Essays on Empirical Corporate Finance

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Introduction

This doctoral thesis consists of three essays on empirical corporate finance and is submitted to the Department of Finance at the Norwegian School of Economics in partial fulfillment of the requirements for the completion of the degree of Doctor of Philosophy at NHH.

These three essays explore three important areas in empirical corporate finance. The first paper investigates whether time invariant characteristics can explain changes in shareholders wealth for different type of acquirers. The second paper investigates the industry wealth effect of acquisitions through time. That is, the second essay explores the evolution of the announcement returns to competitors of the acquirers through time. The third paper investigates the market reaction to brand capital shock using an quasi-exogenous shock: the Academy awards ceremony.

While the topics may differ among themselves, these three papers share an underlying methodology: they all three employ the event study methodology to investigate different research questions in empirical corporate finance.

Event study as a method

Why are we interested in announcement returns and event studies? To answer this important question, let us take a step back. Classical finance theory asserts that asset prices should reflect all the available information at time t[1] (see Fama, Fisher, Jensen, and Roll (1969), Fama (1970), Fama (1991)). In other words: "the ideal is a market in which prices provide accurate signals for resource allocation" (Fama (1970), p. 383). If markets are efficient then we should observe a change in stock price when new information is available (e.g. earnings announcement, merger announcement).

[1]In this case t represents the point in time and the stock price should reflect all the information available at different point in time, that is: $\forall\ t$.

To study these changes in stock prices around corporate events we can use an event study, the purpose of which is to study the behavior and reaction of firm's stock prices around a common or individual corporate event. That is, an event study allows us to investigate how production-investment decisions affect security prices.

The event study is a popular methodology as it allows researchers to study different research questions across different disciplines. For example, Patell (1976) investigates the return variance around the disclosure of corporate forecasts of future earnings. Campbell and Wasley (1996) and Beaver (1968) explore abnormal trading volume using an event study methodology. Eckbo (1983) uses an event study to investigate the collusion hypothesis for horizontal mergers.

Kothari and Warner (2007) find that from 1974 to 2000 more than 500 papers applying the event study methodology were published in the five leading journals: *Journal of Finance* (JF), *Journal of Financial economics* (JFE), *Review of Financial Studies* (RFS), *Journal of Financial and Quantitative Analysis* (JFQA), and the *Journal of Business* (JB). As we can see, thanks to its flexibility and wide range of applications the event study methodology became a cornerstone method in empirical finance. Yet, the statistical format of event studies still follows the table outlined by Fama, Fisher, Jensen, and Roll (1969). That is - even after four decades - the key objective of an event study still remains estimating the mean and cumulative mean abnormal return around an event and summarize the results in a table as in the classical Table in Fama, Fisher, Jensen, and Roll (1969).

As finance research has evolved through the years, the event study methodology has undergone some major changes. First, the availability of daily data return allowed researchers to have a more precise estimate of the returns around the event thus providing a more reliable methodology to account for variation in stock returns. Second, the methods for long-horizon event studies have improved. Thanks to new econometric insights, long-horizon event studies have become more reliable despite joint-test problems and low statistical power[2]. Third, researchers have found solutions to account for cross-correlation for an event that is clustered at a particular date or affect more than one firm.

How to perform an event study

The idea behind a event study is simple: at a certain date t the firm announces - or observes - a corporate event[3]. Depending on the event, it may involve one or more firms in the same or in different industries.

Assume that the event occurs at time 0 ($t = 0$). Let us also assume that a firm i is publicly traded and its security (share) is denoted as S_i. The return on the security S_i for time t is denoted as R_{it} and can be decomposed as:

$$R_{it} = \tilde{R}_{it} + e_{it} \tag{i.1}$$

where $\tilde{R}_{it}$ is the expected return on security i (estimated using a model of expected returns[4]) and e_{it} is the fraction of the return which is unexpected (see Brown and Warner (1985) and Campbell, Champbell, Campbell, Lo, Lo, and MacKinlay (1997)). We can define the component e_{it} as a direct measure of the unexpected change in the security price (abnormal return, AR_{it}). That is, e_{it} can be rewritten as:

$$AR_{it} = e_{it} \Rightarrow AR_{it} = R_{it} - \tilde{R}_{it} \tag{i.2}$$

For example, e_{it} at time $t = 0$ is the one-day unexpected change in security S_i due to a specific corporate event[5].

In case of anticipated events (such as a merger) or for small stocks, research has found that

[2]Nevertheless, Fama (1991) argue that short-horizon event studies represents the "[...] cleanest evidence we have on efficiency" (p. 1602).

[3]This event may occur on different points in time (e.g. earning announcements) or it may occur on a specific date (e.g. the announcement of a regulatory change).

[4]The choice of which model of expected returns is left to the authors of the study. Yet, Brown and Warner (1985) show that - for daily returns - the choice of the model does not influence the results.

[5]This simple framework is not limited to the abnormal return on a security i but it can be extended to other variables (e.g. trading volume).

cumulative abnormal returns over a specified event window are a better estimate for announcement returns[6]. In other words, the unexpected change e_{it} at time $t = 0$ does not entirely capture the unexpected changes due to the news. For a time period between t_1 and t_2 we can define CAR as:

$$CAR(t_1, t_2) = \sum_{t=t_1}^{t_2} AR_t \tag{i.3}$$

where AR_t is the abnormal return at time t as in equation i.2.

How can we use announcement returns to test for economic hypotheses? Usually researchers perform several cross-sectional tests using abnormal returns as the dependent variable. In other words, announcement returns are regressed against a set of characteristics defined *a priori*[7]. Depending on which economic hypothesis is tested, researchers specify an *ex-ante* economic model that can explain the heterogeneity in announcement returns. As a result, modern event studies (e.g. cross-sectional analyses) follow a basic regression analysis as:

$$AnnRet_{i,L} = \alpha + \gamma X' + \epsilon_i \tag{i.4}$$

where $AnnRet_{i,T}$ is the announcement return (abnormal return or cumulative abnormal return) for firm i for horizon length L ($L = t_2 - t_1 + 1$), X' is a vector of characteristics, γ is the vector of estimated coefficients for characteristics X', and ϵ_i is the error term.

This dissertation contains three papers which all apply the event study approach. In the first paper, I investigate whether total shareholders wealth can be explained by time invariant characteristics using a modified event study methodology. In the second paper, I use a standard event study method to investigate the merger announcement returns of competitors to the acquirer over time.

[6] As for models of expected returns, the choice between using abnormal returns (ARs) or cumulative abnormal returns (CARs) is left to the authors. The chosen event window is also chosen by the authors.

[7] These characteristics can be firm specific (e.g. firm size), industry specific (e.g. Herfindahl-Hirschman Index), or event specific (e.g. deal characteristics for a merger).

In the third paper, we investigate whether shock to brand capital are incorporated in the stock prices using a standard event study methodology. All these three papers have as dependent variable announcement returns and on the right hand side various characteristics that explain the cross-section (or longitudinal) data.

Time invariant characteristics and shareholders wealth: Evidence from M&A activity

Since 1980s the number of merger and acquisition (M&A) transactions steadily increased reaching an unprecedented record number of deals. According to two reports by the IMAA Institute[8], since 1985 more than 790,000 transactions were announced worldwide - with a record year in 2017 (52,740 transactions) - for a total value of over USD 57 trillion. Starting in 1985, in the United States more than 325,000 transactions were announced. That is, the number of transactions in the United States alone represents a 40% share of the total number of transactions globally (IMAA (2021a)). Yet, after more than thirty years, one unresolved question remains: what is the source of takeover gains?

As first noted by Jensen and Ruback (1983), financial economists have recognized the elusiveness of takeover gains. Despite the multitude of large sample studies, researchers only identified a relatively small number of determinants of acquirer performance, leaving the majority of the variation unexplained. That is, even after three decades the gains determinants are still elusive. For example, with a sample of more than twelve thousands transactions, Moeller, Schlingemann, and Stulz (2004) find that their extensive list of determinants result in an adjusted R-squared of just over 5%. Smaller sample studies such as in Masulis, Wang, and Xie (2007), Harford, Humphery-Jenner, and Powell (2012) resulted in comparable adjusted R-squared values. If an extensive list of regressors can only explain a small portion of the variation in bidders takeover gains, what are then the sources of such gains? Are takeover gains determined by firm-specific

[8]See IMAA (2021b), IMAA (2021a).

skills, or determined by some other factors?

Anecdotal evidence shows that some firms persistently engage in and deliver successful mergers and acquisitions. Berkshire Hathaway, IBM, or General Electric - among others - are notable examples of these successful acquirers engaging in wealth-creating mergers. Perhaps these type of acquirers possess some unobservable characteristics or skills that influence the gains from a takeover. Golubov, Yawson, and Zhang (2015) test whether bidders have some unobservable time-invariant characteristics that can better explain the heterogeneity in bidder returns. The authors find that firms that repeatedly engage in mergers and acquisitions have some unobservable firm-specific characteristics that can explain a larger variation in takeover gains.

In this paper, I investigate whether these unobservable characteristics - captured by firm fixed-effects - can explain changes in shareholders total wealth. I define changes in shareholders total wealth as the cumulative abnormal return in dollars from the merger announcement. Specifically, cumulative abnormal dollar returns are estimated using the methodology by Malatesta (1983) and are centered around the event window (-2,+2).

Why should we use dollar returns instead of percentage returns? When a merger is announced the announcement return incorporates two different effects: the economic impact of the announcement and the effect of the announcement itself. When returns are estimated in percentage and cross-section tests are performed, it is difficult to distinguish between the two effects. Thus, when bidders fixed effects are used as regressors to capture time-invariant characteristics their interpretation require caution. By using cumulative abnormal dollar returns we can investigate whether acquirers unique characteristics can explain the total dollar value of the merger announcement.

This paper finds that frequent acquirers - those firms that acquire more than five targets in a three-year window period - fixed effects can explain approximately the same variation in cumulative returns, whether they are expressed in percentage value or dollar value. For all the other acquirers (those that acquire only one target or those that acquire less than five targets in a three-year period) the variation in cumulative abnormal dollar returns explained by bidder fixed effects is lower than Golubov, Yawson, and Zhang (2015). That is, for frequent acquirers bidder fixed effects appear to explain the total economic dollar impact of the merger announcement. On the other hand, for all the other type of acquirers bidder fixed effects capture a minimal portion of the variation in cumulative abnormal dollar returns. This paper also identifies significant industry fixed effects in acquirer announcement dollar returns: in cross-sectional regressions with bidder announcement dollar returns as the dependent variable, the inclusion of bidder industry fixed effects nearly has the same explanatory power as in Golubov, Yawson, and Zhang (2015)for the so-called "frequent acquirers".

Overall, the results are robust to different event window specifications as well as different sample compositions. While at this stage the source of takeover dollar gains is still elusive, I provide evidence that cumulative abnormal dollar returns can be partially explained by acquirer time-invariant characteristics.

The industry wealth effect of acquisitions through time

In their comprehensive reviews of the empirical literature on mergers and acquisitions, Jensen and Ruback (1983) and Roll (1986) made three important conclusions: (1) Shareholders of target firms realize economically large gains, (2) gains to bidder shareholders are small but positive on average, (3) the sources of takeover synergies are 'elusive' but most likely do not emanate from increased market power.[9] Nearly four decades later, these three conclusions have been largely confirmed based on the much larger samples of mergers and acquisitions made possibly by machine-readable databases (Betton et al., 2008). While knowledge of the fundamental sources of takeover synergies continues to elude researchers, there is growing evidence of economic links between those sources

[9] The latter conclusion is based on the empirical tests pioneered by Eckbo (1983).

and industrial organization (Eckbo, 2014). In other words, whatever the synergy sources, their value are most likely influenced by—and influence—industrial competition and supply networks. The purpose of this paper is to explore this intuition further in terms of the time-trend of the valuation impact of merger announcements on the merging firms' industry rivals.

A precondition for positive bidder gains from acquisition activity is that bidders—and not just targets—own some of the core resources that are necessary to produce synergy gains. Dessaint, Eckbo, and Golubov (2019) offer a novel perspective on how bidder-specific takeover gains have evolved through time. They motivate the time-series analysis by referring to the substantial changes in the corporate governance of US firms that has taken place since the 1980s. To the extent that those governance improvements have reduced agency costs and improved the efficiency of corporate investments, average bidder gains may also have changed with time. They find that bidder fixed effects are declining while the component of bidder gains that is *common* across bidders has been steadily increasing relative to the 1980s.

Dessaint, Eckbo, and Golubov (2019) suggest that the decline in bidder fixed effects—and concomitant increase in the common component of bidder gains—is evidence that takeover synergies have become less bidder-specific over time. As a result, bidder bargaining power has also declined on average. Bidders have low bargaining power when the resources required to create synergies for the most part resides within the target.

This paper extends the notion of declining bidder-specific synergies to the closest competitors of the acquiring firms. To the extent that the resources required to generate bidder-specific synergies are available throughout the industry in which the bidder operates, we should also see a trend towards a decline in the industry wealth effect of acquisition announcements. That is, firms in the main industry of bidders may act as potential competitors for the target or as potential targets for the bidder. Controlling for industry characteristics and/or bidder fixed effects, I identify a small but statistically significant negative time-trend in the average announcement return for the portfolio of the top five competitors of the acquirers. Announcement returns are estimated as the announcement return for a portfolio of the top five competitors of the acquirer using standard event study methodology. Starting in 1990, the decline in the industry wealth effect is around -2 basis point per year. To put it in context, the average decline of two basis points represents approximately 10% of the average unconditional competitor CARs. That is, the negative economic magnitude of the time-trend variable is considerable when compared to the average competitors cumulative abnormal return. The results are robust to a series of robustness tests and additional analysis.

The negative time-trend in competitor CARs may be consistent with two hypotheses. First, as more firms engage in mergers, the decline in CARs can be explained by a decrease in the expected gains from engaging in a merger. That is, competition among actual and potential bidders may result in a declining cumulative abnormal return. Second, as more firms engage in mergers the level of information conveyed at the merger announcement may decrease. As a result, we should observe a negative trend in competitor CARs. While the source of this decline in competitor CARs remains a puzzle it appears that a strong correlation between this negative trend and mergers with a high degree of information asymmetry exists.

And the CAR goes to... Shock to Brand Capital: Evidence form the Oscars (joint with Nataliya Gerasimova, NHH)

During the last few decades, intangible capital has become a major fraction of company capital both in the US and in Europe. The existing literature focuses mainly on the long-term relationship between intangible assets and financial markets. Regrettably, the question of how quickly companies benefit from intangible assets has received little attention in the literature, largely due to the endogenous concerns. In this paper, we aim to fill this gap by focusing on a specific form of intangible capital — brand capital — and investigating how quickly the effect of random and unexpected brand exposures gets incorporated into the stock returns.

To document this random and unexpected brand exposures we use a novel exogenous shock: the Academy Awards ceremony, known as the Oscars. Why does the Oscars might matter for the brand capital? There are at least two channels: The Oscars sets a company apart from its competitors, and it has the ability to affect consumer behavior. The Oscars is one of the most recognizable annual events in the U.S. and worldwide. According to the Academy of Motion Picture Arts and Sciences, the event covers a global audience of "several hundred million in 225 countries". Most of the Oscars' interviews begin with a question, "What are you wearing?". Success on the red carpet could provide prestige for designers, stars and generate long-term profits for luxury brands. The red carpet presents "a great and free opportunity" for a designer to reach an audience that expands beyond the fashion set, said Ariel Foxman, editor of fashion magazine InStyle. "It's free marketing," Foxman said. "Advertising dollars are so expensive, and marketing budgets are so fractured these days with social media, digital media, print media and television media, so it's more valuable than ever" (see Business of Fashion (2014)).

How does the Oscars ceremony differ from the other instruments of building the brand capital? The main challenge of investigating whether companies extract financial value from their brand value is the endogenous nature of other methods such as advertising and endorsement contracts. The existing literature mostly provides evidence of a positive correlation between brand equity and a company's performance. We claim that the Oscars ceremony is an exogenous shock to brand capital. It is generated externally and not directly related to the fundamentals of the company. The red carpet plays the role of external expertise. It might induce changes in brand value but not due to a company's strategy.

To document the role of the Oscars red carpet, we perform a two-step procedure. First, we estimate the predicted stock returns from a market model over Friday before the ceremony and the Monday and Tuesday after it. We compute the CARs as the sum of abnormal returns. We then test whether the Oscars ceremonies are shocks to the brand value of holding companies by running an Ordinary Least Squares (OLS) estimation. We find that holding companies whose brands appear on the red carpet of the Oscars have 1.12 percentage points higher three-day CARs than their peers. The effect is significant after controlling for Book-to-Market, size, endorsement contracts, and major company-specific news. In addition, there is a significant change in investor attention during the days of the ceremonies. Following Da, Engelberg, and Gao (2011) and Buchbinder (2018), we measure attention by computing abnormal Google's search volume index (SVI) of the companies' names. The holding companies whose brands were chosen by actresses experience a higher SVI compared to their peers.

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Time invariant characteristics and shareholders wealth: Evidence from M&A activity *

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Abstract

In this paper, I investigate whether time invariant characteristics can explain cumulative abnormal dollar returns. When returns are estimated in percentage value, testing economic hypotheses on the total economic dollar impact is difficult. By using cumulative abnormal dollar returns (or total shareholders wealth) we can clearly tests whether time-invariant characteristics can explain the total economic dollar impact of a merger. I find that frequent acquirers (those bidders who acquire more than five targets over a three-year period) possess some unique characteristics that explain the variation in the total economic dollar impact of a merger as in the case of percentage returns. For all the other type of acquirers, I find that bidder fixed effects result in a lower explanatory power for the total economic dollar impact than percentage returns.

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1.1 Introduction

Since 1980s the number of merger and acquisition (M&A) transactions steadily increased reaching an unprecedented record number of deals. According to a report by the IMAA Institute (IMAA (2021b)), since 1985 more than 790,000 transactions were announced worldwide - with a record year in 2017 (52,740 transactions) - for a total value of over USD 57 trillion. Starting in 1985, in the United States more than 325,000 transactions were announced. That is, the number of transactions in the United States alone represents a 40% share of the total number of transactions globally (IMAA (2021a)). Yet, after more than thirty years, one unresolved question remains: what is the source of takeover gains?

As first noted by Jensen and Ruback (1983), financial economists have recognized the elusiveness of takeover gains. Despite the multitude of large sample studies, researchers only identified a relatively small number of determinants of acquirer performance, leaving the majority of the variation unexplained. That is, even after three decades the gains determinants are still elusive. For example, with a sample of more than twelve thousands transactions, Moeller, Schlingemann, and Stulz (2004) find that their extensive list of determinants result in an adjusted R-squared of just over 5%. Smaller sample studies such as in Masulis, Wang, and Xie (2007), Harford, Humphery-Jenner, and Powell (2012) result in comparable adjusted R-squared values. If an extensive list of regressors can only explain a small portion of variation in bidders takeover gains, what are then the sources of such gains? Are takeover gains determined by firm-specific skills, or determined by some other factors?

Anecdotal evidence shows that some firms persistently engage in and deliver successful mergers and acquisitions. Berkshire Hathaway, IBM, or General Electric - among others - are notable examples of these successful acquirers engagin in wealth-creating mergers. Perhaps these type of acquirers possess some unobservable characteristics or skills that influence the gains from a takeover. Golubov, Yawson, and Zhang (2015) test whether bidders have some unobservable time-invariant characteristics that can better explain the heterogeneity in bidder returns. They find that firms who repeatedly engage in mergers and acquisitions have some unobservable firm-specific characteristics, captured by bidder fixed effects, that can explain a larger variation in takeover gains. Furthermore, they find that frequent acquirers takeover gains are persistent: successful acquisitions prompt additional successful acquisitions. As in Jaffe, Pedersen, and Voetmann (2013), Golubov, Yawson, and Zhang (2015) find that acquirer acquisitions skills are unrelated to managerial turnover or c-level executive skills. That is, the skills or resources required to generate higher bidder gains are not attributable to c-level executives. Furthermore, for frequent acquirers it appears that their bidder gains are unrelated to deal-specific characteristics (e.g. method of payment).

In this paper, I investigate whether these unobservable characteristics - captured by firm fixed-effects - can explain changes in shareholders total wealth. That is, I investigate whether bidder fixed effects can explain some of the heterogeneity in changes in shareholders total wealth defined as the cumulative abnormal return in dollar value from the merger announcement around the event window (-2,+2). I estimate, cumulative abnormal dollar returns - or changes in total shareholders wealth - following the methodology developed by Malatesta (1983).

When a merger is announced the stock price reaction to the event incorporates two different effects: the economic impact of an event and the effect of the transaction announcement[1]. When returns are estimated in percentage and cross-section tests are performed, it is difficult to distinguish between the two effects. Thus, when bidders fixed effects are used as regressors to capture time-invariant characteristics their interpretation require caution. When returns are estimated in dollar value, unlike in percentage returns, we can clearly estimate the total economic dollar value of the merger announcement.

[1]Following Malatesta and Thompson (1985) the total economic impact of a merger can be defined as "the capitalized value of future net cash flows resulting from the event's occurrence" (p. 237). In other words, the economic impact (cumulative abnormal dollar return) is the net present value of the merger event.

This paper shows that frequent acquirers - those firms that acquire more than five targets in a three-year window period - fixed effects can explain approximately the same variation in takeover gains, whether they are expressed in percentage or dollar returns. For all the other type of acquirers (those that acquire only one target or those that acquire less than five targets in a three-year period) the variation in takeover dollar gains explained by bidder fixed effects is lower than Golubov, Yawson, and Zhang (2015). In other words, frequent acquirers have unobservable characteristics (captured by bidder fixed effects) that can explain a good portion of the variation of the economic impact of the merger transaction. I also show that the larger the transaction the higher variation in cumulative abnormal dollar returns can be explained by bidder fixed effects. That is, the higher the economic impact the better bidder fixed effects can explain the variation in cumulative abnormal dollar returns.

Industry settings may have a considerable impact on explaining changes in total wealth for stockholders of frequent acquirers. While individual investors can diversify the idiosyncratic risk inherent to the industry where bidders operate through their individual holdings, the value of the aggregate holdings may be affected. As a result, the total stockholders wealth - as a group - may be sensitive to industry unobservable components. The notion that industry influence the synergistic gains or the likelihood of deal completion is well-documented. Cai, Song, and Walkling (2011) provides evidence on how industry affects the returns for subsequent bidders and how the market can anticipate merger activity. Ahern and Harford (2014) show that stronger product market connections among firms result in higher cross-industry mergers. Golubov, Yawson, and Zhang (2015) recognize the influence of industry characteristics on takeover gains. This paper tests whether industry time-invariant characteristics may also capture some of the variation in cumulative abnormal dollar returns. To test this hypothesis, I substitute bidder fixed effects with 4-digit SIC industry fixed effects. This paper finds that in industries where the acquiring firms operate appear to influence cumulative abnormal dollar returns. For frequent acquirers the R-squared values remains stable regardless whether takeover gains are expressed in dollars or in percentage. On the other hand, for all the other types of acquirers the resulting R-squared values are lower when cumulative abnormal returns are expressed in dollar values rather than in percentage values.

Why replicating the analysis by Golubov, Yawson, and Zhang (2015) by estimating takeover gains in dollar values rather than percentage values? There are several advantages of using dollar returns as the dependent variable in such analysis. For example, takeover gains expressed in dollars are a better estimator of a "buy-and-hold" strategy on the acquiring firm total assets. Yet, cumulative abnormal dollar returns can be good estimates of the total synergies generated by the takeover. Finally, dollar values are a good estimator for the additional shareholder value created by the merger transaction. Overall, I find that there are at least five main reasons why dollar returns may provide interesting insights.

First, unlike cumulative abnormal percentage returns, cumulative abnormal dollar returns capture the changes in the acquiring firm shareholders total assets. Malatesta (1983) argues that cumulative abnormal percentage returns do not capture the changes in bidders shareholders total wealth. That is, for the shareholders of the acquiring-firm, the same percentage return has different effects on their wealth whether the bidder is a large firm or a small firm. In other words, a return of one percent changes the shareholders wealth more if the acquiring-firm is a large firm compared to a small firm. Furthermore, dollar returns focus on the firm as a whole entity while percentage returns are individual to each shareholder of the firm.

Second, both Malatesta (1983) and Malatesta and Thompson (1985) argue that cumulative abnormal dollar returns may be used as an investment performance index. This investment performance index measures a specific investment strategy: *buy-and-hold* the entire firm during the takeover period. While individual investors have different strategies available to them, this buy-and-hold strategy is only available to the stockholders group, as a whole, of the acquiring-firm. As a result, shareholders attention to the stock price and the changes in the total wealth may increase around the merger announcement.

Third, cumulative abnormal dollar returns may be a good estimator for the total synergy gains between the acquiring and the target firm. For example, Bradley, Desai, and Kim (1988) use dollar returns to estimate the overall increase in shareholders wealth due to synergistic gains from the takeover. The authors find that a successful takeover increases the combined total wealth of the two firms by approximately 7%.

Fourth, the finance literature has mainly focused on estimating the impact of takeover activities on shareholders total wealth. To that end, to estimate the impact in total shareholders wealth, cumulative abnormal dollar returns can be used as a good estimator. For example, using dollar returns Moeller, Schlingemann, and Stulz (2005) find that during the 1990s firms appeared to have engaged in wealth-destructing takeovers rather than wealth-creating investments.

Finally, the increased use of stock options in managerial compensation has resulted in managerial decision making being more sensitive to the share price and shareholder wealth. That is, managers of the firm have increased their awareness of the effect of an acquisition on the total shareholder wealth. As a result, they may be more inclined to undertake only "safe" takeovers which could increase the nominal share price but with only marginal returns for individual shareholders. For example, Datta, Iskandar-Datta, and Raman (2001) document a robust positive relation between managerial compensation and stock price performance around and following acquisition announcements. Furthermore, they find that equity-based compensation appear to explain post-acquisition stock price performance.

Overall, investigating takeover gains expressed in dollars and their source is meaningful to better understand mergers and acquisitions transactions. This paper finds that repetitive acquirers (frequent acquirers) have some time-invariant characteristics that can explain both cumulative returns in percentage and dollar terms. As a result, it appears that some bidders have one or more unique characteristics that can explain part of the variation in takeover gains, regardless of the unit of measurement. Yet, given the recent increase in awareness in stock prices by - among others - analyst, investors, and managers such an analysis helps to distinguish which firms may create value for their shareholders. As in Moeller, Schlingemann, and Stulz (2005), I find a decline in wealth creation during the period 1998-2001. I find that frequent acquirers seem to earn positive dollar returns during the period 1998-2001 but appear to engage in wealth-destructing mergers during the 2008 financial crisis. Additionally, I find that frequent acquirers appear to earn positive returns when the acquiring firm take over an unrelated target, a private target, or finance the takeover with only cash. Furthermore, I find that shareholders of acquiring-firms - other than frequent acquirers - earn positive returns only when a private target is acquired or the operation is financed only with cash.

This paper adds to multiple strands of the literature on firm takeovers. First, this paper contributes to the literature on "fixed effects". For example, Bertrand and Schoar (2003) use managers fixed effects to explain a wide range of corporate decisions, Lemmon, Roberts, and Zender (2008) find that leverage ratios are driven by unobservable time-invariant characteristics captured by fixed effects. Graham, Li, and Qiu (2011) use a 10-year panel data set and fixed effects to test whether managerial teams are miscalibrated. Golubov, Yawson, and Zhang (2015) provide evidence on how time-invariant characteristics can explain a significant part of the variation in bidders returns. This paper contributes by supplying a revised study of the work by Golubov, Yawson, and Zhang (2015) and expanding the analysis to total shareholder wealth. Using acquirers fixed effects on changes in shareholders wealth can provide an alternative methodology to differentiate firms with good acquisition capabilities to deliver a good return for shareholders as a group.

Second, this paper contributes to the literature which estimates the wealth effect of merger transactions. Malatesta (1983) provides a methodology and evidences regarding the importance for estimating dollar returns. Moeller, Schlingemann, and Stulz (2005) provide evidence of wealth destruction during the period 1998-2001. This paper contributes by expanding the sample period of Moeller, Schlingemann, and Stulz (2005) and by using the methodology outlined by Malatesta (1983) to different types of acquirers. As in Moeller, Schlingemann, and Stulz (2005), I find a trend of wealth-destructive acquisitions during the period 1998-2001. However, I provide evidence that the wealth destruction phenomenon observed by Moeller, Schlingemann, and Stulz (2005) may to a large extent be driven by occasional acquirers during the 1998-2001 period.

Finally, this study contributes to the larger literature on mergers and acquisitions. Compared to the existing literature, this paper provides evidence on how repetitive acquirers (either occasional or frequent acquirers) may - on average - engage in wealth-creating takeovers. Yet, it provides evidence on how bidder fixed effects can explain not only cumulative abnormal percentage returns but also cumulative abnormal dollar returns. Additionally, I present new evidence on how industry-specific time-invariant characteristics are persistent and may contribute to explain changes in shareholders wealth around the takeover announcement. Lastly, this paper validates the notion of how frequent acquirers time-invariant characteristics may influence takeover gains or synergies.

The remainder of the paper is organized as follows. Section 1.2 presents the sample used, the screening of the sample, and the methodology used to investigate the research question. Section 1.3 illustrates the empirical methods used in this paper. In Section 1.4, I first demonstrate the equivalence of the sample used in this paper to the one used by Golubov, Yawson, and Zhang (2015) and then present the main analysis contained in this paper. Section 1.5 contains various robustness tests for this paper. Section 1.6 summarizes and discusses the key results from this paper and their implications for the existing literature. Finally, Section 1.7 presents some concluding remarks and suggestions for further studies.

1.2 Sample selection

The M&A transaction data are provided by SDC platinum US M&A database. The sample period starts on January 1^{st}, 1990 and ends on December 31^{st},2011. To construct the final sample of M&A transactions, I follow Fuller, Netter, and Stegemoller (2002), Masulis, Wang, and Xie (2007), and Golubov, Yawson, and Zhang (2015). In other words, I impose the following restrictions:

1. The bidder must be a US publicly listed company acquiring a domestic target. The target can be a publicly listed, private, or a subsidiary firm.

2. The acquisition must be completed (as indicated by Thomson Financial SDC US M&A database).

3. The acquirer must own less than 50% of the target firm at the date of announcement and achieve 100% after.

4. The transaction value has to exceed $1 million and 1% of the bidder's market capitalization 11 days before the announcement.

5. The bidder's stock price data for 300 trading days prior the announcement are available and accounting data for the bidder (year-end immediately before the announcement) are available from Compustat.

