estimation only exploits within-firm variations in the past merger experiences. Notice that firm fixed effects capture *time-invariant*, unobservable firm-specific acquisitiveness whereas past acquisition experiences are *time-varying* measures within a firm.

Using firm fixed effects in our model is crucial in the sense that we might obtain spurious positive  $\beta_1$  from the cross-sectional variations in past acquisition experiences. Suppose that a firm is consistently good at doing acquisitions. The firm's ability will be positively associated with merger announcement returns, and at the same time the firm will engage in more merger activities because it has competence in acquiring firms. Therefore there could be a positive association between past acquisition experiences and frequency of future acquisitions even if firms do not exhibit reinforcement learning behavior in merger decisions. Given that our specification is stringent, finding positive  $\beta_1$  is strong evidence of reinforcement learning behavior.

Table 2 presents results from the fixed effects logit regressions in Equation (4) that are estimated using a conditional logit specification. In Panel A of Table 2, we define *Past Acquisition Experiences* as *Transaction Value Weighted Return*. Column (1)-(3) use raw returns and column (4)-(6) use abnormal returns as announcement returns in constructing *Transaction Value Weighted Return*. We find significant positive coefficients on past acquisition experiences across all experience windows and also for both types of announcement returns. These results suggest that firms experiencing higher announcement returns on acquisitions are significantly more likely to engage in merger activities in the following year. Using *Equally Weighted Return* and *Success Ratio*, we obtain similar results as shown in Panels B and C of Table 2. To provide a sense of the economic magnitude of our results, we calculate the marginal effects of a one standard deviation increase in *Past Acquisition Experiences* on the probability of announcing acquisitions in the following year. Since the conditional logit estimation does not directly estimate the fixed effect coefficients, we are not able to calculate the marginal effects from the conditional logit estimates. Hence we adopt a linear probability model with year and firm dummy variables *only for* calculating the marginal effects.<sup>9</sup> In column (6) of Panel A the marginal effect of *Past Acquisition Experiences* is 1.25%, which is 6.37% increase relative to the unconditional mean of the dependent variable (19.62%). This is economically meaningful in the sense that the marginal effect of *Past Acquisition Experiences* is greater than that of cash flow (0.83%), one of the most significant determinants of merger frequency.

Among the controls, we find that when firms have more cash flow they tend to be more acquisitive, since cash alleviates financing constraints. More investment opportunities, measured by Q, tend to lead to more mergers. Finally, the effects of size and leverage on acquisitions are negative. Similar to the reasoning related to cash flow, firms that are high leveraged tend to be less acquisitive since they are more likely to be financially constrained.

That there is a negative effect of size on acquisitiveness seems counterintuitive at a glance. As pointed out by Moeller et al. (2004), the size of acquiring firm is negatively associated with the announcement return regardless of the method of financing and status of targets. On the other hand, there could be a mechanical positive relation between size and acquisitiveness because, in general, the assets of a firm increase as the result of a merger. Therefore, if there were no effect of *Past Acquisition Experiences* on acquisitiveness, we should obtain a negative mechanical relation between *Past Acquisition Experiences* and merger activities. Given this mechanical negative relation, finding a positive effect of *Past Acquisition Experiences* on future merger activities is strong evidence of reinforcement learning behavior. Indeed, if we omit the *Past Acquisition Experiences* 

 $<sup>^{9}</sup>$ The linear probability model also yields significant positive coefficients on our main variable, *Past Acquisition Experiences*, in all specifications.

regressor, we find a positive coefficient on size.

To complement the previous results, we also use the total number of deals for a given year as a dependent variable and estimate the effects of past acquisition experiences using the negative binomial or Poisson regression. Consistent with the previous results, firms experiencing higher announcement returns on acquisitions engage in a higher number of merger activities in the following year (not reported).

## 4.2. Deal Strategy Level Evidence

To strengthen our argument about reinforcement learning behavior, we now examine firms' behavior at the specific deal strategy level, public vs. private targets and within- vs. acrossindustry targets, using the following fixed effects logit regression:

$$Pr\{Y_{i,t}^{Target \ \theta} = 1 | Past \ Acquisition \ Experiences_{i,t}^{Target \ \gamma}, \ X_{i,t}\}$$

$$= F(\beta_i + \beta_t + \beta_1 Past \ Acquisition \ Experiences_{i,t}^{Target \ \gamma} + X'_{i,t}B)$$

$$where \ \theta, \ \gamma \in \{public, \ private\} \ or \ \{within \ industry, \ across \ industry\}$$
(5)

where  $Y_{i,t}^{Target \,\theta}$  is a binary variable having the value 1 if the firm i announced at least one merger bid in which the target is type  $\theta$  in year t; *Past Acquisition Experiences*<sub>i,t</sub>^{Target \gamma} is a transaction value weighted average of announcement returns of merger bids for type  $\gamma$  target during the past 10 years. We predict  $\beta_1$  to be positive only when  $\theta = \gamma$ . In other words, acquisition experiences with a certain type of target will have a more significant impact on future merger decisions with the same type of target than with other types of targets.

Panel A of Table 3 examines the status of target firms. Acquisition experience with public targets significantly predicts subsequent acquisition of public targets (significant coefficient of 1.37 in the specification (1)), but not of private targets (coefficient of 0.86 in the specification (2)). Similarly, acquisition experience with private targets is significantly associated with subsequent

acquisitions of private targets (1.12 in the specification (3)) but not of public targets (-0.17 in the specification (4)).

In another domain of strategies, within and across industry targets, we obtain similar results (Panel B of Table 3). A firm that experienced high stock returns in announcing acquisitions of within-industry targets is more likely to engage in the same type of deal in the following year (1.53 in the specification (1)). Experience with across-industry targets is also positively associated with a propensity to acquire other across-industry targets (0.62 in the specification (3)), but the coefficient is not significant. One possible reason for the insignificance is that within-industry targets are all in the same one industry, i.e., acquirer's industry, whereas across-industry targets are spread out in all other industries, leading to less predictive power. Overall, past successful M&A strategies are more likely to be repeated in subsequent acquisitions.

#### 4.3. Asymmetric Responses in Positive and Negative Experiences

To see if there are differential effects of positive and negative experiences, we separate *Past Acquisition Experiences* into two parts:

 $Positive \ Past \ Acquisition \ Experiences = Past \ Acquisition \ Experiences \times \mathbb{1}_{\{Past \ Acquisition \ Experiences \ge 0\}}$   $Negative \ Past \ Acquisition \ Experiences = -Past \ Acquisition \ Experiences \times \mathbb{1}_{\{Past \ Acquisition \ Experiences < 0\}}$ 

Including positive and negative past acquisition experiences in our basic regression (4) yields the following:

$$Pr\{Y_{i,t} = 1 | Past Acquisition Experiences_{i,t}, X_{i,t}\}$$

$$= F(\beta_i + \beta_t + \beta_1 Positive Past Acquisition Experiences_{i,t} + \beta_2 Negative Past Acquisition Experiences_{i,t} + X'_{i,t}B)$$
(6)

Table 4 shows that the propensity to engage in subsequent mergers responds asymmetrically

to past acquisition return experiences in positive and negative domains. Moreover, the patterns of the asymmetry vary across the experience windows. Whereas merger activities are more sensitive to the negative experiences in a short window (3 years), they are more responsive to the positive experiences in a long window (10 years).

## 4.4. Who Becomes a Serial Acquirer?

Finally, we examine the role of past acquisition return experiences in becoming a serial acquirer using the following fixed effects logit regressions.

$$Pr\{Y_{i}^{SerialAcquirer} = 1 | Value Weighted CARs_{i,t}, X_{i,t}\}$$

$$= F(\beta_{ind} + \beta_{t} + \beta_{1}Value Weighted CARs_{i,t} + X_{i,t}'B)$$
(7)

where  $Y_i^{SerialAcquirer}$  is a binary variable having 1 if the firm i is classified as a serial acquirer; Value Weighted  $CARs_{i,t}$  is our main variable, transaction value weighted announcement returns during the first fiscal year when the firm announces at least one acquisition.<sup>10</sup> Accordingly, the firm-level control variables are measured at the same first fiscal year. Note that Equation (7) is a cross-sectional regression in which explanatory variables may come from different years across firms depending on the first fiscal year when the firm announces at least one acquisition. We include industry and year fixed effects. We expect  $beta_1$  to be positive.

In Table 5 we show that firms experiencing high announcement returns in early acquisitions are indeed more likely to become serial acquirers. This is robust to the alternative definition of serial acquirers as used by Karolyi et al. (2015) (Column (2)).

<sup>&</sup>lt;sup>10</sup>As a robustness test, we define serial acquirers as firms that acquired more than five targets over the sample period (Karolyi et al. (2015)). The corresponding definition of *Value Weighted CARs*<sub>*i*,*t*</sub> is transaction value weighted announcement returns of up to the *first* five merger announcements over the sample period.

# 5. Do Past Experiences Lead to More Value-Destroying or Value-Enhancing Mergers?

We investigate whether acquisition experiences lead firms to engage in more value-destroying or value-enhancing mergers, measured by the acquirer's announcement returns and by changes in operating performance.

### 5.1. Market Reaction

First we examine whether acquisition experiences affect the propensity to engage in more value-destroying or value-enhancing mergers by employing the same regression specification as Equation (6) but replacing  $Y_{i,t}$  with either  $Y_{i,t}^{VD}$  or  $Y_{i,t}^{VE}$ :

$$Pr\{Y_{i,t}^{VD(VE)} = 1 | Past Acquisition Experiences_{i,t}, X_{i,t}\}$$

$$= F(\beta_i + \beta_t + \beta_1 Positive Past Acquisition Experiences_{i,j} + \beta_2 Negative Past Acquisition Experiences_{i,t} + X'_{i,t}B)$$

$$(8)$$

where  $Y_{i,t}^{VD(VE)}$  is a binary variable where 1 indicates that the firm engages in value-destroying (VD) (or value-enhancing (VE)) mergers in a given year t. We use a sign of transaction value weighted average of abnormal returns in year t to define value-destroying and value-enhancing mergers. If the sign is negative (positive), a firm is classified as engaging in value-destroying (value-enhancing) mergers. We include firm and year fixed effects and cluster standard errors by firm.

Firms that recently experienced high announcement returns may believe that subsequent acquisitions are likely to generate similarly rewarding outcomes. As a consequence, they tend to overestimate the cash flows from potential deals and misclassify a negative-NPV project as a positive-NPV project. Likewise, a firm with low market returns on past acquisition announcements becomes more cautious in selecting future merger deals and therefore is less likely to participate in value-destructive deals. Accordingly, we expect that  $\beta_1$ , the coefficient on the positive acquisition experiences, is positive (negative) for value-destroying (value-enhancing) mergers whereas  $\beta_2$ , the coefficient on the negative acquisition experiences, is negative (positive) for valuedestroying (value-enhancing) mergers.