6. Multiple deals announced on the same day by the same firm are excluded.

7. One time acquirers are excluded.

These seven restrictions result in a final sample of 10,218 transactions involving 2,446 unique firms. Following Golubov, Yawson, and Zhang (2015) I divide the observations in three sample. The first sample includes all the 10,219 transactions. The remaining two samples contains acquirers who conducted multiple deals over a short period of time. The first sub-sample consists of those bidders who completed between two and four deals within a three-year window. I refer to this first sub-sample as "occasional acquirers". This sample includes 6,193 transactions made by 1,622 unique bidder. Acquirers who completed five or more deals within a three-year window are referred as the ”frequent acquirers” sample. The number of transactions and unique bidders included in this last sample is substantially lower: 2,634 deals made by 277 unique bidders. That ism this more stringent definition greatly reduces the total number of transactions included. While marginally different, the samples of transactions are in line with previous studies: Masulis, Wang, and Xie (2007), Golubov, Petmezas, and Travlos (2012), Harford, Humphery-Jenner, and Powell (2012), and Golubov, Yawson, and Zhang (2015). Compared to the original study by Golubov, Yawson, and Zhang (2015), the sample and sub-samples used in this paper differ over two dimensions.

First, I exclude all ”one-time” acquirers. These one-time acquirers represent 2,600 additional transactions that could be included - but are not - in the final sample. These additional 2,600 acquirers represent approximately 20% of the total sample. As a result, the potential total number of transactions could increase to 12,618, in line with the total number of transactions by Golubov, Yawson, and Zhang (2015). While the majority of the transactions are performed by bidders who acquired at least two target firms, including one-time acquirers may produce undesirable results. If one-time acquirers are included in the transactions sample, it could artificially increase the adjusted R-squared of the regression. As bidder fixed effects capture the difference between the firm's cumulative abnormal return and the non-zero constant and the other regressors in the regression model, the coefficients of the fixed effects would match that difference. As a result, the adjusted R-squared of the regression model would be artificially inflated as for the one-time buyers the fixed effects the adjusted R-squared would be 100%. By excluding these one-time acquirers I remove this undesired mechanical effect on the adjusted R-squared.

Second, the occasional acquirers sample includes all those bidders who conducted at least two acquisitions but less than five. Golubov, Yawson, and Zhang (2015) defines ”occasional” acquirers as those bidders that completed at least two deals in a three-year period. This could potentially include frequent acquirers as they completed at least two transactions in a three-year window. In this paper, I try to differentiate between those acquirers that are similar to frequent acquirers but do not acquire more than four targets in a three-year window. As a result, by removing those firms that completed more than five deals over a three-year window I can better differentiate the unique characteristics between the two types of acquirers. That is, I remove any confounding effect that could influence any statistical inference. Finally, by differentiating the two types of acquirers we can gain useful insights regarding those bidders that are marginally different from frequent acquirers.

1.3 Empirical strategy

To investigate whether bidder fixed effects can explain part of the heterogeneity in acquirer returns, I employ a two stage approach. In the first stage, I check whether the sample used in this paper is similar to the one used in Golubov, Yawson, and Zhang (2015). That is, I start by replicating the analysis by Golubov, Yawson, and Zhang (2015) and examine whether I obtain similar results. In the second stage, I estimate the cumulative abnormal dollar returns for acquirers and repeat the multivariate regression analysis as in Golubov, Yawson, and Zhang (2015). Finally, I investigate the uniqueness of bidder fixed effects in explaining the heterogeneity in acquirer cumulative abnormal dollar returns.

1.3.1 First stage: estimating acquirer announcement returns

Takeover gains (or hereafter Cumulative Abnormal Returns, CARs) expressed in percentage values are estimated using a standard event study methodology. First, as in Golubov, Yawson, and Zhang (2015), I estimate the coefficients of a market model with the CRSP *value-weighted* index as the benchmark market index. The coefficients are estimated using an estimation window from 300 to 91 trading days prior the bid announcement. Second, I estimate the abnormal returns for the event window (-2,+2) as the difference between the actual stock return and the predicted stock return. Third, I estimate the cumulative abnormal returns as the sum of the abnormal returns over the event window (-2,+2). Finally, I replicate the Table 2 of Golubov, Yawson, and Zhang (2015) and compare the results. That is, if the sample constructed in this paper is similar to the one in Golubov, Yawson, and Zhang (2015), we should not find any considerable differences in the regression analysis results.

1.3.2 Second stage: estimating cumulative abnormal dollar returns

After ensuring the comparability between the sample used in this paper and the one used in Golubov, Yawson, and Zhang (2015), I then estimate changes in total shareholders wealth (cumulative abnormal dollar returns) around the merger announcement. Unlike percentage takeover gains, the estimation of cumulative abnormal dollar returns does not have a standard methodology that can be used. Searching through the finance research literature, two methodologies to estimate dollar returns stand out: Malatesta (1983) and Moeller, Schlingemann, and Stulz (2005). Malatesta (1983) defines total shareholders wealth - or cumulative abnormal dollar returns - as the residual error from a modified value-weighted market model methodology. On the other hand, Moeller, Schlingemann, and Stulz (2005) define total shareholders wealth as the change in the bidder's market capitalization over the event window.

This paper employes the methodology outlined by Malatesta (1983) over Moeller, Schlingemann, and Stulz (2005) for two reasons. First, compared to Moeller, Schlingemann, and Stulz (2005), Malatesta (1983) provides a comparable methodology to the standard event study methodology. Second, Malatesta (1983) provides a way to distinguish abnormal changes in total shareholders wealth unlike Moeller, Schlingemann, and Stulz (2005). If the methodology by Moeller, Schlingemann, and Stulz (2005) was to be used it would impact the comparability between this paper and Golubov, Yawson, and Zhang (2015). That is, comparing the R-squared values would require extreme caution. In the next paragraph, I outline in details the methodology by Malatesta (1983) to estimate abnormal dollar returns or changes in shareholders wealth.

Abnormal Dollar Return

Assume the following market model of excess returns applies to the generating process for security returns:

$$\widetilde{R}_{jt} - R_{ft} = \alpha_{jt} + \beta_{jt}(\widetilde{R}_{mt} - R_{ft}) + \widetilde{e}_{jt}, \tag{1.1}$$

where

$\widetilde{R}_{jt}$ = rate of return on security or portfolio j over period t,

$\widetilde{R}_{mt}$ = contemporaneous rate of return on the value-weighted market portfolio,

R_{ft} = risk-free return over t, and

$\widetilde{e}_{jt}$ = standard errors normally distributed with zero mean and variance $\sigma^2(\widetilde{e}_j)$

The Ordinary Least Squares (OLS) estimates of the two parameters of Eq. (1.1) would result in an unbiased linear forecasting model for the excess return, conditional on the information set available at t-1. As a result, the forecasting error can be expressed as:

$$\widetilde{U}_{jt} = \widetilde{R}_{jt} - \widehat{\alpha}_j - \widehat{\beta}_j \widetilde{R}_{m,t} - (1 - \widetilde{\beta}_j) R_{f,t}. \tag{1.2}$$

In this situation, the error term can be interpreted as a measure of the impact of new information on the value of portfolio j or firm j. Assume that date t is a period where the new information arrives, then the residual $\widetilde{U}_{jt}$ can be related to the event. Let $\widetilde{U}$ be the residual of the regression, the abnormal dollar return for the transaction is defined as:

$$\widetilde{AD}_j = \widetilde{U}_{j,t} V_j \tag{1.3}$$

where V_j is the market-capitalization of firm j. Cumulative abnormal dollar returns (CADRs) are then estimated as:

$$\widetilde{CADR}_j = \sum_{t=-2}^{T=2} \widetilde{AD}_{j,t} \tag{1.4}$$

where $U_{j,t}$ is the residual from the regression model in Eq.1.1 and V_j is the equity market value of firm j. For each transaction, I estimate the coefficient of the regression model in Eq.1.1 using the stock returns between 300 to 91 trading days before the deal announcement. Daily excess market returns and risk free rates are provided by the Kenneth French Data Library. The abnormal dollar return is then estimated following the formula in Eq. 1.2 where V_j is the market capitalization 11 days before the deal announcement. Cumulative abnormal dollar returns are then estimated over the event window (-2,+2). I choose to estimate the parameters in Eq. 1.1 using the same estimation window as in Golubov, Yawson, and Zhang (2015) in order to produce a meaningful comparison of the results between the two different abnormal returns specifications. Nevertheless, to remove any nominal price adjustments that occurred during the sample period, I adjust the equity market value using the price level in January 2000 as the reference price level.

1.3.3 Summary statistics

Table 3.3 provides a first glance to the sample used in this paper. As we can observe, the typical merger wave pattern is present in the sample. We can see two peaks - in the total number of transactions - during the period 1997-1998 and 2005. The cross-sectional mean cumulative abnormal percentage return is around 1.19% in line with the existing literature. Moeller, Schlingemann, and Stulz (2004) find an average CAR of 1.10%, Betton, Eckbo, and Thorburn (2008) find an average CAR of 0.73%, de Bodt, Cousin, and Roll (2018) find an average CAR of 1.71%. The average cumulative abnormal percentage return fluctuates over time with its highest value in 1992 and its lowest value in 2000.

Moving to cumulative abnormal dollar returns it can be see how, on average, a M&A transaction creates value for the shareholders of the acquiring firms. Cumulative abnormal dollar returns experienced a sharp decrease in 1998 as well as during the dot com bubble in 2000. This negative trend is consistent with the trend of wealth-destructive takeovers found by Moeller, Schlingemann, and Stulz (2005). Overall, we can see how around period of financial crisis the standard deviation of cumulative abnormal dollar returns increases. Moreover, as expected, the standard deviation of percentage returns increases during period of market turmoil. On average, M&A transactions remain a wealth-increase investments for shareholders of the acquiring firms.

Table 1.2 provides additional information on cumulative abnormal dollar returns by different types of acquiring firms: frequent acquirers, occasional acquirers, and remaining acquirers. Looking at the first three columns of Table 1.2, we can see how firms that are not frequent or occasional acquirers follow a similar trend as the two other groups of acquirers. Yet, the total number of acquisitions made by these remaining acquirers is, on average, lower than the number of acquisitions of occasional or frequent acquirers. On average, occasional acquirers engage in wealth-enhancing takeover as frequent acquirers. Looking at the last columns, frequent acquirers appear to perform better during the dot com bubble crisis in 2000 compared to the remaining firms in the sample. On the other hand, occasional acquirers performs relatively well in 2008 with a higher number of transactions than the other two groups combined.

At *prima facie*, looking at Table 3.3, it appears that the sample at hand does not systematically differ from the others used in the existing literature. The unconditional average cumulative abnormal percentage return does not differ from previous studies and the pattern of merger waves is present. The negative trend in cumulative abnormal dollar returns does not greatly differ from the one found in Moeller, Schlingemann, and Stulz (2005). Yet, the total number of transactions by frequent acquirers (2,634) does not differ from the one used in Golubov, Yawson, and Zhang (2015) indicating a strong likeness between the two samples.

1.4 Results

This section presents the main results of this paper. As in the empirical strategy section, a two stage approach is adopted. In the first part, the results of replicating the study by Golubov, Yawson, and Zhang (2015) are presented and briefly discussed. In the second part, the results of the regression with cumulative abnormal dollar return as the dependent variable are presented and discussed.

1.4.1 Acquirer gains

Table 1.3 contains the results of the replication of the study by Golubov, Yawson, and Zhang (2015). That is, I estimate four different OLS regression models with bidder cumulative abnormal percentage returns as the dependent variable. Column (1) reports a model that employs only bidder fixed effects as main regressors. Column (2) add year fixed effects to the regressors of column (1). Column (3) includes year and bidder fixed effects as well as deal specific characteristics. Finally, Column (4) includes all the previous regressors and bidder-specific characteristics. The F-statistic reported in all panels are the F-statistic relative to the overall significance of the regression models.

Moving from Column (1) to Column (4) in Panel A of Table 1.3, the adjusted R-squared increases by almost 40 percentage points, from 8% to 11%. Compared to Golubov, Yawson, and Zhang (2015), the full sample R-squared statistics are lower than what previous reported. The reason for this difference lie in the additional restriction imposed during the sample construction. Compared to Golubov, Yawson, and Zhang (2015), I do not include one-time acquirers as to control for the mechanical increase in the R-squared values. When applied to one-time acquirers, bidders fixed effects would capture the difference between the non-zero constant and the actual value. As a result, for one-time acquirers, fixed effects would explain the entire variation in takeover gains creating thus a bias. As in Golubov, Yawson, and Zhang (2015) bidder fixed effects can still explain a similar variation in bidders' cumulative abnormal percentage returns.

Looking at Panel B - the occasional acquirers sample - the adjusted R-squared values are not dramatically different compared to Panel A. Yet, while the definition of occasional acquirers slightly differ from the one used in Golubov, Yawson, and Zhang (2015), the adjusted R-squared and F-statistic are not dramatically different.

Finally, the most interesting result comes form Panel C of the same table: the sample of frequent acquirers. Looking at Panel C, we can seen that the adjusted R-squared from running an OLS regression with bidder fixed effects as the main regressors is around 2.4%. These results are not far from the results in Table 2 in Golubov, Yawson, and Zhang (2015). It appears that deal characteristics still play a role in explaining cumulative abnormal percentage returns. Finally, the adjusted R-squared monotonically increases across the different model specifications reaching a value of 5.8 percentage points in the last column. Overall, looking at the results it appears that the sample of frequent and occasional acquirers that I identified are similar to those in Golubov, Yawson, and Zhang (2015).

The reader may still observe a minimal difference between the sample used in this study and those used in previous studies. I argue that - while modest - this difference may be due to different reasons. First, the database employed in this study (SDC Platinum) is slightly different from the one used in other studies (Thomson Reuters) despite they are provided by the same data provider. Second, it could be due to the additional restriction I imposed in this study (see Section 1.2.1). Finally, the different definition of occasional acquirers used in this analysis may result in different adjusted R-squared values for the sample of occasional acquirers.

1.4.2 Cumulative abnormal dollar returns

After establishing the similarity of the sample used in this paper and the one in Golubov, Yawson, and Zhang (2015), I proceed with the second part of the analysis. Table 1.4 contains the results of the regression models estimations when cumulative abnormal dollar returns are used as the dependent variable. As in Table 1.3, the results for the full sample are contained in Panel A. Panel B contains the results for the occasional acquirers and Panel C contains the results for the frequent acquirers sample.

For the full sample and for the sample of occasional acquirers (Panel A and Panel B) cumulative abnormal dollar returns are minimally explained by time-invariant characteristics. For these two samples, the adjusted R-squared values are close to each other and, on average, are lower compared to the values reported in Table 1.3. On the other hand, the interesting results are in Panel C in Table 1.4. When frequent acquirers unique fixed effects are used, they appear to explain the same amount of variation in cumulative abnormal dollar returns compared to standard cumulative abnormal percentage returns. In other words, frequent acquirers appear to have unique characteristics that can explain part of the variations in returns regardless whether they are in percentage or in dollar returns.

I investigate how cumulative abnormal dollar returns differ across the three samples. I explore the three samples across three different dimensions: relatedness, target status, and payment method. By dividing the samples into these three dimensions, I can further investigate which type of deals are most beneficial to shareholders of the acquiring firms.

Frequent acquirers seem to profit from unrelated acquisitions as the t-test suggest in Column (3) in Table 1.5. In this case, I define the bidder and target as related when they operate in the same industries with a common two-digit SIC code (following Golubov, Yawson, and Zhang (2015)). Unlike frequent acquirers, occasional acquirers seem to exhibit positive cumulative abnormal dollar returns irrespective whether the bidders and targets are related or not. Finally, the results for the full sample are similar to those for the occasional acquirers sample.

Moving to the next dimension - target status - it can be seen that when a public target is acquired, the average 5-day cumulative abnormal dollar return is negative. Frequent acquirers seem to engage in wealth-destructive M&A deals more than occasional acquirers when they bid for a public target. These results are consistent with the existing literature on takeovers and M&A. For example, Eckbo (2014) and Moeller, Schlingemann, and Stulz (2004) report an average negative cumulative abnormal return when public targets are acquired.

Finally, acquisitions financed by stock are associated with a negative cumulative abnormal dollar return. Looking at Column (5) in Table 1.5 it appears that frequent acquirers shareholders wealth decline more when the firm engage in a stock-financed acquisition. These results are in line with Moeller, Schlingemann, and Stulz (2004) where they find a negative relationship between bidders cumulative abnormal percentage returns and stock-financed deals. The results are robust across all the three samples and event-window specifications.

From Table 1.5 it appears that frequent acquirers shareholders total wealth increases when the management engages in an acquisition of a public target firm which core business may be unrelated to the acquiring firm. Yet, shareholders increase their wealth when the acquisitions are exclusively financed with cash.

1.4.3 Industry settings and cumulative abnormal dollar returns

It is a well-established result that industry plays a significant role in takeover transactions: Song and Walkling (2000), Shahrur (2005), and Cai, Song, and Walkling (2011). When a transaction is announced, industry settings can influence the observed variation in takeover gains. To test this hypothesis, I repeat the regressions in Table 1.3 and Table 1.4 by replacing the unique bidder fixed effects with 4-digit SIC industry fixed effects. If bidders fixed effects capture unique time-invariant characteristics, we should find that the average R-squared values for te regression models are lower. As bidder fixed effects capture some of the industry characteristics, the resulting R-squared values would partially capture such influence.

Table 1.6 contains the regression model results when bidders fixed effects are replaced with industry fixed effects and takeover gains are expressed in percentage. As in previous tables, Panel A contains the results for the full sample, Panel B for the occasional acquirers sample, and Panel C for the frequent acquirers sample. Staring from Panel A, it can be seen that when industry fixed effects are used, the total number of unique dummy variables is reduced from 2,446 to 458. This drastic reduction in the number of unique fixed effects is reflected in the lower adjusted R-squared value compared to the one found in Panel A in Table 1.3. Panel B contains the regression models results for the occasional acquirers sample. As in Panel A, the unique number of fixed effects is dramatically reduced (from 1,622 to 368 unique dummy variables) and is reflected in the lower adjusted R-squared value for the regression models. Finally, Panel C contains the results for the frequent acquirers sample. Consistently with the previous two panels, the unique number of fixed effects is reduced from 277 to 129. In relative terms, however, the reduction in the number of unique fixed effects is lower than for the previous two panels. Looking at the adjusted R-squared values for the frequent acquirer sample, industry fixed effects can explain half of the variation of bidders fixed effects. Industry fixed effects, when applied to percentage cumulative abnormal returns, appear to have a marginal statistical power to explain the overall variation in returns.

Now I repeat the same analysis by using cumulative abnormal dollar returns as the dependent variable. Table 1.7 reports the OLS regression results for changes in shareholders wealth. As in Panel A and Panel B in Table 1.6 industry fixed effects result in lower adjusted R-squared values for the full and occasional acquirers samples. The regression model results are stable across all the four different specifications Panel C contains interesting results for the sample of frequent acquirers. When unique bidder fixed effects are replaced by unique 4-digit SIC industry fixed effects the latter can explain the same variation in takeover gains irrespective whether cumulative abnormal returns are in percentage or in dollar values. Industry fixed effects appear to influence cumulative abnormal dollar returns estimated around the announcement of a transaction.

So far, I show that bidders fixed effects can explain the same amount of variation in takeover gains - irrespective of the measurement unit - for frequent acquirers. Industry settings appear to explain the same amount of variation in cumulative abnormal dollar returns and cumulative abnormal percentage returns for frequent acquirers. Splitting the transactions sample according to three dimensions provide additional insights for further research. Generally, the results are in line with the existing literature and do not dramatically differ.

1.5 Robustness of the results

Fixed effects - by definition - are dummy variables that capture a constant difference across groups of observations. That is, to one single group of observations correspond one unique dummy variable. However, using a dummy variable, such as fixed effects, does not guarantee that it captures the firm unique characteristics. Golubov, Yawson, and Zhang (2015) argue that bidders fixed effects result in a higher adjusted R-squared value compared to an extensive list of regressors, especially for repetitive acquirers such as frequent acquirers. They provide evidence that bidder fixed effects capture these unique characteristics and following this analysis it appears to be confirmed. Bidder fixed effects appear to explain the same amount of variation in takeover gains irrespective of the measurement units used (percentage or dollar returns). The reader may fear that these results are driven by a sample selection bias (screening criteria in Section 1.2.1) or the choice of a specific event window. I provide additional evidence that these results are robust to a series of tests.

1.5.1 First robustness test: increasing the transaction value threshold

I firstly start by investigating whether the results are robust to different sample specifications. I gradually decrease the number of transactions included in my sample by increasing the transaction value threshold. By progressively increasing the transaction value, I can test whether the statistical power of these unique fixed effects is affected by what type of transactions is included. I create three additional sub-samples accordingly to their transaction value: transactions above USD 3 mil., USD 5 mil., and USD 10 mil. Table 1.8 through Table 1.10 contain the results of the analysis for cumulative abnormal return in percentage terms. For all the three tables, the adjusted R-squared increases as I gradually increase the transaction value threshold. The average percentage decrease in sample size is around 6% as the transaction value threshold increases. While the total number of unique acquirers decreases by the same magnitude for both occasional and frequent acquirers, the adjusted R-squared increases for frequent acquirers while it remains stable for the other types of acquirers. Specifically, for the full sample, the adjusted R-squared remains stable around 10% for a model where only bidder fixed effects are included as the main independent variables. As for the full sample, bidders fixed effects applied to the occasional acquirers sample result in an average 8% adjusted R-squared value, and it remains stable across the three tables. Finally, for the frequent acquirers sample, bidder fixed effects can explain, on average, 4% of the total variation in takeover gains. Yet, as the transaction value threshold increases to USD 10 mil., bidders fixed effects alone can explain up to 7% of the variation in cumulative abnormal returns. Finally, I repeat the same analysis by replacing bidders fixed effects with industry fixed effects. In order to save space, I do not report the results. however, the adjusted R-squared follows the same pattern as in Table 1.8, Table 1.9, and Table 1.10.

Next, I perform the same robustness tests substituting cumulative abnormal percentage returns with cumulative abnormal dollar returns as the dependent variable in the regression models. Table 1.11 through Table 1.13 report the results for the robustness tests. We can see that the results remain stable when cumulative abnormal dollar returns are used as the dependent variable. As for cumulative abnormal percentage returns, the resulting adjusted R-squared from the regression models exhibit the same trend. It slightly increases for all the three samples as the transaction value threshold increases. Overall, the results remain stable regardless the number of transactions included or the measurement unit used for takeover gains. Yet, the regression model joint-significance remain stable despite different sample specifications. Finally, when industry fixed effects replace bidders fixed effects the results remain stable across the three different additional samples.

1.5.2 Second robustness test: excluding withdrawn mergers

Perhaps, excluding withdrawn mergers may have an effect on the adjusted R-squared values for the various regression models. Unreported results show that results remain stable whether takeover attempts are included in the final sample. Additionally, to fully test whether the sample used in this paper is consistent with samples used in Golubov, Yawson, and Zhang (2015), I include all the transactions by "one-time" buyers. When these transactions are included in the full sample, the adjusted R-squared value jumps to approximately 20%, in line with existing results.

1.5.3 Third robustness test: different event windows

I test for three additional event windows (-1,+1), (-3,+3), and (-5,+5). The unreported results show that the average adjusted R-squared value remains stable across all the three different event window specification. On average, only including bidder fixed effects results in an average adjusted R-squared of 8 percentage points. As for the full sample, results for occasional acquirers and frequent acquirers remain stable. Overall, the event window seem not to have any material impact on the statistical significance of the results.

Additionally, I investigate whether event windows affect the average cumulative abnormal dollar return. As it can be seen in Table 1.5, the results remain stable over different event window specifications. Overall, it appears that on average the firms exhibit a positive cumulative abnormal dollar return when they acquire private firm financing the acquisition with cash. For occasional acquirers there is not a statistical difference in cumulative abnormal dollar returns whether they acquire a related target or an unrelated target. Overall, it appears that the market react more favorably when an unrelated target is acquired.

1.5.4 Additional robustness test

To fully replicate the work by Golubov, Yawson, and Zhang (2015) - and check the sample used in this paper - I test whether acquirer returns are persistent. In unreported results, I find that CEO turnover does not appear to have any effect on the persistency of acquirer's abnormal returns. These results are in line with what previously found by Golubov, Yawson, and Zhang (2015) therefore, confirming that the sample used in this paper appears not to be statistically different from the one employed in previous studies.

These robustness results show that time-invariant characteristics (bidder fixed effects) seem to explain part of the variation in cumulative abnormal dollar returns. When applied to the frequent acquirers sample, bidder fixed effects seem to explain the same variation in takeover gains regardless the measurement unit used. These results are robust to different transaction value thresholds, deal completion, industry fixed effects, and event windows.

1.6 Discussion

This paper investigates whether bidders time-invariant characteristics can explain variation in takeover gains when the latter are expressed as cumulative abnormal dollar returns. Investigating cumulative abnormal dollar returns is important to understand the impact of merger activity for the firms involved over different dimensions. As discussed in the introduction, cumulative abnormal dollar returns can be considered either as an investment performance index or as a buy-and-hold strategy for the whole firm. Percentage cumulative abnormal returns, on the other hand, are only focusing on the individual shareholder holdings. Hence, investigating cumulative abnormal dollar returns and the determinants of such returns can help understanding whether these returns can be explained by a time-invariant firm characteristic.

To test whether firm characteristics can explain changes in total shareholders wealth, I substitute cumulative abnormal returns (in percentage values) with cumulative abnormal *dollar* returns as the dependent variable. I find that bidders fixed effects can only explain a minimal fraction in cumulative abnormal dollar returns for the full sample of takeover transactions as well as the occasional acquirers transaction sample. On the other hand, when fixed effects are the main regressors in a model with cumulative abnormal dollar return as dependent variable, they result in a similar adjusted R-squared value as the original study by Golubov, Yawson, and Zhang (2015). The analysis suggests that frequent acquirers possess some unique characteristics which are captured by bidders fixed effects irrespective of the measurement unit used as dependent variable. However, these bidders fixed effects may not be entirely unique to bidders. When industry fixed effects are used, the amount of variation that can be explained remains unchanged. (Column (1) of Panel C, Table 1.4 and Column (1) of Panel C, Table 1.7. Yet, industry fixed effects can explain a minimal variation in cumulative abnormal dollar returns when applied to the full and occasional acquirers takeover samples.

Frequent acquirers appear to be a distinct type of acquirers as they systematically differ from the other bidders. They possess unique time-invariant characteristic - captured by firm fixed effects - which can explain the variation in takeover gains both in percentage and dollar values. Frequent acquirers time-invariant characteristics appear to explain a larger variation in cumulative abnormal dollar returns as the transaction value increases. The higher the transaction value the more variation in cumulative abnormal dollar returns can be explained by firm fixed effects. The decrease in the number of unique frequent acquires fixed effects appear not to be the reason of the increase in adjusted R-squared. Occasional acquirers unique number of bidders decreases by the same percentage as frequent acquirers, however their adjusted R-squared value remain stable around 8%. Overall, it appears that bidders fixed effect seem to truly capture time-invariant characteristics that acquirers possess.

Could the higher adjusted R-squared for frequent acquires be explained by different sizes? As frequent acquirers engage more frequently in M&A activity their size could be a key determinant for bidders returns. When compared to occasional acquirers, the difference in acquirer size (expressed as the natural logarithm of the market capitalization) between the two sample is lower than 1.5 percentage points. As a result, difference in firm size between frequent and occasional acquirers seem not to be the main characteristics. Likewise, for all the other acquirer characteristics. Yet, frequent acquirers deliver higher dollar returns for their shareholders when they acquire unrelated businesses, private targets, or they exclusively use cash as payment method.

1.6.1 Bidder vs. industry fixed effects

Are fixed effects truly capturing the unique time-invariant characteristics of bidders? If industry fixed effects can explain the same variation in cumulative abnormal dollar returns for frequent acquirers, are these dummy variables reliable? I argue that bidder fixed effects truly capture some of these unique characteristics for two reasons.

First, bidders fixed effects do capture some of the variation in takeover gains irrespective of the measurement unit used in the dependent variable. Table 1.4, Table 1.11, Table 1.12, and Table 1.13 clearly show that bidder fixed effects can, somehow, explain the variation in cumulative abnormal dollar returns. The effect is clearly stronger for frequent acquirers as the results show. Thus, it can be argued that frequent acquirers appear to possess unique characteristics that are reflected in takeover gains. If bidder fixed effects would not capture these characteristics we should observe a clear difference between the adjusted R-squared values between the two dependent variable specifications: percentage and dollar values. As it can be seen, this is not the case as the adjusted R-squared remains virtually unchanged irrespective of the measurement unit of the dependent variable. The results are robust to a set of robustness tests performed (see Section 1.5).

Second, the reader may be concerned that industry fixed effects can explain the same variation in cumulative abnormal dollar returns for the frequent acquirer sample. Acquirers may be influenced by industry characteristics such as industry size, number of firms, and industry competition. As a result, as these characteristics may be captured by both industry fixed effects and bidders fixed effects they may result in similar explanatory power for cumulative abnormal percentage returns. Looking at Panel C in Table 1.6 and Panel C in Table 1.7 we can see that industry fixed effects only have similar explanatory power as bidder fixed effects only for the percentage returns. On the other hand, for cumulative abnormal dollar returns, industry fixed effects are weakly significant in explaining the variation of cumulative abnormal dollar returns. That is, the F-statistic is only significant at the 10%. We can see that the number of 4-digit SIC industries where frequent acquirers is wide, 128 unique industries. The number of unique 4-digit SIC industry fixed effects is approximately half of the number of unique bidder fixed effects (128 unique SIC industry fixed effects and 277 unique bidders fixed effects). As a result, the virtually unchanged R-squared value may be a byproduct of the OLS regression. Additionally, it can be argued that industry settings only influence, to some extent, changes in shareholders wealth for frequent acquirers while the results with bidder fixed effects are of first order. Yet, I argue that - while surprising - industry fixed effects should be viewed as complimentary to the main results of this paper (Table 1.4, Table 1.11, Table 1.12, and Table 1.13).

Altogether, it appears that frequent acquirers have unique time-invariant characteristics that can explain takeover gains. These unique characteristics explain part of the variation in bidders percentage returns and changes in stockholders wealth. What can explain the remaining variation in takeover gains? Deal synergies could potentially describe the remaining portion of total variance in cumulative abnormal returns both in percentage and dollar units. Unfortunately, devising a standardized empirical strategy to capture these synergies is challenging at this time.

1.6.2 Key takeaway

Overall, except for frequent acquirers, it appears that time-invariant characteristics can explain a minimal variation in changes in wealth of the acquiring-firm shareholders. Frequent acquirers, on the other hand, appear to have a unique time-invariant characteristic that can explain at least 4% in the variation in both bidders cumulative abnormal dollar returns and cumulative abnormal percentage returns. Compared to other type of acquirers, the adjusted R-squared for the frequent acquirers sample is 60% higher than for the occasional acquirer sample or the full sample. Frequent acquirers shareholders earn abnormal positive abnormal dollar returns when the firm acquires an unrelated, private target financing the acquisition with cash. Results are robust to different transaction value thresholds, event windows, and the inclusion of withdrawn deals. These results shed a light on how changes in shareholders wealth may be explained by an unobservable time-invariant bidder characteristic. Yet, it shows how frequent acquirers are substantially different from other acquiring firms.