Following a large body of prior literature, we view acquiring firms' stock returns around the announcement date as a proxy for the performance of acquisitions. This approach assumes that the market's assessment of the acquisition is an unbiased estimate of the impact of an acquisition on the wealth of acquirers' shareholders. These short-window returns are relatively less subject to misspecification than other measures of acquisition performance, such as long-window return measures. Nevertheless, using announcement returns is subject to the concern that they may incorporate the market's reassessment of the stand-alone value of the bidder (e.g., a lack of internal growth opportunities). If this is the case, the first deal announced by a given acquirer will be the most affected one. Our specification (Equation (8)), by construction, does not use the first announced deal for every acquiring firm because it requires the past acquisition experiences variable, which mitigates this inference problem. Moreover, in the next section, we examine operating performance after merger completion to directly gauge the value of the acquisition to the acquirer.

Panel A of Table 6 reports the results from the fixed effects logit regressions in Equation (8). The coefficients on *Positive Past Acquisition Experiences* are positive and significant in columns (1), (3), and (5), but significantly negative in columns (2), (4), and (6), suggesting that firms with higher positive return experiences are more likely to engage in value-destroying mergers and less likely to engage in value-enhancing mergers. The coefficients on *Negative Past Acquisition Experiences* are significantly negative in columns (1), (3), and (5), but significantly positive in columns (2), (4), and (6), indicating that firms with more negative return experiences are less likely to undertake value-destroying mergers and more likely to initiate value-enhancing mergers.

Our interpretation of these results is that positive announcement return experiences lead firms

to overestimate cash flows from subsequent deals and hence misclassify a negative-NPV project as a positive-NPV project. On the other hand, poor acquisition experiences make firms more cautious when making subsequent merger decisions (i.e., they perform greater due diligence after a run of bad outcomes), and future mergers turn out to be value-enhancing.

Interestingly, we find that firms are more responsive to past acquisition experiences in the *neg-ative* domain than to those in the *positive* domain for both value-destroying and value-enhancing mergers. Formal statistical tests show that (the absolute value of) coefficients on positive and negative experiences are significantly different from each other for all specifications but (5). For example, in column (4), the coefficient on positive experiences (1.7395) is significantly different from that on negative experiences (7.2040) at the 1% level (p-value 0.000). This is consistent with a *pessimism bias*: investors who experience losses form overly pessimistic beliefs about investment options; they overreact to outcomes in the negative domain relative to outcomes in the positive domain (Kuhnen, 2015). Hence our finding provides real-world evidence of a pessimism bias that is consistent with the experimental findings by Kuhnen (2015).

Second, given that a firm announces a merger, we examine cumulative abnormal returns of the acquiring firm's stock around the announcement date:

$$CAR[-1,+1]_{i,j,t} = \beta_i + \beta_t + \beta_1 Positive Past Acquisition Experiences_{i,t}$$
(9)  
+  $\beta_2 Negative Past Acquisition Experiences_{i,t} + X'_{i,t}B + Y'_{i,j}C + \epsilon_{i,j,t}$ 

where  $CAR[-1, +1]_{i,j,t}$  is a cumulative abnormal return on the bidder i's stock over a three-day window around the announcement date of merger bid j in fiscal year t; *Positive (Negative) Past Acquisition Experiences*<sub>i,t</sub> is based on a transaction value weighted average of announcement returns over the past 3-, 5-, and 10-year windows;  $X_{i,t}$  is a set of firm characteristics of firm i at year t; and  $Y_{i,j}$  is a set of deal characteristics of deal j by firm i. Closely following Harford et al. (2012), we include an extensive list of explanatory variables that are known to determine acquirer returns in the literature. We use size, Q, leverage, and cash flow for firm characteristics. Deal characteristics are relative size, industry relatedness of the target, friendly dummy, a set of target listing status dummies, and the method of payment. We also include firm and year fixed effects to control both for time trends in market reactions to merger bids and for the potential persistence of market reactions within a firm. We cluster standard errors by firm because firms may have unobservable acquisition skill; thus announcement returns may be autocorrelated within the firm. We predict  $\beta_1$  to be negative whereas  $\beta_2$  to be positive.

Panel B of Table 6 shows the result of estimating Equation (9). The market reaction is significantly negatively associated with *Positive Past Acquisition Experiences* and positively related to *Negative Past Acquisition Experiences*. The effect of acquisition experiences on the future announcement returns is economically significant as well. One standard deviation increase in positive acquisition experiences leads to a 1.10%, 1.28%, or 1.59% decrease in three-day abnormal returns to a subsequent deal announcement, whereas a one standard deviation increase in negative acquisition experiences leads to an increase of 1.85%, 1.27%, or 1.50% three-day abnormal returns to a subsequent merger announcement when acquisition experiences are measured as transaction value weighted average of announcement returns over the past 3-, 5-, 10-year windows respectively.

These results can be viewed as follows. The market views bids made by a firm after good acquisition experiences as suboptimal, knowing that a firm's greater acquisitiveness can lead to an increased propensity to undertake negative-NPV mergers. Similarly, the market appreciates merger bids that a firm makes subsequent to poor acquisition experiences, knowing that the firm has done more due diligence in contemplating the merger.

These results, shown in Table 6, also help us to rule out the alternative explanation that firms may learn about their M&A skills through successful experiences. It is reasonable to assume that firms with high past announcement returns will learn that they possess superior skills in making acquisitions and therefore engage in more takeover activities afterward. If this were true, we should observe both a positive association between positive acquisition experiences and valueenhancing merger frequencies and persistence in announcement returns over time. However, our results are inconsistent with firms learning about their acquisition skills.

## 5.2. Operating Performance

While announcement returns reflect the market's expectations for the merger, operating performance can measure ex-post outcome. We examine the post-merger operating performance of the groups with positive and negative return experiences in a univariate setting and in a multivariate framework. We use return on assets (ROA) to measure operating performance.

As discussed by Healy et al. (1992), accounting earnings and book value of assets can be affected by the choice of payment and the accounting method used in the transaction. If an acquisition is financed by debt or cash, the acquirer's post-merger earnings will be lower than if the same transaction entails an exchange of stock because net income is calculated after deducting interest expenses, but before the payout of dividends. If the acquirer chooses the purchase accounting method, it recognizes the target's identifiable assets and liabilities at their fair market value and then recognizes the excess payment over the fair market value as goodwill. In contrast, under the pooling-of-interest method, the book values of the target's assets and liabilities are simply added to the acquirer's balance sheet; thus no goodwill is recorded.<sup>11</sup> Since the fair value of assets plus goodwill typically exceeds the book value of assets, the purchase method results in lower earnings in subsequent years due to higher amortization and depreciation expenses.<sup>12</sup> Finally, the purchase method consolidates the financial statements of the acquirer and the target from the date of the transaction, whereas the pooling method consolidates the results of the two

<sup>&</sup>lt;sup>11</sup>SFAS 141 (Business Combination) rules out the use of the pooling-of-interest method for acquisitions undertaken after June 30, 2001. Prior to SFAS 141, acquirers were allowed to use the pooling method in "mergers of equals" where the transaction satisfies 12 requirements mostly related to deal structure and firm characteristics.

<sup>&</sup>lt;sup>12</sup>SFAS 142 (Goodwill and Other Intangible Assets) removes goodwill amortization and requires firms to perform a two-step impairment test at least annually, effective for fiscal years beginning after December 15,2001. Prior to SFAS 142, goodwill was amortized over its useful life, no longer than 40 years.

firms from the beginning of the year of merger. Hence higher earnings are reported for the first year of the merger under pooling than under the purchase method.

To deal with the concerns about the effects of financing and accounting methods on *reported* earnings, we use operating income before interest, taxes, depreciation, and amortization as the numerator of our operating performance measure. In addition, to mitigate the effects of financing and accounting methods on asset base, we use the average of goodwill-adjusted total assets as the denominator of our measure. While ROA with goodwill measures the acquirer's ability to create value over the premium paid for acquisitions, ROA without goodwill is a more proper measure of the acquirer's performance in comparison with that of its peers.<sup>13</sup> Custódio (2014) finds that adjusting goodwill from book assets significantly decreases q-based measures of the diversification discount, suggesting the importance of considering the difference between the acquirer's and its industry peers' book assets due to goodwill recognition from merger transactions. Therefore we define ROA as operating income before interest, taxes, depreciation, and amortization (EBITA) scaled by the average of goodwill-adjusted total assets (AT - GDWL).

In the univariate test, we follow the extant literature and use industry-adjusted changes in ROA around mergers to examine the effect of acquisition experiences on post-merger performance. We divide each acquisition into either a Positive or Negative Return Experience group based on the acquirer's experiences over the past 10 years. We examine time-series of operating performance of acquirer from fiscal years t-3 to t+3 where t indicates the merger completion year. Since operating performance may be affected by industry-wide factors, we subtract the median value of ROA in the same Fama-French 48 industry from the acquirer's ROA. Due to the possibility of preexisting differences in operating performance between the Positive and Negative Return Experience groups, we compute changes in the three-year average ROA from the pre-(t-3 to t-1) to post-(t+1 to t+3) merger period and compare the changes between the two groups.

<sup>&</sup>lt;sup>13</sup>Our results remain unchanged when we do not subtract goodwill from total assets.

Next, to investigate the performance changes around mergers in a multivariate setting, we regress ROA of each year from t-3 to t+3, excluding merger completion year t, on the acquisition experiences controlling for the same set of firm and deal characteristics as used in the previous analysis. As discussed by Gormley and Matsa (2014), using an industry-adjusted dependent variable to control for unobserved heterogeneity across industries produces inconsistent estimates. In contrast, including industry fixed effects generates consistent estimates. Hence we include industry fixed effects with the dependent variable being the ROA of the acquirer (*not* industry-adjusted ROA). Specifically, we estimate the following OLS regression:

$$ROA_{i,j,t} = \beta_{ind} + \beta_t + \beta_1 Positive Return Experiences Group_{i,t}$$

$$+ \beta_2 POST_{i,j,t} + \beta_3 Positive Return Experiences Group_{i,t} \times POST_{i,j,t}$$

$$+ X'_{i,t}B + Y'_{i,j}C + \epsilon_{i,j,t}$$

$$(10)$$

where  $ROA_{i,j,t}$  is acquirer i's ROA for corresponding deal j in one of the years from t-3 to t+3, excluding the merger year. Positive Return Experiences  $Group_{i,t}$  is a binary variable where 1 indicates the positive transaction value weighted average of abnormal returns over the past 10 years, and 0 otherwise. POST is a binary variable where 1 indicates the post-merger period for deal j, and 0 otherwise.  $X_{i,t}$  is the same set of firm characteristics of firm i at year t, and  $Y_{i,j}$  is the same set of deal characteristics of deal j by firm i as in Equation (9). We include year fixed effects to control for the time trends in operating performance and cluster standard errors by firm. We predict  $\beta_3$  to be negative. Note that there are six observations for each deal and that multiple mergers of a firm in a given year have deal characteristic control variables with different values but share the same value of firm-year level variables, including the dependent variable.

Table 7 shows the results. In Panel A we report time-series of the industry-adjusted operating performance of the acquirer from fiscal years t-3 to t+3 for positive and negative return experience groups. The results show that operating performance deteriorates after acquisitions for the groups with both positive and negative return experiences, but the drop is significantly larger for

the group with positive returns.<sup>14</sup> The mean decline in the 3-year average industry-adjusted ROA is 1.56% for the group with positive returns and 0.74% for the group with negative returns. The panel also reveals that the group with positive returns performs better prior to the mergers and that there is no difference in performance between two groups after the mergers. This indicates that firms with positive return experiences suffer greater declines in operating performance. [!!!]

Panel B of Table 7 presents the results of estimating Equation (10). Consistent with the univariate results, we find significantly negative coefficients on *Positive Return Experience Group* X POST, indicating that the decline in performance is more pronounced for deals announced by firms with positive return experiences. After controlling for firm and deal characteristics, we still find that changes in operating performance after mergers are 0.65 percentage points lower for positive return experience group than for those that experienced negative returns.

#### 5.3. The Role of Corporate Governance

In this section we examine whether the financial expertise of acquirers' boards and institutional ownership of acquirers affects the behavior of serial acquirers. We add a dummy variable indicating well-governed acquirers as well as interaction terms between this dummy variable and past acquisition experiences in Equation (8):

$$Pr\{Y_{i,t}^{VD(VE)} = 1 | Past Acquisition Experiences_{i,t}, High_{i,t}, X_{i,t}\}$$

$$= F(\beta_i + \beta_t + \beta_1 PPAE_{i,t} + \beta_2 NPAE_{i,t} + \beta_3 High_{i,t} + \beta_4 PPAE_{i,t} \times High_{i,t} + \beta_5 NPAE_{i,t} \times High_{i,t} + X'_{i,t}B)$$

$$(11)$$

<sup>&</sup>lt;sup>14</sup>It is a well-documented finding that, on average, acquiers underperform after the merger both in terms of longterm stock returns and operating performance (Rau and Vermaelen (1998) and Bouwman et al. (2009) among many others). Similar to our findings, Harford et al. (2012) also report declines in the operating performance after the merger for both groups of acquires with and without entrenched managers. However, as pointed out by Eckbo (2014), Wang (2013), and Savor and Lu (2009), without identifying appropriate counterfactual (i.e., how the acquirers would have performed had they not engaged in the deal), we cannot conclude that decline in performance indicates the acquirers perform worse due to the acquisitions. In this study, we focus on the differences in post-merger performances between the groups with positive and negative return experiences.

where  $P(N)PAE_{i,j}$  refers to Positive(Negative) Past Acquisition  $Experiences_{i,j}$ , respectively, and  $High_{i,t}$  is a dummy variable set to 1 if firm-year observations are in the highest tercile of institutional ownership (or financial expertise on corporate boards) for each year.

Table 8 presents evidence that firms with higher institutional ownership are less likely to engage in value-destroying deals after positive return experiences, whereas firms with a higher fraction of financial experts on boards are more likely to initiate value-enhancing acquisitions after negative return experiences. Hence institutional ownership mitigates serial acquirers' excessive acquisitiveness following good experiences while financial expertise on boards helps identify valueenhancing deals after bad outcomes.

## 6. Direct and Indirect Channels for Acquisition Experiences: CEO Overconfidence

## 6.1. The Effect of Past Experiences on CEO Overconfidence

To tease out a direct effect of past acquisition experiences and an indirect effect of past acquisition experiences, possibly through CEO overconfidence, on acquisitiveness, we first test whether CEOs' overconfidence is formed by their past acquisition experiences using the CEO overconfidence measure used by Campbell et al. (2011) and Hirshleifer et al. (2012). Since we do not have detailed information on a CEO's stock option holdings, especially on remaining option duration, we have to rely only on option moneyness to determine CEO beliefs. As pointed out by Malmendier et al. (2011) and Hirshleifer et al. (2012), the options-based overconfidence measure relying only on the moneyness of options could proxy for past stock return performance rather than for CEO overconfidence. Therefore, we control for buy-and-hold stock returns over the past fiscal year(s) as suggested by Malmendier et al. (2011) and Hirshleifer et al. (2012). Including the stock returns also controls for stock market driven takeovers (Shleifer and Vishny, 2003; Dong et al., 2006).

$$Pr\{Overconfidence_{i,t} = 1 | Past Acquisition Experiences_{i,t}, Runup_{i,t}\}$$
(12)  
$$= F(\beta_{ind} + \beta_t + \beta_1 Positive Past Acquisition Experiences_{i,t} + \beta_2 Negative Past Acquisition Experiences_{i,t} + \beta_3 Runup_{i,t})$$

where  $O_{i,t}$  is a binary variable where 1 signifies overconfident CEO at firm i in year t, *Positive/Negative Past Acquisition Experiences* are based on a transaction value weighted average of cumulative abnormal returns around the announcement date over the past 3, 5, and 10 years *within CEOs' tenure*, and *Runup*<sub>i,t</sub> is buy-and-hold stock returns over the lesser of the CEO's tenure or one year (or seven years). We use the Fama-French 48 industry classification for industry fixed effects,  $\beta_{ind}$ .

As shown in Panel A of Table 9, acquisition experiences within a CEO's tenure make the CEO more overconfident. The results are robust to controlling for buy-and-hold stock returns over the past fiscal years as suggested by Malmendier et al. (2011) and Hirshleifer et al. (2012).

Interestingly, CEO overconfidence is only responsive to the *positive* return experiences in all specifications (Panel B of Table 9). This result is consistent with a self-serving bias of CEOs. That is, individuals tend to attribute their firm's success to their own abilities and efforts, but ascribe firm failure to external factors not under their control.

#### 6.2. Horse Race: Past Experiences vs. CEO Overconfidence

Next we examine a direct effect of past acquisition experiences and an indirect effect of past acquisition experiences through CEO overconfidence on acquisition decisions using the following fixed effects logit regression:

$$Pr\{Y_{i,t} = 1 | Past Acquisition Experiences_{i,t}, Overconfidence_{i,t}, Runup_{i,t}, X_{i,t}\}$$
(13)

$$= F(\beta_{ind} + \beta_t + \beta_1 Positive Past Acquisition Experiences_{i,t})$$

 $+ \beta_2 Negative \ Past \ Acquisition \ Experiences_{i,t} + \beta_3 Overconfidence_{i,t} + \beta_4 Runup_{i,t} + X'_{i,t}B)$ 

where  $Y_{i,t}$  is a binary variable having the value 1 if the firm i announced at least one merger bid in year t that was eventually completed,  $X_{i,t}$  is the same set of firm level controls, and all other variables are the same as in Equation (12).

Table 10 along with the results in Table 9 presents both direct and indirect effects of acquisition experiences on merger decisions. Negative return experiences discourage firms from engaging in acquisitions in the following year whereas positive return experiences do not provoke more mergers in the subsequent year *in the presence of* CEO overconfidence. Consistent with Malmendier and Tate (2008), overconfidence significantly predicts a firm's acquisitiveness. As shown in Table 9, we can conclude that one of the mechanisms through which positive return experiences affect corporate merger decisions is through CEO overconfidence, whereas negative return experiences directly reduce the acquisitiveness of firms.

To compare the economic significance, we calculate the marginal effects of a one standard deviation increase in negative acquisition experiences and overconfidence at their means.<sup>15</sup> A one standard deviation increase in negative acquisition experiences reduces merger frequency by 2.64%, whereas the same increase in the overconfidence measure increases acquisitiveness by 2.05% in specification (4). These marginal effects are economically meaningful in the sense that they are 8.83% and 6.56% of the average fitted probabilities at the means (29.91% and 31.25%) respectively.

 $<sup>^{15}</sup>$ Note that the average fitted probabilities and marginal effects are calculated from the *standard* logit regressions with year and industry dummy variables *only for* this purpose. We acknowledge possible incidental parameter problems in these specifications, but we confirm that the estimates from these specifications are very close to those from conditional logit regressions.

More important, the economic significance of negative return experiences is comparable to that of CEO overconfidence, as shown by Malmendier and Tate (2008).

### 6.3. Fairlie-Blinder-Oaxaca Decomposition

Past acquisition experiences could drive not only CEO overconfidence measure but also other variables that affect corporate acquisition decisions such as cash flow, Q, size, and leverage. Therefore there could be secondary channels through which past acquisition experiences affect merger decisions. To formally assess the influence of past acquisition experiences on merger frequency via secondary channels, we adopt the Fairlie-Blinder-Oaxaca decomposition method developed by Blinder (1973), Oaxaca (1973), and Fairlie (2005).

This method measures how much of the difference in merger frequency between the high and low return experience groups can be explained by differences in control variables such as cash flow, Q, size, and leverage, and most important, the CEO overconfidence measure. We first run a logit regression of the acquisition dummy on all control variables, omitting the past acquisition experiences regressor. Using the decomposition technique, we then compute the marginal effect of group mean differences for seven collections of the control variables, including year and industry dummies. For a given pairing across groups,<sup>16</sup> marginal effects are the sequence of changes in predicted frequencies, obtained by sequentially changing each control variable's value from its group mean for the low-return experience group to its mean for the high-return experience group. Sequencing of the changes in the control variables are randomized, repeated (1,000 times) and averaged to obtain marginal changes in merger frequency and test statistics.<sup>17</sup>

We obtain decomposition estimates for high positive and low positive return experience groups

<sup>&</sup>lt;sup>16</sup>One-to-one matching of observations from the two groups is essential to calculate marginal effects. If the sample sizes of the two groups are different, we draw a random subsample of the large group equal in size to the small group to make one-to-one matching. See Fairlie (2005) for details.

<sup>&</sup>lt;sup>17</sup>Marginal changes can be sensitive to the ordering of variables in the case of non-linear regression models such as logit or probit. See Fairlie (2005) for details.

as well as for high negative and low negative return experience groups to gauge the magnitude of the secondary channel via CEO overconfidence across positive and negative return experiences.

Table 11 shows results from the Fairlie-Blinder-Oaxaca decomposition. Panel A presents decomposition estimates for the high positive and low positive return experience groups. The total difference in merger frequency between the two groups is 2.07%, of which only 0.88% can be explained by all variables. Note that a significant portion, 20.15% (47.44%), of the total difference (explained difference) is solely explained by overconfidence. This is consistent with our results, shown in Table 10, that positive return experiences affect corporate acquisitiveness mostly through CEO overconfidence.