1.7 Conclusions

In this paper, I investigate whether bidder fixed effects can explain part of the variation in cumulative abnormal dollar returns. Bidder fixed effects result in similar adjusted R-squared values for frequnet acquirers. Time-invariant characteristics result in a lower adjusted R-squared value for firms other than frequent acquirers. Frequent acquirers appear to have a time-invariant characteristic - reflected both in cumulative abnormal percentage returns and cumulative abnormal dollar returns - captured by bidder fixed effects. Put differently, the unique bidder fixed effects appear to explain the total economic impact of the merger transaction (cumulative abnormal dollar returns). On the other hand, for all the other type of acquirers, fixed effects capture a minimal variation in cumulative abnormal dollar returns. These results are robust to different event window specification as well as different sample compositions (higher threshold for transaction value).

Furthermore, by replicating their work by Golubov, Yawson, and Zhang (2015) I show how the transactions sample used in this study does not drastically differ from their sample. Yet, I show that cumulative abnormal dollar returns follow the same decline in shareholders wealth found in Moeller, Schlingemann, and Stulz (2005). I document, however, that this negative trend in shareholders wealth during the period 1998-2001 can be explained by the lower and negative dollar returns by occasional and frequent acquirers. Nevertheless, by using the estimation methodology by Malatesta (1983), I provide a more precise estimate of cumulative abnormal dollar returns that can be attributed to the merger announcement.

I show that industry fixed effects can explain part of the variation in acquirer dollar returns. Industry settings appear to explain a minimal variation in cumulative abnormal dollar returns except for frequent acquirers. I test whether industry plays a role by substituting bidder fixed effects with industry fixed effects. I find that, for frequent acquirers, industry fixed effects have a similar explanatory power to bidders fixed effects when cumulative abnormal dollar returns are the dependent variable in the regression models. I argue that cumulative abnormal dollar returns may be influenced by industry characteristics such as industry size.

I show that frequent acquirers earn positive abnormal dollar returns when they acquire targets who are unrelated to their core business or are private firms and for those acquisitions financed by cash. Occasional acquirers earn positive abnormal dollar returns only when they acquire a private target and the acquisition is cash financed. Overall, the results are robust to different event window specifications as well as different sample compositions.

To conclude, changes in total shareholders wealth can be partially explained by a time-invariant characteristic unique to bidders. Yet, frequent acquirers have unobservable time-invariant characteristics that can explain variation in cumulative abnormal percentage returns and cumulative abnormal dollar returns. That is, frequent acquirers fixed effects capture some unobservable characteristics that explain the total economic dollar impact of the merger announcement. While at this stage the source of takeover gains is still elusive, further research is needed to discover these unobservable characteristics.

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TABLE 1.1: SAMPLE DISTRIBUTIONS

The sample contains all completed US mergers and acquisitions between 1990 and 2011 listed on SDC. The acquiring firms are publicly traded US firms acquiring 100% of a public, private, or subsidiary target whose transaction value is above $1 million and 1% of the acquirer's market value. Acquiring fjrms with missing financial data and/or stock price data are excluded. Cumulative abnormal dollar returns are expressed in thousands of dollars.

	Cumulative Abnormal Returns			Cumulative Abnormal Dollar Returns			
Year	Mean	Median	SD	Mean	Median	SD	N
1990	0.019	0.015	0.079	3,716	1,522	14,201	151
1991	0.012	0.007	0.070	1,303	997	15,736	194
1992	0.027	0.016	0.080	3,947	1,655	20,442	293
1993	0.017	0.007	0.077	1,063	926	18,581	411
1994	0.013	0.003	0.073	758	296	15,892	515
1995	0.007	0.001	0.073	621	128	12,236	561
1996	0.015	0.008	0.075	2,399	1,383	18,429	671
1997	0.018	0.010	0.083	2,240	1,456	19,402	867
1998	0.006	-0.003	0.088	-1,886	-543	30,791	819
1999	0.017	0.010	0.092	2,657	1,283	35,104	638
2000	0.003	0.000	0.108	-2,066	8	48,599	519
2001	0.018	0.007	0.096	3,892	1,031	35,981	457
2002	0.010	0.003	0.088	859	370	27,655	475
2003	0.012	0.007	0.076	2,159	1,373	24,119	479
2004	0.009	0.006	0.070	2,826	1,625	25,498	528
2005	0.007	0.002	0.067	1,578	435	24,788	529
2006	0.010	0.006	0.065	3,027	1,845	29,982	511
2007	0.011	0.005	0.066	3,913	2,325	29,396	490
2008	0.005	0.005	0.080	1,798	1,229	30,691	324
2009	0.015	0.000	0.087	4,156	167	30,524	226
2010	0.009	0.002	0.063	2,644	496	30,843	283
2011	0.010	0.005	0.060	3,212	1,930	37,311	278

Table 1.2: Sample distributions by type of acquirers

The sample contains all completed US mergers and acquisitions between 1990 and 2011 listed on SDC. The acquiring firms are publicly traded US firms acquiring 100% of a public, private, or subsidiary target whose transaction value is above $1 million and 1% of the acquirer's market value. Acquiring fjrms with missing financial data and/or stock price data are excluded. The first three columns of the table contain the sample of firms that are not classified either as occasional or frequent acquirers. The following three columns contain the occasional acquirers sample. Occasional acquirers are defined as those acquiring firms who acquired between two and four firms in a three-year window period. The last three columns contain the frequent acquirers sample. Frequent acquirers are defined as those firms who acquired more than five firms in a three-year window period. Cumulative abnormal dollar returns are expressed in thousands of dollars.

	Remaining Acquirers			Occasional Acquirers Sample			Frequent Acquirers Sample		
Year	Mean	SD	N	Mean	SD	N	Mean	SD	N
1990	6,725	11,321	37	2,497	14,981	89	3,596	15,020	25
1991	1,274	17,086	34	1,148	14,678	128	1,949	18,643	32
1992	5,772	22,440	40	5,176	18,881	176	188	22,507	77
1993	2,195	16,686	58	3,893	16,968	225	-4,424	20,895	128
1994	851	13,201	56	1,607	15,487	289	-718	17,297	170
1995	3,438	11,869	64	-2	11,553	338	813	13,627	159
1996	2,969	19,465	74	3,045	17,970	371	1,151	18,841	226
1997	1,453	15,881	87	1,737	18,946	456	3,158	20,858	324
1998	2,808	27,189	89	-1,175	29,660	486	-5,012	33,897	244
1999	869	34,647	79	4,405	33,875	384	-372	37,810	175
2000	-6,508	41,160	74	-2,267	48,975	330	1,368	51,960	115
2001	-864	36,396	63	3,699	34,264	291	7,347	40,229	103
2002	-246	24,112	74	388	27,856	315	3,535	29,832	86
2003	3,801	22,164	62	825	24,409	301	4,742	24,293	116
2004	4,135	23,680	85	3,328	25,136	331	345	27,853	112
2005	3,221	22,737	62	1,412	25,755	350	1,199	22,968	117
2006	5,009	31,490	85	3,420	29,309	312	473	30,751	114
2007	657	26,714	73	4,677	30,430	304	3,959	28,287	113
2008	1,319	25,880	54	4,259	31,043	210	-6,385	32,423	60
2009	1,276	26,119	42	3,337	32,006	152	11,823	28,195	32
2010	3,299	32,200	46	1,539	31,773	181	5,674	26,671	56
2011	11,616	39,139	54	-715	36,956	174	7,800	35,164	50

Table 1.3: Acquirer fixed effects

This table reports the results of the regression models of acquirer cumulative abnormal returns for the merger announcement for the three different samples. Panel A contains the full sample. Panel B contains only the sample of occasional acquirers. Panel C contains only the sample of frequent acquirers. The sample contains all domestic M&A transactions completed between 1990 and 2011 present on SDC platinum database. Occasional acquirers are defined as those acquirers who completed between two and four acquisitions during a three-year window period. Frequent acquirers are defined as those acquirers who completed at least five acquisitions during a three-year window period. Bidder CARs are regressed on acquirer fixed effects and additional control variables specified in columns (1)-(4). Deal characteristics include relative size, relatedness, tend and hostile indicator, and status/payment method interaction indicators. Acquirer characteristics include acquirer size (the natural logarithm of the market capitalization of the acquiring firm), Tobin's Q, free cash flow, leverage, run-up, and the standard deviation of the run-ups. The F-statistics report the joint significance of the regression model. The R^2 and Adjusted R^2 are reported. Symbols $***$, $**$, and $*$ denote significance at the 1%, 5%, and 10% level, respectively.

	Dependent variable:			
	CAR(-2,+2)			
	(1)	(2)	(3)	(4)
	None	Year FE	Deal Chars., year FE	Acquirer and deal chars, year FE
Panel A: Full sample				
Bidder FE	Y	Y	Y	Y
Year FE	N	Y	Y	Y
Observations	10,218	10,218	10,218	10,218
R^2	0.30	0.30	0.32	0.33
Adjusted R^2	0.08	0.08	0.10	0.11
F Statistic	1.35***	1.38***	1.48***	1.52***
Panel B: Occasional acquirer sample				
Bidder FE	Y	Y	Y	Y
Year FE	N	Y	Y	Y
Observations	6,193	6,193	6,193	6,193
R^2	0.32	0.32	0.34	0.35
Adjusted R^2	0.07	0.08	0.11	0.11
F Statistic	1.30***	1.32***	1.44***	1.47***
Panel C: Frequent acquirer sample				
Bidder FE	Y	Y	Y	Y
Year FE	N	Y	Y	Y
Observations	2,634	2,634	2,634	2,634
R^2	0.13	0.15	0.16	0.17
Adjusted R^2	0.02	0.04	0.05	0.06
F Statistic	1.24***	1.35***	1.40***	1.52***

Table 1.4: Acquirer fixed effects - Cumulative Abnormal Dollar Return

This table reports the results of the regression models of acquirer cumulative abnormal dollar returns for the merger announcement for the three different samples. Panel A contains the full sample. Panel B contains only the sample of occasional acquirers. Panel C contains only the sample of frequent acquirers. The sample contains all domestic M&A transactions completed between 1990 and 2011 present on SDC platinum database. Occasional acquirers are defined as those acquirers who completed between two and four acquisitions during a three-year window period. Frequent acquirers are defined as those acquirers who completed at least five acquisitions during a three-year window period. Bidder CADRs are regressed on acquirer fixed effects and additional control variables specified in columns (1)-(4). Deal characteristics include relative size, relatedness, tend and hostile indicator, and status/payment method interaction indicators. Acquirer characteristics include Tobin's Q, free cash flow, leverage, run-up, and the standard deviation of the run-ups. The F-statistics report the joint significance of the regression model. The R^2 and Adjusted R^2 are reported. Symbols $***$, $**$, and $*$ denote significance at the 1%, 5%, and 10% level, respectively.

	Dependent variable:			
	CADR(-2,+2)			
	(1)	(2)	(3)	(4)
	None	Year FE	Deal Chars., year FE	Acquirer and deal chars, year FE
Panel A: Full sample				
Bidder FE	Y	Y	Y	Y
Year FE	N	Y	Y	Y
Observations	10,218	10,218	10,218	10,218
R^2	0.26	0.26	0.27	0.27
Adjusted R^2	0.03	0.03	0.04	0.04
F Statistic	1.11***	1.12***	1.16***	1.16***
Panel B: Occasional acquirer sample				
Bidder FE	Y	Y	Y	Y
Year FE	N	Y	Y	Y
Observations	6,193	6,193	6,193	6,193
R^2	0.28	0.28	0.29	0.30
Adjusted R^2	0.02	0.03	0.04	0.04
F Statistic	1.09**	1.10***	1.14***	1.15***
Panel C: Frequent acquirer sample				
Bidder FE	Y	Y	Y	Y
Year FE	N	Y	Y	Y
Observations	2,634	2,634	2,634	2,634
R^2	0.14	0.15	0.16	0.18
Adjusted R^2	0.04	0.05	0.05	0.06
F Statistic	1.37***	1.43***	1.47***	1.56***

Table 1.5: Cumulative Abnormal Dollar Return: Deal characteristics comparison

This table contains the different results for two sample t-tests across three different dimensions: deal relatedness, target public status, and method of financing. Panel A contains the full sample. Panel B contains only the sample of occasional acquirers. Panel C contains only the sample of frequent acquirers. The sample contains all domestic M&A transactions completed between 1990 and 2011 present on SDC platinum database. Occasional acquirers are defined as those acquirers who completed between two and four acquisitions during a three-year window period. Frequent acquirers are defined as those acquirers who completed at least five acquisitions during a three-year window period. The event windows used to estimated CADRs are specified across rows. Cumulative abnormal dollar returns are expressed in thousands of dollars. Symbols $***$, $**$, and $*$ denote significance at the 1%, 5%, and 10% level, respectively.

	Dependent variable:								
	CADR								
	Related	Unrelated	T-test	Public	Private	T-test	Stock	Cash	T-test
	(1)	(2)	(1)-(2)	(3)	(4)	(3)-(4)	(5)	(6)	(5)-(6)
Panel A: Full sample									
[-1,+1]	1473.055	1950.640	-1.0133	-4384.958	1899.197	-9.2764***	-1039.340	3434.511	-7.9534***
[-2,+2]	1530.117	2172.110	-1.1174	-5282.166	2028.987	-8.8997***	-1377.821	3762.748	-7.4915***
[-3,+3]	1211.979	1907.734	-1.0401	-5797.579	2020.505	-8.2499***	-1379.094	3311.749	-5.8713***
[-5,+5]	633.1344	1083.0752	-0.54272	-5590.328	1212.411	-5.7621***	-2517.132	3175.927	-5.7269***
Panel B: Occasional acquirer sample									
[-1,+1]	2005.022	1540.664	0.76646	-4181.667	1934.535	-6.9972***	-592.319	3351.203	-5.3996***
[-2,+2]	2061.300	1719.407	0.46647	-5037.165	2166.049	-6.9094***	-736.1724	3515.7244	-4.8357***
[-3,+3]	1882.720	1781.276	0.11898	-4502.438	2027.776	-5.3594***	-763.0898	3607.4826	-4.2603***
[-5,+5]	1693.712	1223.279	0.44429	-4513.246	1712.567	-4.0883***	-1506.083	4117.467	-4.3805***
Panel C: Frequent acquirer sample									
[-1,+1]	-206.7921	3859.5140	-4.134***	-5454.031	1866.101	-5.5075***	-2001.208	3658.364	-5.0137***
[-2,+2]	-207.7086	3814.1394	-3.3289***	-6899.052	1782.737	-5.2892***	-3020.692	4307.071	-5.2306***
[-3,+3]	-899.5242	2529.4853	-2.4283***	-9379.633	1882.790	-6.0625***	-3025.094	3089.990	-3.7517***
[-5,+5]	-1932.121	2333.653	-2.4428***	-7891.7562	461.3413	-3.571***	-4189.770	1997.228	-3.0421***

TABLE 1.6: INDUSTRY FIXED EFFECTS - CUMULATIVE ABNORMAL RETURN

This table reports the results of the regression models of acquirer cumulative abnormal dollar returns for the merger announcement for the three different samples. Panel A contains the full sample. Panel B contains only the sample of occasional acquirers. Panel C contains only the sample of frequent acquirers. The sample contains all domestic M&A transactions completed between 1990 and 2011 present on SDC platinum database. Occasional acquirers are defined as those acquirers who completed between two and four acquisitions during a three-year window period. Frequent acquirers are defined as those acquirers who completed at least five acquisitions during a three-year window period. Bidder CARs are regressed on acquirer 4-digit SIC industry fixed effects and additional control variables specified in columns (1)-(4). Deal characteristics include relative size, relatedness, tend and hostile indicator, and status/payment method interaction indicators. Acquirer characteristics include acquirer size (the natural logarithm of the market capitalization of the acquiring firm), Tobin's Q, free cash flow, leverage, run-up, and the standard deviation of the run-ups. The F-statistics report the joint significance of the regression model. The R^2 and Adjusted R^2 are reported. Symbols $***$, $**$, and $*$ denote significance at the 1%, 5%, and 10% level, respectively.

	Dependent variable:			
	CAR(-2,+2)			
	(1)	(2)	(3)	(4)
	None	Year FE	Deal Chars., year FE	Acquirer and deal chars, year FE
Panel A: Full sample				
Industry FE	Y	Y	Y	Y
Year FE	N	Y	Y	Y
Observations	10,218	10,218	10,218	10,218
R^2	0.06	0.07	0.10	0.10
Adjusted R^2	0.02	0.02	0.05	0.06
F Statistic	1.44***	1.50***	2.09***	2.23***
Panel B: Occasional acquirer sample				
Industry FE	Y	Y	Y	Y
Year FE	N	Y	Y	Y
Observations	6,193	6,193	6,193	6,193
R^2	0.071	0.08	0.11	0.12
Adjusted R^2	0.01	0.02	0.05	0.06
F Statistic	1.20***	1.26***	1.85***	1.92***
Panel C: Frequent acquirer sample				
Industry FE	Y	Y	Y	Y
Year FE	N	Y	Y	Y
Observations	2,634	2,634	2,634	2,634
R^2	0.06	0.07	0.09	0.11
Adjusted R^2	0.01	0.02	0.03	0.04
F Statistic	1.21*	1.34***	1.47***	1.72***

Table 1.7: Industry fixed effects - Cumulative Abnormal Dollar Return

This table reports the results of the regression models of acquirer cumulative abnormal dollar returns for the merger announcement for the three different samples. Panel A contains the full sample. Panel B contains only the sample of occasional acquirers. Panel C contains only the sample of frequent acquirers. The sample contains all domestic M&A transactions completed between 1990 and 2011 present on SDC platinum database. Occasional acquirers are defined as those acquirers who completed between two and four acquisitions during a three-year window period. Frequent acquirers are defined as those acquirers who completed at least five acquisitions during a three-year window period. Bidder CADRs are regressed on acquirer 4-digit SIC industry fixed effects and additional control variables specified in columns (1)-(4). Deal characteristics include relative size, relatedness, tend and hostile indicator, and status/payment method interaction indicators. Acquirer characteristics include Tobin's Q, free cash flow, leverage, run-up, and the standard deviation of the run-ups. The F-statistics report the joint significance of the regression model. The R^2 and Adjusted R^2 are reported. Symbols $***$, $**$, and $*$ denote significance at the 1%, 5%, and 10% level, respectively.

	Dependent variable:			
	CADR(-2,+2)			
	(1)	(2)	(3)	(4)
	None	Year FE	Deal Chars., year FE	Acquirer and deal chars, year FE
Panel A: Full sample				
Industry FE	Y	Y	Y	Y
Year FE	N	Y	Y	Y
Observations	10,218	10,218	10,218	10,218
R^2	0.06	0.06	0.07	0.07
Adjusted R^2	0.01	0.01	0.02	0.03
F Statistic	1.24***	1.27***	1.52***	1.54***
Panel B: Occasional acquirer sample				
Industry FE	Y	Y	Y	Y
Year FE	N	Y	Y	Y
Observations	6,193	6,193	6,193	6,193
R^2	0.07	0.08	0.09	0.09
Adjusted R^2	0.01	0.02	0.03	0.03
F Statistic	1.22***	1.24***	1.44***	1.47***
Panel C: Frequent acquirer sample				
Industry FE	Y	Y	Y	Y
Year FE	N	Y	Y	Y
Observations	2,634	2,634	2,634	2,634
R^2	0.08	0.09	0.10	0.12
Adjusted R^2	0.03	0.04	0.04	0.06
F Statistic	1.65***	1.66***	1.72***	1.92***

Table 1.8: Acquirer fixed effects - Transactions above USD 3 M

This table reports the results of the regression models of acquirer cumulative abnormal returns for the merger announcement for the three different samples. Panel A contains the full sample for transactions above \$3 millions. Panel B contains only the sample of occasional acquirers. Panel C contains only the sample of frequent acquirers. The sample contains all domestic M&A transactions with transaction values above \$3 millions completed between 1990 and 2011 present on SDC platinum database. Occasional acquirers are defined as those acquirers who completed between two and four acquisitions during a three-year window period. Frequent acquirers are defined as those acquirers who completed at least five acquisitions during a three-year window period. Bidder CARs are regressed on acquirer fixed effects and additional control variables specified in columns (1)-(4). Deal characteristics include relative size, relatedness, tend and hostile indicator, and status/payment method interaction indicators. Acquirer characteristics include acquirer size (the natural logarithm of the market capitalization of the acquiring firm), Tobin's Q, free cash flow, leverage, run-up, and the standard deviation of the run-ups. The F-statistics report the joint significance of the regression model. The R^2 and Adjusted R^2 are reported. Symbols $***$, $**$, and $*$ denote significance at the 1%, 5%, and 10% level, respectively.

	Dependent variable:			
	CAR(-2,+2)			
	(1)	(2)	(3)	(4)
	None	Year FE	Deal Chars., year FE	Acquirer and deal chars, year FE
Panel A: Full sample				
Bidder FE	Y	Y	Y	Y
Year FE	N	Y	Y	Y
Observations	9,611	9,611	9,611	9,611
R^2	0.31	0.32	0.34	0.34
Adjusted R^2	0.09	0.10	0.12	0.13
F Statistic	1.42***	1.45***	1.56***	1.61***
Panel B: Occasional acquirer sample				
Bidder FE	Y	Y	Y	Y
Year FE	N	Y	Y	Y
Observations	5,864	5,864	5,864	5,864
R^2	0.32	0.33	0.35	0.36
Adjusted R^2	0.08	0.09	0.12	0.12
F Statistic	1.34***	1.36***	1.49***	1.51***
Panel C: Frequent acquirer sample				
Bidder FE	Y	Y	Y	Y
Year FE	N	Y	Y	Y
Observations	2,424	2,424	2,424	2,424
R^2	0.14	0.16	0.17	0.19
Adjusted R^2	0.04	0.05	0.06	0.08
F Statistic	1.34***	1.44***	1.53***	1.67***

Table 1.9: Acquirer fixed effects - Transactions above USD5 M

This table reports the results of the regression models of acquirer cumulative abnormal returns for the merger announcement for the three different samples. Panel A contains the full sample for transactions above \$5 millions. Panel B contains only the sample of occasional acquirers. Panel C contains only the sample of frequent acquirers. The sample contains all domestic M&A transactions with transaction values above \$5 millions completed between 1990 and 2011 present on SDC platinum database. Occasional acquirers are defined as those acquirers who completed between two and four acquisitions during a three-year window period. Frequent acquirers are defined as those acquirers who completed at least five acquisitions during a three-year window period. Bidder CARs are regressed on acquirer fixed effects and additional control variables specified in columns (1)-(4). Deal characteristics include relative size, relatedness, tend and hostile indicator, and status/payment method interaction indicators. Acquirer characteristics include acquirer size (the natural logarithm of the market capitalization of the acquiring firm), Tobin's Q, free cash flow, leverage, run-up, and the standard deviation of the run-ups. The F-statistics report the joint significance of the regression model. The R^2 and Adjusted R^2 are reported. Symbols $***$, $**$, and $*$ denote significance at the 1%, 5%, and 10% level, respectively.

	Dependent variable:			
	CAR(-2,+2)			
	(1)	(2)	(3)	(4)
	None	Year FE	Deal Chars., year FE	Acquirer and deal chars, year FE
Panel A: Full sample				
Bidder FE	Y	Y	Y	Y
Year FE	N	Y	Y	Y
Observations	9,001	9,001	9,001	9,001
R^2	0.31	0.32	0.33	0.34
Adjusted R^2	0.09	0.10	0.12	0.12
F Statistic	1.40***	1.43***	1.54***	1.57***
Panel B: Occasional acquirer sample				
Bidder FE	Y	Y	Y	Y
Year FE	N	Y	Y	Y
Observations	5,449	5,449	5,449	5,449
R^2	0.32	0.33	0.35	0.35
Adjusted R^2	0.08	0.09	0.11	0.11
F Statistic	1.34***	1.36***	1.46***	1.47***
Panel C: Frequent acquirer sample				
Bidder FE	Y	Y	Y	Y
Year FE	N	Y	Y	Y
Observations	2,260	2,260	2,260	2,260
R^2	0.14	0.16	0.18	0.19
Adjusted R^2	0.04	0.05	0.07	0.08
F Statistic	1.37***	1.46***	1.57***	1.70***

Table 1.10: Acquirer fixed effects - Transactions above USD10 M

This table reports the results of the regression models of acquirer cumulative abnormal returns for the merger announcement for the three different samples. Panel A contains the full sample for transactions above \$10 millions. Panel B contains only the sample of occasional acquirers. Panel C contains only the sample of frequent acquirers. The sample contains all domestic M&A transactions with transaction values above \$10 millions completed between 1990 and 2011 present on SDC platinum database. Occasional acquirers are defined as those acquirers who completed between two and four acquisitions during a three-year window period. Frequent acquirers are defined as those acquirers who completed at least five acquisitions during a three-year window period. Bidder CARs are regressed on acquirer fixed effects and additional control variables specified in columns (1)-(4). Deal characteristics include relative size, relatedness, tend and hostile indicator, and status/payment method interaction indicators. Acquirer characteristics include acquirer size (the natural logarithm of the market capitalization of the acquiring firm), Tobin's Q, free cash flow, leverage, run-up, and the standard deviation of the run-ups. The F-statistics report the joint significance of the regression model. The R^2 and Adjusted R^2 are reported. Symbols $***$, $**$, and $*$ denote significance at the 1%, 5%, and 10% level, respectively.

	Dependent variable:			
	CAR(-2,+2)			
	(1)	(2)	(3)	(4)
	None	Year FE	Deal Chars., year FE	Acquirer and deal chars, year FE
Panel A: Full sample				
Bidder FE	Y	Y	Y	Y
Year FE	N	Y	Y	Y
Observations	7,794	7,794	7,794	7,794
R^2	0.32	0.33	0.34	0.35
Adjusted R^2	0.10	0.11	0.13	0.14
F Statistic	1.46***	1.49***	1.59***	1.63***
Panel B: Occasional acquirer sample				
Bidder FE	Y	Y	Y	Y
Year FE	N	Y	Y	Y
Observations	4,719	4,719	4,719	4,719
R^2	0.32	0.33	0.35	0.35
Adjusted R^2	0.08	0.09	0.11	0.12
F Statistic	1.33***	1.35***	1.46***	1.48***
Panel C: Frequent acquirer sample				
Bidder FE	Y	Y	Y	Y
Year FE	N	Y	Y	Y
Observations	1,921	1,921	1,921	1,921
R^2	0.17	0.19	0.21	0.22
Adjusted R^2	0.07	0.08	0.10	0.10
F Statistic	1.70***	1.76***	1.87***	1.91***

Table 1.11: Acquirer fixed effects Cumulative Abnormal Dollar Return - Transaction above USD3 M

This table reports the results of the regression models of acquirer cumulative abnormal returns for the merger announcement for the three different samples. Panel A contains the full sample for transactions above $3 millions. Panel B contains only the sample of occasional acquirers. Panel C contains only the sample of frequent acquirers. The sample contains all domestic M&A transactions with transaction values above $3 millions completed between 1990 and 2011 present on SDC platinum database. Occasional acquirers are defined as those acquirers who completed between two and four acquisitions during a three-year window period. Frequent acquirers are defined as those acquirers who completed at least five acquisitions during a three-year window period. Bidder CADRs are regressed on acquirer fixed effects and additional control variables specified in columns (1)-(4). Deal characteristics include relative size, relatedness, tend and hostile indicator, and status/payment method interaction indicators. Acquirer characteristics include Tobin's Q, free cash flow, leverage, run-up, and the standard deviation of the run-ups. The F-statistics report the joint significance of the regression model. The R^2 and Adjusted R^2 are reported. Symbols $***$, $**$, and $*$ denote significance at the 1%, 5%, and 10% level, respectively.

	Dependent variable:			
	CADR(-2,+2)			
	(1)	(2)	(3)	(4)
	None	Year FE	Deal Chars., year FE	Acquirer and deal chars, year FE
Panel A: Full sample				
Bidder FE	Y	Y	Y	Y
Year FE	N	Y	Y	Y
Observations	9,612	9,612	9,612	9,612
R^2	0.26	0.26	0.27	0.27
Adjusted R^2	0.02	0.03	0.04	0.04
F Statistic	1.10***	1.11***	1.16***	1.16***
Panel B: Occasional acquirer sample				
Bidder FE	Y	Y	Y	Y
Year FE	N	Y	Y	Y
Observations	5,864	5,864	5,864	5,864
R^2	0.28	0.28	0.30	0.30
Adjusted R^2	0.02	0.03	0.4	0.04
F Statistic	1.09**	1.10***	1.15***	1.16***
Panel C: Frequent acquirer sample				
Bidder FE	Y	Y	Y	Y
Year FE	N	Y	Y	Y
Observations	2,424	2,424	2,424	2,424
R^2	0.14	0.16	0.17	0.18
Adjusted R^2	0.04	0.05	0.06	0.07
F Statistic	1.41***	1.45***	1.49***	1.59***

Table 1.12: Acquirer fixed effects Cumulative Abnormal Dollar Return - Transactions above USD5 M

This table reports the results of the regression models of acquirer cumulative abnormal returns for the merger announcement for the three different samples. Panel A contains the full sample for transactions above $5 millions. Panel B contains only the sample of occasional acquirers. Panel C contains only the sample of frequent acquirers. The sample contains all domestic M&A transactions with transaction values above $5 millions completed between 1990 and 2011 present on SDC platinum database. Occasional acquirers are defined as those acquirers who completed between two and four acquisitions during a three-year window period. Frequent acquirers are defined as those acquirers who completed at least five acquisitions during a three-year window period. Bidder CADRs are regressed on acquirer fixed effects and additional control variables specified in columns (1)-(4). Deal characteristics include relative size, relatedness, tend and hostile indicator, and status/payment method interaction indicators. Acquirer characteristics include Tobin's Q, free cash flow, leverage, run-up, and the standard deviation of the run-ups. The F-statistics report the joint significance of the regression model. The R^2 and Adjusted R^2 are reported. Symbols $***$, $**$, and $*$ denote significance at the 1%, 5%, and 10% level, respectively.