On the other hand, in the negative domain of return experiences, overconfidence does not contribute at all (-22.1% of contributions in Panel B of Table 11) to the total difference in merger frequency between the high negative and low negative return experience groups. In fact, the negative contribution of overconfidence implies that the group difference in overconfidence goes in the opposite direction from the total difference in merger frequency. This is again consistent with our previous results that negative return experiences directly curb firms' tendency to undertake acquisitions, but not through CEO overconfidence.

## 7. Conclusion

Using a large sample of U.S. firms, we find that past acquisition return experiences significantly and strongly predict the likelihood of subsequent acquisitions, after controlling for aggregate time-series shocks, economic factors, rational learning about acquisition skill, and firm fixed effects. Moreover, past successful M&A strategies, such as public vs. private targets and within- vs. across-industry targets, are more likely to be repeated in future acquisitions. These findings are consistent with the prediction of reinforcement learning: firms are likely to repeat (avoid) choices that produced good (bad) outcomes in the past. We also find that firms that experience higher announcement returns in early acquisitions have a greater chance of becoming serial acquirers.

To distinguish reinforcement learning from Bayesian (rational) learning, we examine value consequences of serial acquirers. We document that serial acquirers with greater positive (negative) return experiences are more likely to initiate value-destroying (value-enhancing) mergers in terms of both market reaction and operating performance. This finding helps us rule out two different types of rational learning that could affect firms' merger decisions: that a firm learns about its own fixed talent by doing M&As or that it can improve its acquisition skill through serial acquisitions. Our interpretation of these value consequences is that positive announcement return experiences lead firms to overestimate cash flows from subsequent deals and hence misclassify a negative-NPV project as a positive-NPV project. On the other hand, poor acquisition experiences make firms more cautious (e.g., to exert greater due diligence after a run of bad outcomes) when making subsequent merger decisions, and future mergers turn out to be value-enhancing. We also discover that higher institutional ownership mitigates serial acquirers' excessive acquisitiveness following good experiences, whereas financial expertise on corporate boards helps identify valueenhancing deals after bad outcomes.

Finally, we investigate the relative importance of firms and CEOs in explaining our findings. We find that CEO overconfidence increases after past firm successes but is immune to failures. This result is consistent with a self-attribution bias, one common source of overconfidence documented by the psychology literature. In a horse race between past experiences (positive and negative) and CEO overconfidence, we find that CEO overconfidence partially subsumes the effect of positive return experiences. However, negative return experiences directly curb firms' acquisitiveness. To formally assess the influence of past acquisition experiences on merger frequency via secondary channels, we adopt the Fairlie-Blinder-Oaxaca decomposition method and obtain similar results. Overall, our findings highlight the importance of behavioral biases of serial acquirers in better understanding the dynamics of the acquisition decisions.

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Fig. 1. An ecdotes of Reinforcement Learning Behavior in Acquisition Decisions: A GCO Corp & Lennar Corp

The figures depict histories of merger announcements of two example firms in the Fortune 500 companies: AGCO Corp and Lennar Corp. CAR[-1,+1] is the equally weighted average of announcement returns given a fiscal year. Announcement returns are abnormal returns over a three-day window starting one day before the announcement date where abnormal returns are the difference between raw returns and value-weighted market index returns. Each text box linked to bars indicates the names of target firms. AGCO Corporation manufactures and distributes agricultural equipment, like grain storage and tractors, and replacement parts. Lennar Corporation is a national homebuilder with operations in 40 markets in 17 states in the United States.

#### Table 1: Descriptive Statistics

Panel A presents descriptive statistics of *Past Acquisition Experiences*. We define it as transaction value weighted average of announcement returns during the past 10 years. Announcement returns are abnormal returns over a three-day window starting one day before the announcement date where abnormal returns are the difference between raw returns and value-weighted market index returns. We separately display distributions of Past Acquisition Experiences by positive and negative ones. Panel B shows mean differences of firm-level variables across positive and negative return experience groups. Positive (Negative) Return Experience group has positive (negative) Past Acquisition Experiences over the past 10 years. Freq of Acquisitions represents the frequency of participating in acquisitions that are eventually completed, *Cashflow* is earnings before extraordinary items plus depreciation normalized by the beginning-of-the-year capital (property, plants, and equipment), Q is the ratio of market value of assets to book value of assets at the beginning of the year, ln (Total Assets [\$m]) is the log of total assets at the beginning of the year, Leverage is total debt over total assets at the beginning of the year, and CEO Overconfidence is a binary variable where 1 signifies overconfident CEO following Campbell et al., 2011. Panel C presents mean differences of deal-level variables across positive and negative return experience groups. RAW[-1,+1] is the cumulative raw return of the acquirer's stock over a three-day window starting one day before the announcement, and CAR/-1, +1 is the cumulative abnormal return of the acquiring firm's stock over the same window using the difference between raw returns and value-weighted market index returns. *Relative Size* is the deal value divided by the market value of the bidding firm's equity 11 days prior to the announcement date, *Relatedness* indicator variable set to one if the acquirer and target are operating in the same industries with a common two-digit Standard Industrial Classification code and zero otherwise, Friendly a binary variable with a value of 1 if the bid is reported as friendly, Public, Private, Subsidiary a indicator variable having 1 if the bid is for a public, private, and subsidiary target, and Cash (Stock) a binary variable where 1 indicates that the acquisition was financed by 100% of cash (stock). \*\*\*, \*\*, \* indicate a difference that is significant at the 1%, 5%, and 10% levels, respectively. The sample period runs from 1983 to 2013.

I and III Distributions (		incquiettite	п царение	11000				
Variables	Mean	10th pct	25th pct	Median	75th pct	90th pct	Std.Dev.	Num.Obs
Past 10yr Acquisition Exp Positive Exp Negative Exp	0.011 0.049 -0.038	-0.055 0.005 -0.089	-0.020 0.013 -0.052	0.006 0.031 -0.025	0.036 0.064 -0.011	0.083 0.115 -0.004	$0.064 \\ 0.053 \\ 0.040$	$39,862 \\ 22,541 \\ 17,321$

Panel A: Distributions of <i>Past</i>	Acquisition Experiences
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Panel E	3: Firm	-Year	Level	Variables	bv	Positive	and	Negative	Return	Experience	$\mathbf{es}$
					~ . ,		~~~~	a togator to			$\sim \sim$

Variables	Me	ean	Mean Differences	Num	.Obs.
	Positive	Negative	Positive - Negative	Positive	Negative
	Return Exp	Return Exp		Return Exp	Return Exp
Freq of Acquisitions	0.204	0.192	$0.012^{***}$	22,541	17,321
Cash Flow	0.412	0.330	0.082**	22,330	$17,\!178$
Q	1.740	1.790	-0.050***	21,368	15,820
ln (Total Assets [\$m])	6.560	6.940	-0.380***	22,484	17,283
Leverage	0.249	0.227	$0.022^{***}$	22,397	17,211
CEO Overconfidence	0.370	0.329	$0.041^{***}$	5,342	4,372

#### Panel C: Deal Level Variables by Positive and Negative Return Experiences

Variables	Me	ean	Mean Differences
	Positive Return Exp	Negative Return Exp	Positive - Negative
RAW $[-1, +1]$	0.014	0.007	0.007***
CAR[-1,+1]	0.012	0.006	$0.006^{***}$
Relativesize	0.192	0.166	$0.026^{***}$
Relatedness	0.638	0.639	-0.001
Friendly	0.994	0.995	-0.001
Public	0.142	0.218	-0.076***
Private	0.496	0.475	$0.021^{**}$
Subsidiary	0.362	0.307	$0.055^{***}$
Cash	0.295	0.266	$0.029^{***}$
Stock	0.152	0.219	-0.057***
Num.Obs.	6,460	4,524	

Table 2: Reinforcement Learning Beha	avior: Do Pa	st Acquisition	n Return Ex	periences Lea	ad to More M	ergers?
This table presents results from the fixed effects log The dependent variable is a binary variable where 1 s Past Acquisition Experiences over the past 3.	ogit regressions 1 indicates tha 3, 5, and 10 ve	that are estimate the firm made ear windows. I	ated using a c at least one r n Panel A (B	onditional logit nerger bid in a $g$ ), we define $Pc$	specification in given year. Our ast Acquisition	Equation (4). main variable <i>Experiences</i>
as transaction value weighted (equally weighted Announcement returns are raw (or abnormal) ret	<li>average of turns over a t</li>	announcement hree-day windo	returns duri w starting on	ng the corresp e day before th	onding experie 1e announcemen	nce windows. at date where
abnormal returns are the difference between raw 1 a ratio of number of successful deals to total num	returns and v nber of deals o	alue-weighted r during the corr	narket index i esponding ext	teturns. In pan berience window	iel C, we use $S$ vs where we def	uccess Ratio, ine successful
deals as ones with positive raw (or abnormal) ret	turns. We me	asure <i>Cashflow</i>	as earnings 1	before extraordi	inary items plus	s depreciation
normalized by the beginning-of-the-year capital (p) of assets at the beginning of the year, $Leverage$ as	s total debt or	s, and equipmenver total assets	nt), $Q$ as the at the beginn	ratio of market ing of the year	value of assets , and $Size$ as the function of $Size$ as the set of $Size$ and $Size$	to book value ne log of total
assets at the beginning of the year. Note that the n vear and firm dummy variables <i>only for</i> this purp	marginal effect ose. Uncondit	s shown in Pan ional mean of o	el A are calcu dependent vary	lated from the liable is also bas	inear probabilit; ed on the samp	y models with le used in the
inear probability models. The sample period runs clustered by firm. ***, **, * indicate significance a	the from $1983$ to at the $1\%, 5\%,$	2013. Standard and 10% levels	l errors in par , respectively.	entheses are rob	oust to heterosk	edasticity and
Panel A: Transaction Value Weighted Retur	rn					
		Pred	licting Acquire	r (Acquirer = 1	( -	
	Value We	ighted Raw Ret	urn	Value We	ighted Abnorma	ıl Return
	Exper	ience Windows		Ex	perience Windo	WS
	3yr	5yr	10yr	$_{(A)}^{3yr}$	5yr	10yr
	(T)	7	0	(1)	(0)	0