	Dependent variable:			
	CADR(-2,+2)			
	(1)	(2)	(3)	(4)
	None	Year FE	Deal Chars., year FE	Acquirer and deal chars, year FE
Panel A: Full sample				
Bidder FE	Y	Y	Y	Y
Year FE	N	Y	Y	Y
Observations	9,002	9,002	9,002	9,002
R^2	0.26	0.26	0.27	0.27
Adjusted R^2	0.02	0.03	0.04	0.04
F Statistic	1.09***	1.11***	1.15***	1.16***
Panel B: Occasional acquirer sample				
Bidder FE	Y	Y	Y	Y
Year FE	N	Y	Y	Y
Observations	5,449	5,449	5,449	5,449
R^2	0.28	0.29	0.30	0.30
Adjusted R^2	0.03	0.03	0.04	0.04
F Statistic	1.10**	1.11***	1.15***	1.16***
Panel C: Frequent acquirer sample				
Bidder FE	Y	Y	Y	Y
Year FE	N	Y	Y	Y
Observations	2,260	2,260	2,260	2,260
R^2	0.14	0.16	0.17	0.18
Adjusted R^2	0.04	0.05	0.06	0.07
F Statistic	1.42***	1.45***	1.49***	1.59***

Table 1.13: Acquirer fixed effects Cumulative Abnormal Dollar Return - Transactions above USD10 M

This table reports the results of the regression models of acquirer cumulative abnormal returns for the merger announcement for the three different samples. Panel A contains the full sample for transactions above $10 millions. Panel B contains only the sample of occasional acquirers. Panel C contains only the sample of frequent acquirers. The sample contains all domestic M&A transactions with transaction values above $10 millions completed between 1990 and 2011 present on SDC platinum database. Occasional acquirers are defined as those acquirers who completed between two and four acquisitions during a three-year window period. Frequent acquirers are defined as those acquirers who completed at least five acquisitions during a three-year window period. Bidder CADRs are regressed on acquirer fixed effects and additional control variables specified in columns (1)-(4). Deal characteristics include relative size, relatedness, tend and hostile indicator, and status/payment method interaction indicators. Acquirer characteristics include Tobin's Q, free cash flow, leverage, run-up, and the standard deviation of the run-ups. The F-statistics report the joint significance of the regression model. The R^2 and Adjusted R^2 are reported. Symbols $***$, $**$, and $*$ denote significance at the 1%, 5%, and 10% level, respectively.

	Dependent variable:			
	CADR(-2,+2)			
	(1)	(2)	(3)	(4)
	None	Year FE	Deal Chars., year FE	Acquirer and deal chars, year FE
Panel A: Full sample				
Bidder FE	Y	Y	Y	Y
Year FE	N	Y	Y	Y
Observations	7,795	7,795	7,795	7,795
R^2	0.26	0.27	0.28	0.28
Adjusted R^2	0.02	0.03	0.04	0.04
F Statistic	1.10***	1.11***	1.16***	1.16***
Panel B: Occasional acquirer sample				
Bidder FE	Y	Y	Y	Y
Year FE	N	Y	Y	Y
Observations	4,719	4,719	4,719	4,719
R^2	0.28	0.28	0.30	0.30
Adjusted R^2	0.02	0.03	0.04	0.04
F Statistic	1.09**	1.10**	1.14***	1.16***
Panel C: Frequent acquirer sample				
Bidder FE	Y	Y	Y	Y
Year FE	N	Y	Y	Y
Observations	1,921	1,921	1,921	1,921
R^2	0.16	0.17	0.19	0.20
Adjusted R^2	0.06	0.06	0.07	0.08
F Statistic	1.56***	1.58***	1.59***	1.71***

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The industry wealth effect of acquisitions through time*

Damiano Maggi†

May 2021

Abstract

In this paper, I investigate how the average announcement return to competitors of the bidder evolved through time. By forming equally-weighted of the top five competitors of the bidder, I find that the average announcement return for competitors declined. Starting in 1990, the competitor CARs have declined by on average two basis point reaching 0.85 percentage points less by the end of 2018. I also find that this negative trend is mainly present in the sample of non-horizontal mergers and the sample of mergers involving a private target.

JEL classification: G14, G34

Keywords: Mergers, acquisitions, rivals, synergies, year-trend

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†NHH - Norwegian School of Economics, Damiano.Maggi@nhh.no - All remaining errors or typos are my own.

2.1 Introduction

In their comprehensive reviews of the empirical literature on mergers and acquisitions, Jensen and Ruback (1983) and Roll (1986) made three important conclusions: (1) Shareholders of target firms realize economically large gains, (2) gains to bidder shareholders are small but positive on average, (3) the sources of takeover synergies are 'elusive' but most likely do not emanate from increased market power.[2] Nearly four decades later, these three conclusions have been largely confirmed based on the much larger samples of mergers and acquisitions made possibly by machine-readable databases Betton, Eckbo, and Thorburn (2008). While knowledge of the fundamental sources of takeover synergies continues to elude researchers, there is growing evidence of economic links between those sources and industrial organization Eckbo (2014). In other words, whatever the synergy sources, their value are most likely influenced by—and influence—industrial competition and supply networks. The purpose of this paper is to explore this intuition further in terms of the time-trend (if any) of the valuation impact of merger announcements on the merging firms' industry rivals.

A precondition for positive bidder gains from acquisition activity is that bidders—and not just targets—own some of the core resources that are necessary to produce synergy gains. Consistent with this view, Golubov, Yawson, and Zhang (2015) show that, notwithstanding the inclusion of a large set of observable firm- and deal-specific explanatory variables, bidder fixed effects are large and statistically significant in the cross-section of acquisition-announcement returns. They associate such fixed effects in bidder announcement returns with bidders possessing an "extraordinary" ability to identify valuable acquisition targets. Maggi (2018) shows that, for some acquirers, the fixed effects are much weaker when bidder announcement returns are measured in dollar values rather than in percentage terms. Thus, bidder firm size likely plays an important role in the generation of synergy gains. Furthermore, Maggi (2018) identifies significant industry fixed effects in acquirer announcement dollar returns: in cross-sectional regressions with bidder announcement

[2]The latter conclusion is based on the empirical tests pioneered by Eckbo (1983).

dollar returns as the dependent variable, the inclusion of bidder industry fixed effects nearly has the same explanatory power as in Golubov, Yawson, and Zhang (2015)for the so-called "frequent acquirers". A consistent interpretation of this finding is that the ownership of the resources required to generate positive takeover synergies are to some extent owned throughout the industry of the bidder firm. Another consistent interpretation of this finding is that the value of the synergies are influenced by industrial competition among the firms in the same industry of the bidder.

Dessaint, Eckbo, and Golubov (2019) offer a novel perspective on how bidder-specific takeover gains have evolved through time. They motivate the time-series analysis by referring to the substantial changes in the corporate governance of US firms that has taken place since the 1980s. To the extent that those governance improvements have reduced agency costs and improved the efficiency of corporate investments, average bidder gains may also have changed with time. While there is no significant change in the *unconditional* average bidder gains over the period 1980-2017, they find that bidder fixed effects are declining while the component of bidder gains that is *common* across bidders has been steadily increasing relative to the 1980s. The annual increase in the common component of average bidder gains is 15 basis points (bps). In other words, while the unconditional average bidder gain remains constant (at about 1%), controlling for changes in the composition of bidders over the sample period shows that the common component of average bidder gains reaches 5% by 2017. The unconditional average bidder gain remains constant only because bidder fixed effects decline over the same period.

Dessaint, Eckbo, and Golubov (2019) suggest that the decline in bidder fixed effects—and concomitant increase in the common component of bidder gains—is evidence that takeover synergies have become less bidder-specific over time. As a result, bidder bargaining power has also declined on average. Bidders have low bargaining power when the resources required to create synergies for the most part resides within the target. This is the case, e.g., when the synergies arise from simply replacing inefficient target management. From the bidder side, this requires the ability to finance the takeover as well as some expertise in hiring a new management team. Since a relatively large number of potential bidders may be in a good position to do this—including financial buyers such as private equity funds—competition among bidders drive the bulk of the synergy gains to the selling target shareholders. Conversely, bidder gains are more bidder-specific—and bidders in a stronger bargaining position—when synergy gains emanate from placing the target firm inside the bidder's unique product distribution network. The idea that lower bidder fixed effects and a higher average common component of bidder gains means less bidder-specific synergies over time further suggest that bidder gains should decrease *unconditionally*. Since this is not what the data shows (bidder gains remain stable at around 1%), Dessaint, Eckbo, and Golubov (2019) hypothesize that bidders must be receiving a smaller fraction of a larger total synergy gain later in the sample period, which the their evidence also supports.

This paper extends the notion of declining bidder-specific synergies to the closest competitors of the acquiring firms. To the extent that the resources required to generate bidder-specific synergies are available throughout the industry in which the bidder operates, we should also see a trend towards a decline in the industry wealth effect of acquisition announcements. Controlling for industry characteristics and/or bidder fixed effects, I identify a small but statistically significant negative time-trend in the average industry wealth effect: -2 basis point per year starting from 1990. To put it in context, the average decline of two basis points represents approximately 10% of the average unconditional competitor CARs. That is, the negative time-trend economic magnitude is considerable relative to the competitor average announcement return.

In line with previous studies, the unconditional average 7-day announcement return for the portfolio of the top five competitors is 0.47%. For example, Song and Walkling (2000) report a 6-day average abnormal industry return of 0.56%, Shahrur (2005) reports a 5-day average abnormal industry return of 0.39%. When I split the sample in periods of 9-year, I find that the unconditional average announcement return to competitors has declined over time. That is, even before estimating a linear-trend regression, I observe a declining pattern in competitor CARs, on average competitors still earn a positive return around the announcement date. Finally, as in Song and Walkling (2000) and Shahrur (2005), I find that bidders returns influence the sign of the competitors announcement returns: positive bidder announcement return are linked to positive competitors announcement returns.

In this paper, I define close competitors as the top five firms that are most similar in terms of products to the acquiring firm. Compared to previous studies such as Shahrur (2005), I do not use a Fixed Industry Classification (FIC) to define potential competitors to the acquirer. On the other hand, I use the newly Text-Based Industry Classification (TNIC) provided by G. Hoberg and G. Phillips to define close competitors[3]. Using TNIC data helps to avoid the common shortfalls associated with fixed industry classification. Later in this paper, I will outline these shortcomings and the reasons to prefer TNIC industry classification over a fixed industry classification.

Firms in the main industry of bidders may act as potential competitors for the target or as potential targets for the bidder. Song and Walkling (2000) interpret their evidence on industry wealth effects in terms of the latter possibility—labeled the 'acquisition probability hypothesis'. The evidence of a declining average acquisition-induced industry wealth effect presented here is consistent with the alternative view that industry rivals are potential bidders: As bidder-specific synergies decline, the expected gain from bidding is lowered also throughout the industry. A negative trend, nevertheless, may be consistent with an increased competition among the competitors of the bidders due to a new, more-efficient combined firm (Eckbo (1983)).

The results are robust to a series of robustness tests and additional analyses. First, I estimate the average decline in competitor CARs relative to 1990s. Starting in 2000, the average portfolio of competitors has declined over 2 basis points, reaching almost a total decline of 0.40 percentage

[3]Hoberg and Phillips (2010) and Hoberg and Phillips (2016)

points by 2018. In other words, the time-trend is not mainly driven by the mergers occurred during the 1990s.

Second, I show that the decline in competitor CARs is robust to industry clustering and one time bidders. I also find that the negative time-trend is more accentuated when the deal is a non-horizontal merger (outside the 4-digit SIC industry of the bidder) and when the acquired target is a private firm. In other words, the negative trend appears to be correlated with environments where information asymmetry is present. On average, competitors benefit from the acquisitions announced by the bidder where the market does not have enough information to accurately estimate potential synergies or the stand-alone values of the two merging firms. Finally, industry clustering, event windows, event study methods, and transaction value thresholds do not affect the documented time-trend. Overall, the time-trend appears to be robust and correlated with deals involving a private target firm or a non-horizontal merger.

This paper contributes to the literature of merger and acquisition in several ways. First, it provides a new stylized fact about competitor announcement returns. In line with previous cross-sectional research, I provide evidence of a decline in competitor announcement CARs. This is true both unconditional and conditional to various characteristics.

Second, it contributes to the literature on competitors announcement returns (see Shahrur (2005) and Cai, Song, and Walkling (2011)). Specifically, this paper adds by providing new insights on competitor CARs across four samples: horizontal mergers vs. non-horizontal and public vs. private targets. That is, I show how the time-series of competitors CARs evolves differently depending on some merger features.

Third, I add to the existing literature by providing a revised version of classical studies such as Song and Walkling (2000) and Shahrur (2005). This paper extends the sample period adding approximately two decades worth of additional merger transactions and providing revised summary statistics. Finally, it provides additional evidence on the economic links between the bidder, the industry where it operates, and its closest competitors. I show that trends in bidders CARS influence competitors as well.

The rest of the paper is organized as follow. Section 2.2 develops and introduce two hypotheses that will be tested in the paper. Section 2.3 describes the sample used in this paper, the empirical strategy, and discusses the sample used in this analysis. Section 2.4 presents the main results of the paper and in Section 2.5 robustness checks are discussed. Section 2.6 summarizes the results from the previous sections and provides two potential explanations for the documented time-trend. Finally, Section 2.7 concludes the paper.

2.2 Testable hypotheses

Over the past four decades, the market for corporate control has undergone profound changes. Yet, corporate governance for US publicly traded firms has improved as empirical evidence shows (see Gillan and Starks (2007)). Is it reasonable to think that such profound changes resulted in improved acquisition decisions? Dessaint, Eckbo, and Golubov (2019) find that bidders - on average - have improved their acquisition decision. They find that this improvement is masked by two opposing trends: a common trend and a composition effect. While the acquirer returns have been increasing over the past four decades (the common trend component), this increase has gone undetected due to a decline in the mix of bidders undertaking acquisitions (the composition effect component). Particularly, the authors argue that this decline in the composition effect is linked to a deterioration in the bidders unique resources. As these resources have became less bidder-specific, this resulted in the bidder bargaining power declining over the past four decades. If bidders, over time, have improved their acquisition decision making while experiencing a decline in their resource uniqueness, we should observe competitors benefiting from these changes.

In other words, if the bidder resources are - to some extent - substitutable, competitors of the acquirer may start engaging in merger transactions.

As more firms engage in merger transactions, we should observe a similar time-trend observed in acquirer returns in the overall industry where firms operate. If bidders have less bargaining power over the split of takeover synergies then bidders may earn a lower share of the total combined wealth (the total synergy gains from the merger). As a result, as more bidders compete and accept a lower share of the total combined wealth, the benefits from engaging in mergers and becoming a bidder decreases. That is, we should observe that over time the average announcement return for competitors declines.

Here is a stylized example the hypothesis. Assume two firms (firm A and firm B) operate in the same industry. Firm A conducts several mergers throughout the years while firm B does not. The two firms produce similar products and have similar assets. Also, assume that the resources needed to generate takeover synergies have become less bidder-specific. That is, the resources needed to generate those synergies lie mainly within the target firm. In other words, thanks to its unique resources, the target firm may increase its bargaining position with respect to the acquiring firm and earn a higher share of the total combined wealth. As firm B is similar to firm A and the takeover synergies are driven by the target resources, firm B may have some incentives to engage in acquiring a target. As more mergers in the industry of the bidder are announced the lower the potential for competitors to join the market for corporate control. To summarize, the first testable hypothesis is:

H1: *Does a time-trend of the valuation impact of merger announcements exist?*

H1 - bis: *Is this a negative or positive time-trend?*

To test this hypothesis I estimate the equally-weighted portfolio announcement returns of the closest top five competitors to the acquirer. After estimating the cumulative abnormal returns, I check whether - over time - a pattern in competitor CARs exists.

Next, I investigate the source of this time-trend (if any) in the sample. Hou (2007) finds that industries have a crucial role for news dissemination with respect to the equity market (p. 1137). That is, industries where the bidder and target operate are the primary channel to acquire new information on the state of these industries. Following, and rearranging, the acquisition probability hypothesis by Song and Walkling (2000), we can split the abnormal return, conditional on a merger attempt in the industry, to rival i as:

$$AR_i = \Delta p_i(x_1)\mathbb{E}[\upsilon_i(x_2)], \tag{2.1}$$

where $\Delta p_i(x_1)$ is the change in the probability of an acquisition attempt (or the information flow), $\mathbb{E}[\upsilon_i(x_2)]$ is the expected return to a rival firm's shareholders, x_1 represents a vector of characteristics related to the probability of acquisition, and x_2 represents a vector of characteristics related to the value of the firm. Following Bradley, Desai, and Kim (1983) and Song and Walkling (2000), we need to recognize that the merger attempt could signal the existence of an increase in value of the unique industry-specific resources. That is, the abnormal return for firm i, conditional on a merger attempt could depend solely on such resources and can be written as:

$$AR_i = \mathbb{E}[\upsilon_i(x_2)]. \tag{2.2}$$

As a result, if the time-trend could be driven by a lower information level, $\Delta p_i(x_1)$ (consistent with Hou (2007)), by lower expected gains from engaging in mergers $\mathbb{E}[\upsilon_i(x_2)]$ (consistent with Dessaint, Eckbo, and Golubov (2019)), or by a mix of the two effects.

Here is a stylized example to explain the hypothesis. Assume two firms (firm A and firm B) operate in the same industry. Firm A conducts several mergers while firm B does not. Again, the two firms are similar in terms of products and assets. Now, assume that firm A acquires a target while firm B does not. By announcing this acquisition, firm A conveys information regarding the state of the industry where the bidder and its competitors operate. That is, depending on the characteristics of the merger, different information is revealed. On one hand, the additional information revealed by the merger attempt may decrease due to a lower "learning" form the market. On the other hand, as more potential bidders join the market for corporate control, the time-trend in competitor CARs may be driven by a change in the expected return from a merger.

To summarize, the second hypothesis is:

> **H2:** *Is this time-trend due to changes in expected gains or changes in the information level?*

To test this hypothesis, I split the full sample of transactions according to various dimensions (e.g. horizontal vs. non-horizontal mergers). If the time-trend in competitor CARs is driven by a lower expected return from engaging in mergers, we should observe that the time-trend is presistent across all the sub-samples. That is, regardless whether the sample contains only horizontal or non-horizontal mergers the time-trend should be present. On the other hand, if the time-trend is driven by the level of information conveyed in a merger announcement, we should observe that the time-trend exists only for those samples where information asymmetry is high. That is, the market learns more (at a declining rate) about the current state of the industry when, for example, a private target is acquired.

The next section will discuss more in details the sample and methodology used to test these hypotheses.

2.3 Sample selection and empirical strategy

2.3.1 M&A Data - Sample selection

The initial M&A data needed to construct the sample of competitors are provided by SDC Platinum (Thomson Financial SDC). The initial sample period starts in January 1978 and ends in December 2018. To obtain the final sample, the following filters have been applied:

1. The transaction is classified as merger in SDC Platinum.

2. The announced transaction may be completed or withdrawn.

3. Bidders are public US firms.

4. The target firm can be a publicly or privately held firm.

5. The transaction is classified as "domestic" by SDC Platinum.

6. The transaction value must be larger than USD1 million.

7. The bidders before the transaction owns less than 50% and after the transaction owns 100%.

8. Announcement on the same date by the same company are excluded.

These restrictions result in an initial sample of 62,378 transactions. I then match the bidder identifier (*gvkey*) to the list of Text-based Network Industry Classification (TNIC) data developed by G. Hoberg and G. Phillips (Hoberg and Phillips (2010) and Hoberg and Phillips (2016)). This new industry classification is based on firm pairwise similarity scores recovered using firm filings (10-K) and textual analysis. As a result, *a distinct set of firm centric close competitors is identified, analogous to networks or a "Facebook" circle of friends* (cit. G. Hoberg and G. Phillips). This new industry classification is updated annually and it offers more research flexibility and is more informative than fixed industry classification (as outlined in Hoberg and Phillips (2010) and Hoberg and Phillips (2016)).

To identify competitors of the acquirer, I match the bidder *gvkey* and recover the competitor *gvkey* from the pairwise data entries. During the matching procedure, I control for the mirror image for every pair of the two firms. In a nutshell, I remove any duplicates between a pair of two firms in the TNIC database. I exclude target firms based on the time of acquisitions. That is, if a target firm was a competitor of the acquirer in the year of its acquisition, I exclude it from the sample. The restrictions and the matching with TNIC data result in a final sample of 21,817 deals conducted by 6,309 unique bidders. The final sample period starts in January 1990 and ends in December 2018[4].

Unlike Maggi (2018) and Dessaint, Eckbo, and Golubov (2019), I do not impose the acquirer to conduct at least two deals over the sample period. Note that this requirement would result in a modest reduction in the sample size, from 21,817 transactions to 19,358 transactions. As in Fuller, Netter, and Stegemoller (2002), Golubov, Yawson, and Zhang (2015), Dessaint, Eckbo, and Golubov (2019) almost 90% of the deals in this sample are conducted by repetitive acquirers. That is, in a typical M&A sample, deals conducted by one-time acquirers are not frequent. Nevertheless, imposing such strict restriction could reduce the number of potential transactions included in the final sample and, therefore, this paper's scope [5].

The final transaction sample includes successful and withdrawn merger attempts. Including only successful (completed) deals could create a bias in the results. That is, at announcement of the merger, the change in the share price already incorporates the likelihood of deal completion (see Betton and Eckbo (2000), Betton, Eckbo, and Thorburn (2008)). In other words, investigating only successful mergers could result in a sample selection error. Yet, including only successful merger could bias the results as some horizontal mergers may potentially be blocked by regulators only after some time[6].

[4]The time period 1978-1989 is excluded due to missing or incomplete SDC and TNIC data.
[5]The results are robust to this additional requirement, see Table 2.7
[6]As noted by White and Kwoka (1999) this concern is mitigated by the lenient U.S. antitrust policy during the 1990s.

The final transactions sample spans all the productive industries, from agriculture to real estate. In addition, the sample of M&A shows the typical patterns of merger waves. For example, we can see how the number of deals increases to an absolute peak in 1998 and a relative peak in 2006. Overall, at first sight the sample does not look dramatically different from samples previously used in different studies.

2.3.2 Defining competitors to the acquirer

In this paper, competitors are defined as the firms with the highest similarity score to the acquiring firm following the Text-based Network Industry Classification (TNIC) by G. Hoberg and G. Phillips (see Hoberg and Phillips (2010) and Hoberg and Phillips (2016)). Using this definition of industry classification helps to avoid three problems associated with Fixed Industry Classifications (FIC).

First, one shortfall of fixed industry classification is the heterogeneity in the number of firms across different industries. Forming portfolios using a fixed industry classification could result in a disproportionate amount of firms distributed across different portfolios. For example, one portfolio may contain 100 competitors while another may contain only 10 competitors. Therefore, selecting only the top five firms would help to reduce the heterogeneity in the number of firms across industries. By restricting the number of potential competitors, I ensure that small industries are not penalized and thus not resulting in skewed portfolios.

Second, the choice in which industry the firm belongs (e.g. 4-digit SIC) is an endogenous choice by the firm. As a result, if we were to use a fixed industry classification we may introduce a bias in selecting the competitors to the bidder. For example, the bidder may select itself in a different primary 4-digit SIC than its closest competitors. That is, choosing competitors based on a 4-digit SIC code may result in a sample selection bias.

Third, one shortfall of fixed industry classification is that the firm may have different sources of revenues from different industries. That is, when the bidder chooses a primary fixed industry classification its different revenue streams may not be attributable to only the chosen primary - or secondary - industry classification. As a result, if we were to use fixed industry classification it may create a sample selection error.

Finally, Kahle and Walkling (1996) finds that nearly 80 percent of industry classifications covered by Compustat and CRSP disagree at the 4-digit level. Additionally, they find that a large number of firms change their primary SIC code over time and some data providers may provide only the firm's most recent industry classification.

Here is a stylized example to explain these shortfalls. Assume that *Apple Inc.* acquires a target firm and we investigate the competitor reactions to the announcement. If we were to use a fixed industry classification such as SIC, we would select as competitors all the firms in the self-assigned 4-digit SIC code for*Apple Inc.*: 7372 (Prepackaged Software). However, one of *Apple Inc.* main revenues sources is from producing and selling hardware products such as: iPhones, MacBooks. Another main revenue source for *Apple Inc.* is providing services (see App store, and Apple music). As a result, by using the 4-digit SIC industry code self-assigned to *Apple Inc.*, I could only capture parts of their extensive line of business and revenue sources. Additionally, competitors in the same 4-digit SIC industry may have different streams of revenue than *Apple Inc.*. By using Hoberg and Philips TNIC classification , I can find the closest competitors of *Apple Inc.* without relying on a broader - and static - fixed industry definition such as SIC codes.

To avoid all these shortfalls linked with fixed industry classification, I define competitors as the five firms with the highest similarity scores according to the Text-Based Network Industry Classification (TNIC).

2.3.3 Empirical strategy - Measuring announcement returns

To estimate the market-industry reaction to an M&A transaction announcement, I form equally-weighted portfolios of the top five competitors of the acquirer at the announcement date. I choose to form equally-weighted portfolios to account for any contemporaneous cross-correlation of returns (see Eckbo (1983), Song and Walkling (2000)). When forming these equally-weighted portfolios the year dimension of the industry classification by Hoberg and Phillips is taken into account. Here is two stylized examples of this "restriction".

Let us assume two firms: firm A and firm B. In 1990 firm B is a close competitor of firm A as they produce similar products. Later, in 1991 firm A decides to acquire firm B. As a result, I would include firm B as a competitor of firm A in 1990 but I would exclude firm B from the set of firm A close competitors in 1991.

Let us assume that firm E and firm F are two bidders. Firm F is a close competitor to firm E as their products are similar. Firm E announce a deal both in 1990 and 1991, but firm F announces a deal only in 1991. As a result, I would include firm F as a close competitor of firm E in 1990 but I exclude it in 1991, as firm F announced an acquisition.

After forming these portfolios of the top five competitors to the acquirer, I estimate announcement returns. The traditional approach to evaluate announcement returns is to estimate abnormal percentage returns using standard event study techniques (see Brown and Warner (1985)) and then sum these abnormal returns over a chosen event window. In this paper, the announcement returns (or cumulative abnormal returns) are estimated over a seven-day event window (-3,+3) and are calculated using a simpler market-adjusted model[7].

I choose a simpler market-adjusted model to a more classical market model approach for several reasons. First, by employing a market-adjusted model I would preserve the highest number of

[7] As used, among others, by Fuller, Netter, and Stegemoller (2002) and Cai, Song, and Walkling (2011). The results remain robust when a classical market model is used.

transactions in the final sample. That is, some transactions could be removed because of more stringent requirements relative to stock price data availability (e.g. at least 100 trading days for each stock in the portfolio). As a result, this restriction may create imbalances in the portfolios of competitors. That is, the number of competitors included in the portfolio may be lower than five creating a bias in the results.

Second, some competitors may just have started trading during the estimation period, thus introducing an additional bias. That is, the higher returns following an IPO (for example) may influence the overall return of the portfolio.

Third, as the closest competitors are defined in a given year (see 2.3.1) it is not necessarily that their "competitor" status upholds in the previous year. For example, assume two competing firms (firm A and firm B) announce two separate deals in 1990. However, in 1991 only firm A announce an additional deal and firm B is one of firm A closest competitors. As a result, the coefficients from the market model may be biased as the estimation period includes the previous year merger announcements.

Finally, the higher volatility in the market during the period 1999-2001 and in 2007-2009 could affect the estimates for the market model coefficients. Nevertheless, Brown and Warner (1985) shows that daily data generally present fewer difficulties for event studies regardless of the event study methodology chosen (see also Brown and Warner (1980)).

To sum up, for a portfolio p, the seven-day CAR is defined as:

$$CAR_p = \sum_{t=-3}^{T=3} AR_{p,t}$$

where $AR_{p,t}$ is defined as: (2.3)

$$AR_{p,t} = R_{m,t} - R_{p,t}$$

After estimating the CARs for portfolios of competitors to the acquiring firm, I test the two research questions developed in Section 2.2 using two different approaches. In a nutshell, I run different regression models to test the existence of a time-trend in announcement returns for the top five competitors of the acquiring firm. The most basic regression model is as follow:

$$CAR_{p,t} = \alpha + \beta_X X + \epsilon \tag{2.4}$$

where X is a variable that capture the time-trend in announcement return according to one of the two different approaches. That is, if a time-trend in competitor announcement returns is present the coefficient of the regressor X should be statistically significant. Later I present and provide the results from these two different approaches (see Section 2.4).

2.3.4 Sample distribution and industry clustering

Table 2.1 is the starting point to better understand the sample of transactions used in this paper. Table 2.1 shows the distribution of the sample by year and industry classification. In this table, the industries follows the 48 Fama French industry classification. I chose the 48 Fama French industry classification to avoid presenting a long and extensive list of industries. That is, the 48 Fama French industry classification provide a compact and quick overview of the industries included in this paper.

To equally split the transactions across time, I divide the sample into three intervals of nine years

(1990-1999, 2000-2009, and 2010-2018). The last column of Table 2.1 provides a measure of the relative weight of a certain industry to the overall sample. From Table 2.1 it can be seen that almost half of the deals occur during the period 1990-1999, in line with the existing literature on M&A.

A pattern of industry clustering similar to the one found by Andrade, Mitchell, and Stafford (2001) and Shahrur (2005) is present in the sample. For example, I find the same clustering in the business service industry (FF Industry: 34) as described in Andrade, Mitchell, and Stafford (2001) and Shahrur (2005). Additionally, I find two additional industry clustering in the Banking and Trading Industries (FF Industries: 44 and 47). Overall, these two industry clustering represents one fourth of the transactions in the total sample. The reader may be concerned how this industry clustering can affect the results regarding the estimation of the time-trend in competitor CARs. However, later in this paper, I show that the two industry clustering in the Banking and Trading Industries do not affect the results[8].

2.3.5 Announcement returns to competitors

Table 2.2 shows the annual distribution of mean, median, and standard deviation for competitor cumulative abnormal returns. Additionally, the last two columns of Table 2.2 shows the number of deals announced in a year and its cumulative sum.

Looking at the first three columns, it appears that announcement returns to competitors (CARs) are quite volatile throughout the sample period. The unconditional mean (median) of CAR is around 0.27% (0.19%). The average competitors CAR does not dramatically differ from previous studies (for example Shahrur (2005)). Looking at the last three rows of Table 2.2, we can already see how the unconditional announcement returns have declined over the sample period. In 1990-1999 the mean (median) CAR was around 0.39% (0.23%) while during the period 2010-2018 the

[8] See Table 2.8.

mean (median) CAR was around 0.17%.

Looking at the last two columns, we can see that the typical pattern of merger waves. We have one absolute peak in the number of deals announced (1,654 in 1998) and one relative peak in 2005-2006. Furthermore, we can also see how after a period of economic downturn the number of announced deals dramatically decreases. For example, both in 2001 and in 2009 the number of announced deals decreased by approximately 30% from the previous year.

Table 2.3 shows how announcement returns for competitors portfolios differ across four different dimensions (horizontal transactions, non-horizontal transactions, cash finance transactions, and finally stock financed transactions) and three different samples (Panel A: overall sample, Panel B: sample where the bidder cumulative abnormal return is positive, and Panel C: sample where the bidder cumulative abnormal return is negative). I decide to split the sample according to the nature of the merger (wealth-creating vs. wealth-destructing) to control for differences in the nature (goodness) of the deal.