		-	imhou gimiomai	r — Iamhaul Ia	L)	
	Value 7	Weighted Raw I	Return	Value We	ighted Abnorma	l Return
	EX	perience Windo	SM	Ex	perience Windov	VS
	$3 \mathrm{yr}$	$_{\rm 5yr}$	$10 \mathrm{yr}$	$_{3 \mathrm{yr}}$	$5 \mathrm{yr}$	$10 \mathrm{yr}$
	(1)	(2)	(3)	(4)	(5)	(9)
$Past\ Acquisition\ Experiences$	$.9149^{**}$ (.3822)	$.8654^{**}$ (.4089)	$.9818^{**}$ $(.4495)$	$.9966^{**}$ (.3965)	$1.0355^{**}$ $(.4245)$	$1.1216^{**}$ (.4626)
CashFlow	$.0173^{**}$ (.0085)	$.0219^{***}$ (.0077)	$.0233^{***}$ (.0074)	$.0173^{**}$ (.0085)	$.0219^{***}$ (.0077)	$.0233^{***}$ (.0074)
Q	$.1035^{***}$ (.0236)	$.0949^{***}$ (.0215)	$.0872^{***}$ (.0196)	$.1030^{***}$ (.0235)	$.0943^{***}$ (.0215)	$.0867^{***}$ (.0196)
Size	$3014^{***}$ (.0485)	$2397^{***}$ (.0440)	$1764^{***}$ (.0410)	$3021^{***}$ (.0484)	$2408^{***}$ (.0440)	$1774^{***}$ (.0410)
Leverage	$-2.6054^{***}$ (.2180)	$-2.5664^{***}$ (.1939)	$-2.5715^{***}$ (.1806)	$-2.6060^{***}$ (.2178)	$-2.5683^{***}$ (.1937)	$-2.5735^{***}$ (.1806)
Marginal effects (%) due to $1\sigma$ increase of Past Acquisition Experiences	1.18%	1.08%	1.13%	1.23%	1.24%	1.25%
CashFlow Q	$0.95\%\ 2.83\%$	$1.07\% \\ 2.45\%$	$0.83\%\ 2.20\%$	$0.95\%\ 2.82\%$	1.07% $2.43%$	$0.83\%\ 2.19\%$
Unconditional mean of dependent variable	23.92%	21.68%	19.62%	23.92%	21.68%	19.62%
Year-Fixed Effects Firm-Fixed Effects	${ m Yes}_{ m Yes}$	${ m Yes}_{ m Yes}$	${ m Yes}_{ m Yes}$	${ m Yes}_{ m Yes}$	${ m Yes}_{ m Yes}$	${ m Yes}_{ m Yes}$
# Obs.	15,822	20,918	26, 349	15,822	20,918	26, 349
Pseudo $R^2$	.0455	.0416	.0378	.0456	.0417	.0379

			Predicting Acquin	ter (Acquirer $= 1$ )		
	Equally	Veighted Raw I	Return	Equally V	Weighted Abnorma	l Return
	Ê	sperience Window	IS	E	xperience Window	S
	$_{3 \mathrm{yr}}$	$_{\rm 5yr}$	$10 \mathrm{yr}$	$_{3 \mathrm{yr}}$	$5 \mathrm{yr}$	10yr
	(1)	(2)	(3)	(4)	(5)	(9)
Past Acquisition Experiences	$.9653^{**}$	$1.1420^{**}$	$1.3818^{**}$	$1.0653^{**}$	$1.3100^{***}$	$1.5433^{***}$
CashFlow	$.0176^{**}$	$.0220^{***}$	$.0233^{***}$	$.0176^{**}$	$.0219^{***}$	$.0233^{***}$
	(.0085)	(.0077)	(.0073)	(.0085)	(.0077)	(.0073)
Q	$.1035^{***}$ (.0235)	$.0948^{***}$ (.0214)	$.0869^{***}$ (.0196)	$.1030^{***}$ (.0235)	$.0941^{***}$ (.0214)	$.0864^{***}$ (.0196)
Size	$3016^{***}$ (.0484)	$2394^{***}$ (.0440)	$1766^{***}$ (.0410)	$3022^{***}$ (.0484)	$2404^{***}$ (.0440)	$1777^{***}$ (.0410)
Leverage	$-2.6029^{***}$ (.2181)	$-2.5689^{***}$ (.1941)	$-2.5737^{***}$ (.1808)	$-2.6039^{***}$ (.2179)	$-2.5708^{***}$ (.1940)	$-2.5754^{***}$ (.1808)
Year-Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Firm-Fixed Effects	$\mathbf{Y}_{\mathbf{es}}$	$\mathbf{Y}_{\mathbf{es}}$	Yes	$\mathbf{Yes}$	$\mathbf{Y}_{\mathbf{es}}$	$\mathbf{Y}_{\mathbf{es}}$
# Obs.	15,822	20,918	26, 349	15,822	20,918	26,349
Pseudo $R^2$	.0455	.0417	.0379	.0456	.0418	.0380

Panel B: Equally Weighted Return

T and C Pacebo Fault						
			Predicting Acq	uirer (Acquirer =	= 1)	
	Success R	atio based on Ra	aw Return	Success R	tatio based on Abn	ormal Return
	Ê	xperience Windo	SW		Experience Winde	SWG
	3yr	$5 \mathrm{yr}$	$10 \mathrm{yr}$	$_{3 \mathrm{yr}}$	$5 \mathrm{yr}$	$10 \mathrm{yr}$
	(1)	(2)	(3)	(4)	(5)	(9)
Past Acquisition Experiences	$.1181^{**}$ (.0600)	$.1535^{**}$ (.0646)	$.2107^{***}$ (.0810)	$.1280^{**}$ (.0574)	$.1659^{***}$ (.0625)	$.2023^{***}$ (.0784)
CashFlow	$.0175^{**}$ (.0085)	$.0219^{***}$ (.0077)	$.0231^{***}$ (.0074)	$.0176^{**}$ (.0085)	$.0220^{***}$ (.0077)	$.0233^{***}$ (.0074)
0	$.1052^{***}$ (.0236)	$.0958^{***}$ (.0214)	$.0876^{***}$ (.0195)	$.1046^{***}$ (.0236)	$.0952^{***}$ (.0214)	$.0873^{***}$ (.0195)
Size	$3014^{***}$ (.0484)	$2388^{***}$ (.0439)	$1762^{***}$ (.0409)	$3023^{***}$ (.0484)	$2401^{***}$ (.0439)	$1772^{***}$ (.0410)
Leverage	$-2.5835^{***}$ (.2179)	$-2.5531^{***}$ (.1935)	$-2.5658^{***}$ (.1800)	$-2.5830^{***}$ (.2179)	$-2.5553^{***}$ (.1935)	$-2.5679^{***}$ (.1801)
Year-Fixed Effects Firm-Fixed Effects	Yes Yes	Yes Yes	Yes Yes	Yes Yes	Yes Yes	Yes Yes
# Obs.	15,822	20,918	26, 349	15,822	20,918	26, 349
Pseudo $R^2$	.0454	.0416	.0380	.0455	.0417	.0380

Panel C: Success Ratio

#### Table 3: Reinforcement Learning Behavior: Specific Deal Strategy Level

This table presents results from the fixed effects logit regressions that are estimated using a conditional logit specification in Equation (5). The dependent variable is a binary variable where 1 indicates that the firm made at least one merger bid of which target is type  $\theta$  in a given year, where  $\theta \in \{public, private\}$  or  $\{within industry, across industry\}$ . We define Past Acquisition Experiences in Type  $\gamma$  Target as transaction value weighted average of announcement returns of merger bids for type  $\gamma$  target during the past 10 years where  $\gamma \in \{public, private\}$  or  $\{within industry, across industry\}$ . Announcement returns are abnormal returns over a three-day window starting one day before the announcement date where abnormal returns are the difference between raw returns and value-weighted market index returns. We include the following control variables: Cashflow, Q, Leverage, Size. We measure Cashflow as earnings before extraordinary items plus depreciation normalized by the beginning-of-the-year capital (property, plants, and equipment), Q as the ratio of market value of assets to book value of assets at the beginning of the year, Leverage as total debt over total assets at the beginning of the year. We use the Standard Industrial Classification (SIC) for industry fixed effects. The sample period runs from 1983 to 2013. Standard errors in parentheses are robust to heteroskedasticity and clustered by industry. \*\*\*, \*\*, \* indicate significance at the 1%, 5%, and 10% levels, respectively.

	Predicting $\theta = 0$	, Acquirer (Acqu Public	irer of Type $\theta$ T $\theta = P$	Carget = 1
	$\gamma = \text{Public}$	$\gamma = \text{Private}$	$\gamma = \text{Private}$	$\gamma = \text{Public}$
	(1)	(2)	(3)	(4)
Past Acquisition Experiences in Type $\gamma$ Target	$\begin{array}{c} 1.3697^{**} \\ (.6376) \end{array}$	.8581 (.8875)	1.1161*** (.4009)	1684 $(.5895)$
Controls	Yes	Yes	Yes	Yes
Year-Fixed Effects	Yes	Yes	Yes	Yes
Industry-Fixed Effects	Yes	Yes	Yes	Yes
# Obs.	7,095	18,247	22,604	7,983
Pseudo $R^2$	.0518	.0781	.0298	.0209

#### Panel A: Public vs. Private Targets

#### Panel B: Within- vs. Across-Industry Targets

	Predicting	Acquirer (Acqu	irer of Type $\theta$	$\Gamma arget = 1$ )
	$\theta = V$	Vithin	$\theta = I$	Across
	$\gamma = $ Within	$\gamma = Across$	$\gamma = Across$	$\gamma = $ Within
	(1)	(2)	(3)	(4)
Past Acquisition Experiences in Type $\gamma$ Target	1.5252*** (.3122)	.8610* (.4926)	.6167 (.4473)	$.1358 \\ (.3916)$
Controls	Yes	Yes	Yes	Yes
Year-Fixed Effects	Yes	Yes	Yes	Yes
Industry-Fixed Effects	Yes	Yes	Yes	Yes
# Obs.	25,715	18,517	18,866	24,986
Pseudo $R^2$	.0256	.0268	.0279	.0279

# Table 4: Do Past Acquisition Return Experiences Lead to More Mergers? - Differential Effects of Positive and Negative Experiences

This table presents results from the fixed effects logit regressions that are estimated using a con-The dependent variable is a binary variable where ditional logit specification in Equation (6). 1 indicates that the firm made at least one merger bid in a given year. Our main variable is Positive (Negative) Past Acquisition Experiences over the past 3, 5, and 10 year windows. We define Past Acquisition Experiences as transaction value weighted average of announcement returns during the corresponding experience windows. Announcement returns are abnormal returns over a three-day window starting one day before the announcement date where abnormal returns are the difference between raw returns and value-weighted market index returns. We separate Past Acquisition Experiences into two parts: Positive Past Acquisition Experiences = Past Acquisition Experiences  $\times 1_{\{Past Acquisition Experiences>0\}}$  and Negative Past Acquisition Experiences = -Past Acquisition Experiences  $\times 1_{Past Acquisition Experiences < 0}$ . We include the following control variables: Cashflow, Q, Leverage, Size. We measure Cashflow as earnings before extraordinary items plus depreciation normalized by the beginning-of-the-year capital (property, plants, and equipment), Q as the ratio of market value of assets to book value of assets at the beginning of the year, Leverage as total debt over total assets at the beginning of the year, and Size as the log of total assets at the beginning of the year. The sample period runs from 1983 to 2013. Standard errors in parentheses are robust to heteroskedasticity and clustered by firm. \*\*\*, \*\*, \* indicate significance at the 1%, 5%, and 10% levels, respectively.