Starting from Panel A, we can see how competitor firms earn - on average - a positive announcement return when a new merger is announced. The average competitor CAR ranges from a minimum of 0.08% (t = 4.13) for the (0,2) window to a maximum of 0.27% (t = 6.82) for the (-3,3) event window. The positive average CAR to competitors is consistent with the results by Eckbo (1983), Song and Walkling (2000), and Shahrur (2005). Generally speaking, the positive CARs are around 52% of the total observations in the time-series of announcement returns.

Moving to the right of Panel A, I split the full sample of transactions according to the nature of the merger: horizontal vs. non-horizontal mergers. We can see that rivals earn a higher positive announcement return (0.35% (t = 4.97)) when an horizontal transaction is announced[9]. On the

[9] Horizontal transactions definition follows Shahrur (2005): the acquiring firm and the target are in the same 4-digit SIC code. While in this case the definition of horizontal takeover is dependent on how the industry is

other hand, for non-horizontal mergers competitors - on average - earn a lower return, 0.21% (t = 4.76). Overall, while the average competitors return to horizontal mergers is lower than in previous studies, it is consistent with the evidence presented in Shahrur (2005)[10].

Finally, the last two columns of Panel A show that rivals earns higher returns when the bidder announce the acquisition of a public target rather than a private target firm (0.53% (t = 7.09) vs. 0.12% (t = 3.65))[11]. The results from these two last columns may be consistent with the idea of lower information asymmetry when the bidder acquires a public target. That is, rivals may benefit from the information disclosed at the announcement of a merger involving a public target and the acquirer.

At first sight, the evidence presented in Panel A of Table 2.3 is consistent with previous research. On average, competitors earn a positive announcement return following an acquisition attempt by one of their closest rivals (the acquiring firm). Announcement of horizontal mergers and acquisition of a public firm result in higher positive competitor CARs. This may be consistent with the idea of lower information asymmetry in case of an intra-industry acquisition or an acquisition of a public firm.

Following Berkovitch and Narayanan (1993) and Shahrur (2005), I split the sample into value-creating and value-destroying acquisitions. This definition depends on whether a takeover results in a positive or negative bidder announcement return. This additional analysis will help understanding whether the market learns new information regarding the competitors and the state of the industry when a merger is announced. The total number of transactions is marginally lower (21,081) due to some missing bidder stock return data. Bidders announcement returns are esti-

defined (SIC in this case), it still provides a valuable insight. Nevertheless, using TNIC data to classify a merger as horizontal is not currently feasible.

[10] I find that the (unreported) average five-day announcement return (-2,2) for horizontal merger for the same time period used in Shahrur (2005) is around 0.40%.

[11] On the other hand, in unreported results I still find that competitors on average earn a negative return when they announce the merger with a public target.

mated using a standard event methodology.

Panel B in Table 2.3 reports the percentage CAR to the competitors for the subsample of takeovers where the bidder earns a positive cumulative abnormal return. Compared to the results in Panel A, the announcement returns to the rival firms are significantly higher. The average (-3,3) CAR is around 0.75% (t = 19.71) compared to 0.27% (t = 6.82) to the overall sample of transactions. As in Panel A, in Panel B we can observe that the average competitors CAR is higher when the announced takeover is an horizontal merger or when the firm acquired is a publicly traded company. On average, for this sample we have almost 10% more positive CARs than for the sample used in Panel A.

Panel C in Table 2.3 reports the percentage CAR to the competitors for the subsample of takeover where the bidder earns a negative cumulative abnormal return. As in Panel B, the announcement return to the acquirer appears to influence the CARs to the competitor firms. The average (-3,3) CAR to rival firms is around -0.45% (t = -11.13) while the highest average CAR (-2,2) is around -0.17% (t = -6.46). On average, competitors experience the same decline irrespective whether the announced merger is horizontal or non-horizontal. On the other hand, when the acquirer announces the bid for a publicly traded target, competitors CARs are zero (average t-statistic = 1.00).

As previously discussed, the results may be consistent with the idea of higher/lower information asymmetry. For example, Hietala, Kaplan, and Robinson (2002) argue that takeover attempts reveal information such as: potential synergies, the stand-alone value of the two merging firms, and the value split among firms. As a result, in case both the bidder and the target are public firms, the information disclosure may be limited. That is, the market already has all the information to value potential synergies, the stand-alone values of firms, and the value split of synergies. Thus, competitors may not be affected by such announcement.

Overall, the results are and the sample used in this analysis appears to be in line with previous literature on competitor returns. Competitors CARs are - on average - positive, and not dramatically different from well-established studies. Note that in many of the cases reported in Table 2.3, the magnitude and statistical significance of CARs to competitors increases as the event window increases. Extending the event window would be beneficial to the analysis for at least two reasons. First, it may take few days before the information is fully reflected in the small-firm stock prices (Lo and MacKinlay (1990)). Second, by extending the event window we can capture any information leakage about the merger (Jarrell, Brickley, and Netter (1988), Eckbo (2014)). Finally, bidders announcement returns appear to have an influence over the CARs to the competitor firms. That is, competitor react differently whether a merger is wealth-enhancing or wealth-diminishing.

Overall, it appears that initial sample of transaction used to define competitors does not dramatically differ from the one used in previous studies. To alleviate concerns regarding sample selection I estimate the announcements returns to the sample of bidders. The average (median) 7-day cumulative return for bidders equals to 1.01% (0.29%). The average CAR to acquirers in this sample is consistent with the value found in the existing literature. For example, Dessaint, Eckbo, and Golubov (2019) report a mean (median) for the 7-day cumulative return for bidders equal to 1.04% (0.38%).

2.4 The industry wealth effect since 1990

Until now, the evidence presented in the previous section is consistent with the existing literature on the industry wealth effect. However, to test the hypotheses in Section 2.2, a multivariate regression model is required. This section illustrates the two different approaches used to investigate the existence of a time-trend in competitor CARs. As a first approach, I estimate a regression model where the dependent variable is the competitor portfolio announcement return and the time-trend is estimated using year dummies. As a second approach, I substitute the year dummies with a linear time-trend variable that takes value of one in 1990 and increases of one every year after. In both approaches, I progressively introduce deal characteristics and industry or bidder fixed effects in each new model to control for the heterogeneity in competitor CARs. In other words, adding additional regressors would help to remove any industry or bidder induced cross-sectional variation in competitors announcement returns.

2.4.1 First approach: Year Dummies

As a first approach to estimate any time-trend in industry wealth effect I run four different multivariate regressions with competitors portfolio CARs as the dependent variable. In each new model, I progressively add explanatory variables to control for variation in CARs. The four models are:

$$\begin{aligned}
&\text{Model 1:} && CAR_p = \alpha + \gamma T^{'} + \epsilon_i \\
&\text{Model 2:} && CAR_p = \alpha + \gamma T^{'} + \delta Y^{'} + \epsilon_i \\
&\text{Model 3:} && CAR_p = \alpha + \gamma T^{'} + \delta Y^{'} + IndustryFE + \epsilon_i \\
&\text{Model 4:} && CAR_p = \alpha + \gamma T^{'} + \delta Y^{'} + BidderFE + \epsilon_i
\end{aligned}$$

where **T** represents the vector of annual dummy variables (1990-2018), **Y** is a vector of deal and industry characteristics, $IndustryFE$ are the 3-digit SIC industry fixed effects, and $BidderFE$ are the bidder fixed effects. Deal characteristics include dummy variables for different financing methods (cash or stock), a dummy variable to differentiate the status of the target firm (public or private), one dummy variable for a tender offer, one dummy variable for an hostile takeover, and one dummy variable for horizontal mergers (following Shahrur (2005)). Industry characteristics include the total number of firms in the 3-digit SIC code industry, the size of the industry (expressed as the log of the total industry revenues), Herfindahl Index and market share at the portfolio level and their relative changes (see Shahrur (2005)).

Using two different industry classification (SIC and TNIC) may create a bias in the estimation of the basic regression model (see 2.4). Aggregating industry characteristics at the 3-digit SIC code level and defining competitors using TNIC data could result in wrongly estimating industry characterstics. As a result, the models with industry characteristics and industry fixed effects should be treated as complementary to the main models. That is, I define as main models the basic model (Model 1) and the model where bidder fixed effects are included (Model 4)[12].

Table 2.4 and Figure 1 report the results of this first approach. Figure 1 plots the coefficients relative to the year dummies variables while Table 2.4 reports the coefficients of the regressor models (fixed effects excluded). Starting from the top-left graph in Figure 1, it appears that a negative time-trend in competitors CARs may be present during the period 1990-2018. This negative time-trend is consistent with the decline in the unconditional announcement returns found in Table 2.2. However, as we can see from the top-left corner of Figure 1, the high variation in the error terms has an influence over the sample of competitors CARs. As a result, to control for the heterogeneity in competitor CARs, I add further regressors. The results from estimating Model 2 and Model 3 are plotted relatively in the top-right corner and bottom-left corner of Figure 1. As it can be seen, controlling for industry composition, industry characteristics or deal characteristics does not result in a considerable improvement in the regression model. By employing two different industry classifications (TNIC and SIC) the resulting estimated industry characteristics and fixed effects may not accurately capture the true variation due to industry settings. Additionally, by employing industry fixed effects and industry characteristics at the 3-digit SIC code, I do not account for the possible heterogeneity among the competitors in a same portfolio. For example, assume a portfolio of the top five competitors of firm A is constructed. These five firms may have different 3-digit SIC code among themselves. As a result, when the portfolio return is estimated and industry characteristics - at the 3-digit SIC level - are controlled for, the actual number of

[12]Industry characteristics are still included in the last model. However, unreported robustness tests show that the time-trend effect is stronger when I control only for deal characteristics and bidder industry via bidder fixed effects.

firms in the portfolio belonging in the same 3-digit SIC industry may be just one. Thus, the industry characteristics and industry fixed effects may not properly capture the difference among firms in the same portfolio.

To control for time-invariant deal specific characteristics and bidders characteristics I replace the industry fixed effects with bidder fixed effects (Model 4). In this model, bidder fixed effects can help to control two different effects. First, using bidder fixed effects helps to control for the heterogeneity in the different transaction carried out by different acquirers. Second, bidder fixed effects capture more precisely the variation within the industry where the bidder and its closest competitors operate. That is, by using bidder fixed effects I can overcome some of the problems with industry characteristics and industry fixed effects discussed earlier. The bottom-right graph of Figure 1 plots the estimated year dummies coefficients. We can see how bidder fixed effects helps to highlight and refine the negative time-trend present in the data of competitor CARs.

After controlling for bidder specific information - via bidder fixed effects - it seems that a negative time-trend in competitor CARs exists. Industry fixed effects (defined at the 3-digit SIC code level) and various characteristics appear to only have a marginal effect in explaining CARs to competitors. To some extent, most of the heterogeneity in competitor CARs seem to be driven by the bidder industry and its unique characteristics. Finally, the number of firms in the industry and its relative change over time, change in industry size and the public target dummy variable appear to have some, but low, explanatory power across three out of four models.

The next section will further investigate this time-trend in competitor CARs. Specifically, it outlines the second approach used to estimate the time-trend in the industry wealth effect and the results from the regression models. As a result, it provides an estimation of the average decline in competitor CARs throughout the sample period.

2.4.2 Second approach: linear trend specification

Looking at the bottom right corner plot of Figure 1, the average CAR to competitors appear to experience a decline over the sample period. As a result, to provide an estimation of the average decline over time in competitor announcement returns, I substitute the year dummies in Model 1 through Model 4 with a linear time-trend variable. That is, I impose a linear relationship between the competitors announcement returns and time. As a result, the basic regression model is similar to Equation 2.4 where X is replaced by *Linear Trend*. This linear time-trend variable starts in 1990 with a value equal to one and increases by one each year after 1990. Looking at the bottom-right panel of Figure 1, the trend appears to be slightly non-linear. At this stage, I only impose a linear relationship between returns and time to have an immediate and simpler estimation for this decline in the industry wealth effect. The results from the regression specifications are contained in Table 2.5.

As it can be seen in the top-left corner plot in Figure 1, it appears that a very weak negative trend is present, especially starting from 2000. Nonetheless, the considerable heterogeneity in CARs may affect this first attempt estimating a linear trend. Looking at the results from Column (1), we can see how a weak time-trend is present in the top-left panel of Figure 1 is captured by the *Linear Trend* variable. The estimated coefficient of the linear time-trend variable is statistically significant at standard level. Not surprisingly, its economic magnitude is relatively small: the average yearly decline in competitors returns is around two basis points. Perhaps, the heterogeneity in the sample of competitor CARs may impact the magnitude and statistical significance of the linear trend coefficient.

In Column (2) of the same table, I add deal and industry characteristics to control for the variation in competitor CARs. The coefficient of the linear time-trend variable remains statistically significant at the 10%. The average decrease in competitor CARs is around one basis point per year which translates into a 0.28 percentage points total decline by the end of 2018. Looking at

Column (2) of Table 2.5, we can see how - so far - the results are consistent with the decline in the unconditional average competitor CARs found in Table 2.2.

The average decline in competitor CARs remain stable at one basis point when industry fixed effects (defined at the 3-digit SIC code level) are included in the regression model as in Column (3). That is, by 2018 the average competitors CAR has decreased by almost 0.30 percentage points. Finally, in Column (4), the industry fixed effects are replaced with bidder fixed effects. Looking at the coefficient of the linear time-trend variable, we can see that the average decline in competitors CARs equals to three basis points per year. While the magnitude (3 bps) may appear to be economically insignificant, it represents almost a ten percent yearly decline starting in 1990[13]. By the end of the sample, the average conditional competitor CAR becomes negative and declined by 0.84 percent points.

Is including bidder fixed effects in the analysis of competitor CARs reasonable? The answer to this important question is not straightforward, however, I argue that acquirer fixed effects are reasonable and helpful in analyzing competitor CARs. First, including bidder fixed effects have been shown to help explain the cross-sectional heterogeneity both in acquirers and competitors CARs. Second, bidder fixed effects help control for the possible different type of the acquiring firm itself (e.g. serial acquirers). Third, bidder fixed effects would serve as proxy to capture the variation within the industry of the bidder and their closest competitors. Finally, bidders fixed effects help to capture the decline of acquirer returns documented in Dessaint, Eckbo, and Golubov (2019).

Next, I consider whether the negative trend documented earlier is a statistical artifact. To test the persistency of this negative linear time-trend, I split the original competitor CARs into two additional samples based on wealth-creating and wealth-destructive transactions (see Shahrur (2005)

[13]Dessaint, Eckbo, and Golubov (2019) finds an average increase in bidder CARs of 15 basis points per year which is approximately an yearly increase of ten percent with respect to the unconditional average bidder CAR (1.05%). As a result, we can see how the average decline in competitors CARs is similar to Dessaint, Eckbo, and Golubov (2019).

and Dessaint, Eckbo, and Golubov (2019)). I define wealth-creating transactions as those transactions where the bidder earns a positive CAR and wealth-destructive transactions as those where the bidder earns a negative CAR.

Looking at Panel B (the subsample of competitor announcement returns conditional on a positive bidder CAR) the negative linear time-trend in CARs remain unchanged from Panel A. Nevertheless, both the magnitude and statistical significance of the linear trend variable remain stable across the two additional specifications as seen in Column (2) and Column (3). On the other hand, when bidder fixed effects are included in the regression the linear trend variable becomes insignificant. To some extent the negative linear trend identified in Panel A is persistent for the subsample of transactions where the bidder earned a positive CAR. However, it appears that the information-released by the acquiring firms can explain the negative downward trend.

Panel C of Table 2.5 contains the regression results for the subsample of competitor CARs conditional on a negative bidder CAR. As in Panel A and Panel B, Column (1) through Column (4) contain the results of the four different regression models. We can see that - to some extent - the coefficient of the linear trend variable remains stable and statistically significant. When industry and deal characteristics are included, the linear trend variable coefficient becomes statistically insignificant. One possible explanation may lie in wrongly estimating industry characteristics (see Section 2.4.1). Column (3) includes the regressors in Column (2) with the addition of industry fixed effects. The coefficient of the variable linear is statistical significant at the 10% and with a similar magnitude as in the previous two samples. Finally, when bidder fixed effects are included, the average decline in competitor CARs equals to three basis point per year. Conditional on bidder unique information, industry and deal characteristics, by 2018 competitor CARs declined by 0.84 percentage points. This decline in average competitor CARs is consistent with the bottom right plot of Figure 1. Summarizing, starting from 1990 the average industry wealth effect for competitors has declined reaching an overall decline of 0.84 percentage points by the end of 2018.

Overall, both approaches confirm the existence of a time-trend in competitor CARs. That is, the first hypothesis in Section 2.2 is therefore confirmed. A negative time-trend in competitor CARs is present and significant. This result is robust to two different estimation approaches and two different subsamples. However, looking at the plot at the bottom-right of Figure 1, one may wonder whether the statistical significant negative trend found in Table 2.5 is affected by the considerable decline in industry wealth effect during the 1990s. The next section illustrates the results of re-estimating the regression models in this section with respect to the 1990s.

2.4.3 A linear trend specification relative to the 1990s

In this part of the analysis, I change how the linear time-trend variable is defined and how it is constructed. That is, I use the time period 1990-1999 as the baseline period. That is, the linear time-trend variable takes a value of zero during this nine years. Starting in 2000, the linear time-trend variable increases by one unit every year. Compared to Table 2.5, the interpretation of the coefficient of the linear time-trend variable is slightly different. Here, the coefficient can be interpreted as the average decline in competitor CARs *relative* to 1990s. Table 2.6 contains the results of this new set of multivariate regressions. As in Table 2.5, Table 2.6 is divided into three panels: full sample (Panel A), wealth-creating mergers (Panel B), wealth-destructing mergers (Panel C).

Starting from Column (1) in Panel A, it can be seen how the coefficient of the linear time-trend variable remains statistically significant similar to those in Table 2.5. Moving to Column (2) and Column (3), the results do not dramatically differ to the one previously presented. When industry fixed effects are replaced with bidder fixed effects, the linear trend coefficient becomes statistically insignificant while the economic magnitude remains unaltered.

For wealth-creating transactions we can see a similar pattern as documented in Table 2.5. Overall, the statistical and economic magnitude remains virtually unchanged with respect to Table 2.5.

Nevertheless, the inclusion of bidder fixed effects appear to decrease the statistical significance of the linear trend variable as in Panel A. To some extent, it appears that for wealth-creating takeovers, a negative linear trend is marginally present.

Relative to 1990s, for wealth-destructive activities (Panel C) the average competitor CARs declined by one basis point (Column (1)). When deal and industry characteristics are included, the coefficient of the linear trend variable become statistically insignificant. Adding 3-digit SIC code industry fixed effects does not result in any improvement[14]. On the other hand, by substituting industry fixed effects with bidder fixed effects, the coefficient of the linear trend variable is statistically significant[15]. The average decline in competitors CARs is around 4 basis points per year, resulting in a total decline of 0.72 percentage points by the end of 2018. Overall, for wealth-destructing mergers the negative time-trend earlier identified is persistent.

Thus far, the results appear to show a decline in the average competitor CARs since 1990. In other words, the negative time-trend does not appear to be mainly driven by the dramatic decline in competitors CARs during the 1990s. This negative time-trend is persistent regardless whether the transaction is wealth-creating or wealth-destructing for the acquiring firm. Relative to the 1990s, the average unconditional decrease in competitor CARs is around 2 basis point for the full and wealth-creating samples. On the other hand, starting in 2000 for wealth-destructive transactions the highest competitors CARs decline is around 4 basis points per year. The next section illustrates and presents the results of a series of robustness tests. In addition, it provides the answer to the second hypothesis earlier described in Section 2.2.

[14] As noted earlier, using industry characteristics and variables at the 3-digit SIC code level may not be advisable, as portfolio of competitors are formed using a different industry classification.

[15] Moreover, in unreported results, when the linear trend variable and bidder fixed effects are the only regressors, the statistical significance of the linear trend coefficient increases to a p-value of less than 0.01.

2.5 Robustness tests

Is this negative linear time-trend driven by sample selection or any other confounding factors? To answer this important question I check whether the evidence presented earlier is robust to different tests. First, I test whether the time-trend present in the data is driven a mechanical relationship between one-time bidders and bidder fixed effects. Second, I test whether excluding the banking and trading industry cluster has an effect on the results. Finally, I split the full transactions sample according to various deal characteristics for two different reasons. First, I investigate whether deal characteristics results in a higher/lower time-trend. Second, it provides a natural approach to test the second research question of this paper (see Section 2.2).

2.5.1 Excluding one-time acquirers

Including one-time acquirers could affect the ability to control for bidder heterogeneity in the transactions sample. As bidder fixed effects are dummy variables that capture any variation within the same group, including one-time acquirers may result in the regression model power being overestimated.

One-time acquirer transactions represent a minimal fraction of the total sample: around 12%. That is, the majority of the transactions included in the sample are conducted by repetitive acquirers. As a result, we should not observe any noticeable changes compared to Table 2.5. However, to alleviate any concerns regarding a spurious regression specification and provide an additional robustness test, I exclude all the transactions by one-time acquirers from the sample while maintaining the same four regression models as in Table 2.5.

The economic magnitude and statistical significance of the time-trend variable coefficient remain stable as we can see from Table 2.7. For the full sample of transactions (Panel A) the average decline in CARs ranges from one basis point to three basis points per year. For wealth-creating activities (Panel B), the average decline is around one basis point. Conditional ob bidder fixed effects, for wealth-destructing mergers (Panel C), the average decline is around 3 basis points per year. As more wealth-destructive transactions are announced, competitors CARs decline to 0.85 percentage points by the end of 2018.

The results presented in Section 2.4 do not dramatically change when one-time acquirers are excluded from the sample of transactions. Overall, the decline in average competitor CARs seem not to be impacted - or explained - by one-time acquirers.

2.5.2 Banking and Trading industry clustering

As discussed in Section 2.3, the transactions sample used in this paper exhibits a pattern of industry clustering similar to the one documented in Andrade, Mitchell, and Stafford (2001) and Shahrur (2005). Specifically, I identify three clusters across different industries: Business services, Banking, and Trading industries (see Table 2.1). Relatively to 21,817 transactions (100%), the transactions announced by bidders in the banking and trading industries amount to 5,510 (25%). As a result, the reader may object and argue that mergers in the banking and trading industries may not be informative as those in other industries. That is, mergers conducted by financial firms (e.g. Private Equity Funds or Venture Capitalists) may not be driven by operational - or strategic - synergies. In other words, the strategic objectives between the acquirer and the target firm may substantial differ.

To alleviate any of the concerns discussed regarding mergers conducted by financial firms, I exclude all the transactions that belong to the banking and trading industries. Table 2.8 contains the results of the regression models.

Looking at Panel A, we can see how the economic magnitude of the linear time-trend remains stable. When I control for bidder heterogeneity via bidder fixed effects, the negative time-trend is equal to three basis points per year. Moving to Panel B (the sample of wealth-creating mergers), we see that the banking and trading industry clustering does not affect the results. On average, the coefficients in Panel B equals to the ones in Table 2.5. After controlling for bidder heterogeneity, for wealth-destructing mergers (Panel C), the average decline in competitors CARs is around four basis points per year. By the end of 2018, competitors CARs have experience a decline of 1.12 percentage points.

The negative time-trend presented in Section 2.4 remains stable and seem not be influenced by the industry clustering in the banking and trading sectors.

2.5.3 Additional robustness tests

To further explore the documented decline in average competitors CARs, I divide the original sample across three dimensions: the nature of the takeover, the status of the target, and the payment method. Splitting the original sample across these three dimensions also provides a way to test the second hypothesis formulated in Section 2.2. If the negative time-trend found earlier is driven by an average decline in the expected return from a merger, we should observe the negative time-trend to be present across all the three dimensions. On the other hand, if the negative time-trend is driven by changes in the information disclosed at the announcement, we should observe the negative time-trend to be present only in the dimensions where information asymmetry may be relevant (e.g. Non-horizontal mergers and mergers with a private target). The results of the regression models are in Table 2.9.

Panel A and Panel B respectively contain the results of the first two new subsamples: horizontal mergers and non-horizontal mergers[16]. Unreported results show that the number of horizontal mergers has declined over time reaching a reduction of 40 percent during the period 2010-2018. Despite this decline, horizontal mergers still represent one third of the entire sample (7,303).

[16]See footnote 9.

As we can see from Panel A, for the sample of horizontal mergers, the documented decline in average competitors announcement returns is not present. The linear trend variable remains statistically insignificant despite the four different regression specifications. On the other hand, for non-horizontal transactions (Panel B) we can observe a similar average decline in competitors CARs as observed in Table 2.5. Conditional on bidder heterogeneity (Column (4)), the average competitors CAR has decreased by three basis points starting in 1990.

As the public target status coefficient dummy is significant across all the results (from Table 2.4 through Table 2.8), perhaps it is worth splitting the original sample according to this variable. Panel C and Panel D respectively contain the results of running the same four regression models for the sample of public target firms and for the sample of private target firms. Looking at the sample of publicly traded target firms, no significant trend can be observed across the four columns of Panel C. On the other hand, competitors CARs show a negative time-trend when bidders acquire a private target. Conditional on bidder heterogeneity, the average decline in competitors CARs is around two basis points per year. By the end of the sample period, the average competitor announcement return has declined by 0.56 percentage points. That is, the overall decline in CARs is higher than the unconditional average competitors CAR.

Finally, splitting the original sample by method of payment does not result in any additional useful insight (Panel E and Panel F). On average, competitor CARs decrease by one basis point starting in 1990. However, the results are not robust to the various regression specifications. One possible explanation for such puzzling result may be data quality from the data provider. Around 40% of the observations in the final sample are classified as "Other" or "Unknown" with respect to the method of payment. As a result, omitting almost 40% of the final sample may lead to a sample selection error. In other words, it may lead to non-significant results as found in Panel E and Panel F.

Overall, the decline in competitor CARs documented in Section 2.4 is robust across several dimensions. Unreported robustness tests shows that the results are robust to event study techniques, different event-window specifications, transaction value thresholds, and industry classification. While the unconditional average competitors CAR remains positive and significant, starting in 1990 competitors have experienced a decline in their announcement returns. This negative linear trend seem to be correlated with mergers involving private target firms or non-horizontal mergers. By 2018, the average competitor CAR - conditional on bidder fixed effects - has declined by 1.12 percentage points.

The next section will summarize the main findings of this paper and discuss the implications of the results from this section.

2.6 Key takeaways from a decline in competitor CARs

Over three decades, the average announcement return to competitors has declined. This negative trend appears to be stronger when bidders announce a non-horizontal merger or when they acquire private targets. For example, competitors - on average - earn 0.53 percentage points compared to only 0.12 percentage points in case of the acquisition of a private target (two sample t-test: -4.836). On the other hand, bidders tend to earn a positive CAR when they acquire a private target but earn a negative CAR when the acquisition involves a publicly traded target.

The documented decline in competitors CARs may consistent with two hypotheses: an increased availability of resources to firms in the industry where the bidder operates or the decrease in information conveyed through the merger announcement.

In the first case, as the resource required to generate bidder-specific synergies are available throughout the industry, more competitors may engage in merger transactions. As a result, the bidder bargaining power may decrease as the bulk of the synergy gains lie within the target firm. Thus, the target firm may increase its bargaining power and consequently earn a higher share of the synergies gains generated. On the other hand, as competitors have less incentives to acquire targets - given their lower bargaining power - this would result in a downward trend in announcement returns. This hypothesis seem to be consistent with the results presented in Panel A of Table 2.5.

In the second case, the evidence presented in this paper may consistent with a decrease in the information revealed at the merger announcement. As discussed by Hietala, Kaplan, and Robinson (2002), when a bidder announces a new merger, the announcement itself conveys different information (e.g. the stand-alone value of the bidder firm). Nevertheless, the information revealed should be stronger in case of private target firms, as the deal information asymmetry is high.

This hypothesis seems to be consistent with the results presented in Panel C and Panel D of Table 2.9. When a bidder acquire a public target, the degree of information asymmetry is low as both the bidder and the target are subject to a higher degree of disclosure. As the market and competitors can observe all the available information we should not observe any decline in information. On the other hand, the announcement of the acquisition of a private target conveys new information relative to the state of the industry. As information asymmetry is high, the market will re-evaluate the state of the competitors to the bidder. As more acquisitions are announced and the industry consolidates, the additional information conveyed is lower. As a result, we should observe a negative time-trend in competitors announcement as in Panel D of Table 2.9.

Unfortunately, at this moment the source of this negative trend is unknown. This decline in competitor CARs can be the result of either an increased competition among potential bidders (the current competitors of the bidder) or a decline in the information regarding the state of the industry where the bidder and its competitors operate. Looking at Table 2.9, the time-trend appears to be correlated with transactions where information asymmetry is high. However, future studies should develop a test to clearly distinguish these two hypothesis, for example using a measure to proxy the uniqueness of the resources available in the bidder industry.

2.7 Conclusions

This paper provides novel evidence regarding the industry wealth effect through time. Starting in 1990, the average decline in the top five competitors CARs is around 2 basis points per year. Yet, conditional on bidders and industry heterogeneity, via bidder fixed effects, competitors CARs declined approximately 0.85 percentage points by the end of 2018. That is, the average CAR to the top five competitors to the bidder is negative by the end of the sample period. The negative time-trend is robust to two different estimation techniques: a year dummies specification and a linear time-trend specification.

I investigate whether the time-trend differs conditional on a wealth-creating merger announcement (positive bidder CARs) or a wealth-destructing merger announcement (negative bidder CARs). Conditional on bidder and industry information, the time-trend appears to be more persistent in the case of a wealth-destructing mergers. On the other hand, when bidder information is controlled (via bidder fixed effects), competitors CARs do not show a negative time-trend.

I show that this negative time-trend is not driven by the relatively large number of transactions occurred during the 1990s. Yet, I show that this negative time-trend is not affected by "one-time" bidders (those firms that only acquire one target during the sample period) nor because of a clustering in two industries. Overall, the results remain stable especially when a wealth-destructive merger is announced.

This paper provides additional evidence on competitors CARs. Unlike bidders, on average the top five competitors react positively when the bidder acquire a publicly traded target firm. Additionally, there is no a significant difference in competitors CARs when an horizontal merger is announced. As in the existing literature, the sign of competitors CARs is influenced by the bidder's market reaction. I also document that this negative time-trend is more pronounced when the bidder announces a non-horizontal merger or the acquisition of a private target firm.

The negative time-trend in competitor CARs may be consistent with two hypotheses. First, as more firms engage in mergers, the decline in CARs can be explained by a decrease in the expected gains from engaging in a merger. That is, competition among actual and potential bidders may increase and result in a declining cumulative abnormal return. Second, as more firms engage in mergers the level of information conveyed at the merger announcement may decrease. As a result, we should observe a negative trend in competitor CARs.

If we only consider the results from the full sample of transactions (Table 2.5), the negative time-trend seem to be explained by a decline in the conditional expected return to shareholders. On the other hand, if we consider the results in Table 2.9, the negative time-trend seem to be correlated with mergers where information asymmetry is high.