	Pre	dicting Acquirer (Acqu	uirer $= 1$ )
	Past	Acquisition Experienc	e Windows
	3yr	5yr	10yr
	(1)	(2)	(3)
Positive Past Acquisition Experiences	.4147 (.5656)	$1.1072^{*}$ (.6072)	$\begin{array}{c} 1.7655^{***} \\ (.6723) \end{array}$
$Negative \ Past \ Acquisition \ Experiences$	-1.9919** (.8428)	9126 (.8392)	0130 (.9099)
Controls	Yes	Yes	Yes
Year-Fixed Effects	Yes	Yes	Yes
Firm-Fixed Effects	Yes	Yes	Yes
# Obs.	15,822	20,918	26,349
Pseudo $R^2$	.0458	.0417	.0380

#### Table 5: Becoming a Serial Acquirer and Past Acquisition Return Experiences

This table presents results from the fixed effects logit regressions that are estimated using a conditional logit specification in Equation (7). The dependent variable is a binary variable where 1 indicates that the firm is a serial acquirer. We define serial acquirers as those with more than one year of merger activity over the sample period. Our main variable is Value Weighted CARs, transaction value weighted announcement returns during the first fiscal year when the firm announces at least one acquisition. Announcement returns are abnormal returns over a three-day window starting one day before the announcement date where abnormal returns are the difference between raw returns and value-weighted market index returns. We include the following firm level control variables corresponding to the same first year: Cashflow, Q, Leverage, Size. We measure Cashflow as earnings before extraordinary items plus depreciation normalized by the beginning-of-the-year capital (property, plants, and equipment), Q as the ratio of market value of assets to book value of assets at the beginning of the year, Leverage as total debt over total assets at the beginning of the year, and Size as the log of total assets at the beginning of the year. In Column (2), we use alternative definition of serial acquirers: firms acquired more than five targets over the sample period. Correspondingly, we calculate Value Weighted CARs using up to first five merger announcements over the sample period and we use control variables corresponding to the most recent merger announcement which is used in calculating Value Weighted CARs. We use the Standard Industrial Classification (SIC) for industry fixed effects. Note that the marginal effects shown in this table are calculated from the standard logit regressions with year and industry dummy variables only for this purpose. The sample period runs from 1983 to 2013. Standard errors in parentheses are robust to heteroskedasticity and clustered by industries. \*\*\*, \*\*, \* indicate significance at the 1%, 5%, and 10% levels, respectively.

	Predictin	ng Serial Acquirer (Serial Acquirer $= 1$ )
	(1)	Alternative Definition of Serial Acquirer (2)
Value Weithged CARs	.7246* (.4168)	$1.1004^{*}$ (.5629)
CashFlow	$.0422^{***}$ (.0081)	$.0887^{***}$ (.0129)
Q	$.0357^{**}$ (.0154)	.0080 (.0246)
Size	$.2801^{***}$ (.0336)	$.5021^{***} (.0556)$
Leverage	0777 $(.2230)$	.4008 (.3925)
	1.23%	0.95%
Unconditional mean of dependent variable		
	54.00%	16.67%
Year-Fixed Effects	Yes	Yes
Industry-Fixed Effects	Yes	Yes
# Obs.	4,101	3,893
Pseudo $R^2$	.0867	.1687

Table 6: Do Past Acquisition I	Return Exper	iences Lead	to More Val	ue Destroyin	g or Enhancin	ig Mergers?
Panel A presents results from the fixed effe The dependent variable is a binary variable mergers in a given year. We use a sign of tr and <i>Value Enhancing</i> mergers. If the sign mergers. Our main variable is <i>Positive</i> $(N)$	ects logit regres e where 1 indic ansaction value is negative (po Vegative) Past	isions that are ates that the f weighted aver sitive), a firm Acquisition E	estimated usin irm engages in age of abnorma is classified an <i>Typeriences</i> ov	ag a conditions 1 Value Destroy al returns in a s engaging in ver the past 3,	al logit specificat ying(VD) (or Va given year to defi Value Destroying 5, and 10 year	ion in Equation (8). <i>thue Enhancing(VE)</i> ) ine Value Destroying $\gamma$ (Value Enhancing) windows. We define
<i>Past Acquisition Experiences</i> as transact: dows. Announcement returns are abnormal returns are the difference between raw ret	ion value weigh returns over a t turns and value	ted average of hree-day wind -weighted man	announcemen ow starting one iket index retu	t returns durin e day before the urns. We sepa	ig the correspond e announcement o rate Past Acqu	ding experience win- date where abnormal <i>isition Experiences</i>
into two parts: Positive Past Acquisit Negative Past Acquisition Experiences = control variables: Cashflow, Q, Leverage, S by the beginning-of-the-vear capital (prope	tion Experient = $-Past Acqui$ ize. We measurerty, plants, an	ces = Past sition Experi e Cashflow as d equipment).	Acquisition $1$ ences $\times 1_{\{Past}$ earnings befor O as the ratio	$Experiences \times Acquisition Experiences$ is extraordinary of market va	1 {Past Acquisitio sriences<0}. We i y items plus dep lue of assets to	$n Experiences \geq 0$ and include the following reciation normalized book value of assets
at the beginning of the year, <i>Leverage</i> as the beginning of the year. Panel B reports	total debt over s results from fi	total assets at xed effects OL	the beginning S regression in	s of the year, ε Equation (9).	Size as the l Dependent vari	log of total assets at iable is a cumulative We use the same set
of firm level control variables as in Panel divided by the market value of the biddin	A. We also inc g firm's equity	tude the follo 11 days prior	wing deal leve to the annour	l control varial coment date,	bles: Relative Sc Relatedness indi	<i>ize</i> is the deal value cator variable set to
one if the acquirer and target are operating and zero otherwise, <i>Friendly</i> a binary vari a indicator variable having 1 if the bid i	g in the same in lable with a val s for a public,	idustries with a lue of 1 if the private, and	a common two bid is reporte subsidiary tar <sub>i</sub>	-digit Standarc d as friendly, J get, and <i>Cash</i>	1 Industrial Clas; Public (omitted), (Stock) a bina	sification (SIC) code Private, Subsidiary xy variable where 1
indicates that the acquisition was financed parentheses are robust to heteroskedasticity	d by 100% of c and clustered b	ash (stock). ' y firm. ***, **	The sample po ,* indicate sign	eriod runs fror nificance at the	n 1983 to 2013. 1%, 5%, and 10%	Standard errors in % levels, respectively.
Panel A: Predicting Value Destroying	or Value En	hancing Acq	uirer			
	Predicti	ng Value Destr ]	roying [Value I Past Acquisitic	Enhancing] Acc on Experience	quirer (VD [VE] Windows	Acquirer $= 1$ )
	3y	r	5	yr -		10yr
	VD	VE	VD	VE	ΛD	VE
	(1)	(2)	(3)	(4)	(5)	(9)
Positive Past Acquisition Experiences	$\begin{array}{c} 4.1711^{***} \\ (.8075) \end{array}$	$-2.4318^{***}$ (.7331)	$\begin{array}{c} 4.9158^{***} \\ (.9010) \end{array}$	$-1.7395^{**}$ (.7521)	$7.7343^{***}$ (1.1594)	$-2.3440^{***}$ (.7832)
$Negative\ Past\ Acquisition\ Experiences$	$-8.0297^{***}$ (1.2485)	$\begin{array}{c} 4.7756^{***} \\ (1.0488) \end{array}$	$-8.8492^{***}$ (1.2087)	$7.2040^{***} \\ (1.1201)$	$-10.0798^{***}$ (1.3475)	$10.4000^{***}$ (1.3221)

21,668 .0407

19,566 .0422

16,804 .0421

15,687 .0403

12,604.0458

11,773 .0411

Yes Yes

 $\mathbf{Yes}$ 

Yes Yes Yes

> Year-Fixed Effects Firm-Fixed Effects

Controls

Pseudo  $R^2$ 

# Obs.

#### Panel B: Market Response

		CAR [-1,+1]	
	Past	Acquisition Experience	Windows
	$3 \mathrm{yr}$ (1)	5yr (2)	$\begin{array}{c} 10 \mathrm{yr} \\ (3) \end{array}$
Positive Past Acquisition Experiences	$2161^{***}$ (.0354)	2512*** (.0360)	$3118^{***}$ (.0365)
$Negative \ Past \ Acquisition \ Experiences$	$.3620^{***}$ $(.0601)$	.4285*** (.0513)	$.5027^{***}$ (.0583)
CashFlow	.0016** (.0007)	.0016*** (.0006)	$.0015^{***}$ (.0005)
Q	0009 (.0007)	0007 (.0006)	0006 (.0006)
Size	$0102^{***}$ (.0025)	0086*** (.0023)	$0085^{***}$ $(.0022)$
Leverage	.0070 (.0136)	.0032 (.0118)	.0090 (.0107)
Relative Size	$.0095^{*}$ (.0050)	.0096** (.0045)	$.0084^{**}$ (.0035)
Relatedness	0005 (.0022)	0008 (.0020)	0010 (.0019)
Friendly	0152 (.0141)	0058 (.0110)	.0042 (.0096)
Private	$.0105^{***}$ (.0038)	.0109*** (.0035)	$.0094^{***}$ $(.0032)$
Subsidiary	$.0147^{***}$ $(.0040)$	.0147*** (.0036)	$.0139^{***}$ (.0032)
Cash	$.0057^{***}$ $(.0021)$	.0051*** (.0019)	.0048*** (.0018)
Stock	0080 (.0049)	$0075^{*}$ (.0045)	0064 (.0041)
$Private \times Stock$	.0229*** (.0062)	.0228*** (.0058)	$.0217^{***}$ (.0053)
Marginal effects(%) due to $1\sigma$ increase of			
Positive Past Acquisition Experiences	$-1.10\%^{***}$ (.0018)	-1.28%*** (.0018)	$-1.59\%^{***}$ (.0019)
$Negative \ Past \ Acquisition \ Experiences$	$1.27\%^{***}$ (.0021)	$1.50\%^{***}$ (.0018)	$1.85\%^{***} \\ (.0021)$
Year- and Firm-Fixed Effects	Yes	Yes	Yes
# Obs.	7,910	8,921	9,765
Adjusted $R^2$	.0610	.0720	.0804