This paper explores in detail the industry wealth effect through time and provides results to two important research questions. First, I show that a time-trend in competitors CARs exists and is negative. Second, the source of this decline in competitors CARs remains a puzzle but is correlated with mergers in an environment where information asymmetry matters. Future research should address and explain in detail this industry wealth effect puzzle.

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Figure 1: Year Dummies - Evolution of competitors announcement returns

The four panels plot the coefficients γ for the vector T of year dummies corresponding to the competitor CAR regressions reported in Table 2.4, as follow:

Model 1: $CAR_i = \alpha + \gamma T^{'} + \epsilon_i$

Model 2: $CAR_i = \alpha + \gamma T^{'} + \delta Y^{'} + \epsilon_i$

Model 3: $CAR_i = \alpha + \gamma T^{'} + \delta Y^{'} + IndustryFE + \epsilon_i$

Model 4: $CAR_i = \alpha + \gamma T^{'} + \delta Y^{'} + BidderFE + \epsilon_i$

where Y is a vector containing the deal and industry characteristics, $IndustryFE$ is the set of the 3-digit SIC code industry fixed effects, and $BidderFE$ is the set of the bidder fixed effects. The competitors are sorted into equally-weighted portfolios and the CAR is defined as the 7-day window CAR (-3,3).

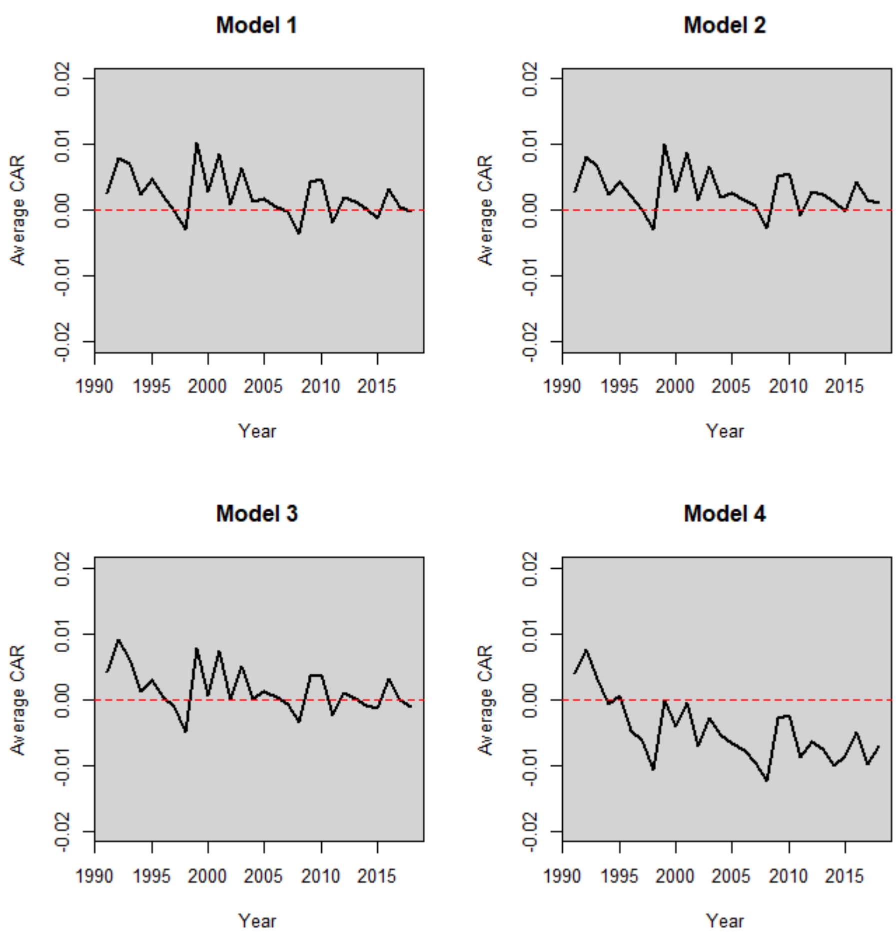

Table 2.1: Distribution of sample by years and Fama-French industry classification

The table presents the distribution of the sample by year and industry classification (Fama French 48 industries). The sample consists of 21,817 merger deals occurred during the period 1990-2018. The merger sample is obtained from SDC Platinum merger database. The merger deals need to be over $1 million, conducted by bidders who are US public firms and are classified as "domestic". Announcements on the same date by the same bidders are excluded. The samples are further divided across three periods (1990-1999, 2000-2009, 2010-2018) to investigate the merger patterns through the sample period.

Industry description	Industry Nr.	1990-1999	2000-2009	2010-2018	Total Nr. deals	% of total
Agriculture	1	19	6	12	37	0
Food Products	2	95	61	66	222	1
Candy & Soda	3	4	2	5	11	0
Beer & Liquor	4	5	8	6	19	0
Tobacco Products	5	0	0	1	1	0
Recreation	6	46	23	8	77	0
Entertainment	7	167	79	55	301	1
Printing and Publishing	8	49	54	39	142	1
Consumer Goods	9	79	32	23	134	1
Apparel	10	40	65	22	127	1
Healthcare	11	336	210	134	680	3
Medical Equipment	12	209	238	152	599	3
Pharmaceutical Products	13	192	246	175	613	3
Chemicals	14	85	66	48	199	1
Rubber and Plastic Products	15	53	29	7	89	0
Textiles	16	45	16	1	62	0
Construction Materials	17	117	93	88	298	1
Construction	18	88	60	69	217	1
Steel Works Etc	19	97	62	38	197	1
Fabricated Products	20	43	3	9	55	0
Machinery	21	247	171	110	528	2
Electrical Equipment	22	65	75	53	193	1
Automobiles and Trucks	23	95	45	35	175	1
Aircraft	24	46	85	53	184	1
Shipbuilding, Railroad Equipment	25	18	8	13	39	0
Defense	26	9	2	4	15	0
Precious Metals	27	12	3	7	22	0
Non-Metallic and Industrial Metal Mining	28	10	9	19	38	0
Coal	29	3	12	14	29	0
Petroleum and Natural Gas	30	364	361	185	910	4
Utilities	31	98	106	95	299	1
Communication	32	534	290	139	963	4
Personal Services	33	100	68	28	196	1
Business Services	34	1,195	1,375	615	3,185	15
Computers	35	408	447	136	991	5
Electronic Equipment	36	333	560	192	1,085	5
Measuring and Control Equipment	37	162	196	106	464	2
Business Supplies	38	67	41	28	136	1
Shipping Containers	39	18	6	11	35	0
Transportation	40	136	104	114	354	2
Wholesale	41	394	204	165	763	3
Retail	42	297	181	97	575	3
Restaurants, Hotels, Motels	43	116	51	37	204	1
Banking	44	1,387	824	589	2,800	13
Insurance	45	259	166	92	517	2
Real Estate	46	54	19	55	128	1
Trading	47	932	651	1,127	2,710	12
Other	48	129	37	28	194	1
	Total	9,274	7,452	5,104	21,817	
	% of total	42.50	34.10	23.40	100	

Table 2.2: Summary statistics - Competitors portfolio announcement returns

The table presents the summary statistics of competitors portfolio announcement returns by year for a sample of U.S. merger deals recovered by SDC Platinum over the period 1990 2018. The merger deals need to be over $1 million, conducted by bidders who are US public firms and are classified as "domestic". Announcements on the same date by the same bidders are excluded. The competitor portfolios are defined as the top five competitors to the acquiring firm in a given year. The top five competitors are defined as the five firms with the highest similarity score following the Text-based Network Industry Classification data by G. Hoberg and G. Phillips. The portfolios are equally-weighted portfolios and Cumulative Abnormal Returns (CARs) are the 7-day event window CARs (-3,3). Symbols $*$, $**$, $***$ denote statistical significance respectively at the 10%, 5%, and 1% level.

Year	Mean CAR	Median CAR	SD CAR	Nr. of deals	Cumulative sum Nr. of deals
1990	0.05	-0.20	0.04	289	289
1991	0.18	-0.03	0.04	355	644
1992	0.58	0.12	0.04	495	1,139
1993	0.92	0.56	0.04	671	1,810
1994	0.32	0.09	0.03	906	2,716
1995	0.47	0.12	0.04	900	3,616
1996	0.34	0.14	0.04	1,170	4,786
1997	0.10	0.21	0.04	1,573	6,359
1998	-0.19	-0.68	0.04	1,654	8,013
1999	1.30	0.19	0.05	1,248	9,261
2000	0.34	0.30	0.06	1,033	10,294
2001	1.16	0.93	0.05	732	11,026
2002	0.20	0.44	0.05	728	11,754
2003	0.65	0.29	0.04	732	12,486
2004	0.29	0.38	0.04	803	13,289
2005	0.04	0.00	0.03	890	14,179
2006	0.17	0.01	0.03	889	15,068
2007	-0.03	-0.18	0.03	761	15,829
2008	-0.46	-0.23	0.04	519	16,348
2009	0.78	0.50	0.04	365	16,713
2010	0.54	0.32	0.03	506	17,219
2011	-0.12	-0.17	0.03	590	17,809
2012	0.22	0.01	0.03	608	18,417
2013	0.21	0.17	0.03	597	19,014
2014	0.12	0.04	0.03	714	19,728
2015	-0.03	0.02	0.03	620	20,348
2016	0.68	0.52	0.04	499	20,847
2017	0.05	0.06	0.03	511	21,358
2018	-0.04	0.19	0.03	459	21,817
1990-1999	0.39***	0.23	0.05	9,274	
2000-2009	0.30***	0.22	0.05	7,452	
2010-2018	0.17***	0.11	0.03	5,104	
Entire Sample	0.27***	0.19	0.04	21,817	

Table 2.3: Announcement period cumulative returns to competitors of the acquirer

This table reports Cumulative Abnormal Returns (CAR) at announcement date of the competitors of the acquirer. The sample consists of 21,817 merger deals occurred during the period 1990-2018. The merger sample is obtained from SDC Platinum merger database. The merger deals need to be over $1 million, conducted by bidders who are US public firms and are classified as "domestic". Announcements on the same date by the same bidders are excluded. CARs to rivals are estimated using equally weighted portfolios of the top five competitor to the acquirer. The table spans across three dimensions: (1) all transactions, (2) Horizontal and Non-horizontal transactions, (3) Public or private targets. Horizontal transactions are defined as in Shahrur (2005). A merger is considered horizontal if the acquirer and the target have the same primary 4-digit SIC code. Panel A reports CARs for the overall sample of merger transactions. Panel B (Panel C) reports CARs for the subsample of mergers with positive (negative) *acquirer CAR*. Acquirer CARs are estimated using standard event study methodology. For each columns, the percentage of positive CARs overall to the sample is reported. The t-statistics are reported below in parentheses. Symbols $*$, $**$, $***$ denote statistical significance.

Panel A: CAR (%) to the overall sample of transactions

	Total transactions		Horizontal transactions		Non-Horizontal transactions		Public targets		Private Targets	
Number of Portfolios	21,817		7,303		14,514		3,012		18,805	
Window	Mean (t-stat)	% Positive	Mean (t-stat)	% Positive	Mean (t-stat)	% Positive	Mean (t-stat)	% Positive	Mean (t-stat)	% Positive
(-1,+1)	0.10***	51.13	0.11***	51.18	0.10***	51.11	0.28***	53.44	0.07***	50.76
	(5.26)		(3.26)		(4.12)		(5.41)		(3.41)	
(-2,+2)	0.14***	51.14	0.17***	51.40	0.12***	51.01	0.40***	54.10	0.10***	50.67
	(5.54)		(3.91)		(3.98)		(6.14)		(3.48)	
(-3,+3)	0.27***	52.07	0.35***	52.87	0.21***	51.66	0.53***	54.78	0.12***	51.63
	(6.82)		(4.97)		(4.76)		(7.09)		(3.65)	
(0,+2)	0.08***	50.61	0.10***	50.32	0.07***	50.76	0.28***	53.34	0.04***	50.18
	(4.13)		(3.00)		(2.90)		(5.76)		(2.11)	

Panel B: CAR (%) to the subsample of transactions with *positive* bidder cumulative abnormal returns

	Total transactions	Horizontal transactions	Non-Horizontal transactions	Public targets	Private Targets
Number of Portfolios	11,142	3,797	7,345	1,286	9,856

Table 2.3 (continued)

Window	Mean (t-stat)	% Positive	Mean (t-stat)	% Positive	Mean (t-stat)	% Positive	Mean (t-stat)	% Positive	Mean (t-stat)	% Positive
(-1,+1)	0.36***	55.32	0.40***	55.11	0.34***	55.43	0.55***	56.92	0.33***	55.11
	(14.05)		(8.88)		(10.90)		(7.31)		(12.29)	
(-2,+2)	0.60***	57.01	0.65***	57.01	0.58***	57.01	0.90***	60.57	0.57***	56.55
	(18.49)		(11.12)		(14.77)		(9.39)		(16.29)	
(-3,+3)	0.75***	58.49	0.85***	59.34	0.69***	58.05	1.19***	60.92	0.69***	58.17
	(19.71)		(12.58)		(15.19)		(10.94)		(17.06)	
(0,+2)	0.36***	55.20	0.39***	54.40	0.34***	55.61	0.55***	57.54	0.33***	54.89
	(14.19)		(8.81)		(11.13)		(7.40)		(12.41)	

Panel C: CAR (%) to the subsample of transactions with *negative* bidder cumulative abnormal returns

	Total transactions		Horizontal transactions		Non-Horizontal transactions		Public targets		Private Targets	
Number of Portfolios	9,939		3,209		6,730		1,690		8,249	
Window	Mean (t-stat)	% Positive	Mean (t-stat)	% Positive	Mean (t-stat)	% Positive	Mean (t-stat)	% Positive	Mean (t-stat)	% Positive
(-1,+1)	−0.17***	46.57	−0.18***	46.85	−0.18***	46.43	0.01	50.74	−0.23***	45.71
	(−6.46)		(−3.49)		(−5.46)		(1.28)		(−7.70)	
(-2,+2)	−0.35 ***	45.06	−0.32 ***	44.83	−0.37 ***	44.60	0.04	49.02	−0.43 ***	43.79
	(−10.10)		(−4.96)		(−8.90)		(0.43)		(−11.24)	
(-3,+3)	−0.45***	45.39	−0.43***	45.57	−0.46***	44.71	0.01	49.85	−0.54***	43.99
	(−11.13)		(−5.70)		(−9.62)		(0.96)		(−12.19)	
(0,+2)	−0.21***	45.71	−0.18***	46.01	−0.24***	45.56	0.09	50.02	−0.28***	44.82
	(−7.99)		(−3.55)		(−7.32)		(1.52)		(−9.41)	

Table 2.4: Top 5 competitors announcement returns - Estimation of the time trend in competitors CARs using year dummies

This table reports the results of the regression analysis of the top five competitor announcement returns (CARs) and related variables for a sample of merger transactions. The merger sample is obtained from SDC Platinum merger database. The merger deals need to be over $1 million, conducted by bidders who are US public firms and are classified as "domestic". Announcements on the same date by the same bidders are excluded. The dependent variable in all four columns is the 7-day event window (-3,3) competitor % CARs. CARs to competitors are estimated using equally weighted portfolios of the top five competitor to the acquirer. The main variables in all columns are year dummies for each year during the period 1990-2018. The coefficients are plotted in Figure 1. Column (1) includes no control variables. Column (2) adds deal and industry characteristics as controls. Column (3) includes deal and industry characteristics and industry fixed effects (defined at the 3-digit SIC code level). Column (4) includes deal and industry characteristics and bidder fixed effects. The *t*-statistics are reported below in parentheses. Symbols $*$, $**$, $***$ denote statistical significance.

	Dependent variable:			
	Competitors CARs: [-3,+3]			
	(1)	(2)	(3)	(4)
	No Controls	Controls	Controls & Ind. FE	Controls & Acq. FE
Nr. Firms		0.00	0.02**	0.02
		[0.18]	[2.47]	[1.51]
Size		−0.01	0.01	0.01*
		[−0.81]	[0.41]	[1.81]
HHI		0.01	0.08	0.05
		[0.04]	[1.50]	[0.67]
Mkt. Share		−0.01	−0.04	−0.03
		[0.64]	[0.83]	[0.40]
Change Nr. Firms		0.00	0.01	0.01*
		[0.27]	[1.17]	[1.82]
Change of Ind. Size		0.01	0.02	0.06**
		[1.49]	[1.26]	[2.52]
Change of Mkt. Share		−0.01	−0.01	0.01
		[−0.38]	[−0.63]	[0.50]
Change HHI-Index		0.01	0.01	0.01
		[0.16]	[0.21]	[0.11]
Cash Transaction		−0.01	−0.01	−0.01
		[−0.50]	[−0.64]	[−0.07]
Stock Transaction		0.01	0.02*	0.01
		[1.41]	[1.73]	[1.16]
Public Target		0.04***	0.05***	0.06***
		[3.74]	[3.95]	[4.51]
Tender		0.04	0.03	0.01
		[1.47]	[1.19]	[0.33]
Hostile		0.08	0.09	0.06
		[0.99]	[1.18]	[0.64]
Horizontal		0.01	0.01	0.01
		[0.63]	[0.96]	[0.42]
Constant	0.05	0.01	−0.03	−0.04
	[0.17]	[0.30]	[−0.26]	[−1.29]
Observations	21,817	21,817	21,817	21,817
Year FE	Yes	Yes	Yes	Yes
Ref.	Figure 1	Figure 1	Figure 1	Figure 1
F Statistic	3.94***	3.65***	1.48***	1.42***

TABLE 2.5: TOP 5 COMPETITORS ANNOUNCEMENT RETURNS - ESTIMATION USING A LINEAR TREND APPROACH

This table reports the results of regression analysis of competitors announcement returns (CARs) for a sample of U.S. mergers. The sample consists of 21,817 merger deals occurred during the period 1990-2018. The merger sample is obtained from SDC Platinum merger database. The merger deals need to be over $1 million, conducted by bidders who are US public firms and are classified as "domestic". Announcements on the same date by the same bidders are excluded. The dependent variable in all four columns is the 7-day event window (-3,3) competitor % CARs. CARs to competitors are estimated using equally weighted portfolios of the top five competitor to the acquirer. The main variable in all columns is a linear time-trend variable during the period 1990-2018. The *Linear Trend* variable takes value of one in 1990 and increments of one unit every year after 1990. Column (1) includes no control variables. Column (2) adds deal and industry characteristics as controls. Column (3) includes deal and industry characteristics and industry fixed effects (defined at the 3-digit SIC code level). Column (4) includes deal and industry characteristics and bidder fixed effects. Panel A reports the results of regression analysis for the overall transactions sample. Panel B (Panel C). reports the results of regression analysis for the subsample of mergers with positive (negative) *acquirer announcement returns*. The acquirer announcement returns is defined as the CAR over the announcement window estimated using standard event study methodology. For Panel B and Panel C the overall number of transactions is lower due to missing stock price data for competitors. The t-statistics are reported below in parentheses. Symbols $*$, $**$, $***$ denote statistical significance.

	Dependent variable:			
	Competitors CARs: [-3,+3]			
	(1)	(2)	(3)	(4)
	No Controls	Controls	Controls & Ind. FE	Controls & Acq. FE
Panel A: Full sample				
Linear Trend	-0.02^{***}	-0.01^{*}	-0.01^{*}	-0.03^{**}
	[−3.04]	[−1.68]	[−1.81]	[−2.16]
Controls	No	Industry & Deal	Industry & Deal	Industry & Deal
Significant Controls		Public Target	Public Target	Public Target
Observations	21,817	21,817	21,817	21,817
F Statistic	9.21^{***}	3.78^{***}	1.35^{***}	1.41^{***}

Note: *p<0.1; **p<0.05; ***p<0.01

Table 2.5 (continued)

Panel B: Subsample of transactions with *positive* bidder cumulative abnormal returns				
Linear Trend	−0.02***	−0.01**	−0.01**	0.01
	[−2.43]	[−1.73]	[−1.67]	[0.29]
Controls	No	Industry & Deal	Industry & Deal	Industry & Deal
Significant Controls		Public Target	Public Target	Tender, Public Target, Nr. Firms
Observations	11,142	11,142	11,142	11,142
F Statistic	32.32***	5.31***	2.19***	1.35***
Panel C: Subsample of transactions with *negative* bidder cumulative abnormal returns				
Linear Trend	−0.02***	−0.01	−0.01*	−0.03*
	[−2.23]	[−1.42]	[−1.65]	[−1.77]
Controls	No	Industry & Deal	Industry & Deal	Industry & Deal
Significant Controls		Public Target	Public Target	Tender, Public Target, Δ Nr. Firms, Δ Ind. Size, Δ Mkt. Share
Observations	9,939	9,939	9,939	9,939
F Statistic	17.06***	4.32***	3.09***	1.78***

Note: *p<0.1; **p<0.05; ***p<0.01

Table 2.6: Top 5 competitors announcement returns - Estimation using linear trend relative to 1990s

This table reports the results of regression analysis of competitors announcement returns (CARs) for a sample of U.S. mergers. The sample consists of 21,817 merger deals occurred during the period 1990-2018. The merger sample is obtained from SDC Platinum merger database. The merger deals need to be over $1 million, conducted by bidders who are US public firms and are classified as "domestic". Announcements on the same date by the same bidders are excluded. The dependent variable in all four columns is the 7-day event window (-3,3) competitor % CARs. CARs to competitors are estimated using equally weighted portfolios of the top five competitor to the acquirer. The main variable in all columns is a linear time-trend variable during the period 1990-2018. The *Linear Trend* variable takes value of one in 2000 and increments of one unit every year after 2000. That is, the *Linear Trend* variable takes value of zero in the period 1990-1999. As a result, the coefficient of *Linear Trend* should be interpreted as the average time-trend relative to the 1990s. Column (1) includes no control variables. Column (2) adds deal and industry characteristics as controls. Column (3) includes deal and industry characteristics and industry fixed effects (defined at the 3-digit SIC code level). Column (4) includes deal and industry characteristics and bidder fixed effects. Panel A reports the results of regression analysis for the overall transactions sample. Panel B (Panel C). reports the results of regression analysis for the subsample of mergers with positive (negative) *acquirer announcement returns*. The acquirer announcement returns is defined as the CAR over the announcement window estimated using standard event study methodology. For Panel B and Panel C the overall number of transactions is lower due to missing stock price data for competitors. The t-statistics are reported below in parentheses. Symbols $*$, $**$, $***$ denote statistical significance.

	Dependent variable:			
	Competitors CARs: [-3,+3]			
	(1)	(2)	(3)	(4)
	No Controls	Controls	Controls & Ind. FE	Controls & Acq. FE
Panel A: Full sample				
Linear Trend	-0.02^{***}	-0.01^{*}	-0.01^{*}	-0.02
	[−3.066]	[−1.76]	[−1.76]	[−1.148]
Controls	No	Industry & Deal	Industry & Deal	Industry & Deal
Significant Controls		Public Target, Δ HHI	Public Target, Horizontal Transaction, Δ HHI	Public target, Ind. Size
Observations	21,817	21,817	21,817	21,817
F Statistic	9.41^{***}	4.98^{***}	2.09^{***}	1.28^{***}
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 2.6 (continued)

Panel B: Subsample of transactions with *positive* bidder cumulative abnormal returns				
Linear Trend	-0.02^{***}	-0.02^{*}	-0.02^{*}	-0.01
	[−2.94]	[−1.93]	[−1.91]	[−0.06]
Controls	No	Industry & Deal	Industry & Deal	Industry & Deal
Significant Controls		Public Target	Public Target, Δ Nr. Firms, Horizontal Transaction	Tender, Public Target, Ind. Size
Observations	11,142	11,142	11,142	11,142
F Statistic	8.657^{***}	3.491^{***}	1.385^{***}	1.499^{***}
Panel C: Subsample of transactions with *negative* bidder cumulative abnormal returns				
Linear Trend	-0.01^{*}	-0.01	-0.01	-0.04^{*}
	[−1.65]	[−0.74]	[−1.11]	[−1.65]
Controls	No	Industry & Deal	Industry & Deal	Industry & Deal
Significant Controls		Public Target	Public Target, Horizontal Transaction	Public Target, Constant Δ Ind. Size, Δ Mkt. Share
Observations	9,939	9,939	9,939	9,939
F Statistic	8.15^{***}	3.44^{***}	3.05^{***}	1.41^{***}

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

TABLE 2.7: TOP 5 COMPETITORS ANNOUNCEMENT RETURNS - ESTIMATION USING LINEAR TREND TWO OR MORE ACQUISITIONS PER BIDDER

This table reports the results of regression analysis of competitors announcement returns (CARs) for a sample of U.S. mergers. The sample consists of 19,358 merger deals occurred during the period 1990-2018. The merger sample is obtained from SDC Platinum merger database. The merger deals need to be over $1 million, conducted by bidders who are US public firms and are classified as "domestic". Announcements on the same date by the same bidders are excluded. The bidder must have acquired at least two or more target firms over the period 1990-2018. The dependent variable in all four columns is the 7-day event window (-3,3) competitor % CARs. CARs to competitors are estimated using equally weighted portfolios of the top five competitor to the acquirer. The main variable in all columns is a linear time-trend variable during the period 1990-2018. The *Linear Trend* variable takes value of one in 1990 and increments of one unit every year after 1990. Column (1) includes no control variables. Column (2) adds deal and industry characteristics as controls. Column (3) includes deal and industry characteristics and industry fixed effects (defined at the 3-digit SIC code level). Column (4) includes deal and industry characteristics and bidder fixed effects. Panel A reports the results of regression analysis for the overall transactions sample. Panel B (Panel C). reports the results of regression analysis for the subsample of mergers with positive (negative) *acquirer announcement returns*. The acquirer announcement returns is defined as the CAR over the announcement window estimated using standard event study methodology. For Panel B and Panel C the overall number of transactions is lower due to missing stock price data for competitors. The t-statistics are reported below in parentheses. Symbols $*$, $**$, $***$ denote statistical significance.

	Dependent variable:			
	Competitors CARs: [-3,+3]			
	(1)	(2)	(3)	(4)
	No Controls	Controls	Controls & Ind. FE	Controls & Acq. FE
Panel A: Full sample				
Linear Trend Trend	−0.01***	−0.01	−0.01*	−0.03**
	[−2.86]	[−0.70]	[−1.75]	[−2.17]
Controls	No	Industry & Deal	Industry & Deal	Industry & Deal
Significant Controls	Constant	Public Target	Nr. Firms, Δ Nr. Firms, Public Target	Δ Nr. Firms, Public Target
Observations	19,358	19,358	19,358	19,358
F Statistic	8.15***	2.60***	1.62***	1.37***
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 2.7 (continued)

Panel B: Subsample of transactions with *positive* bidder cumulative abnormal returns				
Linear Trend	-0.01^{**}	-0.01	-0.01	-0.01
	[−2.44]	[−1.31]	[−1.35]	[−0.47]
Controls	No	Industry & Deal	Industry & Deal	Industry & Deal
Significant Controls	Constant	Stock Trans., Public Target, Constant	Δ Nr. Firms, Stock Trans., Public Target	Stock Transaction, Public Target, Tender
Observations	9,919	9,919	9,919	9,919
F Statistic	5.96^{**}	3.09^{***}	1.33^{***}	1.40^{***}
Panel C: Subsample of transactions with *negative* bidder cumulative abnormal returns				
Linear Trend	-0.02^{**}	-0.01	-0.01^{*}	-0.03^{*}
	[−2.14]	[−1.15]	[−1.75]	[−1.77]
Controls	No	Industry & Deal	Industry & Deal	Industry & Deal
Significant Controls		Public Target, Horizontal	Public Target	Public Target
Observations	8,877	8,877	8,877	8,877
F Statistic	4.59^{**}	3.22^{***}	2.07^{***}	1.98^{***}

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 2.8: Top 5 competitors announcement returns - Estimation using linear trend excluding Baking and Trading industries

This table reports the results of regression analysis of competitors announcement returns (CARs) for a sample of U.S. mergers. The sample consists of 16,307 merger deals occurred during the period 1990-2018. The merger sample is obtained from SDC Platinum merger database. The merger deals need to be over $1 million, conducted by bidders who are US public firms and are classified as ”domestic”. Announcements on the same date by the same bidders are excluded. The bidder must be a firm that is not in either the banking or trading industry. This restriction excludes 5,510 deals from the full sample used in Table 2.4 and Table 2.5. The dependent variable in all four columns is the 7-day event window (-3,3) competitor % CARs. CARs to competitors are estimated using equally weighted portfolios of the top five competitor to the acquirer. The main variable in all columns is a linear time-trend variable during the period 1990-2018. The *Linear Trend* variable takes value of one in 1990 and increments of one unit every year after 1990. Column (1) includes no control variables. Column (2) adds deal and industry characteristics as controls. Column (3) includes deal and industry characteristics and industry fixed effects (defined at the 3-digit SIC code level). Column (4) includes deal and industry characteristics and bidder fixed effects. Panel A reports the results of regression analysis for the overall transactions sample. Panel B (Panel C). reports the results of regression analysis for the subsample of mergers with positive (negative) *acquirer announcement returns*. The acquirer announcement returns is defined as the CAR over the announcement window estimated using standard event study methodology. For Panel B and Panel C the overall number of transactions is lower due to missing stock price data for competitors. The t-statistics are reported below in parentheses. Symbols $*$, $**$, $***$ denote statistical significance.