#### Table 7: Operating Performance

Panel A reports the time-series of industry adjusted operating performance of acquirer from fiscal years t-3 to t+3 where t indicates merger completion year. Operating performance is calculated as return on assets (ROA), defined as EBITDA normalized by average total assets with goodwill adjustment. Positive (Negative) Return Experience group has positive (negative) transaction value weighted average of abnormal returns over the past 10 years. Panel B presents results from fixed effects OLS regression in Equation (10). As suggested in Gormley and Matsa, 2014, we use industry fixed effects with dependent variable being ROA of acquirer from fiscal years t-3 to t+3 excluding t. Our variable of interest is Positive Return Experience Group  $\times POST$ , an interaction term of Positive Return Experience Group and POST. Positive Return Experience Group is a binary variable where 1 indicates High Return Experience group and 0 otherwise. POST is a binary variable where 1 indicates post merger periods and 0 otherwise. Firm level control variables include Cashflow, Q. Leverage, and Size. We measure Cashflow as earnings before extraordinary items plus depreciation normalized by the beginning-of-the-year capital (property, plants, and equipment), Q as the ratio of market value of assets to book value of assets at the beginning of the year, Leverage as total debt over total assets at the beginning of the year, and Size as the log of total assets at the beginning of the year. Deal characteristic variables are Relative Size, Relatedness, Friendly, Public (omitted), Private, Subsidiary, Cash (Stock), and  $Private \times Stock$ . Relative Size is the deal value divided by the market value of the bidding firm's equity 11 days prior to the announcement date, *Relatedness* indicator variable set to one if the acquirer and target are operating in the same industries with a common two-digit Standard Industrial Classification (SIC) code and zero otherwise, Friendly a binary variable with a value of 1 if the bid is reported as friendly, Public (omitted), Private, Subsidiary a indicator variable having 1 if the bid is for a public, private, and subsidiary target, and Cash (Stock) a binary variable where 1 indicates that the acquisition was financed by 100% of cash (stock). The sample period runs from 1983 to 2013. We use the Fama-French 48 industry classification both for industry adjusted operating performance and industry fixed effects. Standard errors in parentheses are robust to heteroskedasticity and clustered by firm. \*\*\*, \*\*, \* indicate significance at the 1%, 5%, and 10% levels, respectively.

	Positive Return Experience (1)	Negative Return Experience (2)	Positive - Negativ (3)
t-3	7.91%	6.95%	0.97%***
t-2	8.22%	7.30%	$0.92\%^{***}$
t-1	8.74%	7.62%	$1.13\%^{***}$
Pre-merger mean performance [A]	8.28%	7.28%	$1.01\%^{***}$
t (merger completion year)	8.31%	7.27%	$1.04\%^{***}$
t+1	7.39%	6.81%	$0.58\%^{*}$
t+2	6.55%	6.46%	0.09%
t+3	6.19%	6.29%	-0.10%
Post-merger mean performance [B]	6.72%	6.54%	0.19%
Post - Pre [B - A]	-1.56%***	-0.74%***	-0.82%***

Panel A: Industry Adjusted Operating Performa	nce of Mergers
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#### Panel B: Operating Performance Regressions

		Return on Assets	
	(1)	(2)	(3)
Positive Return Experience Group	$.0110^{***}$ $(.0034)$	$.0107^{***}$ $(.0034)$	$.0112^{***}$ (.0029)
POST	0035 $(.0023)$	0028 $(.0023)$	0033 $(.0021)$
$Positive \; Return \; Experience \; Group \times POST$	0082*** (.0030)	$0073^{**}$ $(.0030)$	0065** (.0026)
Controls Year-Fixed Effects Industry-Fixed Effects	43 No Yes	No Yes Yes	Yes Yes Yes
# Obs.	$57,\!366$	$57,\!366$	49,630
Adjusted $R^2$	.1516	.1617	.3413

Table 8: Past Acquisition Return Experiences & This table presents results from the fixed effects logit reg to examine differential effects of past acquisition return	and Value Destroy gressions that are estin resperiences on merg	ing or Enhancing nated using a conditi er frequencies across	Mergers - Corporat onal logit specification corporate governance	e Governance in Equation (11) proxies. We use
institutional ownership and financial expertise on corpora data comes from the Thomson Reuters Institutional ( managers as reported on the Form 13F filed with the SEC investors divided by total number of shares outstanding the RiskMetrics. We measure financial expertise on cor	ate boards of <i>acquarer</i> . (13F) Holdings datab. C. We measure institut at the end of fiscal ye arporate boards as the	a as proxies for corpoi ase, which contains cional ownership as th ar t-1. Financial exp e number of financial	ate governance. Institu ownership information te number of shares hel- ertise on corporate bo experts (as indicated	utional ownership by institutional d by institutional ards data is from by RiskMetrics)
designated on the board of directors divided by total nu the highest tercile of institutional ownership (financial ex The dependent variable is a binary variable where 1 ind	mber of board membe cpertise) are classified d dicates that the firm e	ars in fiscal year t-1. as high institutional c ngages in Value Des	For each year, firm-yea wnership (financial ext troying(VD) (or Value	ar observations in pertise): $High=1$ . Enhancing(VE)
mergers in a given year. We use a sign of transaction valuand $Value\ Enhancing\ mergers.$ If the sign is negative (mergers. We define $Past\ Acquisition\ Experiences\ as\ triangle and the set of t$	ue weighted average o (positive), a firm is cl cansaction value weigh	f about returns in assified as engaging i ted average of annou	a given year to define n Value Destroying (1 ncement returns over t	Value Destroying (alue Enhancing) he past 10 years.
Announcement returns are abnormal returns over a thr returns are the difference between raw returns and val	ree-day window starti lue-weighted market i	ng one day before th ndex returns. We se	ne announcement date sparate Past Acquisit	where abnormal ion Experiences
into two parts: Positive Past Acquisition Experie Negative Past Acquisition Experiences = $-Past$ Acquisition to the control variables: Cashflow, Q, Leverage, Size. We meas	ences = Past Acqu uisition Experiences sure Cashflow as earn	isition Experiences × 1 {Past Acquisition E ngs before extraordin	$\times \mathbb{1}_{\{Past\ Acquisition\ E}} \times \mathbb{1}_{\{Past\ Acquisition\ E}}$ <i>xperiences</i> <0}. We incliately hary items plus depreci-	<pre>rperiences &gt; 0} and ude the following ation normalized</pre>
by the beginning-of-the-year capital (property, plants, and beginning of the year, <i>Leverage</i> as total debt over total as of the year. The sample period runs from $1983$ to $2013$ parentheses are robust to heteroskedasticity and clustered	<pre>id equipment), Q as th seets at the beginning c i for column (1)-(2) ar 1 by firm. ***, **, * in</pre>	e ratio of market vall of the year, and <i>Size</i> i d from 2008 to 2013 licate significance at $1$	te of assets to book values the log of total assets for column $(3)$ - $(4)$ . Since $1\%$ , $5\%$ , and $10\%$ le	te of assets at the s at the beginning tandard errors in vels, respectively.
	Val Institutional	ue Destroying [Value Ownership	Enhancing] Acquirer = Financial	= 1 Expertise
	VD (1)	VE (2)	VD (3)	VE (4)
Positive Past Acquisition Experiences [PPAE]	$8.8184^{***}$ (1.3953)	$-2.4337^{***}$ (.9015)	$14.8153^{**}$ (6.5839)	-6.4598 (5.9390)
Negative Past Acquisition Experiences [NPAE]	$-9.7794^{***}$ (1.7836)	$\frac{11.6190^{***}}{(1.4985)}$	$-14.3734^{**}$ (6.2306)	$\frac{11.4813^{**}}{(5.4227)}$
High	$.3127^{***}$ (.0937)	$.2364^{***}$ (.0831)	2275 (.2910)	.2689 (.2813)
$PPAE \times High$	$-3.1406^{**}$ (1.5244)	.5193 $(1.2117)$	1826 (4.6944)	-4.3472 ( $6.8579$ )
NPAE  imes High	5291 (2.1378)	-2.5242 (1.7469)	1.9171 (7.7226)	$14.3706^{*}$ $(7.8923)$
Controls/Year and Firm-Fixed Effects	Yes	Yes	Yes	Yes
# Obs.	18,769	20,900	1,356	1,742
Pseudo $R^2$	.0427	.0398	.0487	.0679

Table 9: The E This table presents results from the fixed (4). The dependent variable is a binary v are <i>Past Acquisition Experiences</i> , <i>Pos</i> past 3, 5, and 10 year windows <i>withim</i> C of announcement returns during the corr window starting one day before the annou market index returns for the same period. et al., 2011 and Hirshleifer et al., 2012. <i>R</i> years). We use the Fama-French 48 indus errors in parentheses are robust to hetero levels, respectively.	Affect of Past A l effects logit reg ariable where 1 s itive Past Acqu JEOs' tenure. W responding exper- mement date wh unup $1(7)yr$ is bu try classification skedasticity and	cquisition Exp ignifies overconfid ignifies overconfid <i>isition Experien</i> <i>e</i> define <i>Past Ac</i> <i>tence</i> windows. A <i>tence</i> windows. A <i>tere</i> abnormal retu buy-and-hold stock for industry fixed clustered by indu	eriences on CF estimated using ent CEO followi ces, and Negat quisition Exper- mouncement re urns are the differ k returns over the returns over the effects. The sam stry. ***, **, *	20 Overconfid a conditional le ng Campbell et <i>ive Past Acqui</i> <i>iences</i> as transc turns are abnor turns are abnor tence between ra e past fiscal yea lesser of the CE nple period runs indicate signific	lence ogit specification al., 2011. Our m <i>isition Experien</i> action value weig mal returns over aw returns and va w returns and va tr as suggested in O's tenure or on from 1992 to 20 from 1992 to 20 ance at the 1%, t	in Equation ain variables ces over the hted average due-weighted Malmendier e year (seven 13. Standard 5%, and 10%
<u>Panel A: Past Abnormal Returns</u>		Predicting O	verconfidence (O	verconfident CE	0 = 1	
1	Expe	erience Windows		Ex	perience Window	s
I	$_{(1)}^{3\mathrm{yr}}$	5yr $(2)$	$\begin{array}{c} 10 \mathrm{yr} \\ (3) \end{array}$	$\begin{array}{c} 3 \mathrm{yr} \\ (4) \end{array}$	5yr $(5)$	$\begin{array}{c} 10 \mathrm{yr} \\ (6) \end{array}$
Past Acquisition Experiences	$\frac{1.9220^{***}}{(.5306)}$	$1.9792^{***}$ (.5251)	$\frac{1.9637^{***}}{(.6278)}$	$1.3255^{**}$ (.5364)	$1.1556^{**} \\ (.5145)$	$1.1470^{*}$ (.6277)
$Runup\ 1yr$	$.6976^{***}_{(.0701)}$	$.6768^{***}$ .(.0689)	$.6607^{***}$ (.0625)			
Runup~7yr				$.8565^{***}$ (.0609)	$.8708^{***}$	$.8566^{***}$ (.0621)
Year- and Industry- Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
# Obs.	5,131	6,075	6,821	5,131	6,075	6,821
Pseudo $R^2$	.0597	.0581	.0519	.0965	.096	.0893
Panel B: Positive vs. Negative Past	Abnormal Ret	urns				
		Predicting	Overconfidence	(Overconfident	CEO = 1) xnerience Windox	SA
	$\begin{array}{c} 3 \mathrm{yr} \\ (1) \end{array}$	$_{(2)}^{\rm fyr}$	$\begin{array}{c} 10 \mathrm{yr} \\ (3) \end{array}$	$\frac{3yr}{(4)}$	$\begin{array}{c} 1 \\ 5 \\ (5) \end{array}$	$\begin{array}{c} 10 \text{yr} \\ (6) \end{array}$
Positive Past Acquisition Experiences	$3.4148^{***}$ (.9632)	$3.6702^{***}$ (.8623)	$3.0399^{***}$ (.9659)	$2.4547^{**}$ (1.0587)	$2.4645^{***}_{(.9175)}$	$1.8982^{*}$ (1.0680)
Negative Past Acquisition Experiences	.0878 $(1.0261)$	$.2856 \\ (1.0293)$	4835 (1.1775)	$.2012 \\ (1.1124)$	$.5977 \\ (1.0851)$	1189 (1.2514)
$Runup\ 1yr$	$.6985^{***}$ (.0696)	$.6790^{***}$	$.6609^{***}$ (.0622)			
Runup~7yr				$.8540^{***}$ (.0612)	$.8681^{***}$ (.0617)	$.8551^{***}$ (.0624)
Year- and Industry- Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
# Obs.	5,131	6,075	6,821	5,131	6,075	6,821
Pseudo $R^2$	.0605	.0591	.0523	6960.	.0966	.0895

$\mathbb{T}_{\mathcal{O}}$ $\mathbb{N}_{\mathcal{O}}$ $\mathbb{N}_{\mathcal{O}}$ $\mathbb{O}_{\mathcal{O}}$ $\mathbb{O}_{\mathcal{O}}$		D		Ducdicting	A continue	
This table presents results from the fixed effects n Equation (4). The dependent variable is a bid in a given year. Our main variable is <i>Pos</i> 10 year windows and <i>Overconfidence</i> . We definant announcement returns during the corresponding e chree-day window starting one day before the an eturns and value-weighted market index returns wo parts: <i>Positive Past Acquisition Experien</i> <i>Negative Past Acquisition Experiences</i> = $-Past$ a binary variable where 1 signifies overconfident CEO f for industry fixed effects. The sample period runs from clustered by industry. Note that the average fitted proj ogit regressions with year and industry dummy variable these specifications, but we confirm that the estimates ***, **, * indicate significance at the 1%, 5%, and 10%	logit regress binary variably sitive (Negat a Past Acq experience win mouncement for the sam ces = Past Acquisition following Cam following Cam following Cam for this and es only for thi from these sp from these sp levels, respect	ions that ar ive) $Past$ ive) $Past$ uisition Expadows. Andate wheree period.AcquisitionExperiencespbell et al., 2(Standard ermarginal effeca purpose. Weecifications arively.	receiver that definition definition Acquisition periences asnouncementabnormal reWe separate $E Experience\times 1 \{P_{ast} Acqui111. We use ttors in parentltors in parentltors in parentltors in very close toe very close to$	using a cond the firm m <i>Experiences</i> transaction v returns are the <i>Past Acqui</i> $S \times 1$ ( <i>Past Ac</i> <i>sition Experience</i> he Fama-Frenc heses are robus reses are robus nesses are robus those from c	ditional logit ade at least over the past value weighted abnormal retu e difference $1$ <i>isition Experi</i> <i>escol</i> . Overc escol. Overc escol to heteroske alculated from alculated from onditional logi	specification one merger 3, 5, and average of urns over a oetween raw <i>riences</i> into <i>mes</i> $\geq 0$ } and <i>onfidence</i> is classification dasticity and the <i>standard</i> the <i>standard</i> regressions.
	Exp	Pre erience Windo	dicting Acquir ows	er (Acquirer = Ext	= 1) perience Windo	SMo
	$\begin{array}{c} 3yr\\ (1) \end{array}$	$\begin{array}{c} 5 \mathrm{yr} \\ (2) \end{array}$	$\begin{array}{c} 10 \mathrm{yr} \\ (3) \end{array}$	$\begin{array}{c} 3 \text{yr} \\ (4) \end{array}$	5yr (5)	$\begin{array}{c} 10 \mathrm{yr} \\ (6) \end{array}$
Positive Past Acquisition Experiences	$^{-1.1193}_{(.7963)}$	.0450 (.9291)	1394 (.9178)	-1.2978 (.8037)	1555 (.9665)	3613 (.9534)
$Negative\ Past\ Acquisition\ Experiences$	$-3.2655^{***}$ (1.0783)	$-2.4318^{**}$ (.9657)	$-2.4661^{**}$ (.9737)	$-3.2491^{***}$ (1.0742)	$-2.4206^{**}$ (.9791)	$-2.4514^{**}$ (.9920)
Over confidence	$.2441^{***}$ (.0701)	$.2506^{***}$ (.0632)	$.2279^{***}$ (.0594)	$.2005^{***}$ (.0673)	$.2107^{***}$ (.0623)	$.1882^{***}$ (.0597)
$Runup\ 1yr$	$.2407^{***}$ (.0636)	$.1916^{***}$ (.0547)	$.1706^{***}$ (.0475)			
Runup Tyr	~	~	·	$.2229^{***}$ (.0453)	$.2009^{***}$ (.0462)	$.1936^{***}$ (.0449)
Avg. fitted prob. $(\%)$ at the mean of						
Negative Past Acquisition Experiences Overconfidence	$29.90\%\ 31.23\%$	$27.77\% \\ 28.68\%$	25.07% $25.92%$	$29.91\%\ 31.25\%$	$27.78\% \\ 28.69\%$	25.08% $25.94%$
Marginal effects (%) of $1\sigma$ increase from the mean of						
Negative Past Acquisition Experiences	$-2.66\%^{***}_{(.0083)}$	$-1.87\%_{(.0071)}^{***}$	$-1.77\%^{***}$ (.0066)	$-2.64\%^{***}_{(.0082)}$	$-1.86\%^{***}_{(.0072)}$	$-1.76\%^{***}_{(.0068)}$
Over confidence	$2.51\%^{***}_{(.0073)}$	$2.46\%^{***}_{(.0063)}$	$2.08\%^{***}_{(.0055)}$	$2.05\%^{***}_{(.0070)}$	$2.05\%^{***}_{(.0062)}$	$1.71\%^{***}_{(.0055)}$
Controls Year- and Industry- Fixed Effects	$_{\rm Yes}^{\rm Yes}$	$_{\rm Yes}^{\rm Yes}$	$_{\rm Yes}^{\rm Yes}$	$_{\rm Yes}^{\rm Yes}$	$_{\rm Yes}^{\rm Yes}$	Yes Yes

8,422 .0145

6,742.0166

5,318.0186

6,742.0150

8,422

5,318 .0168

# Obs. Pseudo  $R^2$ 

#### Table 11: Fairlie-Blinder-Oaxaca Decomposition of the Secondary Effects of Past Acquisition Experiences on Merger Decision

This table presents results from the Fairlie-Blinder-Oaxaca decomposition. This method measures how much of the difference in High and Low Return Experience Groups' merger frequencies can be explained by differences in control variables such as *Cashflow*, *Q*, *Leverage*, *Size*, and most importantly *CEO Overconfidence*. We first run a logit regression of *Acquirer* dummy on all control variables, omitting *Past Acquisition Experiences* regressor. The decomposition technique computes the marginal effect of group mean differences for seven natural collections of the control variables including year and industry dummies. For a given pairing across groups, marginal effects are the sequence of changes in predicted frequencies obtained by sequentially changing each control variable's value from its group mean at the Low- to its mean at the High- Return Experience Group. Sequencing of the changes in the control variables are randomized, repeated (1,000 times), and averaged to obtain marginal changes in merger frequencies and test statistics. Panel A reports decomposition estimates for High Positive vs. Low Positive Return Experience Groups where as Panel B reports those for High Negative vs. Low Negative Return Experience Groups. \*\*\*, \*\*, \* indicate significance at the 1%, 5%, and 10% levels, respectively.

Panel A	: Decom	position	Estimates	of High	Positive	vs Low	Positive	Return E	xperience	Groups
I GHIOI II	· Docom	position	Louinacoo	OI IIIGII		10 100	1 0010100	LOCCULLI L	mportonico	Groups

Variables	Decomposition(%) [A]	z-value	Contributions [A / B]
CEO Overconfidence	$0.417\%^{***}$	3.200	20.15%
Cash Flow	0.115%	1.230	5.53%
Q	-0.070%	-0.590	-3.39%
Size	$0.660\%^{*}$	1.900	31.83%
Leverage	0.052%	1.040	2.49%
Year Dummies	0.003%	0.030	0.16%
Industry Dummies	-0.298%	-0.780	-14.36%
High Positive Return Exp Group M&A Frequencies	30.537%		
Low Positive Return Exp Group M&A Frequencies	28.465%		
Total Difference in M&A Frequencies [B]	2.072%		
Explained Difference in M&A Frequencies	0.879%		
Unexplained Difference in M&A Frequencies	1.194%		

#### Panel B: Decomposition Estimates of High Negative vs Low Negative Return Experience Groups

Variables	Decomposition(%) [A]	z-value	Contributions [A / B]
CEO Overconfidence	$0.294\%^{***}$	2.760	-22.12%
Cash Flow	-0.018%	-0.240	1.33%
Q	0.054%	0.340	-4.06%
Size	0.089%	0.750	-6.70%
Leverage	0.058%	0.460	-4.35%
Year Dummies	-0.008%	-0.060	0.61%
Industry Dummies	0.275%	0.600	-20.70%
High Negative Return Exp Group M&A Frequencies	26.166%		
Low Negative Return Exp Group M&A Frequencies	27.494%		
Total Difference in M&A Frequencies [B]	-1.328%		
Explained Difference in M&A Frequencies	0.744%		
Unexplained Difference in M&A Frequencies	-2.072%		