	Dependent variable:			
	Competitors CARs: [-3,+3]			
	(1)	(2)	(3)	(4)
	No Controls	Controls	Controls & Ind. FE	Controls & Acq. FE
Panel A: Full sample				
Linear Trend	-0.02^{***}	-0.01^{*}	-0.01^{*}	-0.03^{*}
	[−3.30]	[−1.84]	[−1.62]	[−1.87]
Controls	No	Industry & Deal	Industry & Deal	Industry & Deal
Significant Controls	Constant	Δ Nr. Firms, Public Target	Nr. Firms, Δ Nr. Firms, Public Target	Δ Nr. Firms, Public Target
Observations	16,307	16,307	16,307	16,307
F Statistic	10.90^{***}	4.31^{***}	1.14^{**}	1.27^{***}
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 2.8 (continued)

Panel B: Subsample of transactions with *positive* bidder cumulative abnormal returns				
Linear Trend	-0.02^{***}	-0.02^{**}	-0.01^{*}	-0.01
	[−3.05]	[−1.99]	[−1.77]	[−0.22]
Controls	No	Industry & Deal	Industry & Deal	Industry & Deal
Significant Controls	Constant	Nr. Firms, Δ Nr. Firms, Stock Transaction, Public Target	Nr. Firms, Δ Nr. Firms	
Observations	8,565	8,565	8,565	8,565
F Statistic	9.30^{***}	4.40^{***}	1.48^{**}	1.40^{***}
Panel C: Subsample of transactions with *negative* bidder cumulative abnormal returns				
Trend	-0.02^{*}	-0.01	-0.01	-0.04^{**}
	[−1.71]	[−0.74]	[−1.16]	[−1.98]
Controls	No	Industry & Deal	Industry & Deal	Industry & Deal
Significant Controls		Nr. Firms, Δ Nr. Firms, Public Target	Δ Nr. Firms, Public Target, Horizontal	Δ Nr. Firms, Public Target
Observations	7,150	7,150	7,150	7,150
F Statistic	2.93^{*}	3.46^{***}	1.75^{***}	1.68^{***}

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

TABLE 2.9: ADDITIONAL ANALYSIS OF THE LINEAR TREND IN COMPETITORS ANNOUNCEMENT RETURNS

This table reports the results of regression analysis of competitors announcement returns (CARs) for a sample of U.S. mergers. The sample consists of 21.817 merger deals occurred during the period 1990-2018. The merger sample is obtained from SDC Platinum merger database. The merger deals need to be over $1 million, conducted by bidders who are US public firms and are classified as ”domestic”. Announcements on the same date by the same bidders are excluded. The bidder must have acquired at least two or more target firms over the period 1990-2018. The dependent variable in all four columns is the 7-day event window (-3,3) competitor % CARs. CARs to competitors are estimated using equally weighted portfolios of the top five competitor to the acquirer. The main variable in all columns is a linear time-trend variable during the period 1990-2018. The *Linear Trend* variable takes value of one in 1990 and increments of one unit every year after 1990. Column (1) includes no control variables. Column (2) adds deal and industry characteristics as controls. Column (3) includes deal and industry characteristics and industry fixed effects (defined at the 3-digit SIC code level). Column (4) includes deal and industry characteristics and bidder fixed effects.

	Dependent variable:			
	Competitors CARs: [-3,+3]			
	(1)	(2)	(3)	(4)
	No Controls	Controls	Controls & Ind. FE	Controls & Acq. FE
Panel A: Horizontal mergers				
Linear Trend	−0.01	−0.01	−0.01	−0.03
	[−1.37]	[−0.17]	[−0.10]	[−1.22]
Observations	7,303	7,303	7,303	7,303
Controls	No	Industry & Deal	Industry & Deal	Industry & Deal
Significant Controls		Δ Mkt. Share, Public target	Nr. Firms, Δ Mkt. Share, Stock Transaction, Public target	Nr. Firms, Δ Ind. Size, Public target
F Statistic	1.87	3.22***	1.27***	1.29***
Note:				*p<0.1; **p<0.05; ***p<0.01

Table 2.9 (continued)

Panel B: Non-Horizontal mergers				
Linear Trend	-0.01^{***}	-0.01^{**}	-0.02^{**}	-0.03^{**}
	[−2.72]	[−2.04]	[−2.10]	[−2.12]
Observations	14,514	14,514	14,514	14,514
Controls	No	Industry & Deal	Industry & Deal	Industry & Deal
Significant Controls	Constant	Public Target	Public Target	Public Target, Tender Offer
F Statistic	7.38^{***}	1.80^{**}	1.19^{***}	1.51^{***}
Panel C: Public target firms				
Linear Trend	−0.01	0.01	0.01	−0.01
	[−0.934]	[0.042]	[0.233]	[−0.671]
Observations	3,012	3,012	3,012	3,012
Controls	No	Industry & Deal	Industry & Deal	Industry & Deal
Significant Controls		Horizontal	Δ Ind. Size, Horizontal	Cash Transaction, Horizontal
F Statistic	0.87	2.08^{**}	2.25^{***}	1.30^{***}
Panel D: Private target firms				
Linear Trend	-0.01^{***}	-0.01^{*}	-0.01^{*}	-0.02^{**}
	[−2.60]	[−1.71]	[−1.70]	[−1.99]
Observations	18,805	18,805	18,805	18,805
Controls	No	Industry & Deal	Industry & Deal	Industry & Deal
Significant Controls	Constant	Nr. Firms		Δ Nr. Firms
F Statistic	6.74^{***}	1.35	1.09^{*}	1.38^{***}

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 2.9 (continued)

Panel E: Cash financed transactions				
Linear Trend	−0.01	−0.01	−0.01	−0.01
	[−1.59]	[−0.65]	[−0.79]	[−0.48]
Observations	7,810	7,810	7,810	7,810
Controls	No	Industry & Deal	Industry & Deal	Industry & Deal
Significant Controls	Constant	Δ Nr. Firms, Public Target	Δ Nr. Firms, Public Target	Public Target
		Tender		Tender
F Statistic	2.53	3.25***	1.17**	1.19***
Panel F: Stock financed transactions				
Linear Trend	−0.02*	−0.02*	0.00	−0.01
	[−1.86]	[−1.79]	[0.02]	[−1.28]
Observations	6,228	6,228	6,228	6,228
Controls	No	Industry & Deal	Industry & Deal	Industry & Deal
Significant Controls	Constant	Public Target	Hostile, Nr. Firms	Public Target, Hostile
F Statistic	3.45*	1.24	1.48***	1.34***

Note: *p<0.1; **p<0.05; ***p<0.01

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And the CAR goes to...
Shock to Brand Capital: Evidence from the Oscars*

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Abstract

We identify the effect of changes in the brand capital on stock market performance. Using hand-collected data on the red carpet outfits during the Academy Awards ceremonies, we find that companies providing outfits to actresses on the red carpet experience a positive stock market performance with respect to a control group of comparables. This outperformance is unlikely to be attributable to differential risk or company-specific news, while Google search trends suggest the Academy Awards ceremonies have a positive impact on investor attention.

JEL classification: G32, G14, G12, E22

Keywords: Brand, Intangible Capital, Returns, Event Study, Investor Attention

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3.1 Introduction

During the last few decades, intangible capital has become a major fraction of company capital both in the US and in Europe. The existing literature focuses mainly on the long-term relationship between intangible assets and financial markets. Regrettably, the question of how quickly companies benefit from intangible assets has received little attention in the literature, largely due to the endogenous concerns. In this paper, we aim to fill this gap by focusing on a specific form of intangible capital — brand capital — and investigating how quickly the effect of random and unexpected brand exposures gets incorporated into the stock returns. To identify fashion companies experiencing the shock to their brand capital, we collect data on the red carpet of the Academy of Motion Picture Arts and Sciences Awards, known as the Oscars. We find that companies that provide an outfit for an actress to wear on the red carpet earn cumulative abnormal returns (CARs). These CARs might be driven either by only investors' attention alone or by their interplay with fundamental channels — specifically, increasing future sales and competitive viability.

Corrado and Hulten (2010) determine that intangible assets on average account for 33.9% of a company's total capital between 1995 and 2007. The Economist (2018) reports that in 2015 intangible capital accounted for 84% of the value of Standard and Poor's (S&P) 500 firms, up from 17% in 1975. According to The Economist (2014) and Millward Brown estimates, by 2010, the market value of brand capital alone was already above 30% of S&P 500 firms' market capitalization. One of the main functions of brand capital is to build the competitive strength.

Why might the Oscars matter for brand capital? There are at least two channels: the Oscars set a company apart from its competitors, and the Oscars have the ability to affect consumer behavior. The Oscars night is one of the most recognizable annual events in the US and worldwide. According to the Academy of Motion Picture Arts and Sciences, the event covers a global audience of "several hundred million in 225 countries". Most of the Oscars' interviews begin with a question:

“What are you wearing?” Success on the red carpet could provide prestige for designers and stars and generate long-term profits for luxury brands. The red carpet presents “a great and free opportunity” for a designer to reach an audience that expands beyond the fashion set, said Ariel Foxman, editor of fashion magazine InStyle. “It’s free marketing,” Foxman said. “Advertising dollars are so expensive, and marketing budgets are so fractured these days with social media, digital media, print media and television media, so it’s more valuable than ever” (see Business of Fashion (2014)).

How does the Oscars ceremony differ from the other instruments of building the brand capital? The main challenge of investigating whether companies extract financial value from their brand value is the endogenous nature of other methods such as advertising and endorsement contracts. The existing literature mostly provides evidence of a positive correlation between brand equity and a company’s performance. We claim that the Oscars ceremony is an exogenous shock to brand capital. It is generated externally and not directly related to the fundamentals of the company. The red carpet plays the role of external expertise. It might induce changes in brand value but not due to a company’s strategy.

Signaling effect: Advertising can act as a signal of a company’s financial well-being or competitive viability (see Joshi and Hanssens (2009) and Joshi and Hanssens (2010)). The Oscars red carpet shows that a company has a unique value to provide. This competitive advantage puts the company in a favorable position relative to its peers.

Spillover effect: The companies with higher brand value might have higher future sales relative to companies with lower brand value that are otherwise similar. Investors take it into account, hence, this should also have a positive effect on the current market performance of the same companies with relatively higher brand value.

To identify companies present on the red carpet, we collect information about the outfits of all identified celebrities attending the ceremonies for the period 2008-2019. With this information, we classify a company as providing an outfit in a given year if at least one celebrity wears this company's brand. In addition, if one of these celebrities is a nominee, then the company is classified as providing an outfit to a nominee. To construct the history of outfits, we use two main sources, namely the Oscars page and Just Jared. Further, in our analysis we drop information about footwear, accessories, and jewelry due to the high contracting nature of these items. Our sample consists of companies listed on several exchanges, mostly in Europe. We identify a total of 278 outfits whose brands belong to public companies. Most of the companies have several brands, hence, we need to link brands to the companies. As a result, we have a total of 17 publicly traded companies in the sample.

To document the role of the Oscars red carpet, we perform a two-step procedure. First, we estimate the predicted stock returns from a market model over Friday before the ceremony and the Monday and Tuesday after it. We compute the CARs as the sum of abnormal returns. We then test whether the Oscars ceremonies are shocks to the brand value of holding companies by running an Ordinary Least Squares (OLS) estimation. We find that holding companies whose brands appear on the red carpet of the Oscars have 1.12 percentage points higher three-day CARs than their peers. The effect is significant after controlling for Book-to-Market, size, endorsement contracts, and major company-specific news. In addition, there is a significant change in investor attention during the days of the ceremonies. Following Da, Engelberg, and Gao (2011) and Buchbinder (2018), we measure attention by computing abnormal Google's search volume index (SVI) of the companies' names. The holding companies whose brands were chosen by actresses experience a higher SVI compared to their peers.

By providing evidence on whether the change in brand capital gets incorporated into the stock prices, the paper complements the literature on brand capital and on advertising and media coverage.

First, the paper is related to the intangible capital literature focusing on brand capital. Existing papers argue that intangible capital, including brand value, is very important for company value.

Several papers explore the impact of brand on the value and riskiness of a company's overall cash flow. Madden, Fehle, and Fournier (2006) provide evidence of a positive relationship between brand value and stock returns, and show that branding reduces the variability of cash flows and enhances shareholder value as compared to the overall stock market. Larkin (2013) explores the impact of customer brand perception on financial policy. She concludes that positive perception of companies' products reduces volatility of cash flows and insulates firms during periods of recession. Belo, Lin, and Vitorino (2014) report that the stocks of companies with higher brand capital intensity deliver higher returns. Building on Belo, Lin, and Vitorino (2014), Vitorino (2014) proposes a dynamic structural model in which companies invest in both physical capital and intangible brand capital. She uses stock market data to recover the market value of a company's brand. The estimation results show that brand equity accounts for a substantial fraction of a company's market value (about 23%). Belo, Gala, Salomao, and Vitorino (2020) decompose company value into four pieces and interpret advertising expenses as a firm's investment to enhance the value of brand names and increase brand awareness. We add to this literature by identifying an unanticipated shock to a brand value as a potential mechanism to address endogenous concerns. Moreover, this shock is generated outside of a company, that is, it does not directly involve company fundamentals. Also, we are able to quantify an immediate reaction of the stock market to changes in the brand capital.

The paper is also closely related to the literature investigating the outcomes of advertisement on investor attention and company financial characteristics. On the one hand, Grullon, Kanatas, and Weston (2004) show significant effects for the relationship between advertising and company stock returns. Using an event study methodology, Healey and Godes (2014) find that higher advertising expenditures result in a decrease in company stock returns. Lou (2014) and Chemmanur and Yan (2019) find that increases in advertising are associated with abnormally high contemporaneous stock returns. On the other hand, Focke, Ruenzi, and Ungeheuer (2020) and Madsen and Niessner (2019) point out that analyses based on annual advertising budgets may suffer from severe endogeneity problems. Using daily advertising data, Focke, Ruenzi, and Ungeheuer (2020) find evidence that advertising has a positive impact on investor attention, but no impact on returns. Similarly, Madsen and Niessner (2019) document that Google searches are higher on days when companies run print advertisements, but that stock returns are not affected. Using minute-by-minute TV advertising data, Liaukonyte and Zaldokas (2021) conclude that the ad-induced EDGAR searches of the advertiser increase trading volume and contribute to a temporary rise in the stock price. Mayer (2021) finds that ads during college football games create temporary price pressure. Retail investors are net buyers, whereas institutional investors' selling drives the subsequent reversal toward fundamental values. We add to this literature by exploring events that are likely not driven by company choices. However, there is still a choice by a red carpet celebrity, which might change companies' fundamentals. This change might be driven by exogenous shocks in brand exposure, but not by shocks in company expenditures.

Finally, we contribute to the literature on the business of fashion and financial markets. On the one hand, Agrawal and Kamakura (1995) and Elberse and Verleun (2012) show that stock prices increased on the day of the endorsement contract announcement. On the other hand, Ding, Molchanov, and Stork (2011) conclude that announcements do not lead to abnormal returns. In a case study on a scandal involving Tiger Woods, Knittel and Stango (2014) show that his sponsors lost more than 2% in market value. However, the endorsement contracts do not occur spontaneously, likely decreasing the endorsement's impact with consumers and investors. In its framework, our paper is most closely related to Yermack (2011). He examines the effect of Michelle Obama's clothing choices on the stock prices of apparel companies. According to his study, the stock prices of the companies whose outfits she does not wear decrease, while the stock prices of companies providing her outfits go up. Our goal is not to quantify the value of each celebrity. Our interest is primarily in brand value to a company from a financial perspective.

The remainder of the paper is organized as follows. Section 3.2 describes the Oscars background.

Section 3.3 presents the sample selection procedure, defines the variables, and provides summary statistics. Section 3.4 describes our empirical hypotheses and empirical strategy. Section 3.5 presents the main results and provides robustness checks. Section 6 draws conclusions.

3.2 The Oscars Background

The Oscars connect celebrities with the fashion industry through the red carpet. The first ceremony was held in 1929, and starting in the late 1950s, fashion designers (primarily European) have been dressing celebrities for this event. The red carpet tradition has only been present at the Oscars since 1961. In recent decades, the Oscars, including the red carpet appearance, differ from other celebrity genres by being broadcast live. The broadcasting allows to mix "intimacy at a distance" and extraordinariness, because when a celebrity appears on the red carpet, they are recognized as a star (see Haastrup (2015)). Moreover, strategic brand consultant Derrick Daye says that "an Oscar nomination is more important now than when it was when the Oscars started... These nominations and awards give you much more of a differentiator than you just being famous... It pulls you away from the group" (see WWD (2016)). Celebrity outfits are critiqued across the internet and other media for weeks. At its core, brand value is affected by how different people — for example, journalists — speak about the brand. These voices can significantly influence a brand's reputation, for better or for worse, and the red carpet is still a prime opportunity to build the buzz that translates into equity (see Launchmetrics (2019)).

For our empirical setting, an appearance on the red carpet should be a surprise. The competition to dress the actresses is very high. The most popular stars have many choices, and the probability that they change their mind at the last minute is considerably high. Often stylists ask designers to produce custom gowns for the superstars, but those stars do not always end up wearing the custom gowns for the award ceremony. Erlanger, a stylist, says that, "There should be an element of surprise, and that's what keeps everyone interested" (see Business of Fashion (2014)).

A fashion writer, Teri Agins, says, “What designers want to do is be associated with celebrities because they’re the fashion role models for the consumer” (see Business of Fashion (2017)). There is no direct link between the red carpet appearance and sales, but the red carpet generates brand awareness for the fashion labels worn by actresses. In 2015, in the US alone, 24.3 million people viewed just the 8:00 p.m. to 8:30 p.m. EST time slot of the Oscars broadcast (see Business of Fashion (2016)). The sports telecasts might have more viewers. However, the Oscars’ audience is skewed differently than those of major sporting events. For example, 30% more TV households with annual incomes greater than $100,000 were watching the Oscars than average TV households were. In other words, there were more viewers in several premium categories that are attractive to fashion brands (see Bain & Company (2019)).

In this paper, we focus on public companies. But to highlight the importance of the Oscars red carpet for the brand capital creation, we provide two examples of stand-alone designers. When Halle Berry received an Oscar for *Monster’s Ball*, she was wearing a dress by Lebanese designer Elie Saab. Later on, Lebanon became an unexpected hub of fashion (see The Wall Street Journal (2016)) After actress Stacy Keibler wore Naeem Khan’s gown to the 2013 Oscars, he sold 30 pieces at $9,000 per and received nearly 40 inquiries. “The exposure is great, no matter what,” he said. “And it often translates to sales” (see Business of Fashion (2017)).

Does Oscars fashion still matter? Alison Bringé, chief marketing officer at data analytics firm Launchmetrics, says that “a brand mention at an award show red carpet is three to five times as valuable as your average brand tag in a standard-issue celebrity post. And, although certain celebrities receive enormous media attention for everything they do, fashion isn’t always a part of those moments, which is why red carpets are still so significant for fashion labels” (see Business of Fashion (2019)).

3.3 Data

In this section, we discuss our datasets and our variables' construction. First, we describe our novel hand-collected fashion dataset and the financial market data. Next, we explain our construction of the main regressors and the attention proxy. Finally, we provide summary statistics for the final sample.

3.3.1 Sample Selection

We hand collect information about guests, Academy Awards nominees, and their outfits for the years between 2008 and 2019. We gather the data on guests and outfits from the Oscars website (*oscar.go.com*), Just Jared website (*justjared.com*) and Google search. The outfit data contain garments designed by private companies as well as publicly traded companies. Due to lack of financial data for private companies, we restrict our sample to public fashion companies that provide an outfit in any of the years during the sample period.

Table 3.1 presents the construction of our sample. First, we collect the names of 1,573 celebrities who attended the Academy Awards ceremony during the period 2008-2019. Next, we exclude 614 observations due to the absence of coverage in the media. Hence, we are able to identify 959 outfits throughout our sample period. Then, we exclude 14 observations because several celebrities were wearing outfits designed by multiple designers. For example, during the 2017 Academy Awards ceremony, actor Ryan Gosling walked the Oscars red carpet wearing a suit by *Gucci* and a shirt by *Anto*. We also have to exclude 594 observations because the outfits were designed by private companies for which we are not able to obtain financial data. Additionally, we exclude 15 observations wherein we are not sure which fashion company provided the outfit. We exclude all 46 outfits by *Christian Dior* due to its cross-ownership with *LVMH*. Additionally, we exclude the outfit provided by *Nike, Inc.*, in 2019.

Our final sample contains 289 observations spanning from 2008 to 2019. We match these observations to their holding companies. We are able to match 289 outfits to 17 unique holding companies that provided outfits to 222 unique celebrities. The sample is balanced in terms of gender representation: we observe 146 outfits wore by male guests and 143 outfits wore by female guests. We then collapse these celebrity-brand observations to the company level. That is, when a company provides an outfit to two or more guests on the red carpet in the same year, we treat that as a single company-year observation. Our final sample consists of 187 company-year observations.

To estimate announcement returns and construct company-specific variables, we use stock price and company data from two sources: Refinitiv Eikon and Compustat. Stock price data are provided by Eikon. End-of-year company financials are provided by Compustat North America Daily (for US-based firms) and Compustat Global Daily (for international firms).

3.3.2 Variable Definitions

To test our two hypotheses, we create two dummy variables for each pair celebrity-company in our sample.[17] The first dummy variable is *Red Carpet*, which equals one if a company provides an outfit to a celebrity present on the red carpet in a specific year. We assign a value of zero if a company does not provide any outfit to celebrities in a specific year. If a guest is nominated in one of the following categories - Best Actor, Best Supporting Actor, Best Actress, Best Supporting Actress - we create a dummy variable *Nominated Red Carpet* that equals one and zero otherwise.

For example, in 2016, *Kate Winslet* was nominated in one of the main four award categories for her role in *Steve Jobs*. She attended a ceremony wearing a *Ralph Lauren* gown. Hence, the dummy variable *Red Carpet* is one. The dummy variable *Nominated Red Carpet* is also one. In 2018, *Salma Hayek* attended a ceremony wearing *Gucci* without being personally nominated for any of the main four award categories. As *Gucci* is owned by the company *Kering*, we conclude

[17] In our sample of holding firms, we do not observe any celebrity choosing the same brand every year. On the other hand, this phenomenon exists for private design labels.

that *Kering* provides the dress that year. The dummy variable *Red Carpet* is one. However, the dummy variable *Nominated Red Carpet* equals zero. In 2010, *Alberta Ferretti* did not provide any dress for any celebrity, and as a result, the *Red Carpet* variable equals zero, as does the *Nominated Red Carpet* variable.

Some celebrities may have signed an endorsement contract with a specific brand. Hence, their choice may be restricted such that the celebrity can only wear that specific brand to major events such as the Academy Awards ceremony. For example, during the period 2014-2017, *Jennifer Lawrence* wore only dresses by *Christian Dior*. These types of endorsement contracts, however, are not very common, especially with respect to apparel. On the other hand, fine jeweler brands sign endorsement contracts more often than designer companies. We exclude jeweler companies from our sample because jewelry endorsement contracts could bias our results.
To control for endorsement contracts in the outfit sample, we hand collect information about these contracts from two specialized websites: *celebrityendorsementads.com* and *celebrityendorsers.com*. We also search for additional information regarding endorsement contracts using Google search. Our search leads to the identification of 20 endorsement contracts in our sample of celebrity-company pairs. Next, we create a dummy variable *Endorsement* for each company-year pair. *Endorsement* equals one if a company has a contract with a celebrity present on the red carpet, and zero otherwise.

We also conduct a search of newspapers and newswire services in LexisNexis data files to identify company-specific events, such as earnings announcements, declaration of dividends, equity offerings, introduction of a new brand, change in company name, mergers and acquisitions, stock splits, management guidance, from two weeks before to two weeks after a ceremony takes place.

Finally, to control for company-specific variation, we construct two additional variables: *Book-to-Market* and *Size*. *Book-to-Market* is defined as lag assets over lag market capitalization of the company, while *Size* is defined as the lag natural logarithmic of the company's total assets. Table 3.2 provides definitions of all the variables used in our paper.

3.3.3 Attention Proxies

To explore investor attention to the red carpet, we borrow a measure of Gamm (2020). We use daily Google SVI for a company's name during the Academy Awards ceremony. Several papers claim that Google SVI is a good proxy for investor attention and captures primarily retail investors' demand for financial information (see Da, Engelberg, and Gao (2011); Buchbinder (2018); Madsen and Niessner (2019)). Although SVI cannot be converted into the actual number of Google searches, larger SVIs within a firm are indicative of greater searches for information. To obtain daily data, we download the data for each year separately.

Following Gamm (2020), we compute abnormal search volume index (ASVI) by using the difference between the $SVI_{i,t}$ on a specific day t and the median SVI value of the same day of the week over the previous ten weeks to account for intraweekly seasonality in internet search behavior. This difference is then normalized by the median SVI value of the same day of the week over the previous ten weeks. We take the natural logarithm of this ratio to reduce skewness. To include days with zero attention ($SVI_{i,t} = 0$), we add one before taking the logarithm:

$$ASVI_{i,t} = ln\Big(1 + \frac{SVI_{i,t} - median(SVI_{i,t,\text{same day of the week, previous 10 weeks}})}{median(SVI_{i,t,\text{same day of the week, previous 10 weeks}})}\Big), \tag{3.1}$$

To compute cumulative abnormal search volume index (CASVI), we sum the abnormal SVI for each day in the required period.

3.3.4 Summary Statistics

During our sample period, the ceremony takes place on a Sunday during the second half of February or the first week of March. To account for any time-zone difference, we define Monday as the day when the financial market reacts to the announcement because it is also the first trading day after the ceremony. That is, we define the Friday before the ceremony as $t = -1$, Monday as the announcement day ($t = 0$), and the Tuesday after the ceremony as $t = 1$.

Table 3.3 provides summary statistics for both fashion and financial datasets. Panel A shows that the average cumulative abnormal return for the full sample is around 0% For almost one-third of the observations (57), the *Red Carpet* dummy equals one. Panel B shows the summary statistics for the sample of menswear. Panel B has a lower number of nominated celebrities than the womenswear sample: 0.14 and 0.16, respectively. The fashion companies in our sample are, on average, large firms with high book-to-market ratios. The average CASVI for companies' names is close to zero. Yet, CASVI is quite volatile. One reason for such volatility may be that companies that provide outfits are searched more heavily during the Oscars ceremony.

3.4 Empirical Strategy

3.4.1 Testable Hypotheses

Our first two hypotheses investigate whether companies that provide an outfit to celebrities have a different market reaction than those who do not. The last two hypotheses investigate whether companies that provide an outfit to celebrities experience a higher Google search volume during the Academy Awards weekend.

The first hypothesis tests whether providing an outfit to anyone present on the red carpet leads to a reevaluation of the company's brand capital. That is, by providing an outfit to a celebrity attending the Academy Awards ceremony, the brand secures itself a platform to show its latest creation.

Hypothesis 1. The fashion companies that provide outfits to *any celebrity* on the red carpet exhibit positive, cumulative abnormal stock returns following the Oscars.

The second hypothesis tests whether providing an outfit to a celebrity who is nominated for one of the four main categories[18] leads to a reevaluation of the company's brand capital on top of just providing an outfit to any celebrity. Companies may have a higher incentive to dress a nominated actress or actor because the expected media coverage will be higher. That is, their design (or brand capital) will be featured more in the media than those that do not dress a nominated actress or actor, leading ultimately to a higher stock price.

Hypothesis 2. The fashion companies that provide outfits to the *nominees* on the red carpet exhibit additional positive, cumulative abnormal stock returns following the Oscars.

To sum up, these two hypotheses test whether by having a distinct design or creative concepts, a brand can make itself more recognizable compared to its peers. By exploiting the randomness of celebrities' outfits and specific brand designs, we are able to test these hypotheses. If individuals and the market are able to differentiate between brands and styles, we should observe a revision in the stock price over the Academy Awards weekend. If this shock to brand capital does not matter, we should not observe any significant cumulative abnormal returns in the stock market. Next, we develop two additional hypotheses to test whether fashion companies experience higher attention during the Oscars ceremony weekend. In Hypothesis 3, we test whether providing an outfit to any celebrity present on the Oscars red carpet leads to a higher abnormal Google search following the Oscars.

Hypothesis 3. The fashion companies that provide outfits to *any celebrity* on the red carpet exhibit positive, abnormal Google searches following the Oscars.

In Hypothesis 4, we test whether providing an outfit to a nominated celebrity on the red car-

[18] The main categories are Best Actress, Best Actor, Best Supporting Actress, and Best Supporting Actor.

pet results in an even higher SVI over the Oscars ceremony weekend. In other words, we test whether by providing an outfit to prime guests such as the Academy Awards nominees, a fashion company can secure a higher media exposure on top of just providing an outfit to any celebrity.

Hypothesis 4. The fashion companies that provide outfits to the *nominees* on the red carpet exhibit additional positive, abnormal Google searches following the Oscars.

To sum up, as a fashion company is exposed to an increased media coverage, investors may look for more news or facts related to the company on Google. That is, we should observe a higher increase in Google search volume for the companies whose outfits were present on the red carpet because it reflects a positive shock to brand capital.

3.4.2 Empirical Strategy

The amount of change in a stock price after an event, relative to its pre-event price, would reflect the market's unbiased estimate of the economic value of that event. If markets are efficient we should then observe a revision in stock prices when new information on the firm is available. To estimate market reaction, an event study is commonly used. In this paper, we explore whether the decision to wear an outfit is viewed by investors as a positive signal, or shock, for a specific fashion company. Investors may have different opinions on the future profit impact of the appearance. These opinions regarding the future prospects and positioning of the company are then immediately reflected in the company's stock returns. Thus by using an event study to test our two main hypotheses, we can measure the abnormal returns of companies dressing celebrities and examine the market's valuation of the signal, or shock to the brand.

Following the event study literature, we first estimate the parameters of a market model for each company by regressing its actual returns on the returns of the MSCI Europe index and a dummy variable *Crisis*. The model coefficients are estimated using an estimation period of 200 to 60 calendar days prior to the Oscars ceremony, that is, we estimate the parameters between

August and December prior to the Oscars to avoid several effects that could bias our coefficient estimates. For example, January represents an important month for fashion companies. During the first weeks of January, the majority of brands are attending fashion weeks showcasing their latest collections. As a result, by including January we could introduce a bias in our market model coefficient estimates. In addition, two additional effects could bias our results. First, the Academy Awards announces the nominees during the first weeks of January. These announcements could potentially affect our estimates. Second, during the first weeks of January stock prices usually increase (the so-called "January effect"). In other words, when we perform a "placebo test" our results may be affected by such stock price movements. To address this potential bias, we winsorize our estimated cumulative abnormal returns at the 1% and 99% levels when we artificially move the date of ceremony to one week after.[19]

Our market model is as follows:

$$R_{it} = \alpha + \beta R_{\text{MSCI},t} + \gamma D_{\text{Crisis},t} + \epsilon_{it}, \tag{3.2}$$

where R_{it} is a return of firm i, $R_{\text{MSCI},t}$ is an MSCI Europe index return, $D_{\text{Crisis},t}$ is a crisis dummy, which equals one for years 2008 and 2009.

We choose to include a dummy variable *Crisis* to control for any abnormal market movements in 2008 and 2009 due to the financial crisis. We choose the MSCI Europe index because the majority of our holding companies are European companies. That is, two-thirds of our fashion companies (11 out of 17) are publicly traded on European exchanges.

To test our main two hypotheses, first, we estimate abnormal returns. Following the literature, we define abnormal return as the difference between the actual stock return minus the predicted stock return from our market model. We then estimate cumulative abnormal returns as the sum of abnormal returns over three trading days (-1,+1). As the Academy Awards ceremony occurs on Sunday, the Monday following the Oscars represents the first available trading day to observe

[19] We use the estimated CARs from a market model for the Academy Awards weekend and the week before. We use the winsorized CARs from a market model when we test our hypotheses the week after the Academy Awards weekend.

any market reaction.

In our second step, to test our first hypothesis, we run the following regression:

$$CAR_{it} = \alpha + \beta_1 D_{it}^{\text{Red Carpet}} + \beta_2 BM_{it-1} + \beta_3 Size_{it-1} + \gamma_i + \delta_t + \epsilon_{it}, \tag{3.3}$$

where CAR_{it} is a cumulative abnormal return of stock i, $Size_{it-1}$ is a natural logarithm of the assets of firm i at the end of the previous year, BM_{it-1} is a Book-to-Market ratio of firm i at the end of the previous year, $D_{it}^{\text{Red Carpet}}$ is a dummy variable that equals one if a company provides an outfit to a celebrity present on the red carpet, γ_i represents the company fixed effects, δ_t are the year fixed effects, and ϵ_{it} is the error term. To control for large outliers (e.g., *LVMH*), we winsorize the Size and the Book-to-Market variables at the 5% and 95% levels. The standard errors are corrected for heteroskedasticity.

To test our second hypothesis, we run the following regression:

$$CAR_{it} = \alpha + \beta_1 D_{it}^{\text{Red Carpet}} + \beta_2 D_{it}^{\text{Nominated Red Carpet}} + \beta_3 BM_{it-1} + \beta_4 size_{it-1} + \gamma_i + \delta_t + \epsilon_{it}. \tag{3.4}$$

Compared to eq. 3.3, eq. 3.4 also includes $D_{it}^{\text{Nominated Red Carpet}}$, a dummy variable that equals one if a fashion company provides an outfit to a nominee, while still including all the other regressors. When we run an OLS regression as in eq. 3.3 and eq. 3.4, we collapse the individual celebrities-fashion companies observations in one observation for fashion company. That is, in case a company provides an outfit to more than one guest/nominee, the two dummy variables (*Red Carpet*, *Nominated Red Carpet*) only take a value of one regardless. We split the analysis according to gender and provide the results for both samples. That is, to differentiate the effect on brand capital based on gender, we first look at the companies that provide an outfit to actresses and then repeat the same analysis for actors.

To test our additional hypotheses (Hypotheses 3 and 4), we perform a similar two-step procedure as in the previous case. In our first step, we calculate the ASVI for the companies names over the Academy Awards ceremony. In our second step, we run an OLS pooled regression for ASVI on one dummy for Hypothesis 3 and two dummies for Hypothesis 4:

$$ASVI_{i,t} = \alpha + \beta_1 D_{it}^{\text{Red Carpet}} + \epsilon_{it}, \tag{3.5}$$

$$ASVI_{i,t} = \alpha + \beta_1 D_{it}^{\text{Red carpet}} + \beta_2 D_{it}^{\text{Nominated Red Carpet}} + \delta_t + \epsilon_{it}, \tag{3.6}$$

where $D_{it}^{\text{Red Carpet}}$ is a dummy variable that equals one if the holding company provides an outfit to a celebrity that is present on the red carpet and zero otherwise, and $D_{it}^{\text{Nominated Red Carpet}}$ is a dummy variable that takes a value of one if a company provides an outfit to a celebrity nominated for one of the four main awards categories and zero otherwise, and finally, δ_t are the year fixed effects. As for Hypothesis 1 and Hypothesis 2, we collapse the individual celebrities-fashion companies observations in one observation for fashion company. However, we split the analysis according to the gender of the Academy Awards celebrities and provide the results for both samples.

3.5 Results

3.5.1 Main Results

Womenswear

Column (1) in Table 3.4 reports the estimates of the OLS regression (as in eq. 3.3) for the sample of companies that provide an outfit to actresses attending the Academy Awards ceremony. Column (1) shows that when a brand provides an outfit to an actress, this company earns a higher CAR. On average, it earns a CAR 1.12 percentage points higher than its peers. The positive and significant coefficient of the variable *Red Carpet* confirms our first hypothesis, that the market reacts positively to a shock in brand value and incorporates the information into the stock price. Column (1) in Table 3.5 reports the estimates of the OLS regression as in eq. 3.4 for the same sample as Table 3.4. When we regress CARs on both the *Red Carpet* dummy and the *Nominated Red Carpet* dummy, the *Nominated Red Carpet* dummy is not significant. In other words, providing an outfit to an Oscar-nominated actress does not yield any additional return on top of that gained by providing an outfit to any actress on the red carpet. Hence, we reject our second hypothesis.

Next, we test Hypothesis 3 and Hypothesis 4. Column (1) in Table 3.6 shows that the names of the companies that provide a dress to an actress on the red carpet experience a higher CASVI over the weekend. In other words, internet users search the names of the holdings more often than during the previous 10 days. Column (1) in Table 3.7 provides no evidence of a higher CASVI for those fashion companies that provide a dress to a female nominee. Thus, we accept Hypothesis 3 and reject Hypothesis 4.

To sum up, we provide suggestive evidence that companies that provide an outfit to an actress on the red carpet earn higher CARs than their peers and experience an increase in Google searches over the Academy Awards weekend. In other words, we conclude that providing an outfit results in a positive shock and increasing attention to brand capital.

Menswear

We now repeat the analysis for the sample of companies that provide an outfit to a male attendee at the Academy Awards ceremony. Specifically, the dummy variables *Red Carpet* and *Nominated Red Carpet* take value of one when a company provides an outfit to an actor and a male nominee attending the Oscars ceremony, respectively.

Column (1) in Table 3.8 tests Hypothesis 1 and reports the estimate of the OLS regression (as in eq. 3.3) for the companies that provide an outfit to actors attending the Oscars ceremony. Providing an outfit to a male celebrity does not result in higher CARs for the companies.

Column (1) in Table 3.9 tests Hypothesis 2 for the companies that provide an outfit to an Oscar-nominated actor. We see no significant additional effects for those companies that provide an outfit to a male nominee present on the red carpet.

Next, we test Hypothesis 3 and Hypothesis 4 for the menswear sample. In Column (2) in Table 3.6, we regress the CASVI of company names over the Oscars weekend on the *Red Carpet* dummy variable and year fixed effects. As for CARs, we do not observe any significant increase in attention to those companies providing an outfit to actors. Column (2) in Table 3.7 shows that providing an outfit to a male nominee also does not result in a higher CASVI for fashion companies.

To sum up, we show that providing an outfit to male celebrities during the Academy Awards ceremony does not lead to significant shock to brand capital or additional attention. We argue that one reason why we do not observe a similar shock in the case of companies that provide outfits to female celebrities is that menswear is not as creative as womenswear. While tuxedos and suits may differ in terms of fabric or color, their style does not. That is, historically, men have chosen more traditional formal apparel. On the other hand, in recent years we saw some men starting to wear more creative outfits. For example, in 2019, the actor *Billy Porter* wore a tuxedo top with a gown. Despite that, the companies included in our sample did not provide such attire. Finally, brand capital has a higher degree of design freedom in womenswear than in menswear. That is, brands can design more elaborate and creative outfits, leading to a more recognizable look on the red carpet.

3.5.2 Robustness Tests

The evidence presented so far shows that companies that provide an outfit to an actress on the Oscars red carpet earn, on average, CARs 1.12 percentage points higher than their competitors. However, we show that providing an outfit to an actor on the Oscars red carpet does not result in higher CARs. We now show that our results are robust to a "placebo" test, to inclusion of company-specific news, and to controlling for endorsement contracts.

Placebo Test

To test whether the significance of the *Red Carpet* dummy variable is due to a "simple" weekend effect, we run two additional OLS regressions by fictitiously moving the date of ceremony. In other words, we move the date of ceremony to either the Sunday before the Oscars ceremony or the Sunday after the Oscars ceremony and calculate the three-day CARs. Column (2) and Column (3) in Table 3.4 and Column (2) and Column (3) in Table 3.5 report the results of these placebo tests. Both coefficients for the *Red Carpet* dummy variable are not statistically significant for the weekend before and weekend after the Academy Awards. Likewise, the coefficients of the *Nominated Red Carpet* dummy variable are not significant during the weekend before and weekend after the Academy Awards. These results support our evidence that the shock to brand capital is attributable only to providing an outfit to a guest present on the red carpet on the night of the Oscars. On average, the remaining variables coefficients are large and statistically significant. We argue that such large significance is mainly driven by the inclusion of year and company fixed effects. That is, the coefficients of company and year fixed effects have a similar magnitude.

To sum up, the results of the "placebo" test suggest that the effect picked up by the *Red Carpet* dummy variable is not simply because of any weekend effect.

Company News

Next, we control for company-specific news. For our sample period, we observe news releases in LexisNexis. One concern is that our dummy variable *Red Carpet* may incorporate such news and thus bias the presented evidence. To control for the news, we construct a dummy variable *News* that equals one if there is major news about the company during the week of the Academy Awards.

Column (1) in Table 3.10 and Column (2) in Table 3.10 report, respectively, the results for the womenswear and the menswear sample. Controlling for company-specific news does not change our main results. That is, we still observe a positive, statistically significant coefficient for the companies that provide an outfit to any woman present on the Oscars red carpet.

Column (1) in Table 3.11 and Column (2) in Table 3.11 report, respectively, the results for the womenswear and the menswear sample. As for Hypothesis 1, controlling for company-specific news does not change the results. Providing an outfit to an Academy Awards nominee does not result in higher additional CARs.

Next, we repeat the analysis for Hypothesis 3 and Hypothesis 4 by including the company-specific news dummy. Column (3) and Column (4) in Table 3.6 report the results for hypothesis 3. Controlling for company news does not alter our results. Companies that provide an outfit to an actress on the red carpet are, on average, searched more by internet users. Column (3) and (4) in Table 3.7 regress the companies' names abnormal SVI on the *Red Carpet* dummy variable, the *Nominated Red Carpet* dummy variable, and the *News* dummy variable. Our results are robust after controlling for company news and nominees dummies. That is, we still observe an increasing attention to the companies that provide an outfit to any actress on the Oscars red carpet and no effect for men.

Overall, we do not find any evidence that including company-specific news significantly changes our results.

Endorsement Contracts

Some celebrities may have signed an endorsement contract with a specific brand. That is, for major events, this celebrity is required to choose and wear an outfit provided by the brand company. Our *Red Carpet* dummy may be influenced by such contracts. In our sample, we observe 20 celebrity-brand contracts spanning the sample period. To control for existing endorsement contracts, we create an additional dummy variable *Endorsement* that equals one if one of the celebrities present on the red carpet has an endorsement contract with the company.

Table 3.12 and Table 3.13 report the results for Hypothesis 1 and Hypothesis 2, respectively.

Column (1) in Table 3.12 shows that the coefficient for the *Red Carpet* dummy variable remains statistically significant with a similar economic magnitude for the womenswear sample after controlling for endorsement contracts. Column (2) in Table 3.12 shows that the coefficient for the *Red Carpet* dummy variable for the menswear sample remains insignificant.

Overall, controlling for preexisting endorsement contracts between celebrities and companies does not significantly impact our evidence. We continue to observe that companies providing an outfit to any actress present on the red carpet still exhibit higher CARs than their peers, thus experiencing a positive shock to their brand capital.

3.6 Conclusion

Using the Oscars ceremony as an exogenous shock to brand capital, we analyze how quickly this information is incorporated into financial market outcomes. In particular, by collecting data on the red carpet outfits, we show that companies that provide dresses to actresses earn higher CARs after controlling for firm factors, company-specific news, and endorsement contracts. We document that CARs are influenced by changes in the brand capital. Based on Google search trends, we also show that the award ceremony has a positive impact on investor attention.

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Table 3.1: Sample selection

This table contains the filters used to construct the final sample. The 187 final observations are at the company level. That is, in case of two celebrities wearing brands owned by the same company, the dummy variable for red carpet equals one. The total number of holding companies is 17 for a sample period of 12 years (2008-2019).

Academy Awards guests	1,573
- Outfits not covered in the media	614
= Matched Academy Awards outfits-guests	959
- Multiple designers	14
- Private companies	594
- Uncertain match	15
= Matched Academy Awards outfits-companies	336
Matched Academy Awards outfits-companies with stock prices data available	336
- Excluding Christian Dior S.A.	46
- Excluding Nike, Inc.	1
= Total outfits-companies match	289
Total outfits-companies match	289
Which of women outfits	146
Which of men outfits	143
Outfits to only women (excluding duplicates)	27
+ Outfits to only men (excluding duplicates)	28
+ Outfits to both women and men (excluding duplicates)	30
+ Not provided outfits (excluding duplicates)	102
= Total observations in the sample (excluding duplicates)	187
Unique number of companies	17
Time period	12 years

Table 3.2: Variable definitions

Variable	Definition	Source	Formula
		Dependent variables: CAR and CASVI	
AR	Abnormal return in excess of a market model (based on the MSCI Europe)	Eikon	$AR_{i,t} = R_{i,t} - \tilde{R}_{i,t}$
CAR (-1,+1)	Three-day cumulative abnormal return centered around the Academy Awards ceremony	Eikon	$CAR_i = \sum_{t=-1}^{T=1} AR_{i,t}$
Abnormal Search Volume Index (ASVI)	Abnormal Google search volume index	Google	$Abn.SVI_{i,t} = ln\Big(1 + \frac{SVI_{i,t} - median(SVI_{i,t,\text{same day-of-the-week, previous 10 weeks}})}{median(SVI_{i,t,\text{same day-of-the-week, previous 10 weeks}})}\Big)$
Cumulative Abnormal Search Volume Index (CASVI)	Cumulative sum of the Abnormal Search Volume Index over the Academy Awards weekend	Google	$CASVI = \sum_{t=-1}^{T=1} Abn.SVI_{i,t}$
		Oscars variables	
Red Carpet (1/0)	Dummy variable for providing an outfit	Hand-Collected outfits data	= 1 if the company provided an outfit to a guest, 0 otherwise
Nominated Red Carpet (1/0)	Dummy variable for providing an outfit to an Academy Awards nominee	Hand-Collected outfits data	= 1 if the company provided an outfit to a nominee, 0 otherwise
		Company-specific variables	
Book-to-Market	Previous year common Shareholders' equity divided by the market cap of the firm	Compustat	$= at/(csho \cdot prc)$
Size	Previous year ln of assets	Compustat	$= log(at)$
		Other variables	
News (1/0)	Dummy variable for company-specific news	LexisNexis	= 1 if the company announced relevant news, 0 otherwise
Endorsement (1/0)	Dummy variable for existing endorsement contract between the company and the guest	celebrityendorsementads.com celebrityendorsers.com	= 1 if an endorsement contract exists, 0 otherwise

Table 3.3: Summary statistics

This table provides the summary statistics of our sample. The sample contains 187 observations for 17 different companies during the period 2008-2019. Panel A contains the full sample whether a company provided an outfit to an actress or not. Panel B contains the full sample whether a company provided an outfit to an actor or not.

Variable	Mean	Median	SD	Nr. Obs
Panel A: Complete Sample - Womenswear				
CAR (-1,+1)	0.00	0.07	2.85	187
Red Carpet	0.31	0.00	0.46	187
Nominated Red Carpet	0.16	0.00	0.36	187
CASVI	-0.01	-0.05	0.40	187
Book-to-Market	0.73	0.40	0.81	187
Size	8.11	7.82	1.65	187
Panel B: Complete Sample - Menswear				
CAR (-1,+1)	0.00	0.07	2.85	187
Red carpet	0.31	0.00	0.46	187
Nominated Red Carpet	0.14	0.00	0.35	187
CASVI	-0.01	-0.05	0.40	187
Book-to-Market	0.73	0.40	0.81	187
Size	8.11	7.82	1.65	187

Table 3.4: Three-day market reaction for the womenswear sample

This table reports the results of the regression models for three-day CARs. The final sample contains 187 company-level observations during the period 2008-2019 for womenswear. CARs are estimated using a market model (MSCI Europe) with an estimation window between 200 and 60 days prior to the Academy Awards ceremony. CARs are regressed on Red Carpet (a dummy that takes a value of one if the company provides an outfit to an actress), Book-to-Market, Size, year fixed effects, and company-level fixed effects. Column (1) reports the results centered around the Academy Awards ceremony weekend. Column (2) and Column (3) are placebo tests where the date of the Academy Ceremony is moved one week earlier (Column (2)) or one week later (Column (3)). The Adjusted-R^2 is reported along with the F-Statistic. Standard errors are reported below in parentheses and are robust to heteroskedasticity. Symbols ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

	CAR [-1,+1]		
	Weekend Oscars ceremony	One week earlier	One week later
	(1)	(2)	(3)
Red Carpet	1.12^{*}	-0.44	-1.10
	(0.66)	(0.58)	(0.72)
Book-to-Market	0.32	0.22	2.56^{***}
	(0.64)	(0.73)	(0.62)
Size	0.02	2.64^{***}	-3.57^{***}
	(0.77)	(0.86)	(0.92)
Intercept	-3.08	-11.37^{**}	12.72^{**}
	(4.80)	(5.20)	(6.38)
Observations	187	187	187
Year FE	Yes	Yes	Yes
Company FE	Yes	Yes	Yes
Adjusted-R^2	0.08	0.10	0.28
F-Statistic	1.52^{*}	1.69^{**}	3.46^{***}

Table 3.5: Three-day market reaction for the womenswear sample, including Nominated Red Carpet

This table reports the results of the regression models for three-day CARs. The final sample contains 187 company-level observations during the period 2008-2019 for womenswear. CARs are estimated using a market model (MSCI Europe) with an estimation window between 200 and 60 days prior to the Academy Awards ceremony. CARs are regressed on Red Carpet (a dummy that takes a value of one if the company provides an outfit to a woman), Nominated Red Carpet (a dummy that takes a value of one if the company provides an outfit to a female Academy Awards nominee), Book-to-Market, Size, year fixed effects, and company-level fixed effects. Column (1) reports the results centered around the Academy Awards ceremony weekend. Column (2) and Column (3) are placebo tests where the date of the Academy Ceremony is moved one week earlier (Column (2)) or one week later (Column (3)). The Adjusted-R^2 is reported along with the F-Statistic. Standard errors are reported below in parentheses and are robust to heteroskedasticity. Symbols ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

	CAR [-1,+1]		
	Weekend Oscars ceremony	One week earlier	One week later
	(1)	(2)	(3)
Red Carpet	1.49*	−0.68	−1.49
	(0.82)	(0.57)	(1.02)
Nominated Red Carpet	−0.76	0.02	−0.10
	(0.79)	(0.65)	(0.95)
Book-to-Market	0.30	0.55	5.12***
	(0.64)	(0.49)	(1.57)
Size	0.03	2.31***	−5.79***
	(0.77)	(0.81)	(1.63)
Intercept	−3.06	−12.03**	18.68**
	(4.86)	(4.83)	(7.57)
Observations	187	187	187
Year FE	Yes	Yes	Yes
Company FE	Yes	Yes	Yes
Adjusted-R^2	0.08	0.13	0.46
F-Statistic	1.50*	1.91***	6.03***

Table 3.6: Cumulative Abnormal Search Volume Index

This table reports the results of the regression models of CASVI centered around the Academy Awards ceremony. The final sample contains 187 company-level observations during the period 2008-2019 for womenswear (Column (1) and Column (2)) and menswear (Column (3) and Column (4)). The CASVI is estimated as the sum of the ASVI for each day over the Academy Awards weekend. The company-level CASVI is regressed on Red Carpet (a dummy that takes a value of one if the company provides an outfit), News (a dummy variable that takes a value of one if the company released additional information during the week), and year fixed effects. Column (1) reports the results for womenswear and Column (2) reports the results for menswear. Both columns exclude the News variable. Column (3) and Column (4) report, respectively, the results for womenswear and menswear, including the News variable but removing year fixed effects. The Adjusted-R^2 is reported along with the F-Statistic. Standard errors are reported below in parentheses. Symbols ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

	CASVI		CASVI	
	Womenswear	Menswear	Womenswear	Menswear
	(1)	(2)	(3)	(4)
Red Carpet	0.16***	−0.08	0.16**	−0.09
	(0.06)	(0.05)	(0.06)	(0.07)
News			0.02	0.04
			(0.11)	(0.11)
Intercept	−0.07	0.01	−0.06*	0.02
	(0.11)	(0.05)	(0.04)	(0.04)
Observations	187	187	187	187
Year FE	Yes	Yes	No	No
Adjusted-R^2	0.04	0.01	0.02	−0.01
F-Statistic	1.68*	1.20	3.19**	0.88

Table 3.7: Cumulative Abnormal Search Volume Index, including Nominated Red Carpet

This table reports the results of the regression models of CASVI centered around the Academy Awards ceremony. The final sample contains 187 holding-level observations during the period 2008-2019 for womenswear (Column (1) and Column (2)) and menswear (Column (3) and Column (4)). The CASVI is estimated as the sum of the ASVI for each day over the Academy Awards weekend. The company-level CASVI is regressed on Red Carpet (a dummy that takes a value of one if the company provides an outfit), Nominated Red Carpet (a dummy variable that takes a value of one if the company provides an outfit to an Academy Awards nominee), News (a dummy variable that takes a value of one if the company released additional information during the week), and year fixed effects. Column (1) reports the results for womenswear and Column (2) reports the results for menswear. Both columns exclude the News variable. Column (3) and Column (4) report, respectively, the results for womenswear and menswear, including the News variable but removing year fixed effects. The Adjusted-R^2 is reported along with the F-Statistic. Standard errors are reported below in parentheses. Symbols ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

	CASVI		CASVI	
	Womenswear	Menswear	Womenswear	Menswear
	(1)	(2)	(3)	(4)
Red Carpet	0.09**	0.03	0.07**	0.02
	(0.05)	(0.04)	(0.03)	(0.04)
Nominated Red Carpet	0.14	−0.01	0.17	0.05
	(0.12)	(0.05)	(0.15)	(0.05)
News			0.04	0.01
			(0.04)	(0.04)
Intercept	−0.08	−0.07	−0.06***	−0.09*
	(0.05)	(0.05)	(0.02)	(0.05)
Observations	187	187	187	187
Year FE	Yes	Yes	No	No
Adjusted-R^2	0.05	0.01	0.03	−0.01
F-Statistic	1.68*	1.03	3.05**	0.54

Table 3.8: Three-day market reaction for the menswear sample

This table reports the results of the regression models for three-day CARs. The final sample contains 187 company-level observations during the period 2008-2019 for menswear. CARs are estimated using a market model (MSCI Europe) with an estimation window between 200 and 60 days prior to the Academy Awards ceremony. CARs are regressed on Red Carpet (a dummy that takes a value of one if the company provides an outfit to a man), Book-to-Market, Size, year fixed effects, and company-level fixed effects. Column (1) reports the results centered around the Academy Awards ceremony weekend. Column (2) and Column (3) are placebo tests where the date of the Academy Ceremony is moved one week earlier (Column (2)) or one week later (Column (3)). The Adjusted-R^2 is reported along with the F-Statistic. Standard errors are reported below in parentheses and are robust to heteroskedasticity. Symbols ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

	CAR [-1,+1]		
	Weekend Oscars ceremony	One week earlier	One week later
	(1)	(2)	(3)
Red Carpet	0.38	0.52	0.85
	(0.46)	(0.49)	(0.60)
Book-to-Market	0.41	0.27	5.19***
	(0.65)	(0.73)	(1.45)
Size	0.26	2.54***	−6.13***
	(0.80)	(0.84)	(1.55)
Intercept	−3.95	−11.15**	19.62***
	(4.95)	(5.10)	(7.06)
Observations	187	187	187
Year FE	Yes	Yes	Yes
Company FE	Yes	Yes	Yes
Adjusted-R^2	0.06	0.10	0.45
F-Statistic	1.41*	1.70**	6.08***

Table 3.9: Three-day market reaction for the menswear sample, including Nominated Red Carpet

This table reports the results of the regression models of CARs centered around the Academy Awards ceremony. The final sample contains 187 company-level observations during the period 2008-2019 for menswear. CARs are estimated using a market model (MSCI Europe) with an estimation window between 200 and 60 days prior to the Academy Awards ceremony. CARs are regressed on Red Carpet (a dummy that takes a value of one if the company provides an outfit to a man), Nominated Red Carpet (a dummy that takes a value of one if the company provides an outfit to a male Oscars nominee), Book-to-Market, Size, year fixed effects, and company-level fixed effects. Column (1) reports the results centered around the Academy Awards ceremony weekend. Column (2) and Column (3) are placebo tests where the date of the Academy Ceremony is moved one week earlier (Column (2)) or one week later (Column (3)). The Adjusted-R^2 is reported along with the F-Statistic. Standard errors are reported below in parentheses and are robust to heteroskedasticity. Symbols ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

	CAR [-1,+1]		
	Weekend Oscars ceremony	One week earlier	One week later
	(1)	(2)	(3)
Red Carpet	0.53	0.44	0.93
	(0.44)	(0.53)	(0.70)
Nominated Red Carpet	−0.45	−0.10	−1.01
	(0.77)	(0.63)	(0.88)
Book-to-Market	0.39	0.58	2.57***
	(0.65)	(0.51)	(0.60)
Size	0.24	2.16***	−3.84***
	(0.80)	(0.78)	(0.93)
Intercept	−3.86	−11.61**	13.59**
	(4.90)	(4.85)	(6.30)
Observations	187	187	187
Year FE	Yes	Yes	Yes
Company FE	Yes	Yes	Yes
Adjusted-R^2	0.06	0.13	0.28
F-Statistic	1.37	1.87***	3.30***

Table 3.10: Three-day market reaction centered around the Academy Awards ceremony, including News

This table reports the results of the regression models of the three-day CARs centered around the Academy Awards ceremony. The final sample contains 187 company-level observations during the period 2008-2019 for womenswear (Column (1)) and menswear (Column (2)). CARs are estimated using a market model (MSCI Europe) with an estimation window between 200 and 60 days prior to the Academy Awards ceremony. CARs are regressed on Red Carpet (a dummy that takes a value of one if the company provides an outfit), News (a dummy variable that takes a value of one if the company released additional information during the week), Book-to-Market, Size, year fixed effects, and company-level fixed effects. The Adjusted-R^2 is reported along with the F-Statistic. Standard errors are reported below in parentheses and are robust to heteroskedasticity. Symbols ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

	CAR [-1,+1]	
	Womenswear	Menswear
	(1)	(2)
Red Carpet	1.12*	0.37
	(0.66)	(0.48)
News	0.24	0.21
	(1.03)	(1.04)
Book-to-Market	0.32	0.40
	(0.65)	(0.67)
Size	−0.01	0.24
	(0.77)	(0.80)
Intercept	−2.99	−3.88
	(4.83)	(4.97)
Observations	187	187
Year FE	Yes	Yes
Company FE	Yes	Yes
Adjusted-R^2	0.07	0.06
F-Statistic	1.46*	1.36

Table 3.11: Three-day market reaction centered around the Academy Awards ceremony, including Nominated Red Carpet and News

This table reports the results of the regression models of the three-day CARs centered around the Academy Awards ceremony. The final sample contains 187 company-level observations during the period 2008-2019 for womenswear (Column (1)) and menswear (Column (2)). CARs are estimated using a market model (MSCI Europe) with an estimation window between 200 and 60 days prior to the Academy Awards ceremony. CARs are regressed on Red Carpet (a dummy that takes a value of one if the company provides an outfit), Nominated Red Carpet (a dummy variable that takes a value of one if the company provides an outfit to an Academy Awards nominee), News (a dummy variable that takes a value of one if the company released additional information during the week), Book-to-Market, Size, year fixed effects, and company-level fixed effects. The Adjusted-R^2 is reported along with the F-Statistic. Standard errors are reported below in parentheses and are robust to heteroskedasticity. Symbols ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

	CAR [-1,+1]	
	Womenswear	Menswear
	(1)	(2)
Red Carpet	1.48*	0.52
	(0.83)	(0.45)
Nominated Red Carpet	−0.74	−0.45
	(0.80)	(0.77)
News	0.15	0.19
	(1.03)	(1.04)
Book-to-Market	0.29	0.39
	(0.65)	(0.66)
Size	0.02	0.23
	(0.76)	(0.79)
Intercept	−3.01	−3.80
	(4.88)	(4.93)
Observations	187	187
Year FE	Yes	Yes
Company FE	Yes	Yes
Adjusted-R^2	0.07	0.05
F-Statistic	1.44*	1.32

Table 3.12: Three-day market reaction centered around the Academy Awards ceremony, including Endorsement

This table reports the results of the regression models of the three-day CARs centered around the Academy Awards ceremony. The final sample contains 187 company-level observations during the period 2008-2019 for womenswear (Column (1)) and menswear (Column (2)). CARs are estimated using a market model (MSCI Europe) with an estimation window between 200 and 60 days prior to the Academy Awards ceremony. CARs are regressed on Red Carpet (a dummy that takes a value of one if the company provides an outfit), Endorsement (a dummy variable that takes a value of one if the guest has signed an endorsement contract with the company), Book-to-Market, Size, year fixed effects, and company-level fixed effects. The Adjusted-R^2 is reported along with the F-Statistic. Standard errors are reported below in parentheses and are robust to heteroskedasticity. Symbols ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

	CAR [-1,+1]	
	Womenswear	Menswear
	(1)	(2)
Red Carpet	1.21*	0.41
	(0.66)	(0.47)
Endorsement	−1.03	−0.56
	(0.85)	(1.75)
Book-to-Market	0.29	0.42
	(0.64)	(0.66)
Size	−0.03	0.27
	(0.77)	(0.80)
Intercept	−2.87	−4.04
	(4.78)	(4.96)
Observations	187	187
Year FE	Yes	Yes
Company FE	Yes	Yes
Adjusted-R^2	0.07	0.05
F-Statistic	1.43*	1.31

Table 3.13: Three-day market reaction centered around the Academy Awards ceremony, including Endorsement Nominated Red Carpet

This table reports the results of the regression models of the three-day CARs centered around the Academy Awards ceremony. The final sample contains 187 company-level observations during the period 2008-2019 for womenswear (Column (1)) and menswear (Column (2)). CARs are estimated using a market model (MSCI Europe) with an estimation window between 200 and 60 days prior to the Academy Awards ceremony. CARs are regressed on Red Carpet (a dummy that takes a value of one if the company provides an outfit), Nominated Red Carpet (a dummy that takes a value of one if the company provides an outfit to an Academy Awards nominee), Endorsement (a dummy variable that takes a value of one if the guest has signed an endorsement contract with the company), Book-to-Market, Size, year fixed effects, and company-level fixed effects. The Adjusted-R^2 is reported along with the F-Statistic. Standard errors are reported below in parentheses and are robust to heteroskedasticity. Symbols ***, **, and * denote significance at the 1%, 5%, and 10% level, respectively.

	CAR [-1,+1]	
	Womenswear	Menswear
	(1)	(2)
Red Carpet	1.55*	0.54
	(0.81)	(0.45)
Nominated Red Carpet	−0.71	−0.41
	(0.79)	(0.77)
Endorsement	−0.94	−0.41
	(0.90)	(0.77)
Book-to-Market	0.27	0.40
	(0.64)	(0.66)
Size	−0.01	0.25
	(0.76)	(0.80)
Intercept	−2.87	−3.94
	(4.84)	(4.92)
Observations	187	187
Year FE	Yes	Yes
Company FE	Yes	Yes
Adjusted-R^2	0.07	0.06
F-Statistic	1.48*	1.36

Essays on Empirical Corporate Finance

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